Political Distortions and Infrastructure Networks in China: A Quantitative Spatial Equilibrium Analysis*

Simon Alder — UNC Chapel Hill

Illenin Kondo — University of Notre Dame

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Abstract

Using the timing of China's highway network construction and political leadership cycles, we document systematic political distortions in the road infrastructure network: the birthplaces of the top officials who were in power during the network's implementation are closer to the actual network, compared to the counterfactual optimal network in a quantitative spatial general equilibrium model. We then use the model to quantify the aggregate costs of distortions in the highway network. Overall, compared to the actual highway network, aggregate income is 1.45 percent higher with the heuristic optimal network and political distortions account for a substantial part of this welfare loss.

Keywords: Transport infrastructure, China, political distortions, network design, internal trade, regional favoritism.

JEL classification: O18, D72, R12, R13, R42, F15, H54.

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1 Introduction

Are national infrastructure investments allocated efficiently? If not, is the distortion due to political factors and what are the aggregate costs of these distortions? With transportation investments accounting for a large fraction of public investments, identifying the determinants of its distortions and quantifying their effects are important questions for policymakers, governments, and international funding organizations. But these questions are also notoriously difficult to answer, one reason being that it is challenging to determine the efficient benchmark against which to compare actual transport network designs. Another difficulty is to quantify the aggregate welfare costs of distortions in the presence of general equilibrium and network effects.

We tackle these problems using a combination of spatial equilibrium modeling and detailed biographical data on politicians. We focus on China, which has undertaken considerable large-scale infrastructure projects, and where top politicians play a key role in the country's centralized economic planning. We use the construction of the National Trunk Highway System (NTHS), a $120 billion project that was launched by the national government in 1992 with the official objective of connecting all provincial capitals and all cities with a population of at least 500,000 (Faber, 2014). This project led to a vast network of 35,000 km of modern highways that was largely completed by 2007.

We ask three questions: i) was this network designed optimally? ii) are the deviations between the actual and optimal networks associated with political factors? iii) what are the aggregate welfare costs of these political distortions? Since the network had a clearly specified objective, we know which cities had to be connected. However, the paths of the highways may make a detour to better serve or connect a city that is neither economically nor geographically well suited to be part of the network. Such a deviation could occur if there is a political bias in favor of that city, for example because it is well connected to the political elite.

Such political bias in our context could be akin to *regional political favoritism*. There is a large literature documenting how political connections can affect public good provision such as road construction. A common form of regional favoritism is that politicians allocate more resources to their home region or their own ethnicity. For example, Hodler and Raschky (2014) find that the birthplaces of political leaders experience systematically higher light intensity than other locations, using a large global panel data set with more than 38,000 subnational regions. Burgess et al. (2015) find that Kenyan districts receive significantly more road expenditures during years when the president is from their own ethnicity. There could be several reasons why the home regions of top politicians may be favored (see for example the extensive review by Golden and Min, 2013). The existing literature also suggests that politicians' connections to powerful leaders and factions of the Chinese Communist Party (CCP) matter for their promotion (see for example Shih et al., 2012). While we do not uncover specific channels of political favoritism in infrastructure investments, we provide novel evidence on political distortions in a major infrastructure project in the context of a large, fast-growing, and centrally-planned economy like China.

Our analysis hinges on two key ingredients. First, we measure the extent to which the NTHS is distorted by comparing it to the optimal network approximation in a spatial equilibrium model. We use a heuristic approximation algorithm similar to Alder (2017) in order to search for the welfare-maximizing network, taking into account the benefits of roads (gains from trade resulting from lower trade costs) and topographical road construction costs. Finding the optimal transport network in the standard spatial equilibrium model used here is challenging because it is not a convex optimization problem and it is infeasible to compare all possible network designs.[1] The heuristic algorithms typically used in the network design literature do not account for general equilibrium effects such as trade diversion, but Alder (2017) proposes a way to combine the heuristic algorithms with a standard spatial equilibrium model. We find that, while the approximation of the optimal network overall has a relatively similar structure to the actual NTHS, there are many deviations that imply that some locations have better access with one network than with the other. The approximation of the optimal network would imply 1.45% higher aggregate GDP per year, net of road construction costs.

Second, we rely on detailed biographical data on Chinese politicians, including their place of birth and their government positions. This data is obtained from China Vitae (2016), which contains biographical data as far back as 1940 on nearly 5,000 Chinese politicians. We focus on the top-ranking politicians in the hierarchy of the Chinese Communist Party (CCP). Specifically, we focus on politicians who held the position of Politburo member, provincial CPC secretary, or provincial governor.[2] We match their birthplaces with the counties from the Census maps, which allows us to geo-code the birthplaces.[3] We can then compute the distance of each county to the actual and optimal highway network; and the difference

[1] Recent work by Felbermayr and Tarasov (2015); Allen and Arkolakis (2016); Fajgelbaum and Schaal (2017) also consider the problem of transport network designs in spatial equilibrium models and we discuss the different approaches below.

[2] Consistent with the structure of the CPC, we treat the mayors and the secretaries of the CPC in the main municipalities of Beijing, Chongqing, Shanghai, and Tianjin as province-level officials.

[3] We used multiple Chinese speaking research assistants to manually verify and match the birthplaces of nearly 400 politicians who held a top-level position in our data set. We are able to match around 75 percent of these birthplaces to a county. When politicians are born in a very large city, typically a prefecture-level city, the county-level match is difficult. The results are also similar when we use an automated name-matching algorithm.

between the two distances captures the extent to which the actual network is distorted.[4]

Our test of whether the NTHS is biased due to political distortions is implemented in a reduced-form regression of the difference between a county's distance to the optimal and actual network on an index for whether this county is the birthplace of a politician who was in office during the planning and implementation phase of the network. We find that there is a statistically significant relationship between the difference of a county's deviation away from the optimal network and the index for place of birth. This suggests that part of the deviation between the two networks can be explained by political factors.

An obvious concern is that there are unobserved characteristics of counties that might matter for how the network was built and that these characteristics are correlated with our explanatory variable for politicians' birthplaces. An example could be the location of universities, which i) may make it more likely that a native of that county has a successful political career; ii) could imply that the county has a high economic potential such that benevolent planners would want to connect it to the new highway network. However, this concern is mitigated by the time variation that we can exploit based on the period when a politician is in power. We restrict our measure of political access (i.e. place of birth of a top politician) to politicians who were in office during the planning and implementation phase of the NTHS. When we include as a placebo an index for the place of birth of politicians who came to power after the completion of the NTHS, we find that it is not significantly correlated with the proximity to the network. The insignificant placebo effect, together with the significant effect of the birthplace of incumbent politicians during planning and construction, suggest that the main effect is not driven by unobserved time-invariant heterogeneity across politicians or birthplaces.

The reduced-form evidence shows that the birthplaces of Chinese officials alters the allocation of transport infrastructure investments. Since the birthplaces of politicians does not explain the entire deviation between the actual and optimal network, we cannot attribute the entire difference of 1.45% in aggregate GDP to the political friction. However, we can use the spatial equilibrium model and the heuristic network design algorithm to construct counterfactual networks with and without the political friction, and then compute the implied aggregate welfare.

In order to construct this counterfactual network, we identify birth counties that are distorted in their network access. We then use the heuristic optimal network design algorithm to construct a 'politically-distorted 'counterfactual network: a network that is optimal

[4]This approach is naturally prone to model misspecification: the actual network might be optimal or less distorted under in the true model. Nonetheless, our findings suggest that, through the lens of a workhorse model, there are deviations from the optimal benchmark and that these deviations are systematically related to political factors. We call these deviations *political* distortions.

under the additional constraint that these 'birthplaces' are connected. To capture the aggregate cost of the political distortions, we compare the aggregate welfare of this politically-constrained 'optimal' network to the welfare in the 'optimal' network where these birthplaces do not have to (but could) be connected.[5] Our results suggest that about one-seventh of the income difference between the actual and optimal network is due to the political distortion.

Finally, we show that the effects of political distortions may be much larger due to amplifications channels absent in the workhorse model. Using light data, we show that birthplaces with politically-driven proximity to the network experience less light growth.

Related Literature Our paper contributes to several strands in the literature, including spatial equilibrium analysis of transport infrastructure, network design, and distributive politics such as regional favoritism. We contribute to the literature on quantitative optimal infrastructure networks by documenting the systematic presence of political distortions. We also contribute to the literature on the political economy of public good provision in the context of a large-scale infrastructure project in one of the world's largest centrally-planned system. The growth of quantitative models of trade in the spirit of Eaton and Kortum (2002) has motivated increased attention to the nature of transportation costs intra- and inter-nationally. Various papers embed a realistic structure of transportation networks in these models in order to estimate the welfare effects of infrastructure networks.[6]

Yet, the design of optimal infrastructure networks has remained a difficult combinatorial problem and as a result very few papers tackle the optimality of the transportation network. Alder (2017) introduces a heuristic recursive search algorithm that reduces the dimensionality of the problem by iteratively forming the optimal network using general equilibrium and network effects in a workhorse spatial trade model à la Donaldson and Hornbeck (2016). This paper uses this framework to construct the benchmark optimal network that meets the official target of the NTHS. Fajgelbaum and Schaal (2017) recently show the analytical and computational tractability of an alternative optimal network formulation nesting a large class of spatial and trade models. Fajgelbaum and Schaal (2017) circumvent the dimensionality issue by introducing congestion frictions and a continuous choice in the level of infrastructure of a specified set of connection or edges. Felbermayr and Tarasov (2015) propose and characterize another formulation that circumvents the dimensionality of the optimal network problem by considering a continuous space, a set of locations on a line.

This paper is also related to the political economy literature on 'regional favoritism' and

[5]Note that the heuristic network design algorithm finds local optima. It is not guaranteed that it converges to the global optimum, but simulations in Alder (2017) show random starting points yield similar net incomes.

[6]See for example Allen and Arkolakis (2014, 2016) for an application to the U.S. highway network and Redding and Rossi-Hansberg (2017) for an overview of quantitative spatial equilibrium approaches.

'distributive politics'. Hodler and Raschky (2014) provide evidence of increased nighttime light intensity in the birth regions of incumbent political leaders, especially in countries with weak political institutions. Golden and Min (2013) provide a detailed review of the literature on distributive politics. Of its 150 surveyed papers, only one is on China: Su and Yang (2000) create an index of provincial representation in the political center and estimate its positive effects on the share of state construction investment between 1978 and 1994. Our paper offers novel evidence on infrastructure distortions using detailed data on the timing of a large-scale infrastructure project, an optimal network benchmark, and biographical data on Chinese politicians. Jia et al. (2015) similarly used biographical data and local economic data to document how both patronage motives and meritocratic factors shape the promotion of Chinese provincial leaders. Shih et al. (2012) also suggest patronage motives and connections are prevalent in the promotion of top Chinese political leaders.

Burgess et al. (2015) use a political economy model to rationalize ethnic favoritism and empirically document ethnic favoritism in the observed road spending in Kenya. They find that, compared to a benchmark network that connects locations based on a measure of market potential, the actual network favors the regions that share the ethnicity of the incumbent president in Kenya.[7] Kahn et al. (2018) study how social connections between politicians affect the decision where industrial parks are located in China. They show that a principle-agent problem arises between the central government and provincial politicians because the latter tend to favor locations to which they have a social connection and this leads to a misallocation of parks. We differ from these approaches by approximating the economically optimal infrastructure network based on a spatial general equilibrium model, which also allows us to quantify the aggregate cost of the distortion.

Jedwab and Storeygard (2017) study economic and political factors in infrastructure investment across 43 sub-Saharan African countries. Jaworski and Kitchens (2016) analyze highways in the US and compare the effects of the built network with historical highway plans that were subsequently altered because of political factors. Frye (2016) estimates the effects of the US highway system on employment. He uses an algorithm from network theory that ranks links by how many shortest paths go through them, which captures how important each link is. He then uses this as an instrument for the timing of highway construction. Glaeser and Ponzetto (2017) study in a theoretical model how voters' information about project costs affects political decisions on investments. Voigtländer and Voth (2014) show how highway construction was used by Hitler to gain political support in Germany. We focus

[7] The authors calculate market potential as the sum of the populations of a location pair divided by their Euclidian distance. Such a measure of market potential is conceptually related to market access in our model, but the measure of market potential does not capture endogenous general equilibrium and network effects.

on the design of the transport network to construct a benchmark and use data on political connections together with a spatial general equilibrium model to quantify the aggregate distortion.

Finally, our paper is related to the literature on the effects of infrastructure on growth in China. In particular, Faber (2014) documents the growth reducing effects of the advent of the NTHS on non-targeted peripheral counties in China using the minimum spanning tree as an instrument. We document a systematic distortion away from the minimum spanning tree that is correlated with incumbent politician birthplaces. We also find evidence of reduced growth in these incumbent politician birthplaces.[8] Baum-Snow et al. (2017) use comprehensive data on transport infrastructure and city growth in China. They find that highways and railroads led to a decentralization of population and industrial output of Chinese cities. Roberts et al. (2012) quantify the effect of Chinese highway network using a New Economic Geography Model across Chinese prefectures. Tombe and Zhu (2017) use a general equilibrium model across Chinese provinces with partial labor mobility and find that reductions in both trade and migration costs contribute to aggregate growth in China. In this paper, we use document political distortions across counties in the implementation of the stated objective of the NTHS and the associated welfare costs in a general equilibrium spatial network similar to the workhorse model of Donaldson and Hornbeck (2016).

2 Data

The aim of this paper is to identify and quantify political distortions in China's NTHS national highway network. This requires detailed geographically coded data on political influence that we then link to the highway network. Furthermore, in order to measure the distortion and quantify its welfare effects, we need to have a model that predicts what the optimal network would have looked like in the absence of the distortion. We therefore use a general equilibrium trade model and design the welfare-maximizing highway network based a heuristic approximation algorithm. This network design problem also requires data on income, topographical information, and a measure of road construction costs. We discuss the different data sources below, but we first highlight key aspects of the NTHS.

[8] Lu and Wang (2016) use detailed firm-level data and new data on the completion dates of NTHS segments to document that incumbent firms in peripheral regions become less productive once connected to the highway system.

2.1 Road Network and Trade Costs

China's National Trunk Highway System The plans for China's NTHS were approved in 1992 and its stated objective was to connect all cities with a population of at least 500,000 and all provincial capitals with modern highways (Faber, 2014). The network was mostly completed by 2007 and consists of about 35,000 km of four-lane highways. The total construction costs were approximately $120 billion. The NTHS was later expanded to include smaller cities, but we focus on the first phase based on the 500,000 threshold. The targeted cities and the resulting network are shown in Figure 1.[9] In addition to the NTHS, we also use maps of the preexisting highway network in 1990 that is available from the MIT Geo Web.[10]

Figure 1: National Trunk Highway System in Mainland China

The black lines show the NTHS that connects the targeted cities (shown in red). The background shows the slope of the terrain of mainland China as a proxy for road construction costs.

Driving Speed and Shortest Path We assume an average driving speed of 120 km/h on the NTHS. The pre-existing national highway network was of lower quality and allowed for

[9] We focus here on the NTHS as discussed in Faber (2014). The modern Chinese highway network is sometimes also referred to as the National Expressway Network (see Alder, 2017).

[10] The highway data is available at `https://geodata.mit.edu/`. The maps of the 2010 national highway network are from ACASIAN (2014).[11] We use the map from 2010 and select the part of the network that correspond to the NTHS.

a driving speed between 80 and 100 km/h.[12] In the following, we will assume that whenever there is a direct NTHS link between two cities, then the driving speed is 120 km/h. Whenever there is no direct NTHS link, then we assume that one needs to travel on a road of lower quality, where the driving speed is 80 km/h, or make a detour to reach the NTHS. This speed assumption is at the lower end of the speed on other national highways, but above the approximately 70 km/h reported for provincial roads. Furthermore, we allow travel on land without roads at a speed 15 km/h. We use a shortest-path algorithm to find the cheapest way to travel from any origin to any destination through the road network. We assume that the shortest path between two cities is chosen based on the travel time. Therefore, the NTHS will not only affect the travel times between the directly connected cities, but it will also affect the travels time between any two cities that use the NTHS as part of the shortest path between them.

Topography and Road Construction Costs In order to determine the path of counterfactual roads and to proxy the road construction costs, we use the shortest paths predicted by the slope of the terrain based on data from Jarvis et al. (2008).[13]

Travel Time and Trade Costs In the general equilibrium trade model, the highway network translates into trade costs and determines bilateral trade flows and the distribution of income across locations. We use a Dijkstra's shortest-path algorithm (Dijkstra, 1959) on a graph in order to find the shortest driving time through the network among all targeted cities.[14] The driving time is then mapped into an iceberg trade cost based on

$$\tau_{ij} = 1 + \omega t_{ij}^{\chi}, \tag{1}$$

where τ_{ij} is the iceberg trade cost between an origin i and a destination j, t_{ij} is the driving time through the road, and ω and χ are scalars. We choose $\chi = 0.8$, which implies that there are some economies of scale in transport and is consistent with the existing literature (see Roberts et al., 2012). The parameter ω governs how the units of time translate to iceberg trade costs and we choose this parameter such that the median iceberg trade cost is 1.25 as in Alder (2017).

[12] The speed assumptions are taken from Faber (2014).

[13] In this case we need to find the shortest path through a surface and we use the fast marching algorithm provided by Kroon and used in Allen and Arkolakis (2014).

[14] Dijkstra's algorithm (Dijkstra, 1959) has been widely applied in the economics literature (see for example Dell, 2015; Donaldson and Hornbeck, 2016). Dijkstra's algorithm is used here to travel through a weighted graph where the weights correspond to the travel times on each link. This is similar to a shortest-path fast marching algorithm through a continuous terrain or a speed map.

The shortest-path algorithm and the assumptions above yield an $N \times N$ matrix of bilateral iceberg trade costs among all N targeted cities. We assume that driving speed is the same in both directions, such that the matrix is symmetric. The targeted cities of the actual network are the 62 cities that fulfill one of the two criteria of being either a provincial capital city or having a population of at least 500,000 in the 1990 census. We will later also include cities that are predicted to be connected because they are birthplaces of high-ranking politicians. Furthermore, for the quantification of the distortion, we will also include a number of cities that could be connected in the counterfactual instead of the political cities.

2.2 China's Political System and Politicians' Birthplaces

Chinese Communist Party The Chinese Communist Party of China (CCP), the largest polity in the world, has a virtual monopoly of power in China. Its structure nests multiple levels of government with a powerful central authority. The CCP structure extends across local townships mapped into nearly two and a half thousand counties, which aggregate to around three hundred municipalities or prefectures that are combined into thirty-one provinces.

The political, economic, and military power is increasingly concentrated across these layers with the highest decision-making body being the Politburo. The Politburo typically consists of twenty to twenty-five members. A smaller inner circle of these Politburo members form the all-powerful Politburo Standing Committee (PSC). The PSC typically consists of five to nine party officials including the General Secretary (the head of the Communist Party), the Premier (the head of the Chinese government), and the chairman of the National People's Congress. Below the Politburo, a national Central Committee of around 200 members sits at the top of the CCP hierarchy. At the provincial level, top leaders include the provincial governor and the provincial party secretary.[15]

Politicians' Birthplaces Using the centralized nature of national policy-making in China, we use data on the birthplace of powerful political leaders to investigate political distortions in the design of a major national infrastructure network, the NTHS. We use the online database China Vitae (2016), which contains extensive biographical details of CCP officials based on Chinese government sources. China Vitae was launched in 2001 and is now operated and maintained by the Carnegie Endowment for International Peace. It contains biographical data on more than 5,000 leaders going as far back as the 8th CCP Congress of 1945–1956.[16]

[15] See Shih et al. (2012) for an excellent discussion of the post-Mao CCP leadership structure and the mechanisms of advancement and promotion.

[16] Jia et al. (2015) also uses this data to study the determinants of the promotion of provincial leaders.

For instance, the former Premier's entry lists his year of birth, his place of birth, and his 40+ career spells at various institutions and locations since joining the CCP.[17]

Local Political Access Measure We extract these biographical data to construct a measure of local political access for each county by aggregating the tenure of local natives in the upper echelon of leadership in a given time period, if any. Using the timing of the planning, approval, and construction of the NTHS[18], we construct the local political access measure for different periods. Table 1 describes the underlying county-level data on the number of politicians in the PSC, or in provincial CCP secretariate, or in provincial governorship who were born in that county.[19]

Table 1: Upper Echelon Native Politicians across Counties

	1992	1997	2002	2007	2012
mean	.021	.023	.029	.034	.033
sd	.151	.153	.171	.190	.191
p95	0	0	0	0	0
p99	1	1	1	1	1
min	0	0	0	0	0
max	2	2	2	2	2
sum	49	53	67	77	76
N	2,289	2,289	2,289	2,289	2,289

In our baseline estimation, in a given period $t = t_1 \ldots t_2$, location i's political access is defined as the period average of the number of its natives that are either PSC members or

[17]In the post-Mao era, changes in leadership roles occur every five years through a carefully orchestrated process, which culminates in a CCP Congress where committee members are selected.

[18]Duncan (2007) documents the implementation of the NTHS and provides details on the planning and construction years. The Government's 9th Five-Year Plan, the 1996-2000 NYFP, called for construct a National Trunk Highway System (NTHS) of expressways linking all cities with a population of more than 500,000 inhabitants and all provincial capitals. Duncan (2007) reports that highway spending quadrupled from 1995 to 1998, partly as a stimulus package in response to the Asian Financial Crisis. Duncan (2007) also documents that 70 percent of the NTHS funding was borrowed against future local or provincial toll revenues, 15 percent from the central government, and the remainder from provincial and local governments. Despite the local funding of the NTHS, implicit financial guarantees from the central government and central network planning justify our focus on the upper level national leaders and provincial leaders in this paper.

[19]We consider the universe of unique 'counties' GB codes from ACASIAN (2014). Some birthplaces were not included as we could not confidently map these China Vitae place names to unique ADM3 GB codes.

provincial governors, if any:[20]

$$\text{Political Access}^i_{t_1,t_2} = \frac{1}{t_2 - t_1 + 1} \sum_{t=t_1}^{t_2} \#\text{politicians born in } i \text{ and `in power' at } t \tag{2}$$

We construct the political access measure for the following time periods: (a) the 1995–2001 period, which is spanned by the 14th and the 15th CCP Central Committee and captures the planning and early implementation period, (b) the 2005–2006 period within the 16th CCP Central Committees that captures the end of the NTHS implementation in 2007, and (c) the 2013–2017 period within the 18th CCP Central Committee that captures the period following the NTHS completion.[21] Descriptive statistics for this measure are shown in Table 2.[22]

Table 2: County-Level Political Access

	early NTHS buildup (14th-15th CCP)	late NTHS buildup (16th CCP)	post NTHS buildup (18th CCP)
mean	.023	.029	.030
sd	.129	.173	.175
p95	0	0	0
p99	.857	1	1
sum	51.9	66.5	69.4
min	0	0	0
max	1.43	2	3
N	2,289	2,289	2,289

Administrative Boundaries We use the administrative boundaries of counties from the 2010 census as provided by ACASIAN (2014) and from China Data Online.

2.3 Income

In order to search for the optimal highway network, we rely on a spatial equilibrium model among the targeted cities. The model takes into account both the trade costs among cities

[20] We also considered network-based measures of local political access using the network structure arising from 'indirect' connections with powerful politicians through overlapping tenures as 'co-workers'. In particular, we used a measure of 'first degree' local political access defined using the natives who worked in the previous three years at the same relatively small institution with a currently powerful politician.

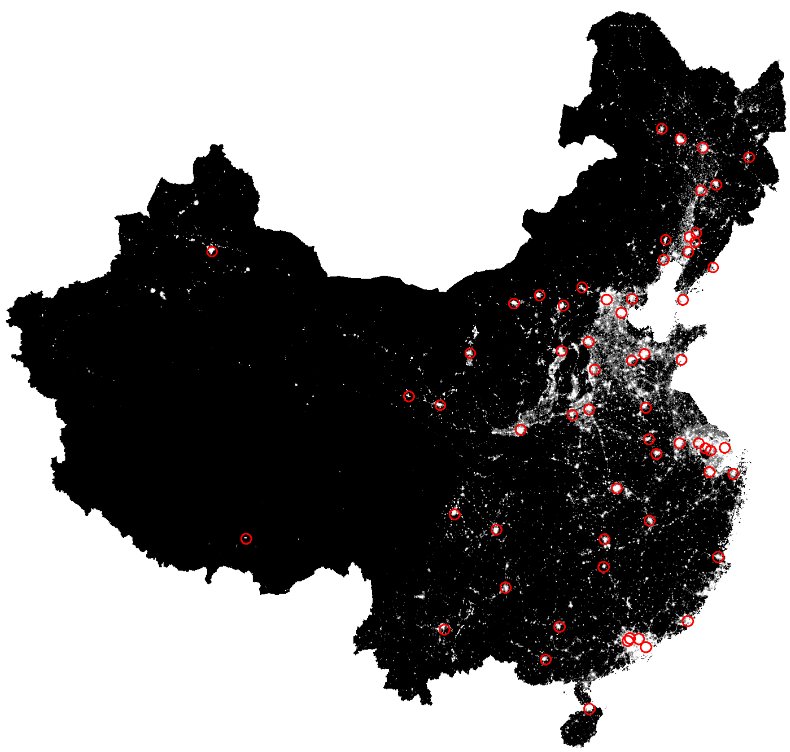
[21] The first two periods start three years after the beginning of the corresponding CCP congress in order to align indirect 'first degree' political access measures to be within the same CCP congress time window.

[22] See also Tables A2, A3, and A4 for the transition matrices in the number of native and incumbent top leaders.

(captured by the travel times through the road network) and their incomes. We use night-time light data from NOAA (2016) as a measure of income because it is available at a spatial resolution of about 1 km, which allows us to measure a city's economic size independent on how administrative boundaries are drawn. Data on lights at night have been used in various contexts and have been shown to correlate strongly with GDP (Henderson et al., 2012). We create buffers of 30 km around each targeted city in the network and then calculate the sum of light within each buffer. The buffers of the targeted cities are shown in Figure 2.

Since the benefits of road construction are measured in terms of light, but we are ultimately interested in the effects on GDP (which we compare with the road construction costs to compute the net gain), we need to translate the light effects to GDP. Using a large panel of countries, Henderson et al. (2012) find a linear relationship between the logarithm of real GDP and the logarithm of light. They estimate an elasticity of around 0.3 and we use this value in order to predict GDP based on lights.

Figure 2: Night light image and targeted cities in mainland China



The maps shows the light density in 1992 and the 30 km buffers around the targeted cities in mainland China.

3 Spatial Equilibrium Model

We use a spatial equilibrium framework in order to design the optimal highway network and then use this as a benchmark against which we can compare the actual network. Furthermore, the equilibrium framework will allow us to quantify the welfare effects of the political distortion. The framework is based on Donaldson and Hornbeck (2016) who use a general equilibrium model of trade among American counties in order to quantify the effect of the expansion of the railway network in the 19th century. Donaldson and Hornbeck (2016) rely on the Eaton and Kortum (2002) model of trade and show that the effect of transport infrastructure can be captured through a measure of market access. As in Alder (2017), we solve the model for real income as measured by light.[23] We assume that population is immobile, because there are restrictions to labor mobility in China due to the Hukou system.[24] We discuss here only the key aspects of the model and refer the reader to Donaldson and Hornbeck (2016) and Alder (2017) for details.

The economy consists of N locations indexed by i and j, denoting the origin and destination of a trade, respectively. Each location produces with a constant returns to scale Cobb-Douglas production function using capital (K), labor (H), and land (L), where capital is the only mobile production factor. The different locations have comparative advantages in the production of different varieties and the productivity follows a Fréchet distribution as in Eaton and Kortum (2002). Trade among locations is subject to an iceberg trade cost. Consumers have CES preferences over varieties and their indirect utility is given by their real income,

$$V(P_i, Y_i) = \frac{Y_i}{P_i}, \tag{3}$$

where P_i is the standard CES price index.

Prices and Market Access The price index can be written as

$$(P_j)^{-\theta} = \kappa_1 \sum_i A_i \left(q_i^{\alpha} w_i^{\gamma}\right)^{-\theta} \tau_{ij}^{-\theta} \equiv CMA_j. \tag{4}$$

θ is the parameter that governs the productivity distribution. q_i is the price of land, w_i is the wage, and α and γ are the corresponding factor shares in the production function. τ_{ij}

[23] Donaldson and Hornbeck (2016) quantify the effect of the railroads through the price of the fixed factor, land.

[24] The cases with full labor mobility (as in Donaldson and Hornbeck (2016)) and no labor mobility (as in this paper) are two extreme cases, with reality somewhere in between. See for example Tombe and Zhu (2017) for a quantitative analysis of labor mobility and trade costs in China and Redding (2016) for a more general analysis.

is the iceberg trade cost. κ contains constants such as the interest rate (which is equalized across locations because of perfect capital mobility). As in Donaldson and Hornbeck (2016) and Redding and Venables (2004), we refer to (4) as 'consumer market access'.

Gravity Eaton and Kortum (2002) show that the trade flow from i to j can be written as

$$X_{ij} = \kappa_1 A_i \left(q_i^{\alpha} w_i^{\gamma}\right)^{-\theta} \tau_{ij}^{-\theta} CMA_j^{-1} Y_j. \tag{5}$$

This is a gravity equation as in many other microfoundations of trade.[25] We can aggregate over destinations and assume balanced trade to obtain a location's income as

$$Y_i = \sum_j X_{ij} = \kappa_1 A_i \left(q_i^{\alpha} w_i^{\gamma}\right)^{-\theta} \sum_j \tau_{ij}^{-\theta} CMA_j^{-1} Y_j. \tag{6}$$

The sum is equal to 'firm market access'. Donaldson and Hornbeck (2016) show that when trade costs are symmetric, then this must equal consumer market access (up to a constant ρ) and they call this simply 'market access' (MA). Hence, income can be written as

$$Y_i = \kappa_1 A_i \left(q_i^{\alpha} w_i^{\gamma}\right)^{-\theta} MA_i, \tag{7}$$

where

$$MA_i = \rho \sum_j \tau_{ij}^{-\theta} MA_j^{-1} Y_j. \tag{8}$$

Real Income In the data, we observe real income as measured by night lights. We therefore write (6) in terms of real income by exploiting the relationship between the price index and market access in (4). Furthermore, we can substitute for the factor prices using the factor shares and income from the Cobb-Douglas production function to obtain real income,

$$Y_i^r = \left(\kappa_2 A_i\right)^{\frac{1}{1+\theta(\alpha+\gamma)}} \left(\frac{\alpha}{L_i}\right)^{\frac{-\theta\alpha}{1+\theta(\alpha+\gamma)}} \left(\frac{\gamma}{H_i}\right)^{\frac{-\theta\gamma}{1+\theta(\alpha+\gamma)}} \left(MA_i\right)^{\frac{1+\theta(1+\alpha+\gamma)}{(1+\theta(\alpha+\gamma))\theta}}, \tag{9}$$

where κ_2 contains κ_1 and ρ. Similarly, market access can be written as

$$MA_i = \rho^{\frac{1+\theta}{\theta}} \sum_j \tau_{ij}^{-\theta} MA_j^{\frac{-(1+\theta)}{\theta}} Y_j^r. \tag{10}$$

Equation (9) shows that income of a location depends on its productivity (A), immobile

[25] See for example Head and Mayer (2014) for a discussion of different microfoundations of the gravity equation.

production factors (L and H), and market access (MA). Equation (10) shows that the effect of transport infrastructure (which affects the shortest paths and thus changes the trade costs τ) affect income through the market access measure. Equations (9) and (10) jointly determine the equilibrium. Furthermore, we assume that capital is perfectly mobile both across domestic locations and internationally.[26]

Market Access and Income Taking the logarithm of equation (9) shows that income can be written as a log linear function of market access with a constant elasticity.

$$\begin{aligned}\ln Y_i^r &= \left(\frac{1}{1+\theta(\alpha+\gamma)}\right)\ln\left(\kappa_2 A_i\right) \\ &+ \left(\frac{-\theta\alpha}{1+\theta(\alpha+\gamma)}\right)\ln\left(\frac{\alpha}{L_i}\right)+\left(\frac{-\theta\gamma}{1+\theta(\alpha+\gamma)}\right)\ln\left(\frac{\gamma}{H_i}\right) \\ &+ \left(\frac{1+\theta(1+\alpha+\gamma)}{(1+\theta(\alpha+\gamma))\theta}\right)\ln\left(MA_i\right). \end{aligned} \tag{11}$$

We will denote the elasticity of income with respect to market access as $\beta = \frac{1+\theta(1+\alpha+\gamma)}{(1+\theta(\alpha+\gamma))\theta}$. This elasticity can be estimated using panel fixed effects that exploits the time variation in market access and income and controls for the fixed characteristics (productivity, land, and labor). For a given β equations (9) and (10) can predict incomes for counterfactual transport infrastructure.[27]

4 Reduced Form Evidence of Political Bias

Our main goal is to estimate the effect of political access on the NTHS design and the resulting welfare costs. We first discuss the intuition behind our approach and then present in detail our empirical strategy and results.

4.1 Intuition on Political Bias and Network Distortions

To illustrate our empirical strategy, we first discuss a simple example where a city is either connected by the network or not, i.e. we abstract from the *distance* to the network. Suppose we know the optimal network structure 'NTHS_{opt}' for achieving the stated goal of connecting

[26]The rental rate of capital is equal to the world interest rate and the price of capital, $r = \bar{r} \times P_K$, where P_K is the price index of the location(s) where capital goods are traded with the rest of the world.

[27]Note that κ_2 contains the nominal interest rate and thus the price of capital, which can depend on trade costs and thus on the network. We will assume that capital is traded with the rest of the world at the national price index and this yields one additional equation besides (9) and (10) that has to be solved in equilibrium.

the cities targeted by the NTHS policy. Such an optimal network would encode all the economic, technical, and financial factors influencing whether or not a location is connected to the NTHS. By contrasting the optimal network with the actual network that was constructed, 'NTHS_{act}', one could tease out the effect of political access on the NTHS implementation.

Let us, for simplicity, define a discrete measure of the deviation in the actual network relative to the optimal network:

$$\Delta\text{NTHS}_{\text{opt,act}}(i) \equiv [\text{NTHS}_{\text{opt}}(i) - \text{NTHS}_{\text{act}}(i)] \in \{-1, 0, +1\}, \tag{12}$$

where $\text{NTHS}_{\text{net}}(i) \in \{0, 1\}$ represents whether location i is a vertex of the network NTHS_{net} or not.

We conjecture that, relative to non-birthplaces, the birthplaces of top politicians are more likely to be connected to the actual NTHS and distorted away from the optimal NTHS benchmark. This idea is illustrated in Table 3, showing higher rates of distorted connections ($\Delta = -1$) and compliant connections ($\Delta = 0$) among birthplaces ($\text{POB}(i) = 1$).[28]

Table 3: A Simple Representation of Connections and Distortions

$\Delta\text{NTHS}_{\text{opt,act}}(i)$ \ $\text{POB}(i)$	0	1
+1	0.35	0.20
0	0.50	0.60
–1	0.15	0.20
sum	1.00	1.00

Building on this intuition, our reduced-form evidence estimates the political bias in the NTHS implementation using the following regression:

$$\Delta\text{NTHS}^i_{\text{opt-act}} = \alpha_0 + \alpha_1 \text{Political Access}^i_{1995\text{–}2001} + \alpha_2 X^i + \varepsilon^i, \tag{13}$$

where $\Delta\text{NTHS}^i_{\text{opt-act}} \equiv \log d(i, \text{NTHS}_{\text{opt}}) - \log d(i, \text{NTHS}_{\text{act}})$ is the (log) distance from location i to the optimal network relative to the actual. The controls $X(i)$ include: various pre-1992 geographic and economic indicators, province-level fixed effects, and the distance from i to the optimal benchmark ($\log d(i, \text{NTHS}_{\text{opt}})$) and to the targeted cities.

Finally, we use the post-NTHS measure – $\text{Political Access}^i_{2008\text{–}2012}$ – as a placebo to check if the effects were simply driven by an intrinsic attribute of the birthplaces of top Chinese

[28] A false positive here is a location that should not have received the direct link to the NTHS according to the optimal network, but it nonetheless did in the actual.

politicians, i.e. by unobserved time-invariant heterogeneity.[29] Before turning to our results, we present our optimal NTHS benchmark.

4.2 A Heuristic Optimal Transport Network Design

In order to measure how politicians might distort the network, we construct a benchmark that reflects what the network could look like in the absence of political distortions. To that aim, we approximate the optimal network in the spatial equilibrium framework of Section 3 using a heuristic network design algorithm. The model predicts how a change in the transport network (and thus a change in the trade costs) affects income across cities. Because it is a general equilibrium framework, it allows us to quantify the aggregate effect on national income and thus the overall benefit of any link in the network. The cost of a link is based on the road construction and maintenance costs and we predict these costs based on the slope of the terrain. Combining the income gains predicted by the model and the road construction costs, we obtain an equation for net income for each network. However, finding the network that maximizes net income is extremely challenging in this framework, because it is a non-convex optimization problem. Intuitively, highway links can be complements in some cases and substitutes in other cases and there is generally no guarantee that the search converges to the global optimum. Furthermore, the combinatorial problem of designing the optimal network among as many as 100 nodes as in our case is so large that it is infeasible to evaluate all possible networks. We therefore rely on a heuristic algorithm similar to Alder (2017) that can be applied to the general equilibrium gravity model used here. Intuitively, the algorithm starts from the full network where all cities are connected to all other cities with a direct modern (NTHS) highway. We then evaluate each link in terms of its effect on income net of road construction costs and remove the least beneficial links. We then check whether there are any empty links that could be added to the network to increase welfare (this could include links that were removed in a previous iteration). Then we remove again the least beneficial links and the algorithm iterates in this fashion and removes and adds links until no further improvements are possible.[30] We discuss these steps in detail below.

[29] One could, for example, expect that cities that tend to be larger or have a university are more likely to produce top politician, but that it also makes sense economically to connect them. The planner, who observes this and maximizes national welfare, might then connect these cities. If we do not observe these characteristics, then we might wrongly attribute the deviation to a political distortion.

[30] Fajgelbaum and Schaal (2017) also consider the problem of designing the optimal transport network, but not in the gravity framework used here. Felbermayr and Tarasov (2015) focus on the optimal distribution of transport infrastructure on a line. Burgess et al. (2015) design networks by sequentially connecting nodes with the highest market potential.

General Equilibrium Income The model in Section 3 predicts a simple relationship between income and market access. Furthermore, we have seen that the effect of transport infrastructure on income is captured by this measure of market access. Donaldson and Hornbeck (2016) show that the framework can be used to predict the effect of counterfactual transport networks. Combining the fixed terms like land, labor, and total factor productivity, we can simplify equation (11) to the following relationship:

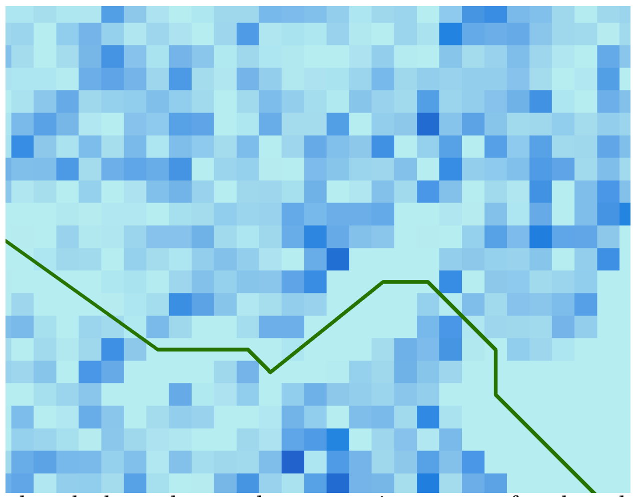
$$Y_i^r = B_i \ (P)^{\frac{-(1-\alpha-\gamma)\theta}{1+\theta(\alpha+\gamma)}} (MA_i)^{\beta} \tag{14}$$

where market access, MA_i, is again given by (10) and P is the price of capital (which is constant across locations but can vary over time and networks). The elasticity of income with respect to market access, β, can be estimated using panel data with variation in trade costs. We do not estimate β for our baseline results and instead use the estimate from Alder (2017) from an Indian highway network. However, we also estimate this elasticity in the appendix using GDP data and the results are similar. Alder (2017) finds an elasticity of light with respect to market access of 0.65. The elasticity of GDP with respect to light is approximately 0.3 (Henderson et al., 2012), which yields an elasticity of GDP with respect to market access of about 0.2.

Recall that the equilibrium market access measures are the solution to (10). For a given network, we determine the iceberg trade costs among all nodes based on a shortest path algorithm as described in Section 2.1. Since we observe both income and travel times with the actual network, we can compute the general equilibrium market access measures and then solve for B_i (productivities and fixed factors) from Equation (14). Holding B_i fixed, one can then compute general equilibrium income for counterfactual networks (i.e. for the implied iceberg trade costs that are derived as the solution to the shortest path problem) by jointly solving Equations (14) and (10). By solving this system of equations, it is therefore possible to compute the gain in income from adding or removing a link from the network. In order to obtain the net effect, one also needs to calculate the road construction cost of each link, which we consider next.

Road Construction Costs and Path through the Terrain The framework described above allows us to predict the effect of a link on aggregate income, but we also need to take into account the cost of forming links. We assume that the cost associated with the construction of a highway network depends on the terrain, in particular on the slope. We again rely on a shortest path algorithm that finds the cheapest way to build a road through a cost-surface determined by slope.[31] Figure 3 shows part of the Chinese terrain where darker pixels represent steeper slope. The green line is the path that is chosen through this cost surface in order to minimize the road construction costs based on Dijkstra's algorithm.

Figure 3: Road construction costs and least-cost path



The maps shows the optimal path through a road construction cost surface based on the slope of the terrain. Darker pixels represent steeper slope.

Using (14) and (10), we predict the change in income that results from adding a link to a given network. Subtracting from this the road construction costs that accumulate along the least-cost path of this link (as illustrated in Figure 3), yields the net benefit of each link. This requires translating the road construction costs (which are in units of the cost surface) to an annual pecuniary cost of constructing this link that we can compare to the income gains. This is a potentially important parameter for the trade-off between the benefits and costs of road construction. Fortunately, there is a straightforward way to calibrate this parameter in a way that best suits our context. In particular, we know that the total construction of the actual NTHS network cost $120 billion (Faber, 2014). Using the road construction cost surface based on the slope of the terrain, we can replicate the NTHS and determine the construction cost of the NTHS in units of the cost surface. The ratio between the costs in USD and the cost surface then yields the factor that we use to obtain the USD cost of any network.

Since our model is static, the effects on income should be interpreted as an annual effect. To annualize the construction costs, we assume an interest rate of 5% and an annual maintenance cost of 12%.[32]

[31] Faber (2014) also approximates the road construction costs based on features of the terrain such as slope and land cover and he discusses the mapping of these features into a cost index. We use the same approach, but focus on slope as a determinant of road construction costs.

[32] Allen and Arkolakis (2014) also assume a capital cost of 5%. They study the U.S. interstate highway

Objective Function We search for the network that maximizes aggregate income net of road construction costs. Given a starting network, we evaluate the net gain from the addition (or removal) of an individual link l of the network as follows:

$$\Delta W_l = \Delta Y_l^r - (r + m)\lambda C_l, \tag{15}$$

where ΔY_l^r is the difference in aggregate real income implied by the solution to Equations (14) and (10) for the network with and without link l, r is the annual interest rate, m is the annual maintenance cost, λ is the factor to translate the construction costs based on the terrain, C_l, to monetary costs.

Heuristic Algorithm The objective function above intuitively captures the benefits and costs of an individual link. It is similar to the objective used in Gastner and Newman (2006) who consider the problem of constructing the optimal network among facilities by balancing the construction costs and total travel time. The key difference is that in our case the benefit is computed from the effect of the reduced travel time on income in a general equilibrium framework, while they use the total travel time.[33] We then use a simple iterative procedure that starts from the fully connected network and evaluates for each link how much its removal would change aggregate net income based on equation (15). The 5% least beneficial links are then removed from the network.[34]

In the second stage, the algorithm evaluates all links that could be added to the network and adds those that yield a positive net gain. The algorithm then goes back to the first stage and removes the least beneficial links. It iterates in this fashion until no further gains are possible while connecting all targeted cities in the network.

network and they report maintenance costs of about 12% of the road construction costs. We use the same capital and maintenance costs, but we recognize that there could be differences in the Chinese context. See Table A1 in the appendix for a summary of all model parameters.

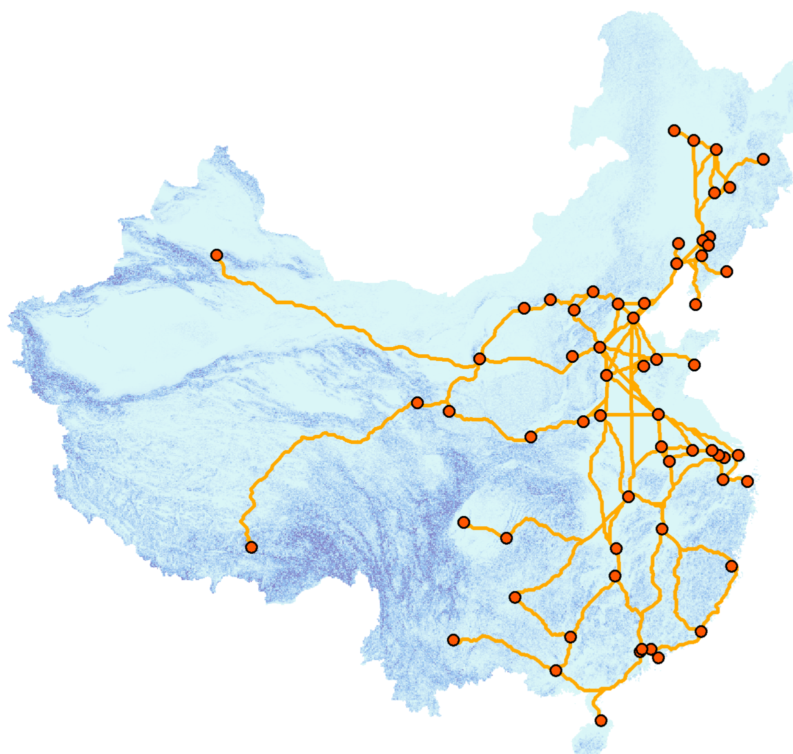
[33] We capture the benefit of a link based on the general equilibrium market access measures that capture indirect network effects of adding or removing a link. In contrast, the objective function in Gastner and Newman (2006) depends on the total travel time (along the shortest path) through the network and it does not reflect the aggregate economic benefit of a link in general equilibrium. Consequently, their objective function does not take into account spillover effects such as trade diversion. Furthermore, their cost of the network are not based on the terrain. They use simulated annealing in order to search for the optimal network and Gastner (2005) compares different algorithms to search for the optimal network, including the iterative approach that we use in this paper. It is important to note that these are heuristic algorithms that do not guarantee that the solution is the globally optimal network. However, Alder (2017) shows that the resulting network is robust to starting from the empty or from random networks.

[34] We remove 5% of the links at once in order to save computing time and avoid redundancies. Alder (2017) discusses the robustness of this approach in more detail.

Network Designs and Comparison to Actual Network The NTHS had the objective of connecting all cities with a population of at least 500,000 and all provincial capitals in a common network. The heuristic algorithm described above approximates the optimal (income-maximizing) network among these nodes. We impose the constraint that all nodes are connected in the network in order to replicate the official strategy. This constraint implies that the marginal costs and benefits may not be equalized in the solution. The resulting network is shown in Figure 4.

In Figure 5, we plot the optimal network (orange line) together with the actual NTHS (black line). We observe that the two networks have a relatively similar structure overall, but there are still substantial deviations in many of the individual links. The difference in net aggregate income between the actual NTHS and the approximation of the optimal network is 1.45% of GDP.[35] In our empirical analysis, we will test whether these deviations can be explained by the birthplaces of politicians.

Figure 4: Approximation of optimal Chinese highway network in mainland China



The maps shows the approximation of the optimal highway network in China based on the heuristic algorithm with the constraint that all targeted cities are connected. The background shows the slope of the terrain of mainland China. The nodes show the location of all cities with a population of at least 500,000 and all provincial capitals.

[35] While this is a substantial amount given the size of the Chinese economy, the difference is substantially smaller than for example the comparison between the Indian Golden Quadrilateral and the corresponding income-maximizing network (see Alder, 2017).

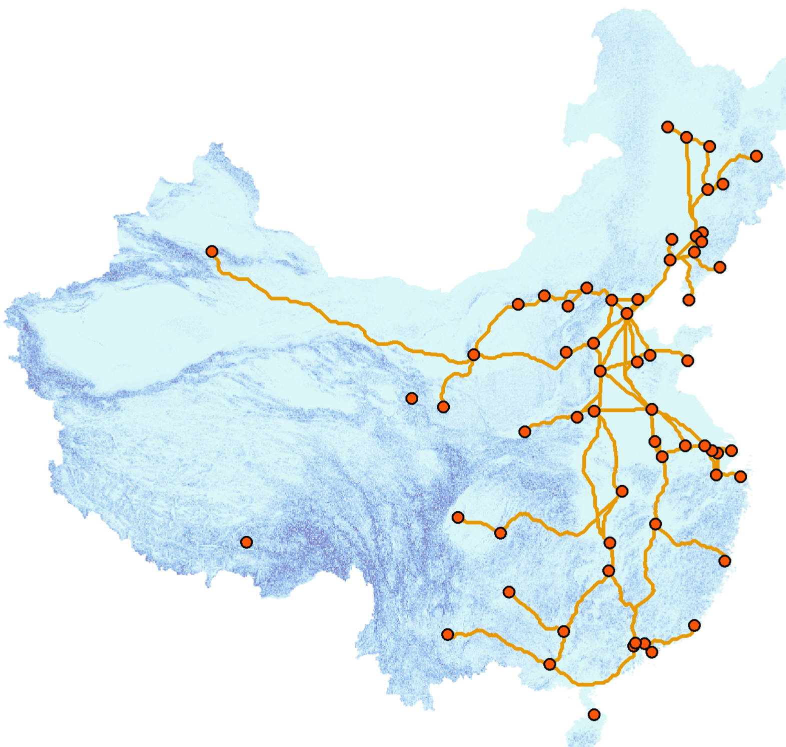
Figure 5: Comparison of actual and optimal highway network in mainland China

The maps shows the approximation of the optimal highway network in China (orange line) together with the actual NTHS (black line). The background shows the slope of the terrain of mainland China. The nodes show the location of all cities with a population of at least 500,000 and all provincial capitals.

An alternative constraint for the design of the network is to impose the same cost as the actual network, but not requiring that all nodes are connected. Using the same heuristic algorithm described above and starting from the full network, we sequentially remove and add links until the total construction costs are equal to the reported actual cost of the NTHS. The result is shown in Figure 6. We observe that the algorithm in this case does not connect the more remote locations that are more expensive to connect, such as Lhasa in the Southwest of China, the administrative capital of Tibet.

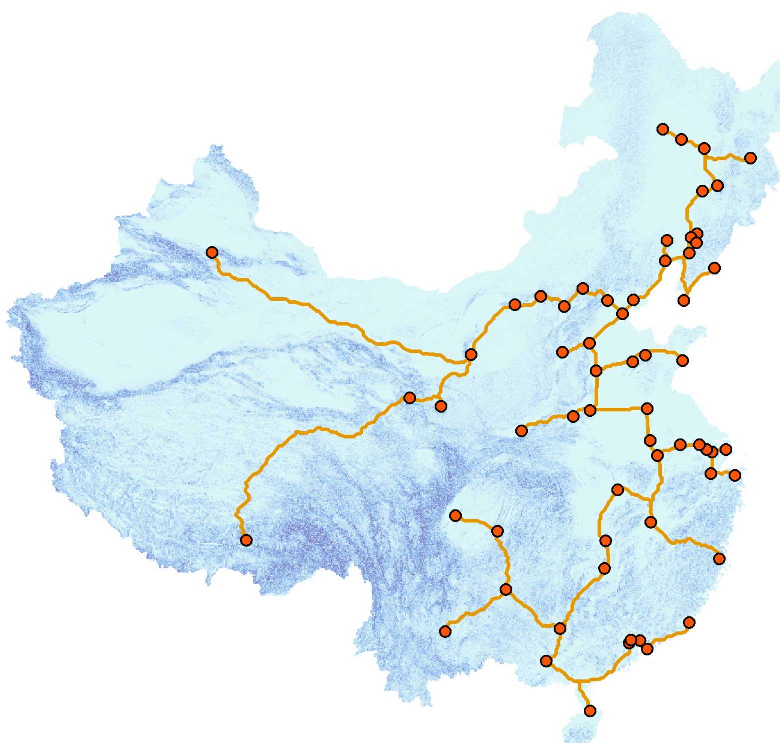
Minimum Spanning Tree as Alternative Network Design As an alternative network design, we also consider the least-cost network. This is also called the minimum spanning tree and it is applied to China by Faber (2014) as an instrument for the actual NTHS. This network design does not take into account the benefit of road construction and instead minimizes the construction cost under the constraint that all nodes are connected. The minimum spanning tree can be computed with Kruskal's algorithm (Kruskal, 1956) and the result is shown in Figure 7.

Figure 6: Heuristic optimal highway network in mainland China with same cost as actual NTHS but not forcing to connect all targets



The maps shows the approximation of the optimal highway network in China based on the heuristic algorithm with the constraint that the road construction costs approximately equal the actual cost of the NTHS. The background shows the slope of the terrain of mainland China. The nodes show the location of all cities with a population of at least 500,000 and all provincial capitals.

Figure 7: Least-cost network (minimum spanning tree) in mainland China



The map shows the least-cost network, i.e. the minimum spanning tree that is computed with the Kruskal (1956) algorithm. The background shows the slope of the terrain of mainland China. The nodes show the location of all cities with a population of at least 500,000 and all provincial capitals.

4.3 Results

Having constructed optimal network benchmarks, we now estimate the political bias in the NTHS design using equation 13:

$$\Delta\text{NTHS}^i_{\text{opt-act}} = \alpha_0 + \alpha_1 \text{Political Access}^i_{1995\text{–}2001} + \alpha_2 X^i + \varepsilon^i.$$

Our baseline results are shown in Table 4. We estimated the political infrastructure bias specified in equation 13 using three different network benchmarks: (i) the budget-constrained heuristic optimal network labeled 'BCT' (see specifications 1–2), (ii) the unconstrained heuristic optimal network labeled 'OPT' (see specifications 3–4), and (iii) the commonly-used minimum spanning tree network labeled 'MST' (see specifications 5–6). Our controls include: province fixed effects, county area size, 1992 county political direct and indirect access measures, the distance to the benchmark network, the distance to railroad network, the distance to the nearest port, the distance to the trunk road network, and the 1992 light intensity.

Table 4: Effect of birthplaces on the deviation from an optimal network $\Delta\text{NTHS}^i_{\text{opt-act}}$

	MST		BCT		OPT	
	$\Delta\text{NTHS}^i_{\text{mst-act}}$		$\Delta\text{NTHS}^i_{\text{bct-act}}$		$\Delta\text{NTHS}^i_{\text{opt-act}}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Political Access$^i_{1995\text{–}2001}$	0.319**	0.308**	0.322**	0.315**	0.315**	0.309**
	(0.141)	(0.144)	(0.143)	(0.147)	(0.141)	(0.146)
Political Access$^i_{2013\text{–}2017}$ (placebo)		0.079		0.048		0.043
		(0.112)		(0.111)		(0.109)
Dist MST	0.672***	0.672***				
	(0.038)	(0.038)				
Dist Optim (NTHS budget)			0.839***	0.839***		
			(0.046)	(0.046)		
Dist Optim					0.815***	0.815***
					(0.056)	(0.056)
Dist Targets	-0.026	-0.027	-0.214**	-0.215**	-0.199**	-0.199**
	(0.067)	(0.067)	(0.084)	(0.084)	(0.084)	(0.084)
Observations	2175	2175	2175	2175	2175	2175
Adjusted R^2	0.357	0.357	0.485	0.485	0.472	0.472

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable in columns 1 and 2 is the difference between each county's distance to the optimal network (with the same cost as the actual network) and the actual network. The dependent variable in columns 3 and 4 is the difference between each county's distance to the (unconstrained) optimal network and the actual network. The dependent variable in columns 5 and 6 is the difference between each county's distance to the minimum spanning tree (MST) and the actual network. The main explanatory variable is an index for politicians' place of birth. All regressions control for initial light density, county area, distance to ports, distance to railroads, distance to trunk roads, and province fixed effects. Standard errors are clustered at the province level.

Across all specifications, we find that locations with more powerful natives at the time of the NTHS implementation also had a distorted proximity to the actual NTHS, compared to the optimal network prescription. In contrast, using the placebo political access variable Political $\text{Access}^i_{2008\text{–}2012}$, we find that the birthplaces of politicians in power *following* the implementation of the NTHS are not more likely to be closer to the actual NTHS relative to the optimal design.

These estimates of the political bias in the transportation network infrastructure naturally motivate the question of the aggregate effects of such distortions. We turn to the model to guide this quantitative investigation, informed by the reduced-form evidence.

5 Aggregate Welfare Effects of Political Bias

5.1 Quantitative Aggregate Effects

Building on the empirical evidence, we use the general equilibrium model to quantity the aggregate welfare effects of the sub-optimal distortions arising from political frictions. The difference in net aggregate income between the actual NTHS and the (unconstrained) optimal network is 1.45% of GDP. However, this difference cannot fully be attributed to the political distortion, since the birthplaces explain only part of the deviation between the actual and optimal network. We therefore construct counterfactual networks with and without the political connections in order to quantify how much of the total distortion can be explained by the birthplaces.

Actual vs. Optimal NTHS To estimate the quantitative effects of political infrastructure distortions, we characterize the spatial equilibrium across N potential nodes that are connected either optimally or sub-optimally due to political frictions.

Because of the computational complexity of the optimal network problem, we restrict the number of potential nodes to $N = 102$ cities chosen to include: (i) the 62 target cities that are targeted by the NTHS mandate, (ii) 20 birthplaces that are the most distorted relative to the optimal benchmark ($\Delta\text{NTHS}^i_{\text{bct-act}} > 0$), and (iii) 20 'counterfactual' non-birthplace cities that are distorted away from the optimal benchmark ($\Delta\text{NTHS}^i_{\text{bct-act}} < 0$).[36]

The 20 birthplaces that are the most distorted are shown in Figure 8 along with the actual and the optimal NTHS paths. Some of these birthplaces are visibly much closer to the actual NTHS than the optimal network design.

[36] We defined $\Delta\text{NTHS}^i_{\text{bct-act}} \equiv \log d(i, \text{NTHS}_{\text{bct}}) - \log d(i, \text{NTHS}_{\text{act}})$ and selected the largest and densest cities based on luminosity.

Using these N cities, we then construct two networks and compare the corresponding welfare values. The first network is a 'politically distorted network' constructed as the optimal network connecting the 62 target cities as well as the 20 birthplaces. The second network is the 'undistorted optimal network' constructed as the optimal network connecting the 62 target cities. In the 'politically distorted network', the counterfactual cities may be connected if it is optimal to do so, but the birthplaces are by construction connected to the network. In the 'undistorted optimal network', both counterfactual cities and birthplaces may nor may not be connected depending on the optimal path joining target cities and the net economic gain.

Figure 8: Actual vs. optimal NTHS and distorted birthplaces in mainland China

The orange lines show the approximation of the optimal network among the 62 officially targeted cities (red dots). The black lines show the actual network. The green dots show the cities that are predicted to be connected based on politicians' birthplaces. The background shows the slope of the terrain of mainland China.

Results We estimate that the welfare gains from eliminating the political frictions from the 'politically distorted network' towards the 'undistorted optimal network', and contrast these welfare gains with the overall welfare gains of moving from the 'actual' network to the 'undistorted optimal network'.

Our main result is that annual income is 0.2 percent lower in the 'politically distorted network' economy compared to the 'undistorted optimal network'. These are non-trivial welfare effects given the size of the China's economy. These welfare effects also represent a conservative lower bound on the effects of political bias. In contrast, the "actual' NTHS network features an annual income that is 1.45 percent less than the 'undistorted network'. One could construct alternative 'politically distorted networks' that explain a larger fraction of the welfare difference between the actual NTHS and the optimal NTHS. Altogether, these results suggest that political frictions to infrastructure networks generate non-trivial aggregate welfare effects in China.

Table 5: Effect of Politically-Driven NTHS Access on Light Growth

	Δ log $\text{light}^i_{\text{2002-2007}}$					
	with instruments for					
	$\Delta\text{NTHS}^i_{\text{mst-act}}$		$\Delta\text{NTHS}^i_{\text{bct-act}}$		$\Delta\text{NTHS}^i_{\text{opt-act}}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Dist MST	0.656***	2.357***				
	(0.180)	(0.403)				
$\widehat{\Delta\text{NTHS}}^i_{\text{mst-act}}$		-3.367***				
		(0.626)				
Dist Optim (NTHS budget)			0.647***	3.052***		
			(0.134)	(0.566)		
$\widehat{\Delta\text{NTHS}}^i_{\text{bct-act}}$				-3.383***		
				(0.712)		
Dist Optim					0.755***	2.966***
					(0.133)	(0.533)
$\widehat{\Delta\text{NTHS}}^i_{\text{opt-act}}$						-3.171***
						(0.672)
Political $\text{Access}^i_{1995-2001}$	0.664		0.623		0.633	
	(1.311)		(1.303)		(1.309)	
Observations	1650	1650	1650	1650	1650	1650
Adjusted R^2	0.171	.	0.174	.	0.176	.
Kleibergen-Paap Wald F	–	15.30	–	9.34	–	9.88

Standard errors in parentheses

Note: Sample restricted using distance to target cities.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Local Reduced Form Evidence

We further illustrate the welfare costs of political frictions in infrastructure networks using local reduced form evidence. To do so, we estimate a light growth regression in the spirit of Faber (2014) to trace out the growth effects of politically-driven NTHS access using the following 2SLS equation:

$$\Delta \log \text{light}^i_{2002\text{-}2007} = \theta_0 + \theta_1 \widehat{\Delta\text{NTHS}}^i_{\text{opt-act}} + \theta_2 Z^i + \eta^i, \tag{16}$$

where the first-stage is based on the political bias (see equation 13 and Table 4),

$$\widehat{\Delta\text{NTHS}}^i_{\text{opt-act}} = \widehat{\alpha}_0 + \widehat{\alpha}_1 \text{Political Access}^i_{1995\text{–}2001} + \widehat{\alpha}_2 X^i.$$

The reduced form evidence of local growth effects is summarized in Table 5. We find that politically-driven proximity to the NTHS is associated with slower light growth.[37] This result suggests that political frictions to infrastructure networks may reduce overall growth, even beyond the standard channels at work in the simple workhorse model: observed distortions to internal trade costs are only the tip of the iceberg of the effects of political frictions to the infrastructure network.[38]

6 Robustness

In this section we discuss the robustness of the network design to international market access, different parameters for the elasticity of light with respect to market access, and dropping the constraint to connect all 62 cities.

6.1 International Ports

The baseline analysis assumes a closed economy and the optimal network therefore does not take into account the connections to the rest of the world. We address this by identifying the eight largest Chinese ports and allow them to have additional weight by increasing their income in proportion to their exports.[39] We use a simple approximation of the trade volumes going through target cities in our sample and then recompute the optimal network.

We obtain the data on the largest ports from Table 4.2. in UNCTAD (2017). The data includes the container port volumes in twenty-foot equivalent units of the 40 largest ports across the world. According to UNCTAD (2017), these ports account for 60% of world trade. Eleven out of the 40 largest port are Chinese and eight of them correspond to our target cities. We assume that these ports account for 60% of China's trade, which allows us to

[37] The F-statistics are slightly marginal, especially when using the deviations from the optimal networks.
[38] Lu and Wang (2016) offer evidence on reduced incumbent firm productivity in the wake of NTHS access.
[39] This approach is based on Donaldson and Hornbeck (2016).

approximate each port's trade in USD by using the total USD amount of global and Chinese trade in 2016.[40] We then add the trade volume of each port to its GDP and recompute the optimal network. The resulting network, shown in Figure 9, is similar to the baseline version. There are very few additional links and the overall structure is the same. One reason for why the addition of international markets in the form of additional demand in port cities does not affect the overall structure, is that the network already connects these port cities well in the baseline.[41] Incorporating international trade through port cities does not significantly change the welfare gain from the optimal network, which is 1.45% compared to the actual network.

Figure 9: Optimal network with port cities in mainland China

The map shows the optimal network when port cities' incomes are increased in proportion to their exports. The green dots show the location of the eight major ports. The red nodes show the location of all cities with a population of at least 500,000 and all provincial capitals. The background shows the slope of the terrain of mainland China.

[40]Ideally we would use trade flows through the major ports in 1992, but we do not currently have this data.

[41]Note that the decision whether or not a link is upgraded to a modern NTHS is binary. There is no additional capacity that is built because there is no congestion. This reduces the incentives to build additional links to target cities when their income increases due to the ports. However, there are a few exceptions in the network where links are added because demand increases overall.

6.2 Estimation of Elasticity

In order to solve for income with counterfactual transport networks, we need to make assumptions on the parameters in the model. A key parameter is the elasticity of income (light) with respect to market access, which we take from Alder (2017).[42] However, it is also possible to estimate this elasticity using the Chinese data. We use the light data in order to construct a panel of income at the county level. Furthermore, we need the maps of the transport network over time. We use the 1990 road maps from the MIT Geo Web (see Section 2.1) and combine them with the maps of the NTHS. We compute the iceberg trade costs pre- and post NTHS construction and solve for market access. This allows us to estimate the elasticity β in equation (14) in long differences from 1992 to 2013. As in Alder (2017), we instrument market access with a version that holds income constant and only varies over time due to the reduction in trade costs. Furthermore, we control for the distance to ports, to the nearest rail, to the coast, and for province fixed effects.

The point estimates of the elasticity (not reported here) are similar to the baseline value and range from 0.459 to 0.724. The resulting structure of the optimal network is not affected substantially by this relatively small variation in the elasticity. Figure 10 shows the resulting network with the largest point estimate 0.724. The difference to the baseline network structure is small, but there are a few additional connections as we would expect.[43] Overall, this suggests that the network design is not sensitive to reasonable variation in the elasticity. The welfare gains of 1.53% from the heuristic optimal network are somewhat larger compared to the baseline of 1.45%. If we use an elasticity of $\beta = 0.459$, then the welfare gains are 1.24%.

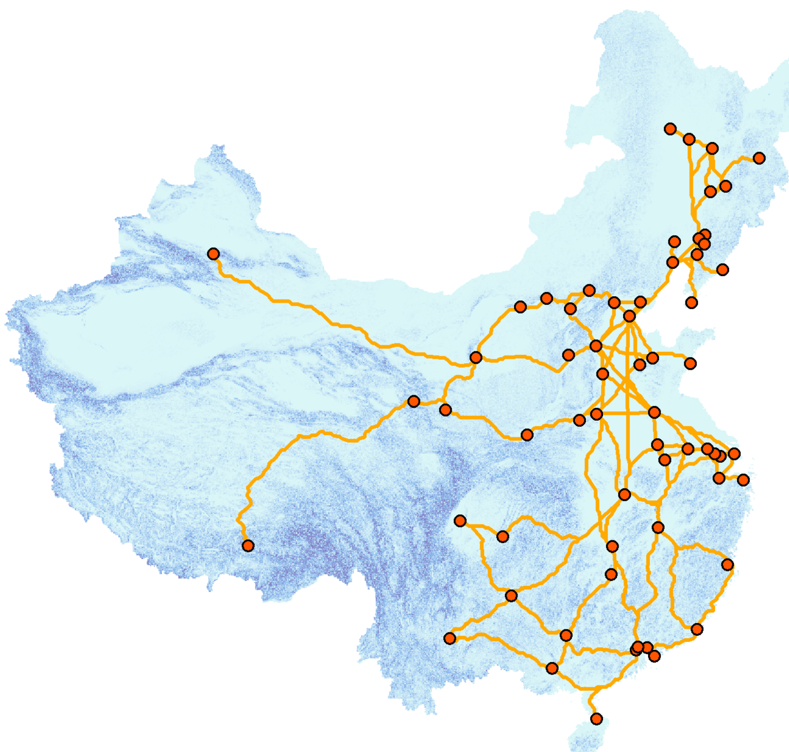
6.3 Dropping Target Cities as Constraint

In our baseline, we impose that the network design algorithm connects all targeted cities because this was specified by the policy. We view this as the relevant comparison to the actual network because it implements the specified policy. However, it also implies that the heuristic optimal network design is constrained. To investigate the relevance of this constraint, we recompute the optimal network with the same algorithm, but we do not impose that all 62 nodes are connected. To first compare the results to the baseline, we instead impose the constraint that the total cost of the network is the same as the actual cost of the NTHS. The result is shown in Figure 11. We observe that the overall structure of

[42] Note that the elasticity in the model is a collection of parameters that are not identified separately. However, it is necessary to also assume values for the trade elasticity θ, which we set to 8, and the combined land and labor share, which we set to 0.7.

[43] If instead we used an elasticity of $\beta = 0.459$ (the lowest point estimate when estimating the effect of market access on income in China), then we again get a similar network that only differs from the baseline by a small number of links that would be dropped.

Figure 10: Heuristic optimal network in mainland China with $\beta = 0.724$



The maps shows the approximation of the optimal highway network in China based on the heuristic algorithm with the constraint that all targeted cities are connected. The background shows the slope of the terrain of mainland China. The nodes show the location of all cities with a population of at least 500,000 and all provincial capitals.

Figure 11: Approximation of optimal highway network in mainland China: same cost as actual network but not forcing to connect all targets

The maps shows the approximation of the optimal highway network in China based on the heuristic algorithm without the constraint that all targeted cities are connected. The background shows the slope of the terrain of mainland China. The nodes show the location of all cities with a population of at least 500,000 and all provincial capitals.

the network is again similar, but a small number of remote nodes are not connected anymore. Since we remove one constraint and add another one, it is not a priori clear in which direction the welfare effect changes. We find that the welfare gains from the heuristic optimal network in this version is 1.41% and thus slightly smaller than in the baseline case where we did not constrain the network to have the same cost as the actual. When we drop both constraints, i.e. we neither impose that all 62 nodes are connected nor that the cost is the same as in the actual, then we find that the welfare gains would be 1.53%. As expected, the welfare gains are largest in this unconstrained case.

7 Conclusion

In the 1990s, China embarked on a major overhaul of its transportation network. The National Transportation Highway System (NTHS) modernized the transportation infrastructure by connecting China's largest cities through a network of 35,000 km. We study potential distortions in such large-scale infrastructure networks in the context of centrally-planned system like China.

Using detailed data on politicians that we match with administrative units and heuristic network optimization techniques, we document that the birthplaces of incumbent political leaders during the highway's implementation are systematically closer to the actual network, compared to the counterfactual optimal network. We quantify the welfare effects of the deviations of the actual network and assess the potential contribution of political distortions to the infrastructure network. Counterfactual networks distorted to favor incumbent leader birthplaces generates non-trivial welfare losses. We also show that, in the data, political distortions are associated with reduced growth using nighttime satellite data.

These findings suggest that political frictions in public infrastructure networks and their misallocative effects merit further empirical and theoretical study.

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A Appendix

B Additional Tables

Table A1: Parameters

Parameter	Value	Role
β	0.2	Elasticity of income with respect to market access
θ	8	Trade elasticity
α	– (enters through β)	Land share in the production function
γ	– (enters through β)	Labor share in the production function
ρ	1	Scalar for $FMA = \rho CMA$
ω	Calibrated to match median iceberg trade cost of 1.25	Scaling of travel time
χ	0.8	Concavity of trade cost in travel time
λ	Calibrated to match ratio of USD cost of NTHS to costs based on topography	Scalar to map road construction cost based on topography to USD costs
r	0.05	Annual cost of capital
m	0.12	Annual maintenance costs

Table A2: Upper Echelon Native Politicians across Counties

1997 \ 2002	0	1	2
0	2253	15	1
1	9	10	0
2	0	0	1

This table shows a two-way frequency table, across counties, of the number of native politicians in the upper echelon of the party in 1997 and in 2002. Most counties have no natives at the top and there is a fair amount of turnover from one congress to the next.

Table A3: Upper Echelon Native Politicians across Counties

2002 \ 2007	0	1	2
0	2239	23	0
1	11	14	0
2	1	0	1

This table shows a two-way frequency table, across counties, of the number of native politicians in the upper echelon of the party in 2002 and in 2007. Most counties have no natives at the top and there is a fair amount of turnover from one congress to the next.

Table A4: Upper Echelon Native Politicians across Counties

1997 \ 2007	0	1	2
0	2236	32	1
1	14	5	0
2	1	0	0

This table shows a two-way frequency table, across counties, of the number of native politicians in the upper echelon of the party in 1997 and in 2007. Most counties have no natives at the top and there is even more turnover after two political cycles.