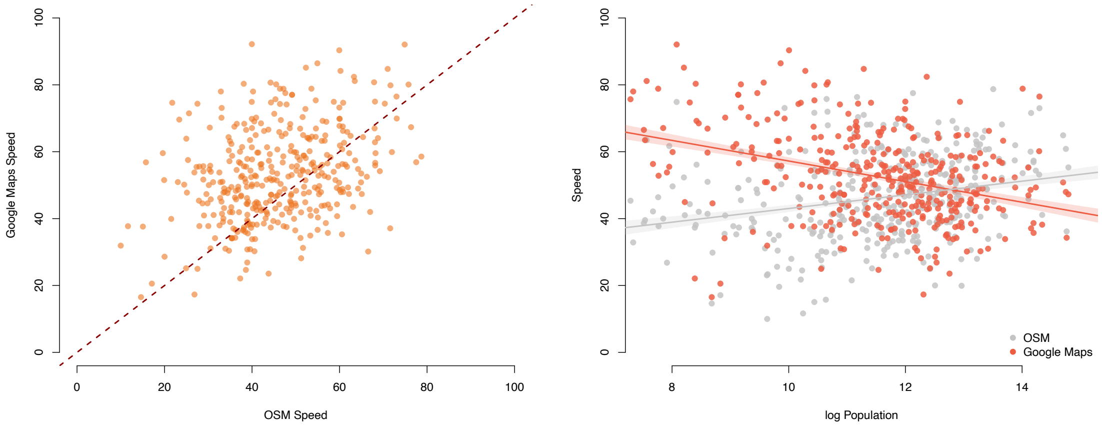
Appendix

A Additional figures and tables

Figure A.1: Cross validation of OSM roads data



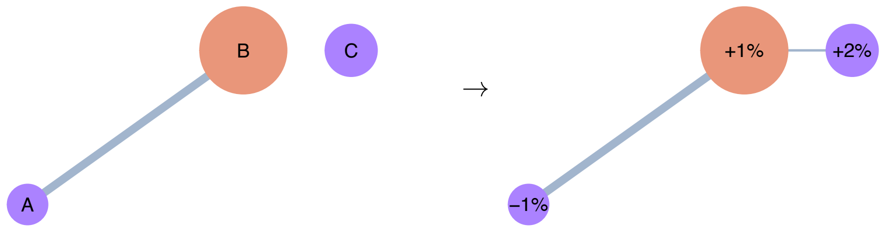
(a) Direct speed comparison

(b) Speed comparison by log population

Cross validation of Open Street Maps (OSM) speed data with Google Maps (GM). I scrape routing information from GM for a random 1% subset of connections. Panel (a) plots the distributions of the resulting speed measures from both providers against each other. Panel (b) plots both speed distributions against the log of the average population between origin and destination grid cells. Regression lines with 95% confidence intervals are overlaid. Note, these speeds are faster than the average speeds reported in the main text of the paper, as they do not include the significant amount of time spent walking in many parts of the network.

Figure A.2: Example where optimal expansion can still lead to local losses

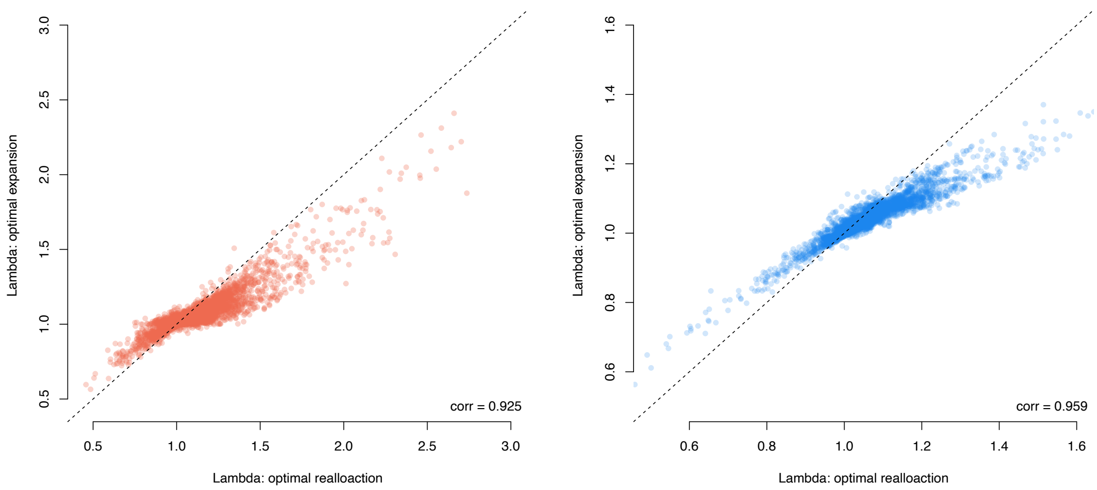
(a) Before (b) After 10% expansion



Example of how optimal expansion can lead to losses in some regions, even when they do not lose any infrastructure. In this example, locations A and C produce the same variety and are small. Location B produces a second variety and is much closer to C but ex-ante only connected to A. Optimal expansion connect B and C, which leads to welfare increases on aggregate, but hurts location A, who can now sell less to B and hence get less of B's variety.

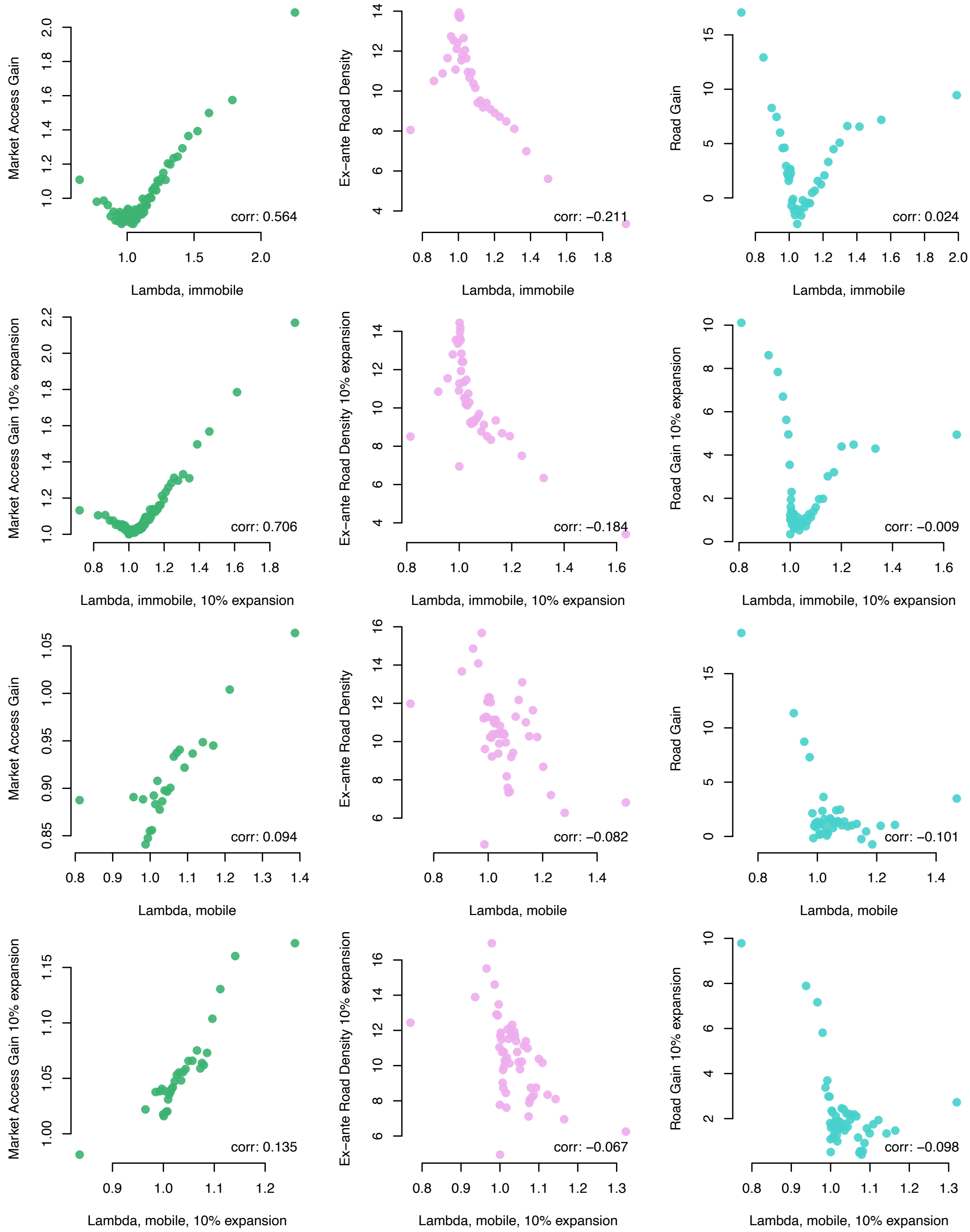
Figure A.3: Reallocation and expansion scenarios

(a) Immobile labor (b) Mobile labor



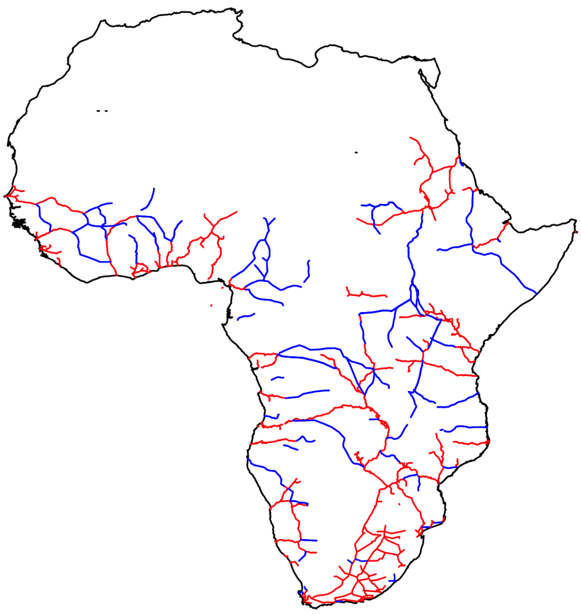
Raw correlations of Λ_{imm} *and* $\Lambda_{imm}^{10\%}$ *and* Λ_{mob} *and* $\Lambda_{mob}^{10\%}$*, respectively.*

Figure A.4: Correlations of Λ with other road network measures



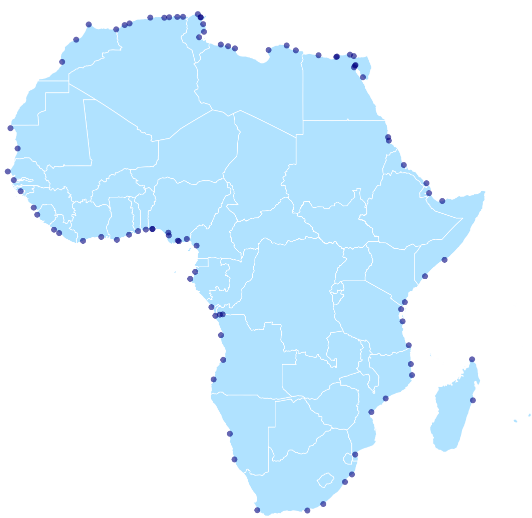
Raw correlations of various Λ measures of infrastructure discrimination with plausible other road network measures. The first row reports scatter plots of Λ_{imm} without labor mobility against a measure of market access change, ex-ante road density, and road gain. Market access is defined as $MA_i = \sum_j (1+\tau_{ij})^{-\sigma} z_j L_j$ where τ_{ij} corresponds to the cost of shipping a quantity of $Q = 1$ over the network. I compute the change in MA from the static network before re-allocation to the optimal one post re-allocation. Ex-ante road density is defined as $I_{i,initial}/L_i$ where $I_{i,initial}$ is the average infrastructure on all links originating at i before re-allocation. Lastly, infrastructure gain is defined as $I_{i,optimal} - I_{i,initial}$, the ratio of average infrastructure orginating in a link after vs before the reallocation exercise. The remaining rows repeat this exercise for $\Lambda^{10\%}_{imm}$, Λ_{mob}, and $\Lambda^{10\%}_{mob}$

Figure A.5: Colonial railway network

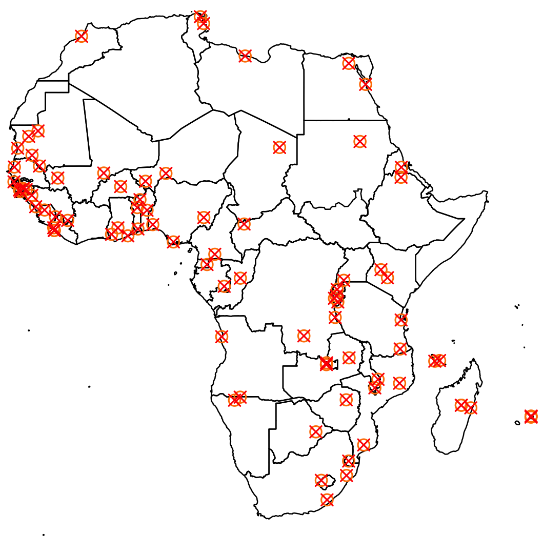


Maps displaying the network of railway lines (red) and placebo railroads (blue). Data from Jedwab and Moradi (2016) and Herranz-Loncán and Fourie (2017). Railroads built by the colonial powers between 1890 and 1960 are printed in red. Lines that were initially planned but never actually built are printed in blue.

Figure A.6: Further spatial data used



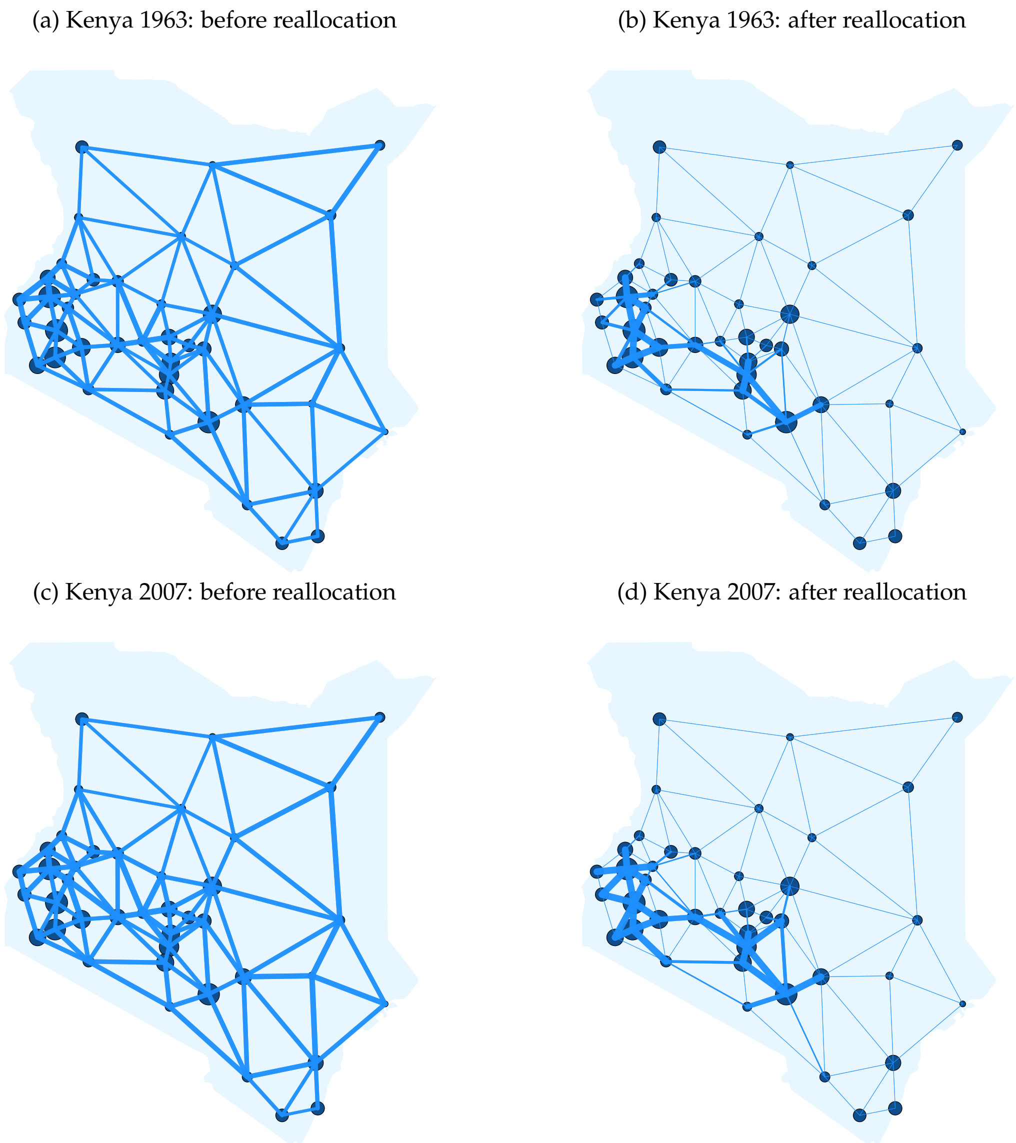
(a) Locations of ports



(b) Leaders' birthplaces

Spatial distribution of ports and leaders' birthplaces across the continent. Ports data is hand-coded from Lloyd's list at https://directories.lloydslist.com/port and corresponds to the 90 biggest ports in Africa. Birthplace data from Dreher et al. (2019).

Figure A.7: Reallocation of historical road networks in Kenya



(a) Kenya 1963: before reallocation

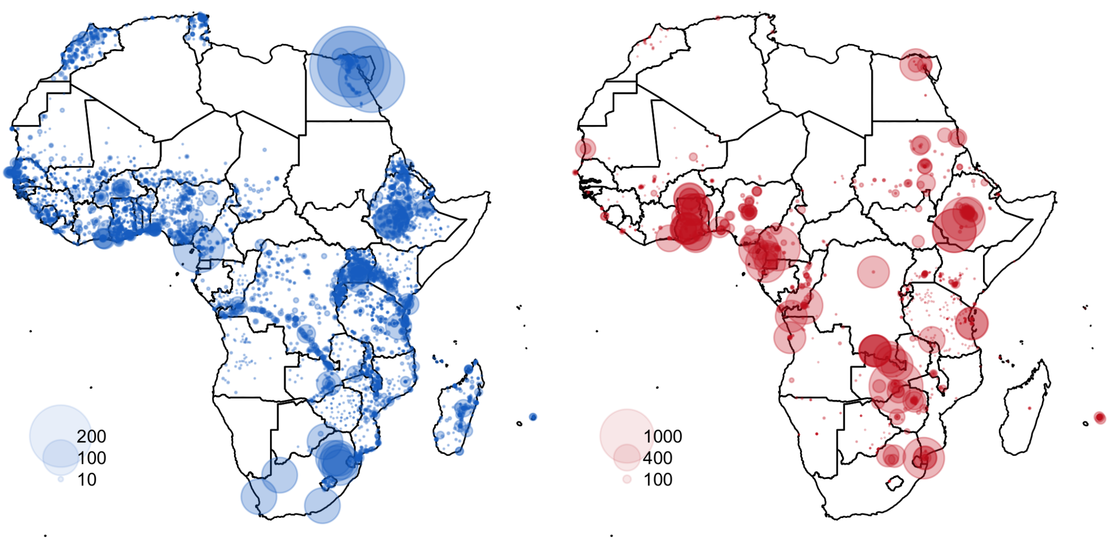
(b) Kenya 1963: after reallocation

(c) Kenya 2007: before reallocation

(d) Kenya 2007: after reallocation

Ex-ante and optimally reallocated road networks for Kenya in 1963 and 2007. Ex-ante roads data from Jedwab and Storeygard (2022). Each dot represents a district with size proportional to its 1962 population (from Burgess et al., 2015). Maps print the reallocation with immobile labor.

Figure A.8: Spatial distribution of development aid projects to African nations



(a) World Bank aid

(b) Chinese aid

Foreign aid projects funded by the World Bank (A.8a) *and China* (A.8b). *Each dot represents one project site with radius proportional to the logarithm of total disbursements flowing to each site. World Bank data comprise all projects approved between 1996–2014. Chinese data include tracked projects between 2000–2011. Map only depicts projects coded with sufficient precision to not be excluded (see Appendix text). If a project has multiple sites, total disbursements are assumed evenly distributed between locations. Data from AidData (2017) and Strange et al. (2017). Legend denotes disbursement values in million 2011 US dollars. Note that the legends have different scales.*

Table A.1: Geographic correlates of infrastructure discrimination measures

	(1) Λ_{imm}	(2) $\Lambda^{10\%}_{\text{imm}}$	(3) Λ_{mob}	(4) $\Lambda^{10\%}_{\text{mob}}$	(5) Housing	(6) Housing (pc)
Population (in 100,000)	0.00227	0.00226	-0.0104**	-0.0144**	0.00468	0.00996***
	(0.00263)	(0.00263)	(0.00458)	(0.00619)	(0.00289)	(0.00349)
Ruggedness	-0.00000267	-0.00000370	0.00000470	0.00000499	-0.00000355	-0.00000551
	(0.00000333)	(0.00000326)	(0.00000308)	(0.00000314)	(0.00000418)	(0.00000340)
Night lights	-0.0148***	-0.0138***	-0.0230***	-0.0222***	-0.00766**	-0.0122**
	(0.00430)	(0.00424)	(0.00496)	(0.00535)	(0.00347)	(0.00592)
Altitude	-0.0000726	-0.0000276	0.000110*	0.000112*	-0.0000418	-0.000238***
	(0.0000532)	(0.0000537)	(0.0000585)	(0.0000626)	(0.0000473)	(0.0000775)
Agr. suitability index	0.0658	0.0808	-0.0225	-0.0404	-0.0741	-0.0844*
	(0.0534)	(0.0511)	(0.0477)	(0.0585)	(0.0514)	(0.0484)
Temperature	-0.0141	-0.00688	-0.00672	0.00204	0.0109	-0.0427**
	(0.0119)	(0.0120)	(0.0117)	(0.0122)	(0.0127)	(0.0170)
Precipitation	0.0000230	-0.00000789	0.00109*	0.00162**	0.00825	0.00404
	(0.000437)	(0.000399)	(0.000594)	(0.000680)	(0.00707)	(0.00373)
Yearly growing days	0.0000557	0.000187	-0.000367	-0.000390	-0.00117	-0.000551
	(0.000293)	(0.000270)	(0.000337)	(0.000391)	(0.00115)	(0.000607)
Malaria prevalence	0.00264	0.00405	-0.00162	-0.000610	-0.000882	0.00108
	(0.00257)	(0.00247)	(0.00198)	(0.00212)	(0.00229)	(0.00262)
$<$ 25 KM from suitable harbor	-0.130	-0.0509	-0.0524	-0.216	1.685	2.477
	(0.0840)	(0.0757)	(0.147)	(0.179)	(1.578)	(2.420)
$<$ 25 KM from navigable river	-0.319**	-0.333**	-0.107	-0.0706	0.0991	0.138*
	(0.158)	(0.155)	(0.125)	(0.125)	(0.0831)	(0.0733)
$<$ 25 KM from navigable lake	0.0397	0.0370	-0.138**	-0.157*	0.0127	-0.00541
	(0.0587)	(0.0643)	(0.0601)	(0.0830)	(0.0519)	(0.0337)
National capital	-0.00962	-0.0259	0.0544	-0.0546	-0.137	-0.231*
	(0.0825)	(0.0850)	(0.0837)	(0.111)	(0.0934)	(0.118)
At national border	-0.152***	-0.152***	-0.0134	0.00541	0.0386	0.0530**
	(0.0189)	(0.0187)	(0.0176)	(0.0179)	(0.0335)	(0.0259)
Road density (z-scored)	-0.187***	-0.197***	-0.155***	-0.186***	-0.0106	-0.115**
	(0.0256)	(0.0254)	(0.0227)	(0.0256)	(0.0514)	(0.0461)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Remaining Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	10158	10158	10158	10158	8580	8384
R2	0.769	0.782	0.887	0.863	0.0533	0.466

Geographic correlates of the various model-implied measures, obtained from a joint regression of Λ on the vector **X**. *Fourth-order polynomials of latitue and longitude, as well as country fixed effects are not printed.*

Table A.2: Geographic correlates of realised and placebo railway lines

	(1) Rail	(2) Placebo	(3) p-value	(4) p-value (joint)	(5) Bias (Λ_{imm})
Population (in 100,000)	3.27	1.96	**0.00**	**0.00**	*(unclear)*
	(7.03)	(4.24)			
Ruggedness	2463.68	1801.06	**0.00**	0.87	*(unclear)*
	(3193.47)	(2458.56)			
Night lights	1.36	0.24	**0.00**	0.33	*(unclear)*
	(5.18)	(0.98)			
Altitude	793.71	786.20	0.43	0.46	*(unclear)*
	(521.08)	(492.70)			
Agr. suitability index	0.37	0.42	**0.00**	0.97	*(unclear)*
	(0.26)	(0.26)			
Temperature	22.74	23.93	**0.00**	0.60	*(unclear)*
	(4.14)	(3.24)			
Precipitation	73.40	91.06	**0.00**	0.18	*(unclear)*
	(45.39)	(37.65)			
Yearly growing days	155.05	199.77	**0.00**	**0.01**	*(unclear)*
	(85.70)	(86.08)			
Malaria prevalence	9.87	12.79	**0.00**	0.33	*(unclear)*
	(9.84)	(9.65)			
$<$ 25 KM from suitable harbor	0.01	0.00	**0.05**	0.43	*(unclear)*
	(0.08)	(0.04)			
$<$ 25 KM from navigable river	0.01	0.01	0.17	0.33	*(unclear)*
	(0.12)	(0.08)			
$<$ 25 KM from navigable lake	0.01	0.02	0.15	0.83	*(unclear)*
	(0.10)	(0.15)			
National capital	0.03	0.02	**0.02**	0.46	*(unclear)*
	(0.16)	(0.13)			
At national border	0.31	0.38	**0.00**	**0.00**	**Against**
	(0.46)	(0.48)			
Road density (z-scored)	0.35	0.24	**0.00**	**0.00**	**In favour**
	(0.74)	(0.89)			

Raw means of different geographic variables for grid cells touched by a colonial railroad (1) or a placebo railroad (2). Column (3) prints p-values of a t-test of no means difference between (1) and (2). Column (4) prints p-values of a regression of all geographic variables at once, plus the other variables used in the main regression (6), *ie country fixed-effects, and higher-order lat-lon polynomials:* $IsRail_{i,c} = \beta_0 + \mathbf{X}_{i,c}\gamma + \delta_c + \epsilon_i$ *Column (5) prints the direction any significant difference from column (4) might bias the main result. To do so, it multiplies direction of the difference from (4) with the direction of the correlation of the covariate with* Λ_{imm}*, taken from column (1) of Table A.1. For example, rail cells have significantly higher road density than placebo cells, and high road density is associtied with lower* Λ_{imm} *values (see Table A.1), so this might bias in favour of the main hypothesis that rail cells have lower* Λ_{imm} *values than placebo cells. Bias is coded as* (unclear) *if either the p-value in column (4) is lower than 0.05, or the p-value against the* H_0 *of zero of the respective covariate in column (1) of Table A.1 is less than 0.05.*

Table A.3: Colonial railroads: mobile labor (upper panel) and ex-ante road density (lower panel)

	Infrastructure discrimination Λ_{mob} (z-scored)				Real	Placebo
	(1)	(2)	(3)	(4)	(5)	(6)
50 KM of Colonial Railroads	-0.106***					
	(0.0195)					
50 KM of Colonial Placebo Railroads		0.101				
		(0.0672)				
50 KM of Colonial Railroads for Military Purposes			-0.119***			
			(0.0311)			
50 KM of Colonial Railroads for Mining Purposes				-0.0982***		
				(0.0314)		
<10KM to railroad					-0.147***	0.00884
					(0.0276)	(0.0244)
10-20KM to railroad					-0.135***	0.0152
					(0.0268)	(0.0264)
20-30KM to railroad					-0.0792***	0.00881
					(0.0268)	(0.0273)
30-40KM to railroad					-0.0496**	-0.000634
					(0.0246)	(0.0179)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Geography Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	10158	10158	10158	10158	10158	10158
R2	0.884	0.884	0.884	0.884	0.885	0.884
	Ex-ante road density (z-scored)				Real	Placebo
	(1)	(2)	(3)	(4)	(5)	(6)
50 KM of Colonial Railroads	0.115***					
	(0.0204)					
50 KM of Colonial Placebo Railroads		0.0533				
		(0.105)				
50 KM of Colonial Railroads for Military Purposes			0.133***			
			(0.0384)			
50 KM of Colonial Railroads for Mining Purposes				0.116***		
				(0.0308)		
<10KM to railroad					0.180***	0.0636*
					(0.0307)	(0.0346)
10-20KM to railroad					0.107***	0.0433
					(0.0264)	(0.0392)
20-30KM to railroad					0.144***	-0.00385
					(0.0268)	(0.0311)
30-40KM to railroad					0.0775***	0.0458
					(0.0285)	(0.0325)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Geography Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	10158	10158	10158	10158	10158	10158
R2	0.861	0.860	0.860	0.860	0.861	0.860

Replication of Table 1, but with Λ_{mob} (upper panel) and ex-ante infrastructure density I^c (lower panel) as dependent variables, both z-scored.

Table A.4: Colonial railroads: New investments

	Infrastructure discrimination $\Lambda^{10\%}_{\text{imm}}$ (z-scored)				Real	Placebo
	(1)	(2)	(3)	(4)	(5)	(6)
50 KM of Colonial Railroads	-0.0689***					
	(0.0227)					
50 KM of Colonial Placebo Railroads		-0.0331				
		(0.0562)				
50 KM of Colonial Railroads for Military Purposes			-0.0850**			
			(0.0357)			
50 KM of Colonial Railroads for Mining Purposes				-0.0554*		
				(0.0299)		
<10KM to railroad					-0.0945***	-0.0340
					(0.0321)	(0.0267)
10-20KM to railroad					-0.111***	-0.0159
					(0.0299)	(0.0275)
20-30KM to railroad					-0.0222	-0.0163
					(0.0326)	(0.0385)
30-40KM to railroad					0.0497	0.0365
					(0.0307)	(0.0294)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Geography Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	10158	10158	10158	10158	10158	10158
R2	0.777	0.777	0.777	0.777	0.777	0.777

	Infrastructure discrimination $\Lambda^{10\%}_{\text{mob}}$ (z-scored)				Real	Placebo
	(1)	(2)	(3)	(4)	(5)	(6)
50 KM of Colonial Railroads	-0.145***					
	(0.0239)					
50 KM of Colonial Placebo Railroads		0.181**				
		(0.0764)				
50 KM of Colonial Railroads for Military Purposes			-0.161***			
			(0.0382)			
50 KM of Colonial Railroads for Mining Purposes				-0.147***		
				(0.0384)		
<10KM to railroad					-0.202***	0.0226
					(0.0345)	(0.0271)
10-20KM to railroad					-0.171***	0.0304
					(0.0324)	(0.0302)
20-30KM to railroad					-0.118***	0.0257
					(0.0315)	(0.0331)
30-40KM to railroad					-0.0735**	0.0118
					(0.0305)	(0.0194)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Geography Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	10158	10158	10158	10158	10158	10158
R2	0.859	0.858	0.859	0.859	0.860	0.858

Replication of Table 1, but with $\Lambda^{10\%}_{imm}$ (upper panel) and $\Lambda^{10\%}_{mob}$ (lower panel) as dependent variables, both z-scored.

Table A.5: Colonial railroads: no market power (optimal reallocation)

	Infrastructure discrimination Λ_{imm} (z-scored)				Real	Placebo
	(1)	(2)	(3)	(4)	(5)	(6)
50 KM of Colonial Railroads	-0.126***					
	(0.0357)					
50 KM of Colonial Placebo Railroads		-0.0610				
		(0.0955)				
50 KM of Colonial Railroads for Military Purposes			-0.149***			
			(0.0508)			
50 KM of Colonial Railroads for Mining Purposes				-0.124**		
				(0.0498)		
<10KM to railroad					-0.174***	-0.0521
					(0.0493)	(0.0407)
10-20KM to railroad					-0.187***	-0.0739
					(0.0452)	(0.0453)
20-30KM to railroad					-0.0472	-0.0302
					(0.0530)	(0.0651)
30-40KM to railroad					0.0945*	0.0564
					(0.0481)	(0.0531)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Geography Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	10158	10158	10158	10158	10158	10158
R2	0.236	0.235	0.236	0.235	0.237	0.235
	Infrastructure discrimination Λ_{mob} (z-scored)				Real	Placebo
	(1)	(2)	(3)	(4)	(5)	(6)
50 KM of Colonial Railroads	-0.254***					
	(0.0504)					
50 KM of Colonial Placebo Railroads		0.0270				
		(0.162)				
50 KM of Colonial Railroads for Military Purposes			-0.298***			
			(0.0697)			
50 KM of Colonial Railroads for Mining Purposes				-0.214***		
				(0.0724)		
<10KM to railroad					-0.331***	-0.0494
					(0.0632)	(0.0588)
10-20KM to railroad					-0.342***	-0.0490
					(0.0580)	(0.0680)
20-30KM to railroad					-0.233***	-0.0386
					(0.0741)	(0.0655)
30-40KM to railroad					-0.170***	-0.0428
					(0.0632)	(0.0545)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Geography Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	10158	10158	10158	10158	10158	10158
R2	0.505	0.502	0.504	0.503	0.508	0.502

Replication of Table 1, but with Λ_{imm} (upper panel) and Λ_{mob} (lower panel) computed without the assumption of traders having market power (from Atkin and Donaldson, 2015) as dependent variables, both z-scored.

Table A.6: Colonial railroads: no market power (optimal expansion)

	Infrastructure discrimination $\Lambda^{10\%}_{\text{imm}}$ (z-scored)				Real	Placebo
	(1)	(2)	(3)	(4)	(5)	(6)
50 KM of Colonial Railroads	-0.117*** (0.0336)					
50 KM of Colonial Placebo Railroads		-0.120 (0.104)				
50 KM of Colonial Railroads for Military Purposes			-0.127*** (0.0471)			
50 KM of Colonial Railroads for Mining Purposes				-0.128** (0.0538)		
<10KM to railroad					-0.168*** (0.0467)	-0.0777* (0.0443)
10-20KM to railroad					-0.167*** (0.0417)	-0.0931* (0.0486)
20-30KM to railroad					-0.0387 (0.0514)	-0.0539 (0.0671)
30-40KM to railroad					0.0917* (0.0529)	0.0634 (0.0569)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Geography Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	10158	10158	10158	10158	10158	10158
R2	0.241	0.240	0.240	0.240	0.242	0.240

	Infrastructure discrimination $\Lambda^{10\%}_{\text{mob}}$ (z-scored)				Real	Placebo
	(1)	(2)	(3)	(4)	(5)	(6)
50 KM of Colonial Railroads	-0.317*** (0.0539)					
50 KM of Colonial Placebo Railroads		-0.00492 (0.168)				
50 KM of Colonial Railroads for Military Purposes			-0.352*** (0.0759)			
50 KM of Colonial Railroads for Mining Purposes				-0.299*** (0.0781)		
<10KM to railroad					-0.417*** (0.0703)	-0.0581 (0.0629)
10-20KM to railroad					-0.401*** (0.0622)	-0.0543 (0.0713)
20-30KM to railroad					-0.309*** (0.0799)	-0.0399 (0.0707)
30-40KM to railroad					-0.215*** (0.0702)	-0.0457 (0.0595)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Geography Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	10158	10158	10158	10158	10158	10158
R2	0.477	0.472	0.475	0.473	0.481	0.472

Replication of Table 1, but with $\Lambda^{10\%}_{imm}$ (upper panel) and $\Lambda^{10\%}_{mob}$ (lower panel) computed without the assumption of traders having market power (from Atkin and Donaldson, 2015) as dependent variables, both z-scored.

Table A.7: Colonial railroads and local amenities

	Housing (z-scored)				Real	Placebo
	(1)	(2)	(3)	(4)	(5)	(6)
50 KM of Colonial Railroads	-0.0161					
	(0.0134)					
50 KM of Colonial Placebo Railroads		0.0852				
		(0.0581)				
50 KM of Colonial Railroads for Military Purposes			-0.00118			
			(0.0260)			
50 KM of Colonial Railroads for Mining Purposes				-0.0291		
				(0.0337)		
<10KM to railroad					-0.0133	0.0286
					(0.0195)	(0.0260)
10-20KM to railroad					-0.0108	0.0292
					(0.0176)	(0.0250)
20-30KM to railroad					0.0125	0.0159
					(0.0203)	(0.0202)
30-40KM to railroad					0.00718	0.0210
					(0.0170)	(0.0159)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Geography Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	8580	8580	8580	8580	8580	8580
R2	0.0533	0.0533	0.0533	0.0533	0.0533	0.0533
	Housing per capita (z-scored)				Real	Placebo
	(1)	(2)	(3)	(4)	(5)	(6)
50 KM of Colonial Railroads	-0.0583***					
	(0.0151)					
50 KM of Colonial Placebo Railroads		0.0195				
		(0.0541)				
50 KM of Colonial Railroads for Military Purposes			-0.0441*			
			(0.0224)			
50 KM of Colonial Railroads for Mining Purposes				-0.0389		
				(0.0250)		
<10KM to railroad					-0.0656***	0.00740
					(0.0214)	(0.0204)
10-20KM to railroad					-0.0619***	-0.0114
					(0.0221)	(0.0219)
20-30KM to railroad					-0.0569***	-0.00989
					(0.0201)	(0.0172)
30-40KM to railroad					-0.0247	0.00361
					(0.0184)	(0.0150)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Geography Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	8384	8384	8384	8384	8384	8384
R2	0.464	0.464	0.464	0.464	0.464	0.464

Replication of Table 1, but with total model-implied housing H_i (upper panel) and per-capita model implied housing h_i (lower panel) as dependent variables, both z-scored.

Table A.8: Regional favoritism: Interaction effects

	Relative road expenditure			
	(1)	(2)	(3)	(4)
Panel A: Kenyan road expenditure over time				
Λ_{imm} (non-democracy)	-2.550**		-2.548**	
	(1.114)		(1.111)	
Λ_{imm} (democracy)		0.503		0.344
		(0.756)		(0.740)
Coethnic district	1.433***	1.206**	1.577***	0.940*
	(0.402)	(0.588)	(0.520)	(0.541)
$\Lambda_{\text{imm}} \times$ Coethnic district			-0.378	0.793*
			(0.725)	(0.446)
Year and District FE	Yes	Yes	Yes	Yes
(Demographic, political, economic, geographic) $\times$ trend	Yes	Yes	Yes	Yes
N	451	410	451	410
R2	0.362	0.215	0.363	0.216

Replication of Table 2, columns 3-4. Yet also adding an interaction effect $\Lambda_{dt} \times coethnic_{dt}$.

Table A.9: Regional favouritism: Optimal expansion immobile labor (top), mobile labor reallocation (middle), mobile labor expansion (bottom)

	Discrimination $\Lambda_{\text{imm}}^{10\%}$		Relative road expenditure	
	(1)	(2)	(3)	(4)
Panel A: entire sample				
Ever in power dummy	-0.103*			
	(0.0532)			
log(1 + Total years in power)		-0.0335		
		(0.0215)		
Panel B: Kenyan road expenditure over time				
$\Lambda_{\text{imm}}^{10\%}$ (non-democracy)			-0.864	
			(0.724)	
$\Lambda_{\text{imm}}^{10\%}$ (democracy)				0.00296
				(0.447)
Year and District FE			Yes	Yes
(Demographic, political, economic, geographic) × trend			Yes	Yes
Country FE	Yes	Yes		
Geography Controls	Yes	Yes		
N	10158	10158	451	410
R2	0.777	0.777	0.356	0.215

	Discrimination Λ_{mob}		Relative road expenditure	
	(1)	(2)	(3)	(4)
Panel A: entire sample				
Ever in power dummy	-0.0374			
	(0.0607)			
log(1 + Total years in power)		-0.0111		
		(0.0275)		
Panel B: Kenyan road expenditure over time				
Λ_{mob} (non-democracy)			-0.239	
			(1.346)	
Λ_{mob} (democracy)				0.582
				(0.931)
Year and District FE			Yes	Yes
(Demographic, political, economic, geographic) × trend			Yes	Yes
Country FE	Yes	Yes		
Geography Controls	Yes	Yes		
N	10158	10158	451	410
R2	0.884	0.884	0.354	0.215

	Discrimination $\Lambda_{\text{mob}}^{10\%}$		Relative road expenditure	
	(1)	(2)	(3)	(4)
Panel A: entire sample				
Ever in power dummy	-0.0463			
	(0.0775)			
log(1 + Total years in power)		-0.0145		
		(0.0335)		
Panel B: Kenyan road expenditure over time				
$\Lambda_{\text{mob}}^{10\%}$ (non-democracy)			-0.810	
			(1.115)	
$\Lambda_{\text{mob}}^{10\%}$ (democracy)				0.0635
				(0.567)
Year and District FE			Yes	Yes
(Demographic, political, economic, geographic) × trend			Yes	Yes
Country FE	Yes	Yes		
Geography Controls	Yes	Yes		
N	10158	10158	451	410
R2	0.858	0.858	0.355	0.215

Replication of Table 2, yet with $\Lambda_{imm}^{10\%}$ (upper panel), Λ_{mob} (middle panel), and $\Lambda_{mob}^{10\%}$ (lower) panel as dependent variables, all z-scored.

B Numerically solving the planner's problem

The full planner's problem on page 5 consists of a very large number of choice variables and hence requires vast computation efforts when solved directly. Fortunately, Fajgelbaum and Schaal (2020) provide guidance on how to transform this *primal* problem into its much simpler *dual* representation. The following section illustrates how to use their derivation to numerically solve my version of the model.

To show how a unique global optimum exists, first note that every constraint of the social planner's problem is convex but potentially for the *Balanced Flows Constraint*. However, the introduction of congestion causes even the *Balanced Flows Constraint* to be convex if $\beta > \gamma$. To see this, note that every part of the lengthy constraint is linear, but for the interaction term $Q^n_{i,k}\tau^n_{i,k}(Q^n_{i,k}, I_{i,k})$ representing total trade costs. Since $\tau^n_{i,k}$ was parameterised as in (1), this expands to

$$Q^n_{i,k}\tau^n_{i,k}(Q^n_{i,k}, I_{i,k}) = \delta^\tau_{i,k}\frac{(Q^n_{i,k})^{1+\beta}}{I^\gamma_{i,k}} \tag{A.1}$$

which is convex if $\beta > \gamma$. Under this condition, the social planner's problem is to maximise a concave objective over a convex set of constraints, guaranteeing that any local optimum is indeed a global maximum.[A.1] $\beta > \gamma$ describes a notion of congestion dominance: increased infrastructure expenditure might alleviate the powers of congestion, but it can never overpower it. It precludes corner solutions in which all available concrete is spent on one link, all but washing away trade costs and leading to overwhelming transport flows on this one edge. If $\beta > \gamma$, geography always wins.

Consider first the full Lagrangian of the primal planner's problem

$$\mathcal{L} = \sum_i L_i u(c_i) - \sum_i \lambda^C_i \left[L_i c_i - \left(\sum_{n=1}^N (C^n_i)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \right] \tag{A.2}$$

$$- \sum_i \sum_n \lambda^P_{i,n} \left[C^n_i + \sum_{k\in N(i)} Q^n_{i,k}(1+\tau^n_{i,k}(Q^n_{i,k}, I_{i,k})) - Y^n_i - \sum_{j\in N(i)} Q^n_{j,i} \right] \tag{A.3}$$

$$- \lambda^I \left[\sum_i \sum_{k\in N(i)} \delta^i_{i,k} I_{i,k} - K \right] - \sum_i \sum_{k\in N(i)} \zeta^S_{i,k} \left[I_{i,k} - I_{k,i} \right] \tag{A.4}$$

$$+ \sum_i \sum_{k\in N(i)} \sum_n \zeta^Q_{i,k,n} Q^n_{i,k} + \sum_i \sum_n \zeta^C_{i,n} C^n_i + \sum_i \sum_n \zeta^c_i c_i - \sum_i \sum_{k\in N(i)} \zeta^I_{i,k} \left[4 - I_{i,k} \right] \tag{A.5}$$

This is a function of the choice variables $(C^n_i, Q^n_{i,k}, c_i, I_{i,k})$ in all dimensions $\langle i,k,n \rangle$ and the Lagrange multipliers $(\boldsymbol{\lambda^C}, \boldsymbol{\lambda^P}, \boldsymbol{\lambda^I}, \boldsymbol{\zeta^Q}, \boldsymbol{\zeta^C}, \boldsymbol{\zeta^c}, \boldsymbol{\zeta^I})$ also in $\langle i,k,n \rangle$. Standard optimisation yields first-

[A.1] This is Fajgelbaum and Schaal Proposition 1.

order conditions which can be collapsed to the following set of equations

$$
\begin{aligned}
c_i &= \left(\frac{1}{\alpha}\Big(\sum_{n'}(\lambda^P_{i,n'})^{1-\sigma}\Big)^{\frac{1}{1-\sigma}}\right)^{\frac{1}{\alpha-1}} \\
C^n_i &= \left[\frac{\lambda^P_{i,n}}{(\sum_{n'}(\lambda^P_{i,n'})^{1-\sigma})^{\frac{1}{1-\sigma}}}\right]^{-\sigma} L_i c_i \\
Q^n_{i,k} &= \left[\frac{1}{1+\beta}\frac{I^\gamma_{i,k}}{\delta^\tau_{i,k}}\max\Big\{\frac{\lambda^P_{k,n}}{\lambda^P_{i,n}}-1,0\Big\}\right]^{\frac{1}{\beta}} \\
I_{i,k} &= \max\Bigg\{\Bigg[\frac{\kappa}{\lambda^I(\delta^I_{i,k}+\delta^I_{k,i})}\Bigg(\sum_n \max\Big\{(\delta^\tau_{i,k})^{-\frac{1}{\beta}}\lambda^P_{i,n}\Big(\frac{\lambda^P_{k,n}}{\lambda^P_{i,n}}-1\Big)^{\frac{1+\beta}{\beta}},0\Big\} \\
&\quad + \sum_n \max\Big\{(\delta^\tau_{k,i})^{-\frac{1}{\beta}}\lambda^P_{k,n}\Big(\frac{\lambda^P_{i,n}}{\lambda^P_{k,n}}-1\Big)^{\frac{1+\beta}{\beta}},0\Big\}\Bigg)\Bigg]^{\frac{\beta}{\beta-\gamma}},4\Bigg\}
\end{aligned}
\tag{A.6}
$$

These directly follow the more general framework outlined in the technical appendix of Fajgelbaum and Schaal applied to my version of the model. In the final equation denoting optimal infrastructure supply, $\kappa = \gamma(1+\beta)^{-\frac{1+\beta}{\beta}}$, and the multiplier λ^I is such that adherence to the *Network Building Constraint* is ensured. Through these algebraic manipulations, I have expressed all choice variables as functions of merely the Lagrange parameters $\boldsymbol{\lambda}^{\boldsymbol{P}}$ over dimensions $\langle i,k,n\rangle$. I can hence recast the entire Lagrangian in much simpler form as

$$
\begin{aligned}
\mathcal{L}(\boldsymbol{\lambda}, x(\boldsymbol{\lambda})) &= \sum_i L_i u(c_i(\boldsymbol{\lambda})) \\
&- \sum_i\sum_n \lambda^P_{i,n}\Big[C^n_i(\boldsymbol{\lambda}) + \sum_{k\in N(i)} Q^n_{i,k}(\boldsymbol{\lambda})(1+\tau^n_{i,k}(Q_{i,k}(\boldsymbol{\lambda})^n, I_{i,k}(\boldsymbol{\lambda}))) - Y^n_i - \sum_{j\in N(i)} Q^n_{j,i}(\boldsymbol{\lambda})\Big]
\end{aligned}
\tag{A.7}
$$

where $x(\boldsymbol{\lambda})$ denote the choice variables as functions of the Lagrange parameters as derived above. Fajgelbaum and Schaal note that thanks to complementary slackness, all other constraints can be readily dropped from consideration and only the *Balanced Flows Constraint* remains part of the problem.

As Fajgelbaum and Schaal further explain, the dual of this problem can now be conceived as the minimisation of

$$\min_{\boldsymbol{\lambda}\geq 0} \mathcal{L}(\boldsymbol{\lambda}, x(\boldsymbol{\lambda}))$$

which is an optimisation problem over merely $\|\boldsymbol{\lambda}^{\boldsymbol{P}}\| = I \times N$ variables. Fajgelbaum and Schaal interpret $\boldsymbol{\lambda}^{\boldsymbol{P}}$ as a field of prices varying over goods and locations. I am left only to minimise equation (A.7) to obtain the price-field $\boldsymbol{\lambda}^{\boldsymbol{P}}$. I implement constrained optimisations within the `fmincon` environment in MATLAB and achieve fairly fast convergence. Solving for smaller networks (like Rwanda or Djibouti) is a matter of seconds, yet the largest countries (Algeria, Angola, DRC, and Sudan) each take about a day of computation time (on a five-year old device, nonetheless). Plugging the derived $\boldsymbol{\lambda}^{\boldsymbol{P}}$ parameters into the various FOCs in (A.6) yields the optimal transport network $I_{i,k}$, trade flows between locations $Q^n_{i,k}$, and consumption patterns C^n_i and c_i.

C Calibration details

C.1 Calibrating structural parameters

Tradable budget share α This parameter captures the Cobb-Douglas budget share households spend on tradable goods. This includes consumption of home-produced goods (ie. food staples) that could in principle be traded. To calibrate this expenditure share, I rely on analysis by Porteous (2022) who calibrate budget shares using data from Nigeria and Angola. They set the share for agricultural tradables to 0.4, non-agricultural tradables to 0.3, and non-agricultural non-tradables to 0.3, respectively. Summing together the two tradables categories, I calibrate $\alpha = 0.7$.

Elasticity of substitution σ There are notoriously many divergent estimates for the trade elasticity of substitution σ (for a review see Head and Mayer, 2014). I rely on a recent review paper by Atkin and Donaldson (2022), which summarises the literature estimating trade elasticities in developing country contexts and recommends using a parameter of $\sigma = 5$. This is slightly higher than the parameter used by Fajgelbaum and Schaal (2020) in their calibration of interregional European trade ($\sigma = 4$), which is not too surprising given that homogeneous agricultural products play a more important role in African regional trade vis-a-vis Europe.

C.2 Calibrating trade costs $\tau_{i,k}$

As described in the main text, I follow Fajgelbaum and Schaal (2020) to assume the following functional form for trade costs between locations i, k for good n:

$$\tau^n_{i,k}(Q^n_{i,k}, I_{i,k}) = \delta^\tau_{i,k} \frac{(Q^n_{i,k})^\beta}{I^\gamma_{i,k}}$$

Trade flows $Q^n_{i,k}$ on the link increase trade costs through the congestion elasticity parameter β, infrastructure $I_{i,k}$ on the link decreases trade costs through the infrastructure elasticity γ. $\delta^\tau_{i,k}$ captures inherent trade costs between the locations, which could in principle depend on any exogeneous or geographical characteristics of the link.

Infrastructure elasticity γ As described in the main text, infrastructure $I_{i,k}$ is parameterised as the average attainable speed between locations i and k. Hence, γ captures the elasticity of trade costs to speed improvements. To calibrate it, I use data from a survey of trucking costs across Africa from Teravaninthorn and Raballand (2009). In particular, the authors investigate transport costs across the "Southern Corridor" from Durban to Dar and estimate that a 20% reduction of delays at border posts across this corridor would reduce total aggregate transport costs by 3-4% (Teravaninthorn and Raballand, 2009, Table 1.3). Delays at border posts are one of the major ways international truck traffic in Africa gets slowed down, so this yields helpful insights into the cost benefits of speeding up transport. The authors note that current delays at the border posts along this corridor amount to about four days or 96hrs (Teravaninthorn and Raballand, 2009, page 9). A search of the route on Google Maps indicates that without border delays, the total driving time of the corridor is about 59hrs, so that a total of 62% of the entire trip is currently spent waiting. The authors further report that about 29.8% of all kilometre-weighted trips in the region go along this corridor. Putting it all together; a reduction of 20% of the 62% of time spent waiting at borders for 29.8% of trips amounts to a 3-4% reduction in aggregate transport costs, or

$$(1 - 0.2 \times 0.62 \times 0.298)^{\gamma} = 1 - 0.035$$

or $\gamma = 0.946$.

Congestion elasticity β To calibrate how much additional cars on the road affect trade costs, I rely on the exercise by Fajgelbaum and Schaal (2017), who compile and aggregate estimates from Wang et al. (2011) of the relationship between car density and speed using data from Georgia, USA. They estimate an average relationship of

$$\text{Speed}_{i,k} \propto Q_{i,k}^{1.2446}$$

Since I posit the relationship between speed and trade costs to be $\gamma = 0.946$, I nest the two and arrive at

$$\beta = 1.2446 \times \gamma = 1.1774$$

Exogeneous trade costs $\delta^{\tau}_{i,k}$ To calibrate $\delta^{\tau}_{i,k}$, I make use of the work of Atkin and Donaldson (2015), who investigate price gaps across space in Ethiopia and Nigeria. The authors have barcode-level data of the same product at different locations across the two countries and find that, in general, prices become higher in areas further away from the supposed origin location of the product (ie. the main port of entry for imported products, or the factory location for home-produced products). They posit that the absolute price gap of a product sold at a location k to the price at the origin location i is a function of transport costs $t(\cdot)$ and a markup charged by intermediaries with market power $\mu(\cdot)$:[A.2]

$$P_k - P_i = t\left(\mathbf{X}_k\right) + \mu\left(\mathbf{X}_k\right),$$

Both t and μ are allowed to vary according to observable characteristics $\mathbf{X}_k$ of the selling location k.

I follow the evidence brought forward in Atkin and Donaldson, who analyse price gaps mainly as a function of distance between origin and destination location. In particular, the authors estimate a log-linear relationship between the two:

$$P_k - P_i = \xi \log\left(\text{Distance (miles)}_{i,k}\right)$$

They estimate that (among trading pairs), this elasticity $\widehat{\xi}$ is 0.0248 in Ethiopia and 0.0254 in Nigeria (Atkin and Donaldson (2015), Table 2, columns (2) and (5)). Interestingly, this elasticity is mediated by market power: more remote areas get charged lower markups by intermediaries who realise that inhabitants of these areas tend to be poorer and thus on a more elastic part of their demand curve. The "pure" distance elasticity of transport costs t is larger: 0.0374 in Ethiopia and 0.0558 in Nigeria.

In the Fajgelbaum and Schaal (2020) framework, price gaps for a good n between locations are

[A.2]This corresponds to equation (2) of Atkin and Donaldson (2015), where I have relabeled their notation for transport costs τ as t, to avoid confusion with the endogeneous trade costs τ in my model.

given by the ad-valorem trade cost parameter $\tau^n_{i,k}$:

$$\begin{aligned} P^n_k - P^n_i &= P^n_i \tau^n_{i,k} \\ \implies \frac{P^n_k - P^n_i}{P^n_i} &= \tau^n_{i,k} \\ \implies \frac{\widehat{\xi} \log \left(\text{Distance (miles)}_{i,k}\right)}{P^n_i} &= \tau^n_{i,k} \end{aligned}$$

Hence, to "translate" the Atkin and Donaldson evidence on absolute (dollar-value) price gaps to my object of inherent ad-valorem "iceberg" trade costs, I need to divide their predicted values of price gaps by the origin price of goods in the barcode-level dataset. Atkin and Donaldson provide these moments in their main text (page 24): the average product in their Ethiopia dataset costs $\overline{P_i} = 43$ cents, while the average product in their Nigeria dataset costs 1.03 dollars. Putting this together, the inherent distance elasticity of ad-valorem price gaps $\widehat{\xi}/\overline{P_i}$ is $0.0248/0.43 = 0.0577$ in Ethiopia and $0.0254/1.03 = 0.02466$ in Nigeria.

However, in the Fajgelbaum and Schaal framework, trade costs are, furthermore, subject to congestion and infrastructure effects, which are non-linear and endogeneous. In other words, the above calibration would be correct for shipping 1 good at speed of 1km/hr across the network, or Q goods at speed $Q^{\beta/\gamma}$. If the actually shipped quantity Q were higher (lower) than that in the current observed equilibrium, my calibration would overstate (understate) this elasticity. Since Atkin and Donaldson (2015) do not have access to data on quantities shipped (which is generally hard to come by), we have no way to directly test for this.

I hence run a fixed-point algorithm to account for this: I treat the price gaps reported in Atkin and Donaldson as equilibrium values, and adjust $\delta^\tau_{i,k}$ until I match them.

In particular, I start by setting $\delta^\tau_{i,k,0} = \widehat{\xi}/\overline{P_i}$ from above, compute the current equilibrium, use it to determine the model-implied ratio of $R \equiv (Q^n_{i,k})^\beta / I^\gamma_{i,k}$, update $\delta^\tau_{i,k,\ell+1} = \delta^\tau_{i,k,\ell}/R$, and iterate until convergence (ie. until equilibrium price gaps coincide with the ones reported in Atkin and Donaldson). This is achieved at

$$\begin{aligned} \delta^{\tau,\text{ETH}}_0 &= \frac{\widehat{\xi}^{\text{ETH}}}{\overline{P}^{\text{ETH}}_i} \cdot 3.915 = \frac{0.0248 \cdot 3.915}{0.43} = 0.2258 \qquad \text{for Ethiopia} \\ \delta^{\tau,\text{NGA}}_0 &= \frac{\widehat{\xi}^{\text{NGA}}}{\overline{P}^{\text{NGA}}_i} \cdot 0.2414 = \frac{0.0254 \cdot 0.2414}{1.03} = 0.006 \qquad \text{for Nigeria} \end{aligned}$$

Averaging the two estimates yields an elasticity of 0.1159, and hence an inherent trade cost term of

$$\delta^\tau_{i,k} = 0.1159 \times \log \left(\text{Distance (miles)}_{i,k}\right)$$

As a robustness exercise, I also use estimates the authors use to purge spatial price gaps of the impact of market power. These can readily be read of columns (3) and (6) of Table 2 of their paper. Using the same procedure as above, I obtain and average elasticity of

$$\delta^{\tau,\text{no-market-power}}_{i,k} = 0.3525 \times \log \left(\text{Distance (miles)}_{i,k}\right)$$

as an inherent trade cost term in a world where intermediaries have no market power.

C.3 Additional details on historical analysis

To calibrate my model to historical roads data from Kenya, I use data from Burgess et al. (2015) and Jedwab and Storeygard (2022). The Burgess et al. (2015) paper provides population, road expenditure shares, as well as centroids of Kenyan districts and their ethnic affiliation.

Using digitised Michelin maps by Jedwab and Storeygard (2022), I merge each road segment to their nearest district-centroid. Segments come with a roads classification (highway, paved, unpaved, and so on), which I translate into average speeds using the same methodology as Jedwab and Storeygard. This leaves me with a *district-level* measure of infrastructure density. To translate this into *edge-level* values, I calibrate the amount of infrastructure $I_{j,k}$ between districts j and k as the average infrastructure density of j and k. I treat two districts as adjacent if the voronoi-diagrams around their centroids touch.

I don't have information on population and productivity of each of Kenya's districts across time. I do, however, have population information for 1962. I project this outward using country-wide population totals (ie. assuming that the relative population share of each district stays constant over time). I also calibrate productivity such that the country's total production matches data on overall GDP of Kenya in each year (using data on population totals and GDP from the World Bank). I again treat the 4 most populous districts as producing their own variety, with the remaining districts producing an "agricultural" fifth variety. Note that I do not include a foreign-country buffer around Kenya, as I don't have historical information on Tanzania's, Uganda's, (South) Sudan's, Ethiopia's, or Somalia's population and productivity.

Assuming all structural parameters from the rest of the paper (which are calibrated on much more recent data) stay the same, this leaves me with enough to compute the optimally reallocated and expanded network with mobile and immobile labor, at each point at which a digitised Michelin map exists.

D Foreign aid and infrastructure discrimination

To investigate whether international development aid is quantitatively associated to my measure of trade network inefficiency, I make use of two datasets of geo-referenced aid flows to Africa. Firstly, AidData (2017) in cooperation with the World Bank, tracks over 5,600 lending lines from the World Bank to African nations and reports precise coordinates of over 60,000 projects financed through these funds, totalling more than 300 billion US dollars. The sample comprises all projects approved between 1996–2014. As Strandow et al. (2011) describe, attributing projects to locations relies on a double-blind coding procedure of various World Bank documents. Secondly, I explore patterns from a similar database on Chinese aid projects by Strange et al. (2017). They resort to reports from numerous local and international media outlets to track official and unofficial financing lines to over 1,500 projects worth 73 billion US dollars in the period 2000–2011.[A.3]

For the purpose of this study, I exclude aid projects with no clear-cut geographical target like unconditional lending lines to the central government or assistance for political parties. I also exclude flows with unknown or only vague information on eventual project location.[A.4] I also ignore

[A.3] As Strange et al. point out, media reports are often based on initial press releases and do not necessarily follow up on the eventual disbursement of every promised dollar. In that, the dataset is likely to capture Chinese funding *commitments* rather than actual *disbursements*. Insofar as donors usually commit to more than they eventually deliver, these figures present an upper bound of realised development assistance. Furthermore, while AidData (2017) claim their dataset on World Bank projects to be exhaustive, the dataset on Chinese aid will naturally miss some unofficial flows, as significant parts of Chinese involvement remain untracked.

[A.4] Specifically, I exclude all projects with a precision code of more than 3 – this corresponds to projects only identified at projects which were still under construction or otherwise not fully completed by the end of 2017. Together, these steps truncate the World Bank sample by 35% and the China sample by 52%. In Figure A.8, I map the spatial distribution of aid projects from both remaining samples. I aggregate the total value of aid disbursements from the remaining 10,786 World Bank projects and 1,420 Chinese projects onto the grid cell level. Of the 10,158 grid cells of my sample, more than 21% have received some form of assistance from either source.[A.5]

Do donor institutions identify places most in need of additional infrastructure? I employ various indicators of aid provision in the standard grid cell level framework based on equation (6). I rely on two measures to quantify the prevalence of foreign aid: the total value of aid disbursements to a grid cell in 2011 US dollars and the number of distinct project sites within a given cell. I also put additional emphasis on infrastructure by separately analysing variation in funds going only to infrastructure projects in the transportation sector.

Table A.10 reports results. Columns (1–4) investigate the spatial distribution of World Bank assistance. The estimates reveal seemingly opposing objectives between the Bank and the social planner. Negative estimates in columns (1) through (4) imply that grid cells receiving more World Bank assistance score lower on the discrimination index Λ_i. Every additional million US dollar flowing into an area is associated with the grid cell being about 0.004 standard deviations too well off. Focusing on transport sector projects only, results are qualitatively similar, yet much stronger. The average transport infrastructure project size of around 3 million US dollars goes to grid cells which stand to lose 0.005 standard deviations of welfare under the reallocation exercise. Similar effects hold on the extensive margin reported in columns (3) and (4). Columns (5–8) present very similar results for Chinese aid. Chinese assistance also systematically flows into privileged cells, with intensive margin point estimates of the association ranging between a quarter and a tenth of the World Bank results. On the extensive margin, more Chinese projects are similarly associated with higher trade network imbalances. For each new development site financed by China in a certain cell, the social planner intervenes and allocates about 0.03-0.04 standard deviations of welfare away from the cell (columns 7–8).

These relationships should by not interpreted as causal effects. Since the placement of aid projects is not random, numerous other channels could account for the patterns depicted in Table A.10. The donor's investment strategies might for example be motivated by increasing returns to scale. If the World Bank believes in an environment with multiple equilibria, where small initial investments set in motion a dynamic of spillover externalities, labour migration, and follow-up investments, it is often the right decision to fund projects in places that will not immediately harness their full capabilities (Krugman, 1991; Duranton and Venables, 2017). These investments will necessarily appear inefficient in promoting optimal trade *today*, yet spur transformative development *tomorrow* (see Michaels et al., 2021). Embedding the reallocation exercise in a New Economic Geography framework of increasing returns and labour mobility might be a valuable extension to better evaluate specific place-based policies.

province-level or above. The remaining entries are geo-coded either exactly (61%), within a 25 kilometre radius (4%), or with municipality-level precision (35%) (Strandow et al., 2011)

[A.5]All disbursements are adjusted to 2011 US dollars. For projects with multiple sites, I assume total disbursement value to be split evenly between sites. On average, these cells receive aid volumes of more than 30 million US dollars. The area receiving the most total World Bank funding is the grid cell containing Uganda's capital Kampala. The biggest beneficiary of Chinese development assistance is a grid cell in the south of Congo-Kinshasa, where Chinese funds of almost 5 billion US dollars helped construct a vast copper mining infrastructure.

Table A.10: International aid and local infrastructure discrimination

	Λ: World Bank				Λ: China			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total disbursements (mil $)	-0.00187***				-0.0000909			
	(0.000635)				(0.0000684)			
Total transport sector disbursements (mil $)		-0.00159				-0.000256*		
		(0.00180)				(0.000133)		
Number of projects			-0.0116***				-0.0127***	
			(0.00253)				(0.00450)	
Number of transport sector disbursements				-0.0147***				-0.0278**
				(0.00367)				(0.0133)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geography Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10158	10158	10158	10158	10158	10158	10158	10158
R2	0.764	0.764	0.765	0.764	0.764	0.764	0.764	0.764

Grid cell level estimations of equation (6) *with z-scored local infrastructure discrimination* $\tilde{\Lambda}_i$ *as dependent variable and different measures of foreign aid flows into grid cells as explanatory covariates. Columns (1–4) investigate World Bank assistance. Column (1) analyses total disbursement value from World Bank projects approved from 1996–2014 in 2011 US dollars, which were completed by 2017. (2) only uses a subset of projects in the transport sector. (3)–(4) use the same data but focus on the number of distinct project sites within each grid cell. Columns (5–8) repeat the same estimations, but with data on Chinese aid projects between 2000–2011. Geography controls, consisting of altitude, temperature, average land suitability, malaria prevalence, yearly growing days, average precipitation, indicators for the 12 predominant agricultural biomes, indicators for whether a cell is a capital, within 25 KM of a natural harbour, navigable river, or lake, the fourth-order polynomial of latitude and longitude, and an indicator of whether the grid cell lies on the border of a country's network. They also include population, night lights, and ruggedness. Chinese aid data are more likely to reflect commitments rather than actual disbursements. Standard errors are clustered on the* 3×3 *degree level and are shown in parentheses.*