Supplementary Material (not for publication)

S.I Supplement: Robustness of Reduced-Form Estimates

Table S1: Electricity Indicator and DMSP-OLS Stable Night Lights (2000-2011)

	Stable Nightlights Mean		
	(1)	(2)	(3)
Intercept	0.160	0.007*	0.002
	(0.130)	(0.004)	(0.009)
Elec. Indicator	3.410***	0.287***	0.088**
	(1.110)	(0.090)	(0.035)
Initial Stable Nightlight Mean		1.030***	1.002***
		(0.017)	(0.000)
Sample	*full*	*full*	*switchers*
Observations	1208	1208	80
R^2	0.052	0.989	1.000
Adjusted R^2	0.051	0.989	1.000

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. All standard errors clustered at district-level. Switchers sample denotes only districts that experienced a switch in electrification status from zero to one between 2000 and 2011. Sample years constrained by availability of DMSP-OLS data.

Figure S1: Sectoral Employment in Ethiopia (1994-2016)

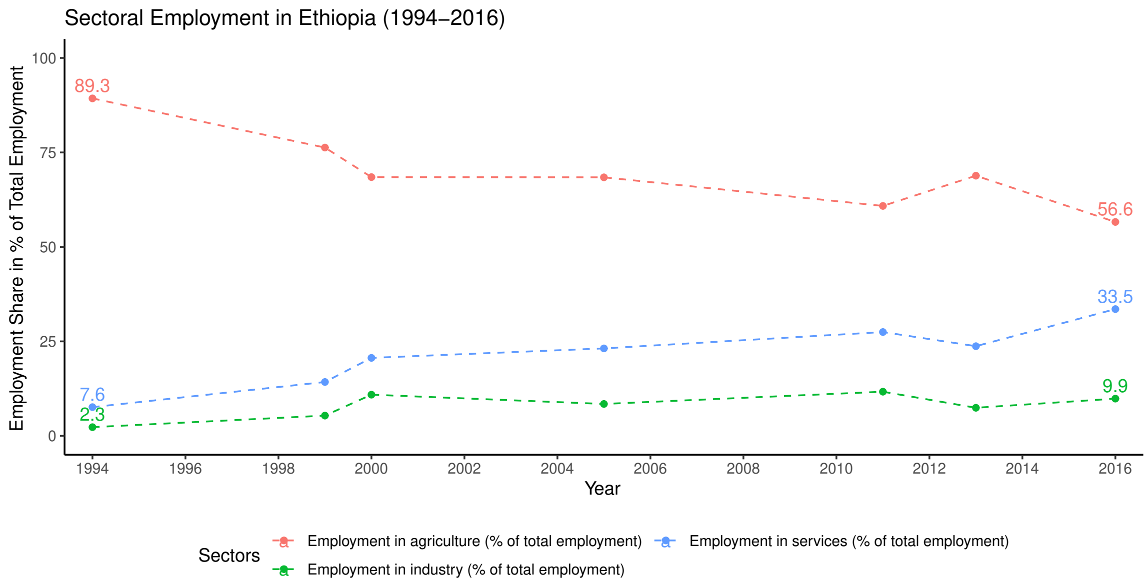


Figure S2: Sectoral Value-Added in Ethiopia (1994-2016)

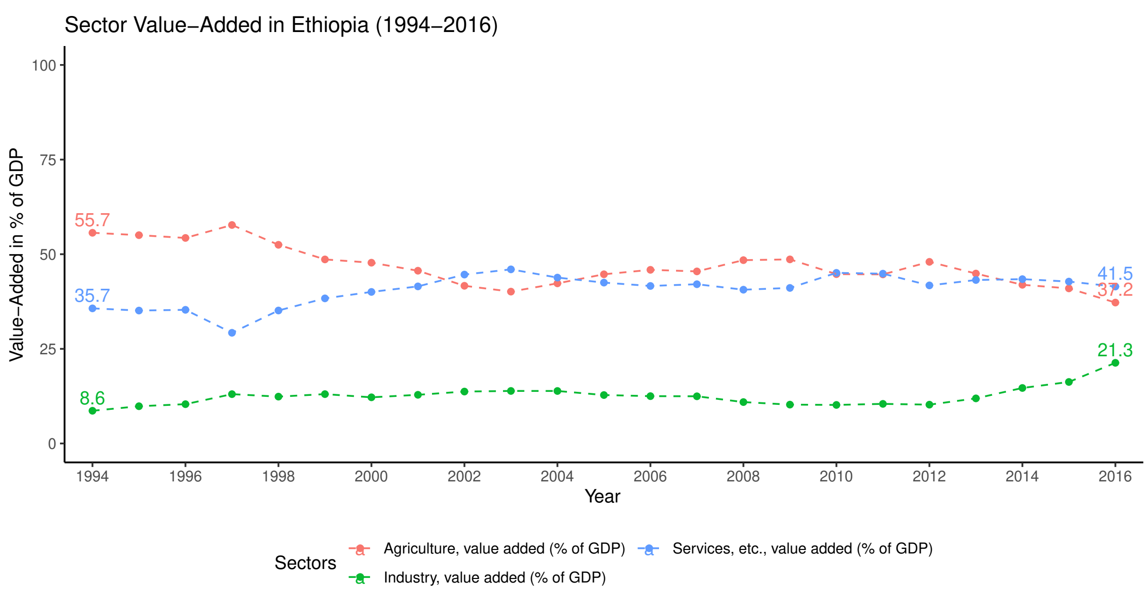


Figure S3: Poverty Headcounts and GDP per Capita in Ethiopia (1994-2016)

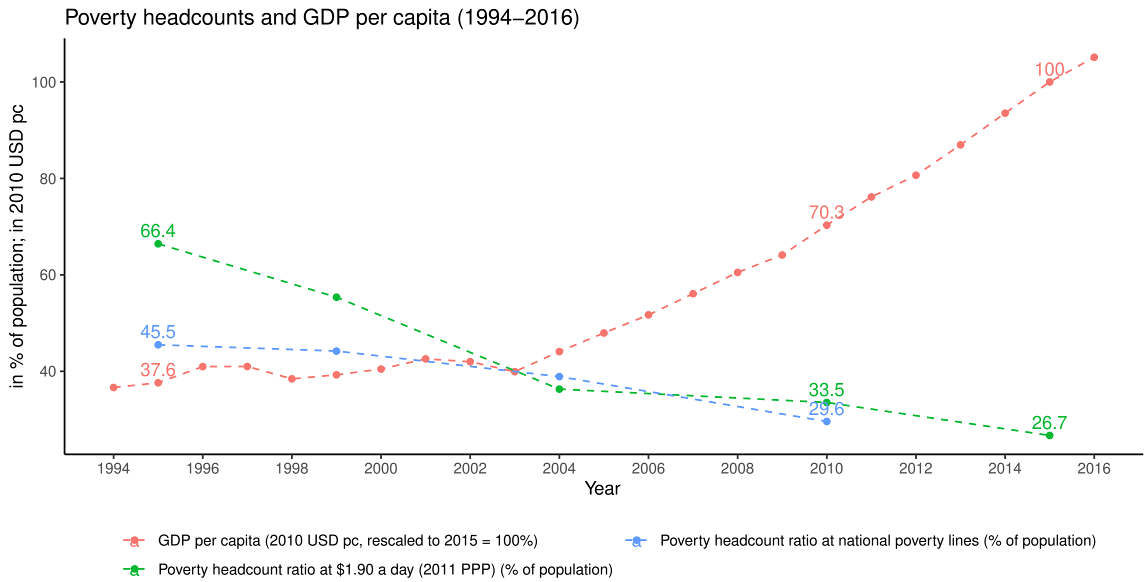


Table S2: Road and Electrification Status in NLFS Sample, Baseline vs Endline

Districts (1999)		Road Ind. 0	1	Total
Elec. Ind.	0	169	158	327
	1	3	57	60
	Total	172	215	387

Districts (2013)		Road Ind. 0	1	Total
Elec. Ind.	0	35	281	316
	1	0	90	90
	Total	35	371	406

Note: Baseline sample includes districts from NLFS (1999) survey round and endline sample includes districts from NLFS (2013 survey round, where districts are only included if they are sampled at least twice in their given survey (i.e. across NLFS 1999, 2005 and 2013). Districts in Addis Abeba and Somali regions are excluded from all NLFS rounds. Midline sample (i.e. NLFS 2005) omitted for clarity of exposition only. Road indicator equals one if district contains at least one all-weather road. Electricity indicator equals one if district hosts electric substation (or falls within 25km radius of substation). The three districts supposedly electrified without road access are: Mena Bale, Odo Shakiso and Sekota (NLFS, 1999), most likely due to measurement error in what constitutes an all-weather road – especially since all three contain ancient and historic trading hubs [Mena Bale (Dolemena town), Odo Shakiso (Shakiso town) and Sekota (Sekota town)].

Table S3: Road and Electrification Status in DHS Sample, Baseline vs Endline

Districts (2000)		**Road Ind.**		
		0	1	Total
Elec. Ind.	0	109	91	200
	1	3	38	41
	Total	112	129	241

Districts (2016)		**Road Ind.**		
		0	1	Total
Elec. Ind.	0	3	195	198
	1	0	65	65
	Total	3	260	263

Note: Baseline sample includes districts from DHS (2000) survey round and endline sample includes districts from DHS (2016 survey round, where districts are only included if they are sampled at least twice in their given survey (i.e. across DHS 2000, 2005, 2011 and 2016). Districts in Addis Abeba regions are excluded from all DHS rounds. Midline sample (i.e. DHS 2005, DHS 2011) omitted for clarity of exposition only. Road indicator equals one if district contains at least one all-weather road. Electricity indicator equals one if district hosts electric substation (or falls within 25km radius of substation). The three districts supposedly electrified without road access are: Kuni, Lasta and Sekota (DHS, 2000), most likely due to measurement error in what constitutes an all-weather road – especially since all three contain ancient and historic trading hubs [Kuni (Bedesa town), Lasta (Lalibela town) and Sekota (Sekota town)].

Figure S4: Endogenous Allocation of Roads over Time (1999-2013)

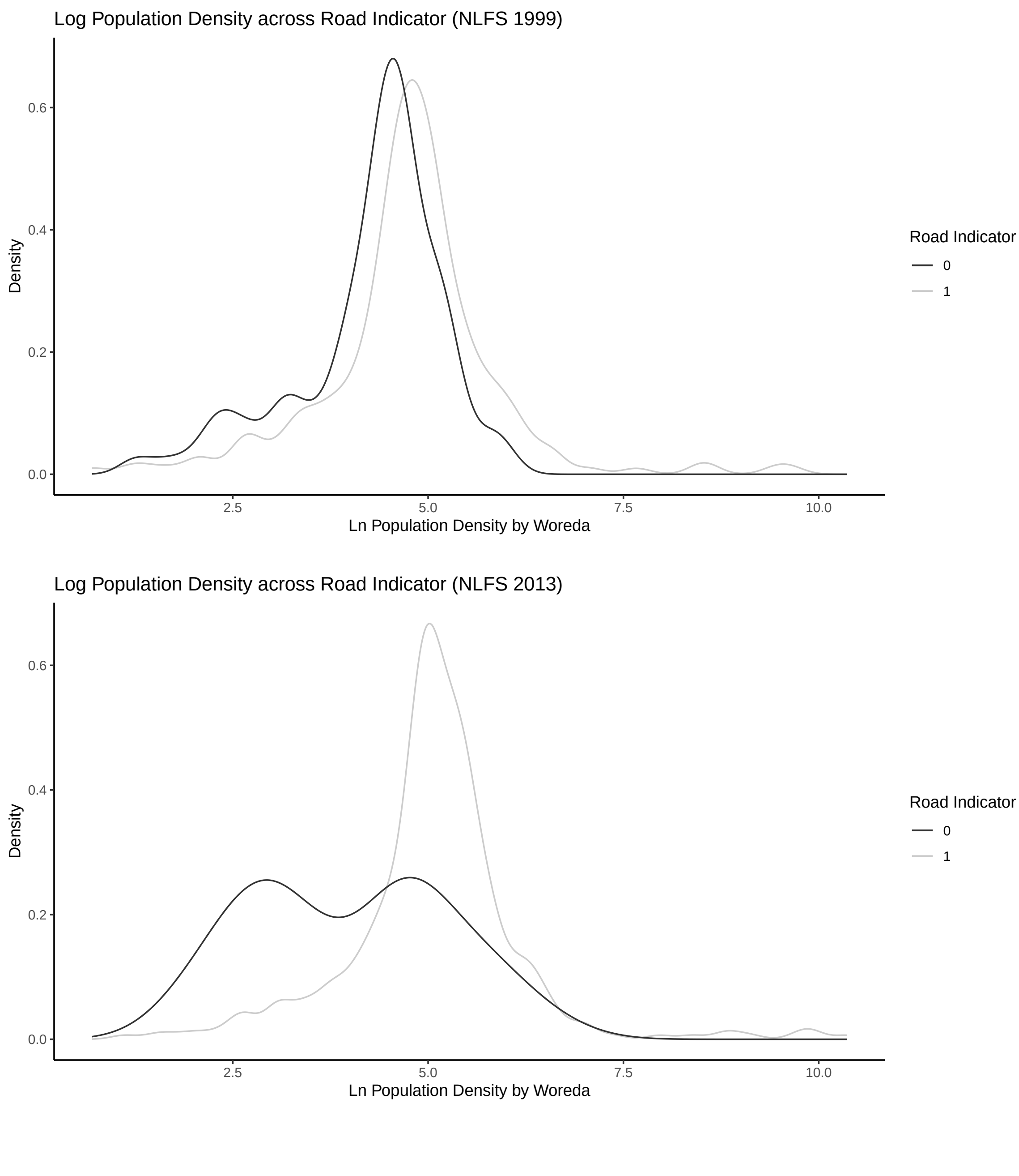


Figure S5: DHS Enumeration Area Locations by Survey Round (2000-2016)

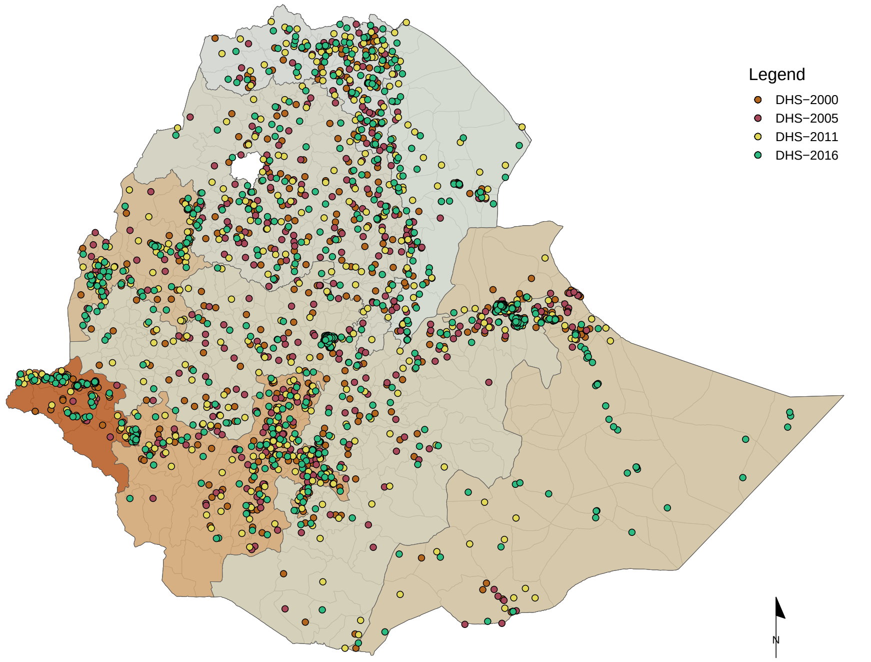


Figure S6: NLFS Sampling of Districts (1999-2013)

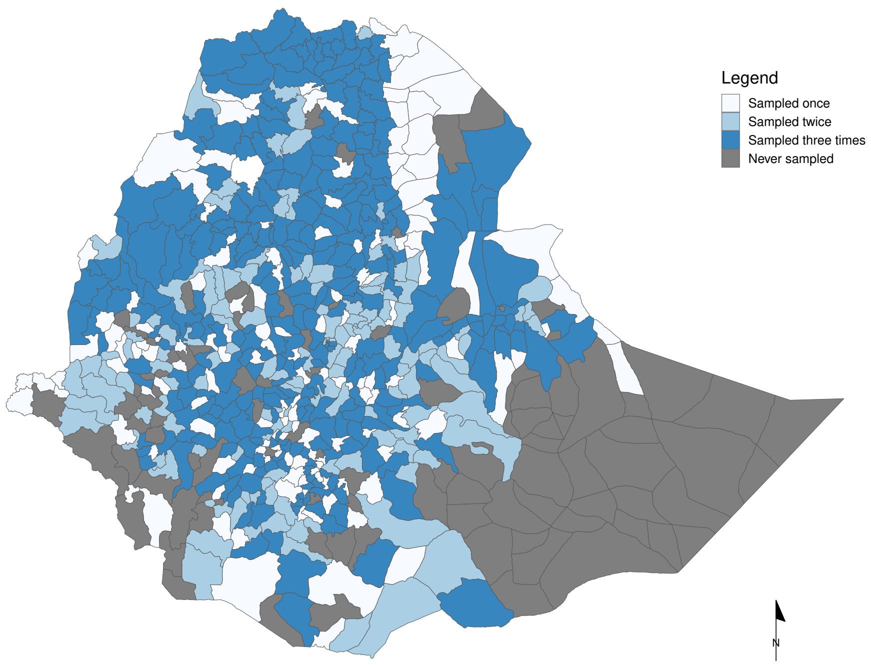


Figure S7: DHS Sampling of Districts (2000-2016)

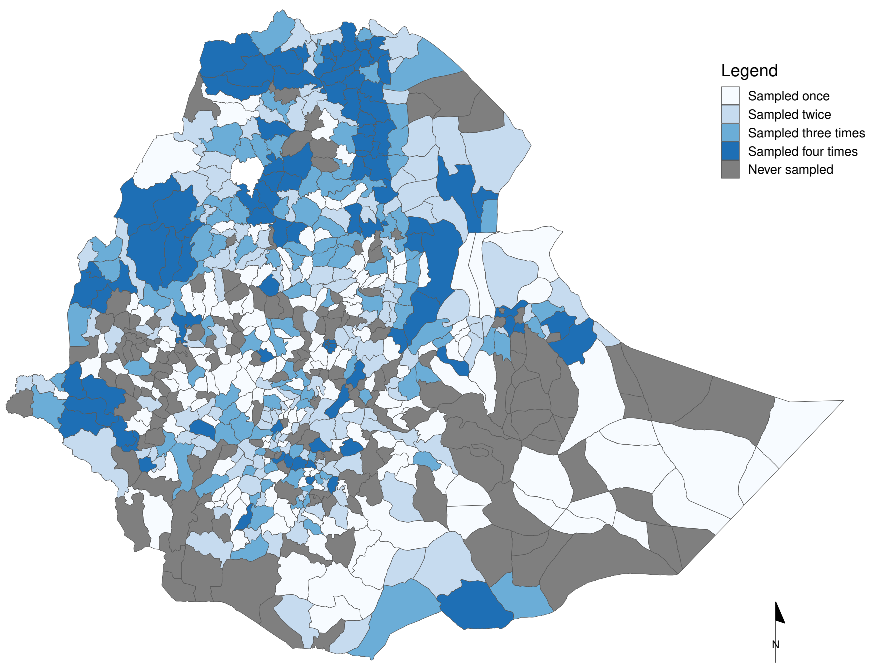


Figure S8: HCES Sampling of Districts (2000-2016)

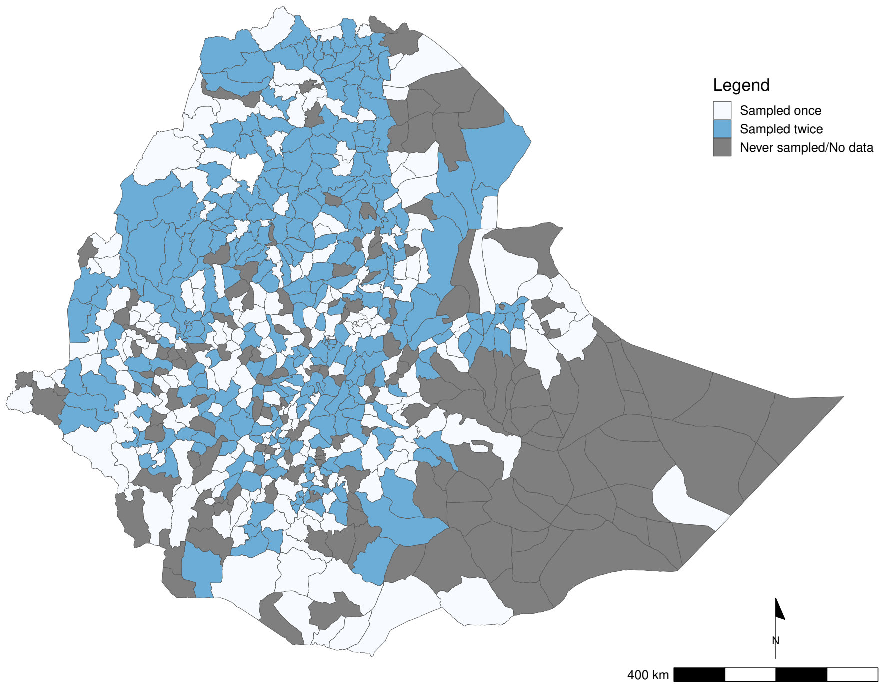


Figure S9: Spatial Variation in Population Density across Ethiopia (2015)

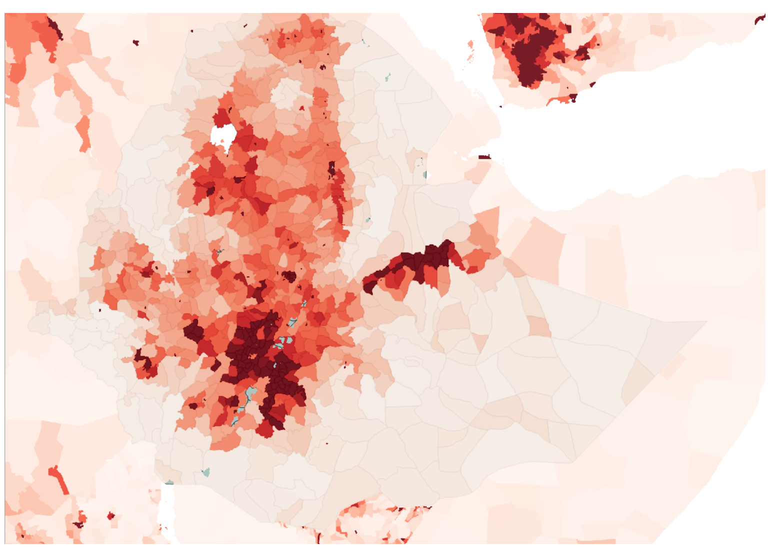


Figure S10: Spatial Variation in Elevation and Terrain Ruggedness across Ethiopia

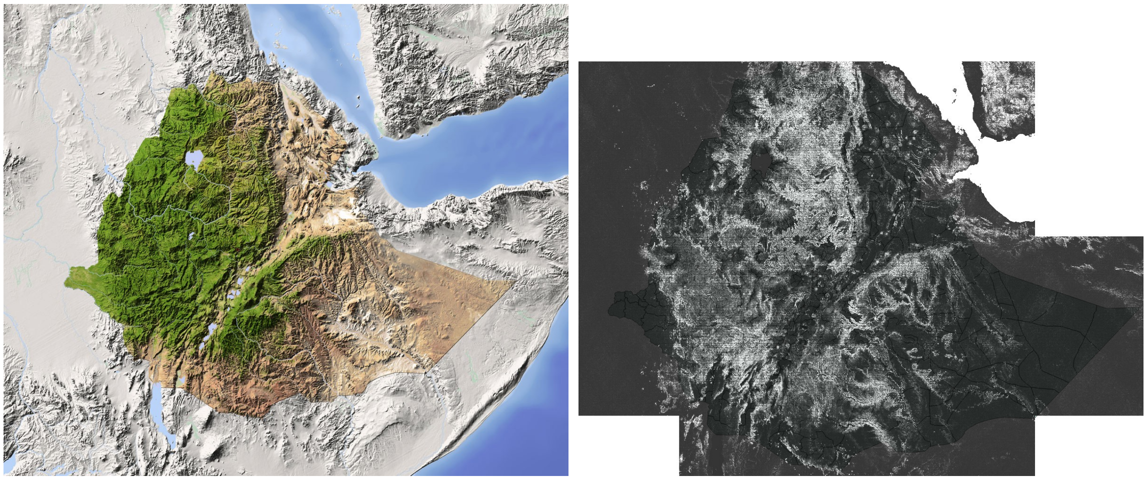


Figure S11: Historic Italian Road Construction in Ethiopia and Eritrea

Figure S12: Reconstructed Italian Colonial Roads and Orthogonal Feeder Roads to Nearby Districts around Debre Berhan (along Dessie–Addis Abeba corridor)

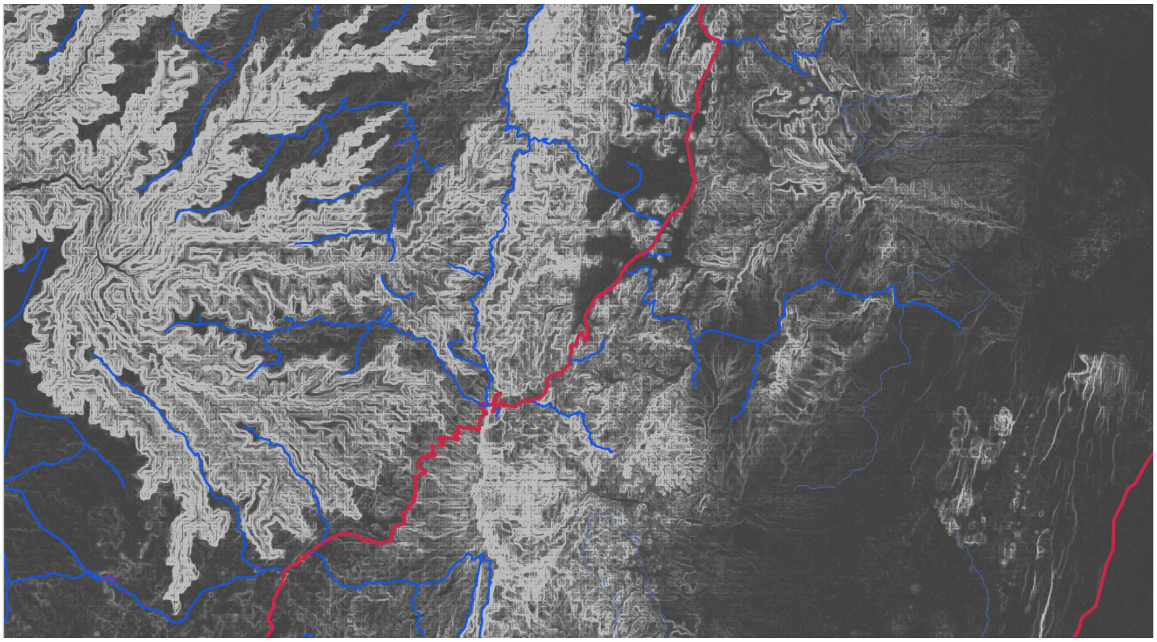


Figure S13: Reconstructed Italian Colonial Roads and Orthogonal Feeder Roads to Nearby Districts around Kulubi (along Harar–Addis Abeba corridor)

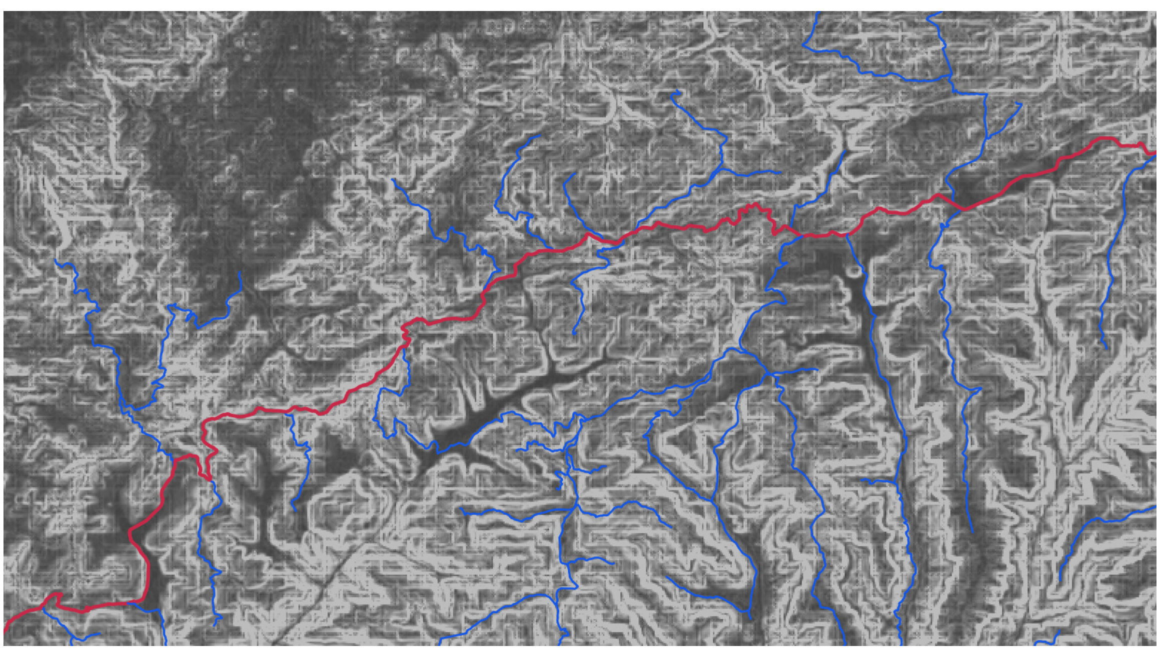


Table S4: First Stage: Roads-IV and Electricity-IV interaction, NLFS sample (1999-2016)

	Roads Ind.	Roads*Elec Ind.
	(1)	(2)
Road IV	0.194***	−0.027
	(0.042)	(0.033)
Road IV*Elec IV	0.082**	0.137***
	(0.035)	(0.046)
Sample	*NLFS*	*NLFS*
Year FE	✓	✓
Region-Year Trend	✓	✓
Controls	✓	✓
Windmeijer cond. F.	27.095	9.156
F-test statistic	11.895	17.676
R^2	0.292	0.380
Adjusted R^2	0.268	0.359
Observations	1163	1163

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. All standard errors clustered at district-level. Sample includes all districts sampled at least twice in NLFS (1999, 2005, 2013), yielding a total of 1163 district-years. Districts in Addis Abeba and Somali regions are always excluded. Road indicator switches to one in year of district receiving at least one all-weather road. Electricity indicator switches to one in year of electric substation being commissioned in district (or district within 25km radius thereof). Roads IV denotes predicted road indicator according to Kruskal least-cost spanning tree that starts off colonial Italian trunk network. Electricity IV denotes predicted electricity indicator according to temporal and spatial variation from hydropower dam-to-Addis corridors coming on line. Region-year-specific time trends for nine administrative regions, excluding Addis and Somali regions. Time-invariant controls: terrain ruggedness, log distance to zone capital, log distance to wholesale argricultural market, log distance to Addis, soil quality, district area. Initial values of time-varying controls: log population density, nighttime luminosity, temperature, standard deviation of precipitation, built-up area and literacy.

Table S5: First Stage: Roads-IV and Electricity-IV interaction, DHS sample (1999-2016)

	Roads Ind.	Roads*Elec Ind.
	(1)	(2)
Road IV	0.241***	0.012
	(0.049)	(0.039)
Road IV*Elec IV	0.058*	0.171***
	(0.033)	(0.055)
Sample	*DHS*	*DHS*
Year FE	✓	✓
Region-Year Trend	✓	✓
Controls	✓	✓
Windmeijer cond. F.	22.197	10.019
F-test statistic	9.142	8.254
R^2	0.339	0.316
Adjusted R^2	0.302	0.278
Observations	999	999

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. All standard errors clustered at district-level. Sample includes all districts sampled at least twice in DHS (1999, 2005, 2013), yielding a total of 999 district-years. Districts in Addis Abeba region are excluded. Road indicator switches to one in year of district receiving at least one all-weather road. Electricity indicator switches to one in year of electric substation being commissioned in district (or district within 25km radius thereof). Roads IV denotes predicted road indicator according to Kruskal least-cost spanning tree that starts off colonial Italian trunk network. Electricity IV denotes predicted electricity indicator according to temporal and spatial variation from hydropower dam-to-Addis corridors coming on line. Region-year-specific time trends for ten administrative regions, excluding Addis regions. Time-invariant controls: terrain ruggedness, log distance to zone capital, log distance to wholesale argricultural market, log distance to Addis, soil quality, district area. Initial values of time-varying controls: log population density, nighttime luminosity, temperature, standard deviation of precipitation, built-up area and literacy.

Table S6: First Stage: Roads-IV and Electricity-IV interaction, full sample (1999-2016)

	Ln(Market Access)	Ln(Market Access)*Elec Ind.
	(1)	(2)
Road IV	0.0003**	−0.6819
	(0.0001)	(1.2198)
Road IV*Elec IV	0.0000	7.1799***
	(0.0001)	(1.8313)
Sample	*full*	*full*
Year FE	✓	✓
Region-Year Trend	✓	✓
Controls	✓	✓
Windmeijer cond. F.	5.8520	15.9320
F-test statistic	6361442.4140	10.5640
R^2	1.0000	0.3050
Adjusted R^2	1.0000	0.2761
Observations	2007	2007

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. All standard errors clustered at district-level. Sample includes all districts sampled at least twice in either NLFS (1999, 2005, 2013; 1163 district-years) or DHS (2000, 2005, 2011, 2016; 999 district-years), yielding a combined total of 2007 district-years. All districts in Addis Abeba region are always excluded. Log of market access measures the log of the sum of each district's access to consumers across all Ethiopian districts, scaled by least-cost transport cost to each district (which change as road construction progresses in the network). Electricity indicator switches to one in year of electric substation being commissioned in district (or district within 25km radius thereof). Roads IV denotes predicted road indicator according to Kruskal least-cost spanning tree that starts off colonial Italian trunk network. Electricity IV denotes predicted electricity indicator according to temporal and spatial variation from hydropower dam-to-Addis corridors coming on line. Region-year-specific time trends for ten administrative regions, excluding Addis region. Survey indicator fixed effects allow separate intercepts for districts sampled only in NLFS, or only in DHS. Time-invariant controls: terrain ruggedness, log distance to zone capital, log distance to wholesale argricultural market, log distance to Addis, soil quality, district area. Initial values of time-varying controls: log population density, nighttime luminosity, temperature, standard deviation of precipitation, built-up area and literacy.

Table S7: Second Stage: Occupat. Change on Roads and Elec., NLFS sample (1999-2013)

	Agriculture	Services	Manufacturing
	(1)	(2)	(3)
Road Indicator	-0.046	0.134^{**}	-0.083^{*}
	(0.086)	(0.063)	(0.047)
Road*Elec Ind.	-0.194	0.106	0.094
	(0.144)	(0.104)	(0.074)
Sample	*NLFS*	*NLFS*	*NLFS*
Year FE	✓	✓	✓
Region-Year Trend	✓	✓	✓
Controls	✓	✓	✓
Windmeijer cond. F.	27.095	9.156	
p-val $\beta_1 + \beta_2 = 0$	0.061	0.008	0.879
p-val $\beta_1 - \beta_2 = 0$	0.456	0.845	0.084
R^2	0.282	0.231	0.132
Adjusted R^2	0.257	0.205	0.102
Observations	1163	1163	1163

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. All standard errors clustered at district-level. Sample includes all districts sampled at least twice in NLFS (1999, 2005, 2013), yielding a total of 1163 district-years. Districts in Addis Abeba and Somali regions are excluded, the latter due to partial omission and non-random sampling of Somali pastoralists in NLFS. Individual answers to survey question about 'current occupation' grouped into sectors according to ISCO major groups. 'Agriculture' denotes aggregated share of district-year survey sample of working age that respond to work in an agricultural occupation. Omitting results for outcome variable 'Currently Not Working', which denotes share of survey sample of working age not currently working. Road indicator and road indicator–electricity indicator interaction denote predicted values from the two first stage specifications. Region-year-specific time trends for nine administrative regions, excluding Addis and Somali regions. Time-invariant controls: terrain ruggedness, log distance to zone capital, log distance to wholesale argricultural market, log distance to Addis, soil quality, district area. Initial values of time-varying controls: log population density, nighttime luminosity, temperature, standard deviation of precipitation, built-up area and literacy. Windmeijer conditional F denotes the Sanderson and Windmeijer (2016) weak instrument F-statistic for multiple endogenous variables, reported separately for the two first stages (columns (1) and (2)).

Table S8: Second Stage: Occupat. Change on Roads and Elec., DHS sample (2000-2016)

	Agriculture	Services	Manufacturing
	(1)	(2)	(3)
Road Indicator	0.055	0.030	−0.091
	(0.100)	(0.075)	(0.065)
Road*Elec Ind.	−0.198	0.083	0.127
	(0.155)	(0.113)	(0.083)
Sample	*DHS*	*DHS*	*DHS*
Year FE	✓	✓	✓
Region-Year Trend	✓	✓	✓
Controls	✓	✓	✓
Windmeijer cond. F.	22.197	10.019	
p-val $\beta_1 + \beta_2 = 0$	0.341	0.297	0.651
p-val $\beta_1 - \beta_2 = 0$	0.237	0.740	0.081
R^2	0.288	0.291	0.136
Adjusted R^2	0.248	0.251	0.088
Observations	999	999	999

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. All standard errors clustered at district-level. Sample includes all districts sampled at least twice in DHS (2000, 2005, 2011, 2016), yielding a total of 999 district-years. Districts in Addis Abeba region are excluded. Individual answers to survey question about 'current occupation' grouped into sectors according to ISCO major groups. 'Agriculture' denotes aggregated share of district-year survey sample of working age that respond to work in an agricultural occupation. Omitting results for outcome variable 'Currently Not Working', which denotes share of survey sample of working age not currently working. Road indicator and road indicator–electricity indicator interaction denote predicted values from the two first stage specifications. Region-year-specific time trends for ten administrative regions, excluding Addis region. Time-invariant controls: terrain ruggedness, log distance to zone capital, log distance to wholesale agricultural market, log distance to Addis, soil quality, district area. Initial values of time-varying controls: log population density, nighttime luminosity, temperature, standard deviation of precipitation, built-up area and literacy. Windmeijer conditional F denotes the Sanderson and Windmeijer (2016) weak instrument F-statistic for multiple endogenous variables, reported separately for the two first stages (columns (1) and (2)).

Table S9: Construction: Occup. [ISIC] on Roads & Elec., NLFS sample (1999-2013)

	Constr.	Ser. [isic]	Ser. incl. Constr.	Man. [isic]	Man. excl. Constr.
	(1)	(2)	(3)	(4)	(5)
Road Indicator	-0.032	0.072	-0.018	-0.050	0.040
	(0.020)	(0.068)	(0.032)	(0.041)	(0.072)
Road*Elec Ind.	0.040*	0.084	0.098*	0.138*	0.124
	(0.024)	(0.111)	(0.058)	(0.071)	(0.119)
Sample	*NLFS*	*NLFS*	*NLFS*	*NLFS*	*NLFS*
Year FE	✓	✓	✓	✓	✓
Region-Year Trend	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Windmeijer cond. F.	27.095	9.156			
p-val $\beta_1 + \beta_2 = 0$	0.774	0.115	0.161	0.221	0.125
p-val $\beta_1 - \beta_2 = 0$	0.039	0.937	0.114	0.040	0.613
R^2	-0.005	0.321	-0.015	-0.032	0.325
Adjusted R^2	-0.040	0.297	-0.050	-0.068	0.302
Observations	1163	1163	1163	1163	1163

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. All standard errors clustered at district-level. Sample includes all districts sampled at least twice in NLFS (1999, 2005, 2013), yielding a total of 1163 district-years. Districts in Addis Abeba and Somali regions are excluded, the latter due to partial omission and non-random sampling of Somali pastoralists in NLFS. Individual answers to survey question about 'current occupation' grouped into sectors according to ISIC industry classifications. 'Agriculture' denotes aggregated share of district-year survey sample of working age that respond to work in an agricultural occupation. Omitting results for outcome variable 'Currently Not Working', which denotes share of survey sample of working age not currently working. Road indicator and road indicator–electricity indicator interaction denote predicted values from the two first stage specifications. Region-year-specific time trends for nine administrative regions, excluding Addis and Somali regions. Time-invariant controls: terrain ruggedness, log distance to zone capital, log distance to wholesale argricultural market, log distance to Addis, soil quality, district area. Initial values of time-varying controls: log population density, nighttime luminosity, temperature, standard deviation of precipitation, built-up area and literacy. Windmeijer conditional F denotes the Sanderson and Windmeijer (2016) weak instrument F-statistic for multiple endogenous variables, reported separately for the two first stages (columns (1) and (2)).

Table S10: Demographics (NLFS), Roads (Kruskal) and Elec. (IVc) (1999-2013)

	Age	Never Married	Married	Divorced
	(1)	(2)	(3)	(4)
Road Indicator	0.223	0.056	-0.027	-0.033
	(0.984)	(0.043)	(0.043)	(0.032)
Road*Elec Ind.	2.162^{*}	-0.053	-0.052	0.087^{***}
	(1.272)	(0.048)	(0.050)	(0.033)
Sample	*NLFS*	*NLFS*	*NLFS*	*NLFS*
Year FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Cragg-Donald F.	9.993			
Windmeijer cond. F.	16.747	13.143		
p-val $\beta_1 + \beta_2 = 0$	0.032	0.941	0.047	0.093
Observations	1208	1208	1208	1208

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. All standard errors clustered at district-level.

Figure S14: Age Distributions by Treatment Complier Status

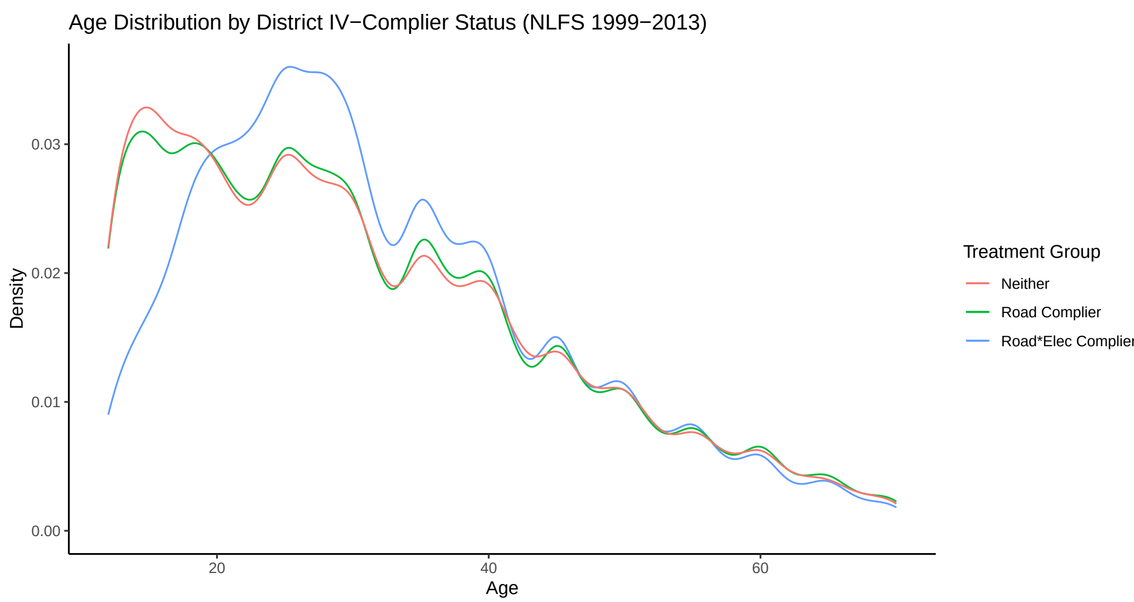


Table S11: Education (NLFS), Roads (Kruskal) and Elec. (IVc) (1999-2013)

	Read/Write	Edu. (Years)
	(1)	(2)
Road Indicator	0.198^{**}	1.083
	(0.094)	(0.712)
Road*Elec Ind.	-0.119	-0.182
	(0.114)	(0.956)
Sample	*NLFS*	*NLFS*
Year FE	✓	✓
Controls	✓	✓
Cragg-Donald F.	9.993	
Windmeijer cond. F.	16.747	13.143
p-val $\beta_1 + \beta_2 = 0$	0.423	0.274
Observations	1208	1208

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. All standard errors clustered at district-level.

Table S12: LFP (NLFS), Roads (Kruskal) and Elec. (IVc) (1999-2013)

	L-Sampled	L-Force	L-Act. Force	LFP rate	LFP-S rate	Notwork
	(1)	(2)	(3)	(4)	(5)	(6)
Road Indicator	20.138	3.890	4.447	-0.002	0.050	-0.006
	(15.343)	(9.256)	(8.689)	(0.029)	(0.050)	(0.006)
Road*Elec Ind.	-37.381^{**}	-11.040	-14.737	0.033	-0.080	0.001
	(18.630)	(9.723)	(9.299)	(0.041)	(0.059)	(0.006)
Sample	*NLFS*	*NLFS*	*NLFS*	*NLFS*	*NLFS*	*NLFS*
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Cragg-Donald F.	9.993					
Windmeijer cond. F.	16.747	13.143				
p-val $\beta_1 + \beta_2 = 0$	0.315	0.408	0.222	0.344	0.530	0.322
Observations	1208	1208	1208	1208	1208	1208

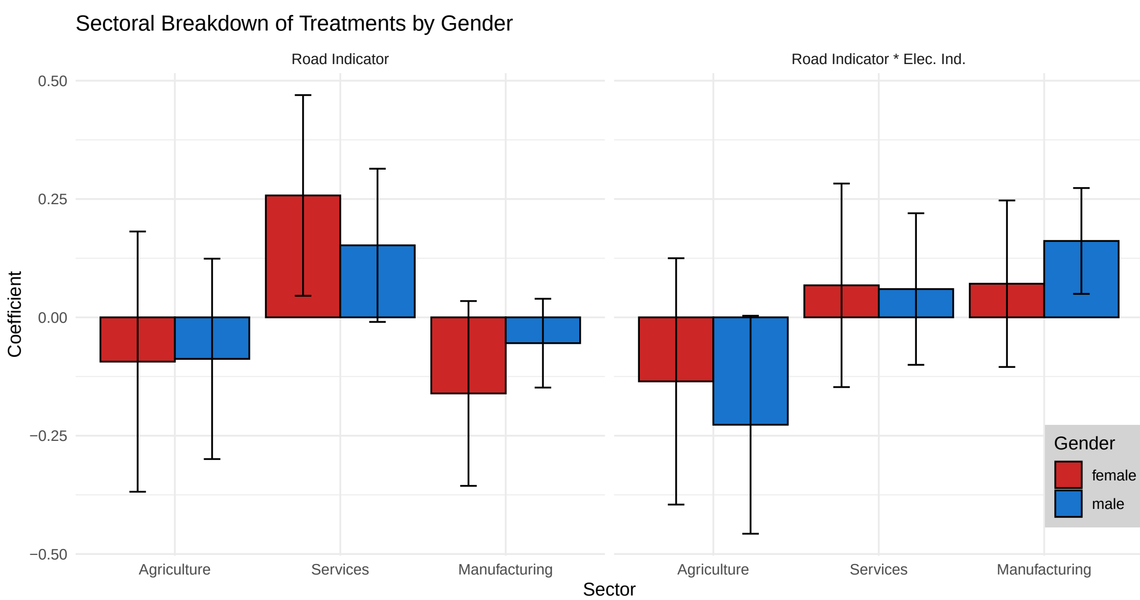
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. All standard errors clustered at district-level. Labour force participation outcomes: no. of sampled people in EA, no. of sampled people in EA of working age, no. of labour-force active people in EA, labour force participation rate ($lfp_e a$), labour force participation based on all sampled people ($lsampledp_e a$).

Table S13: Second Stage: Consumption on Roads & Elec., HCES sample (2000-2016)

	HH Exp. (pc)	HH Size	HH Age	Male Share	Divorced
	(1)	(2)	(3)	(4)	(5)
Road Indicator	−554.825	0.620*	−1.859	0.067	0.014
	(1403.025)	(0.375)	(1.786)	(0.081)	(0.022)
Road*Elec Ind.	3655.196	−0.395	5.023	0.131	0.022
	(3516.415)	(0.738)	(3.600)	(0.103)	(0.039)
Sample	*HCES*	*HCES*	*HCES*	*HCES*	*HCES*
Year FE	✓	✓	✓	✓	✓
Region-Year Trend	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Windmeijer cond. F.	23.01	6.788			
p-val $\beta_1 + \beta_2 = 0$	0.319	0.734	0.052	0.354	0.366
p-val $\beta_1 - \beta_2 = 0$	0.334	0.294	0.681	0.130	0.868
R^2	0.428	0.194	−0.197	0.035	0.204
Adjusted R^2	0.394	0.147	−0.267	−0.022	0.157
Observations	560	560	560	560	560

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. All standard errors clustered at district-level. Sample includes all districts sampled twice in HCES (2000, 2016), yielding a total of 560 district-years. Districts in Addis Abeba and Somali regions are excluded, the latter due to omission Somali region in HCES. Answers provided by household head to survey question about household characteristics and consumption. Road indicator and road indicator–electricity indicator interaction denote predicted values from the two first stage specifications. Region-year-specific time trends for nine administrative regions, excluding Addis and Somali regions. Time-invariant controls: terrain ruggedness, log distance to zone capital, log distance to wholesale argricultural market, log distance to Addis, soil quality, district area. Initial values of time-varying controls: log population density, nighttime luminosity, temperature, standard deviation of precipitation, built-up area and literacy. Windmeijer conditional F denotes the Sanderson and Windmeijer (2016) weak instrument F-statistic for multiple endogenous variables, reported separately for the two first stages (columns (1) and (2)).

Figure S15: Sectoral Breakdown of Treatments by Gender



S.II Supplement: Full Model Derivation

S.II.1 Setup

The theoretical framework is fully derived below. It is most closely related to the original structure of a multi-sector spatial general equilibrium model proposed by Michaels et al. (2011), which combines the canonical Helpman (1998) model with an Eaton and Kortum (2002) structure of Ricardian inter-regional trade. This framework is adapted to the Ethiopian context by adding non-homothetic sectoral demand, which captures both a theoretically and empirically relevant aspect of the Ethiopian economy. Motivated by the empirical results from the reduced-form, a non-tradeable services sector S is also added.

A geography consists of many locations, $n \in N$, of varying land size (H_n) and endogenous population (L_n). Consumers value consumption of agricultural sector final goods, C^T, manufacturing sector final goods, C^M, services, C^S, and land, h, (which one may call 'housing'). Utility of a representative household in location n is assumed to follow an upper tier Cobb-Douglas functional form over goods and land consumption, scaled by a location-specific amenity shock η_n:

$$U_n = \eta_n C_n^{\alpha} h_n^{1-\alpha} \tag{22}$$

I assume $0 < \alpha < 1$. The goods consumption index is defined over consumption of each tradeable sector's composite good and services:

$$C_n = \left[\sum^{K} \psi^K \left(C_n^K + \gamma^K \right)^{\frac{\kappa-1}{\kappa}} \right]^{\frac{\kappa}{\kappa-1}} \tag{23}$$

This second-tier specification of consumer preferences for demand of sectoral composites, introduced by Herrendorf et al. (2013), is the most parsimonious specification that nests the two most prominent theoretical frameworks to study structural transformation: a Baumol (1967) mechanism of differential productivity growth across sectors, which Ngai and Pissarides (2007) formalise, which corresponds to the special case where $\kappa < 1$ and $\gamma^K = 0, \forall K \in \{M, S, T\}$. In contrast, structural transformation driven by non-homothetic demand, which Kongsamut et al. (2001) formalise, corresponds to the special case where $\kappa = 1$, $\gamma^T < 0$, $\gamma^M = 0$ and $\gamma^S > 0$.[105]

I follow a long macroeconomic literature (cf. Herrendorf et al. (2014)) on structural transformation and assume consumption of sectoral composite goods to be complementary, i.e. $0 < \kappa < 1$. Furthermore, I employ a non-homothetic demand structure in line with a related strand of literature, assuming $\gamma^T < 0$, $\gamma^M > 0$ and $\gamma^S = 0$, to ensure that Engel's law of an income elasticity of demand below one in food-producing sectors such as agriculture is embodied (cf. Matsuyama (1992), Kongsamut et al. (2001) and Herrendorf et al. (2013)). As Gollin et al. (2002) and Gollin and Rogerson (2014) highlight, the assumption of non-homothetic preferences due to a subsistence constraint in the traditional, food-producing sector appears essential to match relevant empirical phenomena in low-income countries in Sub-Saharan Africa.

The third-tier of preferences is characterised by standard Dixit-Stiglitz love of variety for both tradeable sectors' goods, C^T and C^M, which I model in the standard CES fashion, where n denotes the consumer's location and i the producer's location, whereas j is a measure of varieties. Consumption of each tradeable sector's good C_n^K where $K = \{M, T\}$ in each location n is defined over a fixed continuum of varieties $j \in [0, 1]$:

$$C_n^K = \left[\sum_{i \in N} \int_0^1 \left(c_{ni}^K(j) \right)^{\nu} dj \right]^{\frac{1}{\nu}} \tag{24}$$

I assume an elasticity of substitution across varieties, ν, such that varieties within each tradeable sector $K = \{M, T\}$ are substitutes for each other, $\sigma = \frac{1}{1-\nu} > 1$. Equation (25) provides the classic Dixit-Stiglitz price index over each tradeable sector's goods:

$$P_n^K = \left[\sum_{i \in N} \int_0^1 \left(p_{ni}^K(j) \right)^{1-\sigma} dj \right]^{\frac{1}{1-\sigma}} \tag{25}$$

Given the assumption of Cobb-Douglas utility in upper-tier consumption across composite goods, C or housing, h, I obtain constant expenditure shares, where P_n

[105] The latter implied utility function corresponds to Stone-Geary preferences.

and r_n denote the composite goods price index and the land rental rate, respectively:

$$C_n = \frac{\alpha}{P_n} I \tag{26}$$

$$h_n = \frac{1-\alpha}{r_n} I \tag{27}$$

On the production side, firms in a given location and tradeable sector produce varieties for consumption in (potentially) many other locations. Production of varieties in both tradeable sectors uses labour and land as inputs under constant returns to scale subject to stochastic location–sector specific productivity draws.

$$Y_n^T = z^T \left(\frac{L_n^T}{\mu^T}\right)^{\mu^T} \left(\frac{h_n^T}{1-\mu^T}\right)^{1-\mu^T} \tag{28}$$

$$Y_n^M = z^M \left(\frac{L_n^M}{\mu^M}\right)^{\mu^M} \left(\frac{h_n^M}{1-\mu^M}\right)^{1-\mu^M} \tag{29}$$

where $0 < \mu^T, \mu^M < 1$ and, z^K denotes the sector-location-specific realisation of productivity z for variety j in sector $K \in \{T, M\}$ and location n. Following Eaton and Kortum (2002), locations draw sector-specific idiosyncratic productivities for each variety j from a Fréchet distribution:

$$F_n^T(z^T) = e^{\left(-A_n^T z^T\right)^{-\theta}} \tag{30}$$

$$F_n^M(z^M) = e^{\left(-A_n^M z^M\right)^{-\theta}} \tag{31}$$

It follows from the properties of the Fréchet distribution that the scale parameters, A_n^T and A_n^M, govern the average sectoral productivity in location n across all varieties, since, for example, larger values of A_n^K decrease $F_n^K(z^K)$ and thus increase the probability of higher productivity draws, z^K, for all tradeable sector varieties $K \in \{T, M\}$ in region n. The shape parameter, θ, determines the variability of productivity draws across varieties in a given location n, with lower θ values implying greater heterogeneity in a location's productivity across varieties. Since the empirical application focuses on sector-location specific average productivity shocks, I assume the shape parameter, θ, to be the same across sectors and locations.

Trade in both sectors' final goods is costly and trade costs are assumed to follow an iceberg structure: more goods have to be produced at origin since parts 'melt away' during transit to its intended destination location for consumption. I denote trade costs between locations n and i as d_{ni}, such that quantity $d_{ni} > 1$ has to be produced in i for one unit to arrive in n. By assumption, within-region consumption of locally produced goods does not incur trade costs, i.e. $d_{nn} = 1$. I also assume that trade costs are the same across sectors ($d_{ni}^T = d_{ni}^M$), symmetric ($d_{ni} = d_{in}$) and that a triangle inequality holds between any three regions i, n, o, $d_{ni} < d_{no}d_{oi}$.

Given perfect competition in both production sectors, the price of a given T-sector variety, $p_{ni}^T(j)$, equals marginal cost, weighted by factor shares, inverse productivity and trade costs (and equivalent expression holds for the price of a given M-sector variety):

$$p_{ni}^T(j) = \frac{w_i^{\mu^T} r_i^{1-\mu^T} d_{ni}}{z_i^T(j)} \tag{32}$$

Similarly standard, relative factor demand equals inverse, factor share-weighted, factor prices, where transport cost cancel out due to the symmetric overuse of factors:

$$\frac{h_i^T}{L_i^T} = \frac{(1-\mu^T)}{\mu^T}\frac{w_i}{r_i} \tag{33}$$

Given Fréchet-distributed productivity shocks per variety (and location), each location (n) will buy a given variety from its minimum-cost supplier location (i):

$$p_{ni}^T(j) = min\{p_i^T(j); i \in N\} \tag{34}$$

Eaton and Kortum (2002) show how such a characterisation of prices and origin-destination trade between locations i and n in varieties j gives rise to a formulation of the share of expenditure destination location n spends on agricultural sector (and equivalently manufacturing sector) final goods produced in origin i:

$$\pi_{ni}^T = \frac{A_i^T \left(w_i^{\mu^T} r_i^{1-\mu^T} d_{ni}\right)^{-\theta}}{\sum_{k\in N} A_k^T \left(w_k^{\mu^T} r_k^{1-\mu^T} d_{nk}\right)^{-\theta}} \tag{35}$$

In this gravity-style equation, the traditional sector's shape parameter, θ, which governs the heterogeneity of within-location productivities across varieties, determines the elasticity of trade with respect to production and trade costs.

This is in contrast to an original Helpman (1998) model, where the elasticity of trade with respect to production and trade costs is determined by the elasticity of substitution between varieties.

As Eaton and Kortum (2002) note, the intuition behind trade between locations in spatial general equilibrium models featuring monopolistic competition and those featuring Ricardian trade are similar, although the underlying mechanics are distinct: in models of monopolistic competition (such as Helpman (1998)), the more substitutable varieties from different locations are, the more sensitive trade between locations becomes to (origin locations') production and (origin to destination location) trade costs. In Ricardian trade models, however, the heterogeneity of varieties in the origin location (determined by θ) determines how sensitive trade becomes to production and trade costs.[106] If the heterogeneity of varieties in a given origin location decreases (i.e. an increase in θ), the more sensitive trade will become to that origin's production and trade costs. In other words, the Ricardian trade model implies an extensive margin effect of production and trade costs, where due to lower technological heterogeneity across varieties, the origin location will turn out to be least-cost supplier for fewer varieties the more expensive or remote it will be relative to all other potential origin locations.

While spatial general equilibrium models that invoke an alternative 'Armington assumption' (cf. Anderson (1979) and Anderson and van Wincoop (2003)) of each location exporting a unique variety will feature adjustment to origin production and trade costs at the intensive margin, the adjustment in models of monopolistic competition with an endogenously determined measure of varieties is not that straightforward. Holding the distribution of population constant across locations, an origin location becoming more costly and/or more remote will indeed cause an intensive margin adjustment of less destination expenditure on the same measure of exported varieties. However, as the labour mobility condition in equation (43) below highlights, the general equilibrium allocation of population across locations will react to a dete-

[106] Eaton and Kortum (2002) discuss this distinction with the contrast between their model's heterogeneity of goods in production to monopolistic competition models' heterogeneity in consumption.

rioration in cost fundamentals, such that fewer workers reside and consume in such a 'worse' origin location. Since the number of varieties produced depends directly on population, a loss of population will necessarily be accompanied by an extensive margin adjustment in the number of produced varieties, too. Thus, a monopolistic competition model with endogenous varieties features both intensive and extensive margin adjustments of trade with respect to production and trade costs, whereas the model presented here features only extensive margin adjustments.

Production of non-tradeable services also uses labour and land as inputs, but output is a single homogeneous 'services good':

$$Y_n^S = A_n^S \left(\frac{L_n^S}{\mu^S}\right)^{\mu^S} \left(\frac{h_n^S}{1-\mu^S}\right)^{1-\mu^S} \tag{36}$$

Throughout, I assume agriculture to be the most and services the least land-intensive sector, $\mu^T < \mu^M < \mu^S$. Without trade in services, the non-tradeable services good's price equals marginal cost:

$$P_n^S = \frac{w_n^{\mu^S} r_n^{1-\mu^S}}{A_n^S} \tag{37}$$

The composite good price index for non-homothetic CES second-tier demand for composite good C_n in a given location n can be derived from Marshallian demands to give:

$$P_n = \frac{\left[\sum_K (\psi_K)^\kappa (P_{K,n})^{1-\kappa}\right]^{\frac{1}{1-\kappa}}}{1 + \frac{\sum_K \gamma^K P_{K,n}}{I_n}} \tag{38}$$

Within each location n, we denote by $\xi_{K,n}$ the share of expenditure allocated to consumption of any sector K's composite good (where $K \in \{M, S, T\}$), that is $\xi_{K,n} = \frac{P_{K,n} C_{K,n}}{I_n}$. Accordingly, given non-homothetic CES demand for sectoral composites, the expenditure share for each sector in a given location depends on the relative (local) price of each sector's (composite) good:

$$\xi_{K,n} = \frac{(\psi_K)^\kappa (P_{K,n})^{1-\kappa}}{\sum_K (\psi_K)^\kappa (P_{K,n})^{1-\kappa}} \left(1 + \frac{\sum_K \gamma^K P_{K,n}}{I_n}\right) - \frac{\gamma^K P_{K,n}}{I_n}, K \in \{M, S, T\} \tag{39}$$

In line with Herrendorf et al. (2013), we assume $\kappa > 0$, while $\kappa = 1$ (under $\gamma^T < 0$ and $\gamma^M > 0$) corresponds to the special case of Stone-Geary preferences.

Given the properties of the Fréchet distribution of productivities, tradeable sectoral price indices can be further simplified to arrive at expressions that only depend on factor prices, productivities and transport cost, as well as parameters. Equation (40) presents the simplified T-sector price index. An equivalent formulation holds for the M-sector.

$$P_n^T = \gamma \left[\sum_{k \in N} A_k^T \left(w_k^{\mu^T} r_k^{1-\mu^T} d_{nk} \right)^{-\theta} \right]^{-1/\theta} = \gamma \left(\Phi_n^T \right)^{-1/\theta} \tag{40}$$

where $\Phi_n^T = \sum_{k \in N} A_k^T (w_k^{\mu^T} r_k^{1-\mu^T} d_{nk})^{-\theta}$ and $\gamma = [\Gamma \left((\theta + 1 - \sigma)/\theta \right)]^{\frac{1}{1-\sigma}}$. $\Gamma(\cdot)$ denotes the Gamma function and I assume $\theta + 1 - \sigma > 0$ to ensure this function is defined. The above simplified tradeable sector price indices can in turn be used to express expenditure shares.

To arrive at a spatial equilibrium, I provide conditions for land market clearing, labour market clearing and a labour mobility condition. For an equilibrium in the land market, total income from land must equal total expenditure on land, where the latter summarises land expenditure by consumers, M-sector firms, T-sector firms and S-sector firms. I assume land is owned by goods-consuming landlords who do not otherwise supply labour. In the empirical setting of Ethiopia, where land is overwhelmingly owned by the state, one may think of landlords as equivalent to the local government which spends its income from land on goods and land consumption itself.

The land market clearing condition can be stated as follows:

$$\begin{aligned} r_n H_n = {} & (1-\alpha) \left[w_n L_n + r_n H_n \right] \\ & + \sum_{k \in N} \pi_{kn}^T \xi_k^T \left(1 - \mu^T \right) \alpha \left[w_k L_k + r_k H_k \right] \\ & + \sum_{k \in N} \pi_{kn}^M \xi_k^M \left(1 - \mu^M \right) \alpha \left[w_k L_k + r_k H_k \right] \\ & + \pi_{nn}^S \xi_n^S \left(1 - \mu^S \right) \alpha \left[w_n L_n + r_n H_n \right] \end{aligned} \tag{41}$$

Similarly, labour market clearing requires that total labour income earned in one location must equal total labour payments across sectors on goods purchased from that location everywhere:

$$\begin{aligned} w_n L_n = & \sum_{k \in N} \pi^T_{kn} \xi^T_k \mu^T \alpha \left[w_k L_k + r_k H_k \right] \\ & + \sum_{k \in N} \pi^M_{kn} \xi^M_k \mu^M \alpha \left[w_k L_k + r_k H_k \right] \\ & + \pi^S_{nn} \xi^S_n \mu^S \alpha \left[w_n L_n + r_n H_n \right] \end{aligned} \tag{42}$$

Finally, and to close the model, free mobility of workers across locations implies that workers will arbitrage away any differences in real wages across locations, such that real wages across all locations must be equalised in equilibrium. In other words, the wage earned by workers in a given location after correcting for land and goods prices, as well as a location's amenity value, must be equalised. Making use of Marshallian demands provided in equations (26)-(27) and the fact that $v_n L_n = w_n L_n$, real wage equalisation across all N locations implies:

$$V_n = \bar{V} = \frac{\alpha^{(\alpha)} (1-\alpha)^{(1-\alpha)} \eta_n w_n}{P_n^{(\alpha)} r_n^{(1-\alpha)}}, \quad \forall n \tag{43}$$

where $P_n = \left[\sum_K (\psi_K)^\kappa (P_{K,n})^{1-\kappa} \right]^{\frac{1}{1-\kappa}} \left(1 + \frac{\sum_K \gamma^K P_{K,n}}{I_n} \right)^{-1}$.

S.II.2 General equilibrium

For each location, and given parameter values $(\alpha, \kappa, \mu^T, \mu^M, \mu^S, \theta, \sigma, \gamma^T, \gamma^M)$, a matrix of trade costs (d_{ni}) and vectors of sectoral productivities (A^T_n, A^M_n, A^S_n), the model admits three equations for the three endogenous variables in each location: land market clearing [eq. (41)], labour market clearing [eq. (42)] and the labour mobility condition [eq. (43)] allow to solve for a general equilibrium of the model in terms of its core endogenous variables wages (w_n), land rental rates (r_n) and population (L_n). Michaels et al. (2011) prove existence and uniqueness for the two-sector version, which follows through to the three-sector non-homothetic CES version presented here.

The endogenous variables of interest for the empirical analysis, sectoral employment, L_n^T, L_n^M, L_n^S (or sectoral employment shares, $\lambda_n^K = L_n^K / L_n$ for each sector $K \in \{T, M, S\}$, respectively) can be derived from the unique solution for wages, rental rates and population with the help of sectoral labour market clearing. Analogous to the labour market clearing condition above, I assume that each sector's labour income has to likewise equal total sectoral labour payments on goods purchased from that location everywhere:

$$w_n L_n^T = \sum_{k \in N} \pi_{kn}^T \xi_k^T \mu^T \alpha \left[w_k L_k + r_k H_k \right] \tag{44}$$

$$w_n L_n^M = \sum_{k \in N} \pi_{kn}^M \xi_k^M \mu^M \alpha \left[w_k L_k + r_k H_k \right] \tag{45}$$

$$w_n L_n^S = \pi_{nn}^S \xi_n^S \mu^S \alpha \left[w_n L_n + r_n H_n \right] \tag{46}$$

As described in Section (6) above, the general equilibrium conditions may also be exploited to back out (empirically unobserved) sectoral productivities given (empirically observed) population and sectoral employment shares via calibration of the model. In contrast to Redding's (2016) hypothetical setting, I am unable to invert the model to solve for unobserved productivities (and amenities) since rental rates are generally not available in the Ethiopian context given the almost exclusively nationalised status of land ownership during my study period. Therefore, instead of inverting the general equilibrium system to determine productivities, I have to calibrate the model to back out the unique combination of sectoral productivities for each location such that the observable data at either baseline or endline of the sample constitutes a spatial equilibrium.

Figure S16: Simulated Change in Manufacturing Shares from Trade Cost Shock

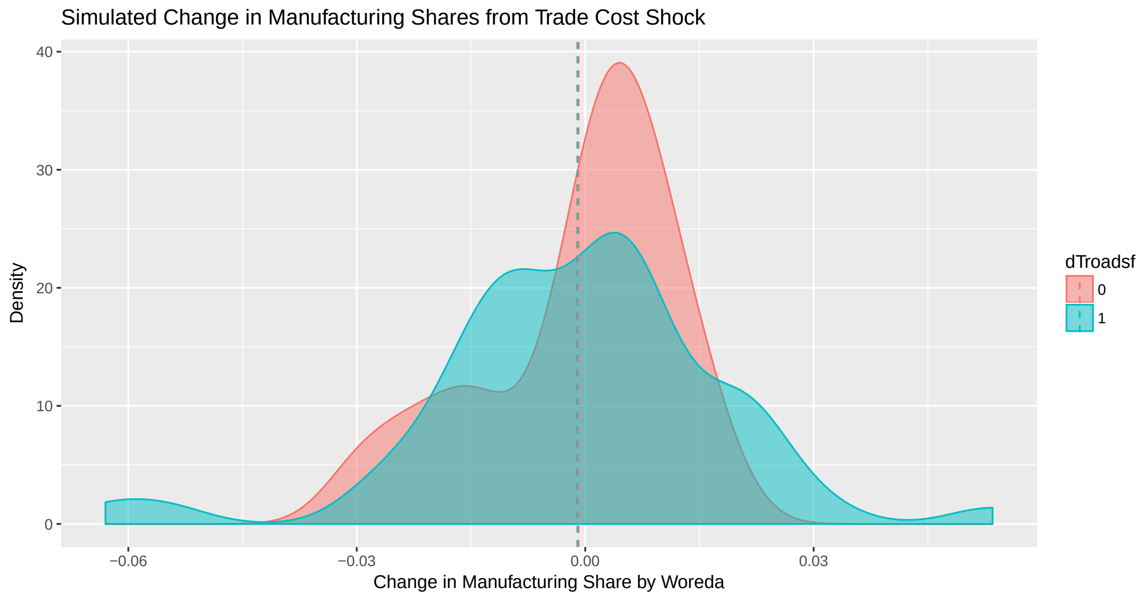
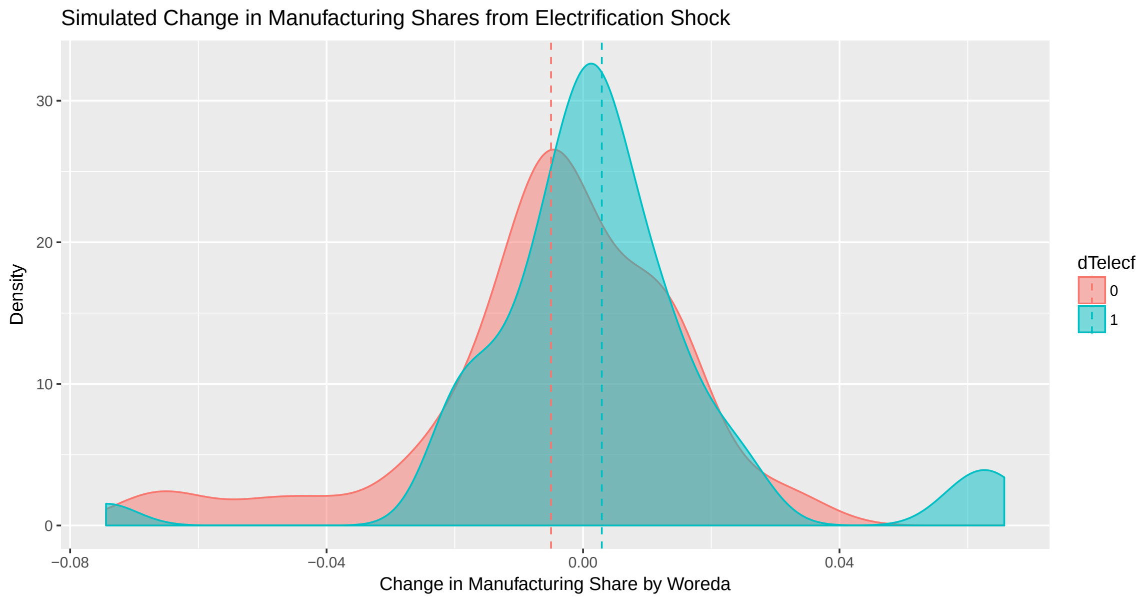


Figure S17: Simulated Change in Manufacturing Shares from Combined Trade Cost and Electrification Shock



S.III Supplement: Data for Structural Estimation

For the structural estimation, I require additional data on model inputs that were either not required or not of primary interest in the reduced-form estimation. In particular, I require information on the supply of land and population information for every district in Ethiopia. I also explain how initial sectoral employment shares for the baseline calibration are derived from NLFS and DHS samples. Furthermore, I provide proxy measures for the productivity in either production sector and wages as additional robustness checks on the fit of the model.

Land supply: With respect to land area, I use arable land derived from satellite imagery, that is land either deemed theoretically inhabitable or suitable for productive use. This choice of proxy is not without potential issues, given that in the model housing for consumers and land used in production are conflated. However, reliable data on the housing stock and its value in Ethiopia is virtually non-existent since the Ethiopian real estate market remains monopolised by government ownership of land, essentially a leftover from the previous, socialist regime in power: all land is owned by the government and firms or residents only obtain non-permanent permission to use their allocated land without technically owning it. Hence, I use arable land as proxy for land supply, which appears reasonable given that land enters all sectors' production as input and even consumers' housing demand will reflect demand for land given prevailing housing construction outside of Addis Abeba.

Population: For population data, I employ Census data at the district-level for 2007/2008 in addition to Census-derived, remotely-sensed population estimates for earlier and later years. Although the NLFS and DHS repeated cross-sections do not include useable information on district-level population, I can nonetheless derive information on the share of the working age population and the labour force participation rate from this data. The latter is used to scale population to arrive at active labour force rates, since large parts of the (on average very young) Ethiopian population are not (yet) active.

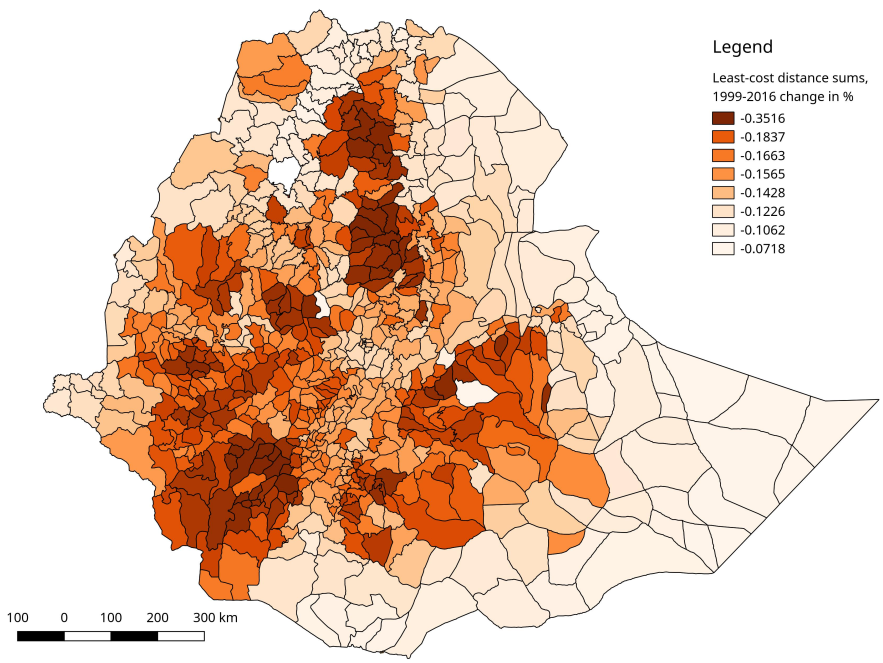
Baseline sectoral employment: Regarding initial sectoral employment shares used in the baseline calibration, the manufacturing and service sector shares relate one for one to the manufacturing and services sectors' employment shares in each district as of 1999/2000. In particular, to maximise the sample of available initial data points, I pool both the first National Labour Force Survey (NLFS) round from 1999/2000 and the first Demographic and Health Survey (DHS) round from 2000. Wherever a district contains enumeration areas from both surveys, the manufacturing share of that district represents the average of enumeration areas across surveys. Using both unbalanced samples, I obtain 1999/2000 manufacturing employment share data for 475 out of the total 689 districts used in the analysis. Out of these 475, 181 districts appear only in the NLFS for the initial period, 58 appear only in the DHS and 236 appear in both. For the missing 214 districts, I impute initial employment shares by relying on the fact that both the NLFS and the DHS are representative at the country- and the regional-level. Hence, any interpolation has to preserve the sample mean. I propose three different imputation methods: firstly, a naive imputation where every missing district value is replaced with the sample mean. Secondly, a random permutation of this sample mean within one standard deviation, while preserving the overall mean and, thirdly, a more sophisticated regression-based approach that predicts (mean-preserving) employment shares based on observable district characteristics.

Proxies for traditional sector productivity: To check model fit, I use agricultural yields as a proxy for traditional sector productivity. Remotely-sensed organic carbon content at shallow soil depths (e.g. 5-20cm) performs well as a proxy for soil fertility and agricultural productivity when compared against lab-in-the-field measures of either, which are obtained by taking physical soil samples or measuring farmer output. I can show that district-averages of organic carbon content at five centimetre depths from remotely-sensed data across Ethiopia appear to fit a Weibull distribution of yields well (results available upon request). This empirical finding is particularly interesting given the assumption of extreme value-distributed traditional sector productivity in the model. Since the reciprocal of a two-parameter Weibull-distributed random variable is Fréchet-distributed, one can easily derive the scale and shape parameters of such a distribution. In particular, if $X \sim Frechet(\alpha, s, m = 0)$, then its reciprocal is Weibull-distributed with parameters: $X^{-1} \sim Weibull(k = \alpha, \lambda = s^{-1})$. Fitting a Weibull distribution to the yield data by Maximum Likelihood results in estimates for the scale parameter (A_n^T) of 31.74 ($s.e. = 0.4661$) and for the shape parameter (θ) of 2.75 ($s.e. = 0.0749$).

Wage proxies: I can derive wage proxies from two sources, firstly, the Retail Price Index raw data contain monthly information on the day rate for unskilled labour in 119 markets from 1998 until 2017 (cf. Subsection 6.1 for more information). This represents a direct measure of wages, albeit it is only available for the subset of market towns, which may vary quite dramatically from rural or more remote labour market conditions. Secondly, I can exploit household expenditure information per capita provided in the nationally representative HCES surveys (cf. Subsection 2.2 for more information) for sampled enumeration areas throughout Ethiopia, from which at least a subset of district wage proxies can be derived. The remaining gaps in coverage can be filled by small area estimation such as in Balboni (2019).

Least-cost distances: In the main model, the construction of new all-weather roads is assumed to affect trade cost by decreasing the effective least-cost distance between potential trading locations across Ethiopia. Table A7 provides a sanity check of this assumption, confirming that the employed procedure to arrive at least-cost distances is meaningful. Least-cost distances are obtained in the following way: terrain, or the difficulty in crossing a given pixel (representing a given stretch of land), is expressed as a terrain ruggedness index value with scores ranging from zero to 45. The full geography of Ethiopia is represented by a graph of approximately 12,000 quadratic pixels, each representing an area of approximately 185 times 185 metres (when measured at the equator). For pixels without an all-weather road in it, I measure the cost to cross the pixel as the distance (in kilometres) to traverse the pixel in North-South or East-West direction times one plus the terrain ruggedness index. For district capital pixels and all-weather road pixels, I set the cost to traverse the pixel as simply the distance covered (i.e. a terrain ruggedness index of zero plus the normalisation of one). Intuitively, my approach is equivalent to understanding a given all-weather road in a pixel to virtually level the terrain in trade cost terms. This procedure yields effective district capital to district capital distances that appear sensible: when benchmarked against state-of-the-art map routing engines such as OpenRouteService, random distance pairs from my distance matrix are very close to the OpenRouteService predicted distances. This manual robustness check also works in cases where no all-weather road connects the district capital to the remaining Ethiopian road network, mostly due to my terrain-avoidance algorithm yielding similar results to software engines with information on non-gravel, earth roads. Unfortunately, OpenStreetMap, the underlying source map, does not have information on Ethiopian roads and settlements beyond 2014. In addition to overcoming the lack of panel information in publicly available map engines, my algorithm is also more robust in the sense of employing a true Dijkstra-frontier recognition procedure.

Figure S18: Relative Dijkstra Algorithm Least-cost Distance Changes across Districts, Single Long Difference (1999-2016)



At least seven distinct zones affected by large transport cost shocks emerge from Figure S18: in particular, they are located in central Amhara (South Wollo, circa 200 km north of Addis), northern Amhara (Wag Himru, circa 400 km north of Addis), northwestern Oromia (Horo Guduru, circa 200 km north-west of Addis), western Oromia (Ilubabor, circa 350 km west of Addis), practically the whole south and southwest of SNNPR (e.g. Kaffa and South Omo, circa 350-500 km south-southwest of Addis), as well as central Oromia (Arsi, circa 150-250 km south of Addis) and eastern Oromia (Harerge, circa 300 km west of Addis). Figure S9 provides the corresponding population distribution to highlight that relative least-cost distance changes from road construction are not an obvious function of density, but empirically interesting.

S.IV Supplement: Sensitivity of Structural Estimation

Figure S19: Sensitivity of Structural Estimation to Non-Homotheticity in Agriculture

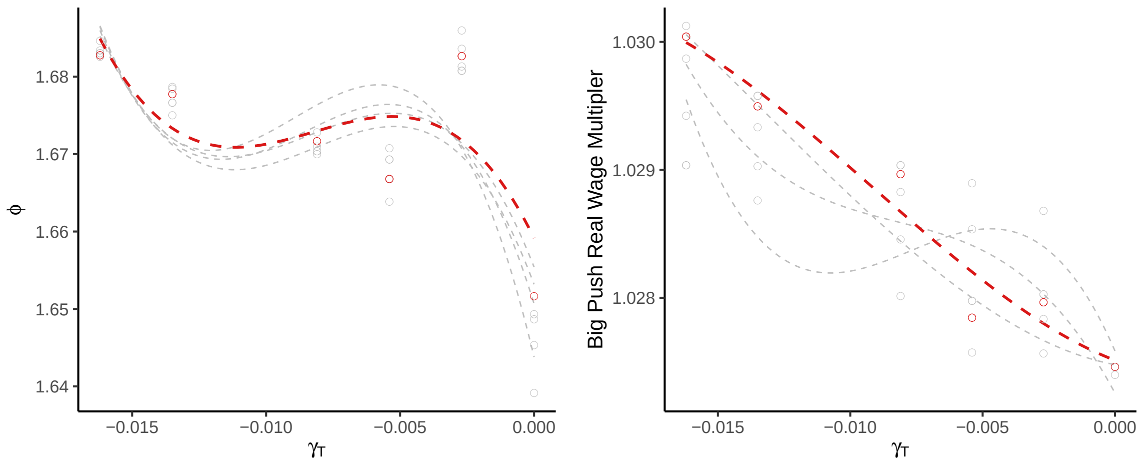


Figure S20: Sensitivity of Structural Estimation to Non-Homotheticity in Manufact.

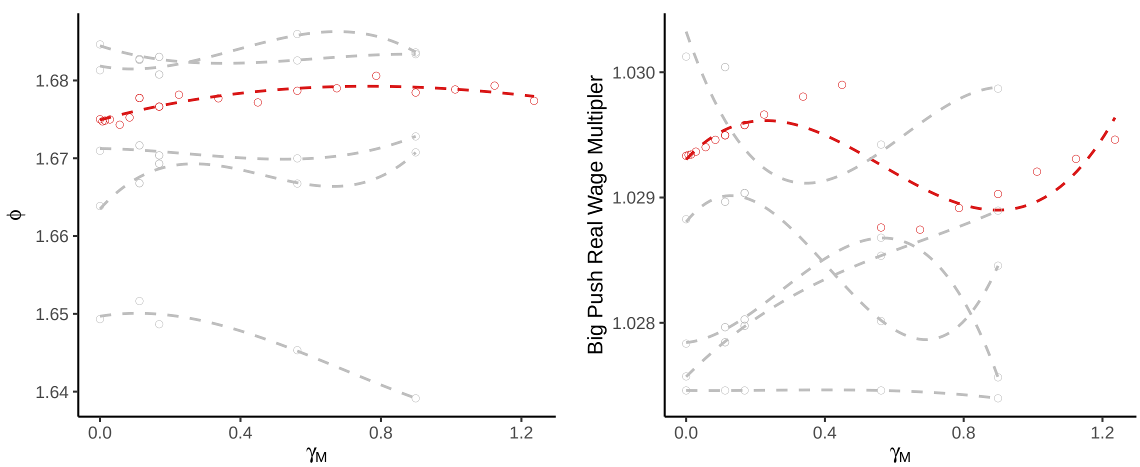


Figure S21: Sensitivity of Structural Estimation to Both Non-Homotheticities