The Impact of Roads on Land-Use Change in Ethiopia: Evidence from Satellite Data

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Abstract

Using satellite-based land cover data for Ethiopia, I examine the relationship between travel costs and the spatial allocation of economic activity. In analyzing a cross-section of land cover data for all of Ethiopia in 2005/2006, I find that proximity to market is positively associated with land being devoted to agriculture, when controlling for soil quality and climatic factors. Additionally, I examine the change in land cover associated with the construction of the Addis Ababa-Adama expressway, using panel data on land cover in a 40-km buffer of the expressway for 2009 and 2016. I find that proximity to the expressway increases the likelihood of a transition in land cover type, both into and out of agriculture. On average, the expressway reduced the likelihood of agricultural land cover for land parcels within an inner buffer of the expressway in the period after it opened. This study contributes to previous literature by employing high spatial resolution GIS data that has not been previously applied to studies of economic geography, by examining data from the African continent – where little empirical work on transportation infrastructure and land cover change has been done –, and by using a comprehensive measure of market access to assess transportation costs.

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1. Introduction

Roads and other transportation infrastructure affect land use through their impact on reducing transportation costs. When firms and commuters make a decision about where to live or locate their operations, they face tradeoffs between land rents and the cost of transportation to market, among other factors. At a given distance to market, transportation is so expensive that it becomes unprofitable to operate or live in an area (von Thünen, 1826; Alonso, 1964). Therefore, reducing transportation costs expands economic activity by increasing market access (Donaldson & Hornbeck, 2016). This paper uses empirical methods to examine the effect of transportation infrastructure on the spatial distribution of land cover types. Land cover reflects land use and thus the forms of economic activity that are taking place in a given area; for instance, agricultural activity can be identified by observing the location and extent of farmland. In this paper, I use Ethiopian data to study whether road construction and upgrading leads to a greater allocation of land to agriculture versus other uses (vegetation, urban or industrialized area), and the magnitude of this effect.

Historically, most of the literature discussing the effect of transportation infrastructure on the spatial distribution of economic activity has been theoretical in nature. However, the number of empirical studies in this area is expanding. Recent contributions consider suburbanization in the United States (Baum-Snow, 2007), trade and income in India (Donaldson, forthcoming), GDP in peripheral regions in China (Faber, 2014), and the size of the eighteenth-century American agricultural sector (Donaldson & Hornbeck, 2016). My paper adds to this literature by examining data from the African continent, where little empirical work has been done, and by using remotely-sensed land cover data to measure economic activity.

Ethiopia makes an interesting case-study on the economic effects of transportation infrastructure because of its geography, level of development, and ongoing expansion of the transport infrastructure network. A circular rural country with a core primate city, Addis Ababa, Ethiopia closely resembles the “Isolated State” developed in von Thünen’s early model of agricultural land. Lacking a domestic coastline, Ethiopian goods destined for export are transported to ports in Djibouti, usually through Addis Ababa. Thus, the country is an ideal place to empirically test established theories of economic geography. Additionally, Ethiopia is a rural, fast-growing country going through a period of significant investment in transportation, making it a suitable location for a study on the impact of road construction and upgrading on the allocation of land to different economic activities.

Few studies make use of new satellite-based data to analyze land use change associated with transportation infrastructure. Remotely-sensed land cover data is advantageous because it is available at relatively high spatial and temporal resolutions over a wide geographic area, allowing changes in land use over time to be observed in detail. Over the last decade, satellite imagery has become more publically accessible and new algorithms and improved processing power have made it possible to extract increasing amounts of data. In this paper, I employ satellite data to classify land cover across Ethiopia and track changes in land cover and associated land use over time, in the proximity of newly built or upgraded roads.

This paper answers the question of how road construction affects the spatial distribution of economic activity by studying the location of land devoted to vegetation, agriculture or urban area in Ethiopia. In the first part of the paper, I use Ethiopia-wide road network data for 2004 and land cover data for 2005/2006 to examine in the cross-section the distribution of land cover types in Ethiopia by distance to roads and to market along the road network. Then, I use panel data to explore in detail the changes in land cover before and after the construction a specific segment of road network, the Addis Ababa-Adama Expressway opened in September 2015. I compare the changes in land cover within an inner buffer of the expressway as compared to land in an outer buffer of the same expressway. This allows me to employ a difference-in-difference approach to estimating the causal effect of transportation infrastructure on economic activity as measured by land cover.

The paper is structured as follows: Section 2 describes the background in Ethiopia and policy applications of this research. Section 3 discusses the relevant literature. Section 4 presents the theoretical model. Section 5 presents the empirical model. Section 6 describes the data collection. Section 7 presents the data and descriptive statistics. Section 8 discusses the results. Section 9 concludes.

2. Background

Based on theory about the positive relationship between reduced transportation costs and economic growth, many countries and development agencies have pursued an infrastructure-centered approach to development that includes massive road network expansions, including China and Ethiopia (Fourie et al., 2015). Since launching the Road Sector Development Program (RSDP) in 1997, Ethiopia has increased the length of its federal and regional road network (asphalt and gravel roads) from 26,500 km to 63,604 km in 2015 (Ethiopian Development Research Institute, 2011; Federal Republic of Ethiopia, 2016). Including all-weather *woreda* roads, Ethiopia's total road network reached 110,414 km in 2015, more than double the length in 2010 and resulting in a decrease in the average time to reach the nearest all weather road from 3.7 hours to 1.7 hours (Federal Republic of Ethiopia, 2016). In Ethiopia's Second Growth and

Transportation Plan (GTP II), the country plans to further increase the all-weather road length to 220,000 in 2019/2020 (Federal Republic of Ethiopia, 2015). In this paper, I provide empirical evidence that rigorously evaluate the impacts of transport infrastructure on economic activity in Ethiopia, as measured through land cover and how it changes over time.

3. Literature Review

A large body of theoretical literature examines the relationship between transportation infrastructure and economic activity. The theoretical literature establishes a tradeoff between transportation costs and land rents, which influences the spatial allocation of economic activity depending on the relative costs of transportation associated with land uses. Additionally, empirical literature supports the hypothesis that a decline in transportation costs leads to an increase in economic activity, including the area of agricultural land.

The model used in this study is based in Johann H. von Thünen's model of agricultural land use, published in his 1826 treatise *The Isolated State*, which founded the field of spatial economics and continues to play a central role in urban theory. Von Thünen imagined a featureless plane with a town at the center supplied by farmers in surrounding fields, who cultivate crops that only differ in yield per acre and transportation costs. Land rents decline with distance from the city center, so farmers face a tradeoff between land rent and transportation costs. "Bid-rent" curves define the rent farmers are willing to pay for land to grow each type of crop at a given distance from town, and form the rent gradient. At the outermost edge of cultivation, land rents fall to zero.

Following a resurgence of interest in spatial economics, later theoretical work extended von Thünen's model and expanded the field of economic geography. Alonso (1964), Muth

(1969), and Mills (1972) developed a monocentric city model wherein workers commuting to a sole center face a tradeoff between the price of housing and transportation. This applies von Thünen's theory to economic activities other than agriculture. In my model, I will consider the effect of transportation costs on the margins between vegetation, agricultural, and urban land cover/use.

Krugman (1991) sought to explain the formation of a town or city itself in his seminal paper on new economic geography. Using a simple two-region model, Krugman proposed that the interaction of economies of scale and transportation costs can cause manufacturing activity to start to concentrate in one region and induce a positive feedback loop that generates further divergence in types of economic activity between regions – creating agglomeration. In my paper, I do not seek to explain the formation of urban centers such as Addis Ababa. However, Krugman's analysis affirms the premise that transportation costs are important for the spatial allocation of economic activity. Krugman's model also helps to explain the patterns of land cover/use observed in Ethiopia, as will be discussed in the results section.

Eaton and Kortum (2002) develop a Ricardian model of international trade that incorporates a role for geography, including transportation costs, as a barrier to trade. This approach provides a framework to simultaneously confront the role of geography and technology in economic activity. Donaldson and Hornbeck (2016) use an Eaton-Kortum model to measure market access and its impact on agricultural land values in the United States, as discussed later in this literature review. This methodology also motivates own calculation of market access.

Economic theory has been applied to a number of empirical studies on the economic effects of transportation infrastructure, though relatively few focus on land use. Chomitz and Gray (1996), Nelson and Hellerstein (1997), Pfaff (1999) estimate the effect of rural road construction on deforestation using von Thünen-type models where land operators allocate land use to maximize expected net benefits from output. Following an iceberg model of transportation costs, they assume the value of agricultural output declines with distance to market. Reducing distance to market then increases the potential rent from agriculture and promotes the expansion of farming activity. Using data from Belize, Mexico, and Brazil the authors find that road construction causes the conversion of forest to agriculture (Chomitz and Gray, 1996; Nelson and Hellerstein, 1997; Pfaff, 1999). As in my analysis, these authors rely on GIS methods using satellite data to classify land cover types. I add to this literature by using a much larger sample area – the whole of Ethiopia – (previous studies use pixel-level data only for a small, regional sample area or else aggregates data to the county level). I am able to do this in part because of new satellite data available, such as the European Space Agency's GlobCover project that began in 2005 and provides land cover data for the whole world.

Donaldson and Hornbeck (2016) use a general equilibrium model from trade theory to estimate the impact of railroad construction in nineteenth-century America on agricultural land value through increased market access. The authors link half of the estimated increase in agricultural land value to agricultural extensification. Drawing from Donaldson and Hornbeck (2016), I consider market access as an explanatory variable for land use. This adds to previous literature on land cover change that only considers road densities or distance to the nearest road, village, or capital (Chomitz and Gray, 1996; Nelson and Hellerstein, 1997; Pfaff, 1999).

Existing studies on transportation infrastructure expansion in Ethiopia focus on poverty reduction and business growth as measures of economic activity. Dercon, Hoddinott and Woldehanna (2012) find that reducing the distance on the road network to the nearest small town by 12km lowers poverty by 35-percent, using a longitudinal dataset collected between 1994 and

2009 in Ethiopia. Shiferaw et al. (2015) estimated that a 1-percent reduction in travel time to major commercial destinations in Ethiopia increases the size of new entrants by 3-percent, using cross-sectional data on firms and transportation networks. My study is different in that it draws from data points covering an entire area, not just towns and cities, and allowing the impact of transportation infrastructure on peripheral areas to be included. Also, my study looks specifically at effects on agricultural activity, which has not been studied previously in Ethiopia to my knowledge. The vast majority of Ethiopians earn their livelihood from agriculture and agricultural products drive Ethiopian GDP (Lavers, 2012), making this an important sector to understand and analyze in a development context.

4. Theoretical Model

The theoretical model in this paper is based on von Thünen's model (1826) and applications of the von Thünen model to deforestation by Chomitz and Gray (1996). Von Thünen imagined an "Isolated State" where profit-maximizing farmers transport their goods across land directly to a central city. This simplistic model in fact bears out very well in the Ethiopian context. Ethiopia is a rural country, where 85 percent of the population depends primarily on smallholder agriculture produced through household labor (Lavers, 2012). The small surplus of crops feeds the urban population, and few agricultural goods are exported in significant proportion (Lavers, 2012).[1] This is in part due to high transportation costs to Djibouti (Ethiopia is landlocked), which make exports often unprofitable (Dercon & Vargas Hill, 2009). Ethiopia's capital, Addis Ababa, is located in the geographic center of circular-shaped Ethiopia

[1] Ethiopia also imports agricultural goods – $1.8 billion worth in 2015 (USDA, 2016). The largest imports by value are for palm oil, sugars and sweeteners, and wheat (USDA, 2016). Ethiopia's main export crops are coffee, oil seeds, soya, and tea (Lavers, 2012).

and has a population 12 times the second-largest city, making it a quintessential primate city (Wubneh, 2013). I am thus confortable using a model that tracks von Thünen closely.

Following von Thünen (1826) and Chomitz and Gray (1996), I assume that each parcel of land has a potential for rent attached (the market value of output minus transportation costs). Land users will devote land to the activity that gives the highest rent. Beyond a certain distance from the city, any economic activity becomes unprofitable because of rising transportation costs and the land is left undisturbed as natural vegetation. The derivation below follows that of Chomitz and Gray (1996).

From Chomitz and Gray (1996), the return to a certain land use is the rent R_{ik}, given by

(1) $$R_{ik} = P_{ik}Q_{ik}(P_{ik}, C_{ik}) - C_{ik}X_{ik}(P_{ik}, C_{ik}),$$

where P_{ik} is the output price, Q_{ik} is the quantity of output, C_{ik} is a vector of input costs, and X_{ik} is a vector of inputs quantities, all for land use k at parcel location i. A land parcel is allocated to land use k if this use gives the highest rent compared to all alternatives for that parcel:

$$R_{ik} > R_{ih} \text{ for all } h \neq i.$$

In my model, I consider three possible types of land uses: idle (natural vegetation), agriculture, and built-up/urban area.

I do not have data on location-specific prices and costs, since they are unobserved. Therefore, I use a reduced-form model that takes observed determinants of price and productivity as inputs. Following von Thünen (1826) and Chomitz and Gray (1996), I assume that spatial differences in farm-gate prices are only due to differences in transportation costs to market, D_i.

(2) $$P_{ik} = \exp[\gamma_{0k} + \gamma_{1k}D_i]$$

$$C_{ik} = \exp[\delta_{0k} + \delta_{1k}D_i],$$

Using an iceberg model of transportation costs, I expect that output prices fall as access costs increase ($\gamma_{1k} < 0$). Here, we can think of output prices as those received by the land owner when they sell their product to a truck driver at the land parcel location. The truck driver receives the same price for all goods at the central market, so offers land owners less money for goods produced at greater distances to market, in order to make up for transportation costs. The model structure is based on an assumption of monopolistic competition.

Also, I expect that input costs rise ($\delta_{1k} > 0$) when land is devoted to a marketed output, so that idle land could have zero access cost.

I use a Cobb-Douglas production function for output per unit of land that includes parcel-specific geophysical factors G_{ik} , such as soil quality and average rainfall, that effect land productivity, from Chomitz and Gray (1996):

(3) $$Q_{ik} = G_{ik}{X_{ik}}^{\beta_k} \qquad [0 < \beta_k < 1]$$

$$G_{ik} = \lambda_{0k}{G_{1i}}^{\lambda_{ik}}{G_{2i}}^{\lambda_{2k}} \ldots {G_{ni}}^{\lambda_{nk}}$$

From equation (3), we have the demand for X:

(4) $$X_{ik} = \frac{C_{ik}}{P_{ik}G_{ik}\beta_k}^{1/[\beta_k - 1]}$$

Then, combining equations (1), (3), and (4):

(5) $$R_{ik} = P_{ik}Q_{ik} - C_{ik}X_{ik} = P_{ik}G_{ik}{X_{ik}}^{\beta_k} - C_{ik}X_{ik} = X_{ik}[P_{ik}G_{ik}{X_{ik}}^{\beta_k - 1} - C_{ik}]$$

$$R_{ik} = {C_{ik}}^{\frac{\beta_k}{\beta_k - 1}}[P_{ik}G_{ik}\beta_k]^{\frac{1}{1-\beta_k}}\frac{(1-\beta_k)}{\beta_k}$$

Thus, we see from the above equation that rent increases as output prices P increase and decreases as input costs C increase, as expected.

If we substitute in the equations in (2) and take logs of the variables, we get:

(6) $$\ln(R_{ik}) = \alpha_{0k} + \alpha_{1k}D_i + \alpha_{2j}ln(g_{1i}) + \cdots + \alpha_{(n+1)j}ln(g_{ni}) + \varepsilon_{ik}$$

where, as before, D_i represents distance to market along the road network and $g_{1i} \cdots g_{ni}$ represent geophysical characteristics of the land parcel i.

For agricultural activity, I expect the coefficients on distance to be negative and the coefficients on geophysical characteristics that increase productivity to be positive (Chomitz and Gray, 1996). This is because it is more profitable to produce crops in areas with lower transportation costs (higher farm-gate prices) and where agricultural productivity is higher. For urban areas, I expect the same negative coefficient on distance but a smaller positive coefficient on the geophysical characteristics, since the land is not farmed but proximity to agricultural areas that supply the town is important to support the town's population.

5. Empirical Model

I estimate the effect of roads on the allocation of land in Ethiopia using two empirical models based on the theoretical framework described in the previous section. The first section a is cross-sectional study, using data for all of Ethiopia in 2005/2006, and the second part is a panel study that examines changes in land cover types before and after the construction of an expressway, in the area surrounding the expressway.

In the first part of the paper, I estimate the probability of devoting parcel i to land use k using a multinomial logit model. I use a multinomial logit model because I am interested in the probabilities associated with three possible discrete land cover outcomes: vegetation (uncultivated land), agriculture, and urban area. I assume that expansions in the extent of agricultural and urban area indicate increases in economic activity, and thus economic growth. It is important to note that my model does not account for increases in productivity (e.g.

agricultural intensification), since this is not possible to measure using my dataset derived from satellite imagery. As discussed in later in my data section, because of the small number of observations of urban area and likely under-estimation of this land cover type, I focus my analysis on the transition from vegetation to urban area.

Logistic models require the assumption that the error terms are independent and identically distributed ($\varepsilon_{ik} \sim iid$) and follow a particular function form. The model is specified by the following equation:

$$Pr(i = k)_t = \frac{\exp\left[\ln\left(R_{ik}\right)_t\right]}{\sum_j \exp\left[\ln\left(R_{ij}\right)_t\right]}$$

(7) $$Pr(i = k)_t = \frac{\exp\left[\sigma_{0kt} + \sigma_{1k}D_{it} + \sigma_{2k}ln(O_{it}) + \sigma_{3k}ln(H_{it}) + \sigma_{4k}ln(R_{it}) + \sigma_{5k}ln(A_{it}) + \sigma_{6k}ln(N_{it})\right]}{\sum_j \exp\left[\sigma_{0jt} + \sigma_{1j}D_it + \sigma_{2j}ln(O_{it}) + \sigma_{3j}ln(H_{it}) + \sigma_{4jt}ln(R_{it}) + \sigma_{5k}ln(A_{it}) + \sigma_{6k}ln(N_{it})\right]}$$

where D represents distance to market (I use a variety of measures, described in the data section), C represents the organic carbon content of the soil, H represents the acidity (pH) of the soil and R represents the long-term average annual precipitation at the land parcel, A represents latitude, and N represents longitude (for rationale on the choice of controls, see below). I classify land according to three potential uses: vegetation (uncultivated land), agriculture, and urban area. As described by the theoretical model, the land user devotes the land at time t to the highest rent available in period t.

This model assumes that the construction or roads is exogenous to agricultural land use, which is potentially a very strong assumption. In cases where roads are installed to curry political favor, the assumption may hold true (Chomitz and Gray, 1996). However, if roads are purposefully placed in more agriculturally suitable areas and the determinants of the suitability are unobserved, the model may overstate the effect of distance to market on the probability of agricultural land use, for instance. I hope to reduce this potential bias by including soil quality indicators: organic carbon content and pH. These are together the best simple indicators of the health status of soil (Nachtergaele et al., 2009). Moderate to high amounts of organic carbon are associated with fertile soils, and acid to neutral soils are the best pH conditions for nutrient availability and suitable for most crops (Nachtergaele et al., 2009). Additionally, I include a variable for long-term average annual rainfall since Ethiopia is a drought-prone country and lack of available water is a main constraint on the ability to grow crops. I also include controls for latitude and longitude, and fixed effects for administrative region (zones).

In the second part of this study, I analyze the land-use change associated with the construction of specific segments of road. Using panel data (compared to cross-sectional data in the first section of the paper) helps to isolate the effects of road construction on land use decisions by allowing me to control for unobserved time-invariant variables.

I use difference-in-differences to estimate the effect of road construction and upgrading on agricultural land cover/use. As a treatment group, I use the land cover in an inner buffer of the newly-constructed Addis Ababa-Adama expressway. My control group is an outer buffer of the road. In September 2015, the Ethiopian government opened the Addis Ababa-Adama expressway, the country's first expressway and toll road. The six-lane expressway connects Ethiopia's two biggest cities – with link roads to major towns along the road – using advanced technologies new to Ethiopia, such as traffic cameras and variable message signs, together with interchanges, overpasses and underpasses. The expressway reduced travel time between Addis Ababa and Adama to 40 minutes from around two hours using the previous paved road (Embassy of Ethiopia in Belgium, 2014).

I estimate the proportion of the land devoted to agriculture as a function of being in an inner buffer of the expressway, the treatment variable:

(8) $Pr(i = agriculture)_t = 1/[1 + \exp(-(\sigma_0 + \sigma_1 Treat_i + \sigma_2 Post_t + \sigma_3(Treat_i * Post_t) + \sigma_4(Area_i * Post_t) + \sigma_5 Soil_i + \sigma_6(Soil_i * Treat_i) + \sigma_7(Soil_i * Post_t) + \sigma_8(Soil_i * Treat_i * Post_t) + \varepsilon_{it}))]$

where $Treat_i$ is a dummy for if the land parcel i is in the treatment group, $Post_t$ is a post-treatment dummy, $Area_i$ captures the percent of agriculture in a 2.5-kilometer buffer of land parcel i, and $Soil_i$ represents the soil quality of land parcel i. The treatment group is the area of land within an inner buffer (20km) of the Addis Ababa-Adama expressway and the control group is the area of land within an outer buffer (40km) of the planned Addis-Ababa-Adama expressway, excluding land in the inner buffer.

The average treatment effect on the treated (ATT) at the time of treatment is defined by:

(9) $$\tau(Treat_i = 1, Post_t = 1) = E[Y^1 | Treat_i = 1, Post_t = 1, Soil_i, Area_i] - E[Y^0 | Treat_i = 1, Post_t = 1, Soil_i, Area_i]$$

where Y^1 and Y^0 are the potential outcomes with and without treatment, respectively. In this case, the outcome Y indicates whether a land parcel is devoted to agriculture. Therefore, $Pr(i = agriculture)_t$ is the same as $E[Y_{it}]$.

The key assumption in a difference-in-difference estimation is that the outcome in the treatment and control group would follow the same time trend in the absence of treatment (the parallel trends assumption). Therefore, in this specification, I assume that the change in land cover in the outer buffer represents the counterfactual change in the inner buffer if no expressway was built, controlling for the soil quality and the concentration of neighboring agricultural activity. This is potentially a strong assumption: if the route of the expressway was chosen based on endogenous factors that affect the trend in land cover transitions, then the assumption may be violated. Additionally, the assumption may be violated if a shock unrelated to the expressway occurs that effects land cover in the treatment and control groups differently (for instance, a localized drought or a policy change in one administrative region but not others).

I minimize the risk of these violations of the parallel trends assumption through how I select the treatment and control groups and through control variables. Since land parcels in the control group are within 20-km of those in treatment group, this enhances the similarities between the two groups. Since I only look at the area within 40-km of one segment of road, climactic factors (rain, temperature, etc.) are likely relatively constant across both groups. Also, by including variables $Area_i$ and $Soil_i$, I allow land cover in areas with a higher concentration of agriculture and better soil quality to change at a different rate over the period of observation. Therefore, I control for differences in these two variables between the treatment and control groups that would effect the rate of transition in land cover types during the period of observation.

6. Data

To estimate equations (7) and (8), I collect data on land cover classification, distance to market, and geophysical characteristics for land parcels in Ethiopia. All data sources are described in detail in the sections that follow.

Both estimations rely on land cover classification to generate the dependent variable. One of the major challenge in using remotely-sensed land cover data is the uncertainty involved in classification and inconsistency of classification schemes between datasets (Russel, 2014). In the first part of my paper, I get around the problem of non-comparability of class definitions by restricting my analysis to a cross-section, using only one dataset. In the second portion, I perform my own land cover classification, which allows me to use a consistent methodology between years. However, there is still the issue of classification inaccuracy. I mitigate this issue by aggregating land cover classes to broad categories where there is less scope for error. For the remaining error, I assume that it is random and so will not affect my estimation.

6.1 Cross Sectional Data

In part (1) of the study, my unit of observation is every land parcel (1-km square cell) in Ethiopia. For each observation, I collect data on land cover classification and two measures of distance to market: distance to roads and market access taking into account transportation costs. I also collect data on geophysical characteristics of each observation: elevation, soil quality, latitude and longitude, and administrative region.

6.1.1 Land cover classification

For my dependent variable in part (1), I use data on land cover processed by the European Space Agency (the ESA). The ESA developed a global land cover dataset using 300-m resolution data from the ENVISAT satellite mission covering the period December 2004 to June 2006, as part of its GlobCover initiative. The project classified land cover according to the UN Land Cover Classification System (LCCS) scheme, with 22 global classes, using a combination of supervised and unsupervised classification methods (Bicheron et al., 2008). Validation of the dataset using stratified random sampling of 3167 points generated an overall area-weighted accuracy rating of 67.1% (Bicheron et al., 2008). This level is similar to the accuracy of other global land cover datasets, such as the USGS-produced IGBP with a total accuracy of 66.9% or the ESA-produced GLC 2000 with 68.6% accuracy (Russel, 2014).

The land covering Ethiopia is divided into sixteen different land cover classes. These encompass types of natural vegetation (shrubs and woodland), different percentages of agricultural activity. There is only one class for urban areas, defined as more than 50-percent built-up. Because of their small spatial extent, urban areas are classified with lower accuracy and tend to be underestimated (Bicheron et al., 2008).

For the bulk of my analysis, I aggregate the data to three classes: vegetation, agriculture (more than 50-percent), and urban area (more than 50-percent). This is because I am interested in categories of land cover that represent distinct economic activities: idle (no) activity, agricultural activity and industrial activity. I also combine measures of agricultural area in order for the definition of agricultural area to be comparable with the urban category. I exclude water bodies, since these cannot be allocated to agriculture or urban area.

6.1.2 Distance to market

My independent variable, distance to market, is derived from road network data coming from the Ethiopia Road Authority (ERA). The ESA road network, surveyed in 2004, is divided into four classes of roads: unknown, rural gravel, unpaved, and paved. I aggregate these into two classes: unpaved and paved, adding the unknown roads to the unpaved category. Using Geographic Information System (GIS) software, I calculate the Euclidian distance (as the crow flies) to each category of road, and cost distance along the road network. Cost distance takes into account travel times across different types of terrain and the method of calculation is described in more detail later in this section.

Following the approach of Donaldson and Hornbeck (2016), I compute a measure of market access using transportation costs along the road network. For every land parcel i (cell in my dataset), I calculate market access by summing the population of Ethiopian cities weighted by the transportation costs to access that city:

(9)
$$\text{MA}_i = \sum_c \frac{Pop_c}{dist_{ic}}$$

where Pop_c is the population city c and $dist_{ic}$ is the distance from land parcel i to city c. I use two measures of distance: Euclidian distance (as the crow flies) and cost distance.

To measure cost distance, I create a grid of transportation costs for the entire Ethiopian landscape. I assume a travel speed of 35km/hour on paved roads and 10km/hour on unpaved roads (Roberts et al., 2012). For terrain that does not include any type of road, I assume a travel speed of 5km/hour. For each cell in my grid of Ethiopia, I then assign a travel cost:

(10)
$$\text{TravelCost}_i = \frac{1}{TravelSpeed_i}$$

Using Geographic Information Systems (GIS) software, I calculate the least-cost path from each land parcel i to city c, based on the travel costs assigned to each cell in the grid of Ethiopia. The path is calculated using tools in the ArcGIS software package which are based on Dijkstra's shortest-path algorithm. Given differences in terrain, the least-cost path is not necessarily the shortest in terms of distance. The cost of this optimal path is then input as the distance measure in equation (8) and I refer to it as "cost distance".

The city location and population data comes from the United Nations Office for the Coordination of Humanitarian Affairs (OCHA) in Ethiopia, accessed through the Humanitarian Data Exchange. I use two datasets: one of cities, towns and villages (2016), and one with woreda (third-level administrative district) populations from the 2007 Ethiopian census. Using satellite-derived night-time light data for 2005, I ranked the size of 2,841 Ethiopian cities and towns based on light intensity within a 5-km buffer of the municipality. Then, I keep the largest city or town in each of 780 woreda, and assign to that city or town the population of the woreda. I restrict my analysis to cities and towns with visible night-time light because these are more urbanized, dense centers. In constructing a measure of market access, I am interested in the distance to these centers because they are the largest markets for the buying and selling of goods.

The primary reason for using woreda rather than city or town population data is because I do not have access to Ethiopian city or town population data. However, I also contend that woreda populations represent a reasonable approximation of the market size of a given city or town (the number of people consuming goods and services in the vicinity of the center).

In summary, I end up with four measures of distance to market: Euclidian distance to any road, Euclidian distance to a paved road, and two measures of market access. My market access measures, calculated from equation (9), are a sum over the populations of 181 woreda, weighted by either the Euclidian or cost distance to reach the largest city or town in that woreda.

6.1.3 Geophysical characteristics

As specified in (7), I add controls for soil quality, average annual precipitation, elevation, longitude and latitude, and administrative region. The soil quality data (soil organic carbon content and pH) comes from the Harmonized World Soil Database (HWSD), a compilation of data from different sources published in 2009 by a consortium of international organizations. HWSD is published at a 30 arc-second (1-kilometer) resolution. Data for Ethiopia in the HWSD comes from the SOTWIS database by the International Soil Reference and Information Center (ISRIC). While the soil quality data is not collected in the same year as the land cover data, I assume that the distribution of soil quality stays constant over time.

Data for average annual precipitation is taken from the Long-Term Annual Rainfall dataset covering the years 1901-2005, published by Harvest Choice (2011).

Mean elevation and the standard deviation of the elevation in each cell comes from the Global Multi-Resolution Terrain Elevation Data (GMTED), available at 30, 15, and 7.5 arc-second resolutions (U.S. Geological Survey and National Geo-Spatial Intelligence Agency, 2010). I download the data at the 30 arc-second resolution to maintain consistency with the HWSD resolution.

I resample all of my raster data files to the 1-kilometer resolution of the HWSD. Then, I project each layer using an Azimuthal Equidistant projection in order to preserve accuracy of distance measurement. Using GIS software, I assign each cell a value for latitude and longitude and use a spatial join to assign the cell to its respective zone (the second-level administrative division in Ethiopia, of which 68 exist).

Each unit of observation is one pixel taken from a unique 1-km x 1-km cell, with the attributes of each layer associated.

6.2 Expressway Data

In the second part of my analysis, I use data on land cover and road location. I collect the geo-coordinates of the Addis Ababa-Adama expressway from the Ethiopian Transportation Authority (ERA, 2016). Then, I use Landsat program imagery to classify land cover in a 40-km buffer of the expressway (USGS, 2009; USGS, 2016). I look at two periods: 2009, before construction began on the expressway, and 2016, after the expressway opened to traffic. For each year, I select the available Landsat image with the least cloud cover in order to minimize the quantity of missing data.

To classify Landsat imagery into distinct land cover categories, I use ISODOATA unsupervised classification methods in ENVI image analysis software. For each image, I divide the land cover into fifteen categories based on reflectance values of the surface. Then, I use visual inspection and reference to Google Maps to assign each category to agriculture or non-agriculture. I exclude land cover that is cloud (less than 10% of the observations) or water. I do not disaggregate the non-agricultural land into types (e.g. vegetation and urban area) due to the limitations of my classification method. There is not a large enough difference in surface reflectance values between urban land cover and other non-agriculture types for me to distinguish between them.

I expect that the quantity of agriculture in the region surrounding a land parcel will impact the probability of transforming from agriculture to something else. Therefore, to control for this effect, I also calculate using GIS software the percentage of land parcels devoted to agriculture in 2009 in a 2.5 km buffer of each observation.

7. Descriptive statistics

7.1 Cross Section

The descriptive statistics for the main variables are shown in Tables 1-3. The sample consists of 1,232,351 one kilometer square cells that cover the entire area of Ethiopia.

The land cover classifications are disaggregated in Table 2. As shown, very little land is assigned to urban area in the ESA dataset. This is expected because Ethiopia is a primarily rural country. However, a contributing factor is also the fact that the smaller spatial extent of urban area introduces higher classification error, leading to underestimation (Bicheron et al., 2008). For this reason, my analysis focuses on the transition between vegetation (forest, shrubland, and grassland) and agricultural land cover.

7.2 Expressway

The descriptive statistics for land cover classification in 2009 and 2016 are shown in Table 4. The sample consists of 487,551 140x140m cells in a 40-km buffer of the Addis Ababa-Adama expressway. I have excluded any cells missing a land cover classification in one or both years because of cloud cover, which obscures the image. Figure 5 shows the classified images of land cover in both 2009 and 2016, with cloud cover a bigger problem in 2009 but still covering less than 10 percent of the image.

As shown in the Table 4, the majority of land parcels in both 2009 and 2016 are devoted to agriculture. However, a higher percentage of land is devoted to agriculture in 2009 versus 2016 (79 percent versus 68 percent). Approximately 66 percent of land devoted to non-agriculture in 2009 transitions to agriculture in 2016 while 15 percent of land that was agriculture in 2009 transitions to non-agriculture.

As acknowledged before, there is a degree of error in land cover classification. Since I cannot physically inspect the land in order to verify and improve my classifications (ground-truthing), the risk of error is increased. Additionally, the two images that I use (for 2009 and 2016) come from different Landsat satellite images – Landsat 8 and Landsat 5, which may affect the detection of surface reflectance and my classification. Therefore, I do not want to over-interpret the fact that a decline in agriculture is observed between the two periods, since part this result may be due to classification error. However, assuming that the error is random, I can still accurately estimate the impact of my treatment variable (the expressway) on land use change between agriculture and non-agriculture by looking at the spatial distribution of land cover transitions.

Descriptive statistics in Table 5 divide observations by their distance to the expressway (within or outside a 20-km buffer). The table shows that land within the inner buffer of the expressway is more likely to be agriculture in both 2009 and 2016, as compared to land outside the inner buffer. Additionally, land closer to the expressway experiences a higher frequency of transitions in both directions – from non-agriculture to agriculture and vice versa – during the period of observation. I will explore these relationships further in my estimation, and offer possible explanations.

8. Results and Discussion

The estimation of β is based on equations (7) and (8). Using data on land cover for the whole of Ethiopia in 2005/2006 and for the change in land cover in a 40-km buffer of the Addis Ababa-Adama expressway after the expressway was built, between 2009 and 2016, I examine the effect of distance to road/market on the probability of devoting a land parcel to agriculture.

8.1 Cross Section

In my first estimation, I analyze a cross section of Ethiopia as a whole. I report the results from a multinomial logit model in Tables 6-9, where the largest category (21% of observations), *Mosaic forest or shrubland (50-70%)/grassland (20-50%)*, is assigned as the base category. The estimated coefficients in Table 6-9 represent the change in the log-odds of a given land cover category relative to the base category for a one-unit change in the variable of interest, holding all other variables constant. Of most interest are the coefficients on the distance variables (distance to road or Addis Ababa and market access).

Interpreting the results, we see a strong negative effect of an increase in distance to capital or roads on the log-odds of urban area relative to the base category. Additionally, we see a smaller negative effect of an increase in distance to capital or road on the log-odds agricultural land classes relative to the base category. All estimations show a positive effect of market access on the log-odds of urban area and agricultural land classes relative to the base category. Again, the effect is stronger for urban areas.

Some categories with smaller numbers of observations shown outsized effects (for instance, the largest effects in all models, either positive or negative, are on regularly flooded broadleaf forest, for which there are only 50 observations). I expect that part of the reason for such a strong effect on this category is because flooded broadleaf forest is heavily concentrated in regions close to road networks and market for climactic reasons. Controls in the model for soil quality, elevation, and latitude and longitude are not fully accounting for climactic factors. Thus, in subsequent estimations, I add a factor variable for 68 administrative zones, in order to control for unobserved characteristics of regions that will affect the prevalence of different land cover types. In addition, I aggregate vegetation and agriculture categories, which reduces the problems posed by small, localized land use categories.

Estimated marginal effects from the logit model are shown in Table 7. My main interest is in the margins between different economic activities (idle land, agricultural activity, and urban service or manufacturing). I focus on the margin between vegetation and agriculture because of the small percentage of urban area in my sample (less than 0.01%) and the systematic underestimation of urban area due to limitations of the classification methods used by the ESA (Bicheron et al., 2008).

The results in Table 11 show statistically significant negative effects of distance to Addis Ababa and positive effects of market access on the probability of devoting a land parcel to agriculture across multiple specifications. The effect on log Euclidian distance to the Addis Ababa shows that a one-percent increase in distance to the capital results in an 12-percent decline in the probability of a land parcel being devoted to agriculture, on average. A one percent increase in cost-distance to Addis Ababa leads to an average 15-percent decline in the probability of agricultural land cover. Finally, a one-percent increase in market access is associated with an average 5-percent increase in the probability of agricultural activity. Note that these are marginal effects taken at the mean – as shown in Figure 8, the marginal effects vary depending on the value of the explanatory variable (and tend to be largest near the mean). However, the signs of the effects are the same and the effects remain statistically significant across all values. The results are consistent with the theory developed by von Thünen, which predicts an increase in agricultural land area at the margins when transportation costs decline.

The estimation results also show an insignificant positive effect of distance to road on probability of agricultural land cover. This suggests that distance to a road matters less than the travel costs to market along the road. Therefore, roads are not important in and of themselves, but in how they reduce travel time to population centers. This result is notable because it is contrary to the result from prior literature focused on the central and South America, which found statistically significant negative effects of distance to road on the probability of agriculture (Nelson and Hellerstein, 1997; Pfaff, 1999). A possible reason for the discrepancy is that differences in the types of terrain and vegetation in Ethiopia versus central Mexico and the Brazilian Amazon mean lower travel times in Ethiopia in the absence of roads, so roads make less of a difference to transportation costs. Additionally, roads in Ethiopia might encourage non-agricultural economic activities nearby, such as residential or industrial uses that are not picked up by the ESA classification system. It is out of the scope of this paper to test these hypotheses.

The interaction terms that include Euclidian distance to Addis Ababa and another explanatory variable reveal how distance to the capital influences the magnitude of the reported effects. The estimated results in Table 11 show a positive coefficient on the interaction between log Euclidian distance to Addis Ababa and log cost-distance to Addis Ababa. So, at larger distances from Addis Ababa, the effect from an increase in the cost of distance to market is larger. Additionally, the coefficient on the interaction term between log market access and log Euclidian distance to Addis is negative, showing that the effect of an increase in market access is weaker at greater distances from the capital.

These results can be explained in several ways. First of all, when travel costs are higher, they matter more to the profitability of farming. Therefore, for land parcels further away from Addis Ababa (the largest market), travel costs may be more likely to make the difference between whether agriculture is a profitable or unprofitable land use.

Additionally, closer to Addis Ababa, there are likely more alternative land uses to agriculture, so that reductions in travel costs may promote expansion in economic activities other than agriculture. This can be explained by the benefits of agglomeration described in Krugman (1991): given larger existing manufacturing and service sectors close to Addis Ababa, the benefits of economies of scale make areas near the capital more attractive for additional manufacturing and service activities. Therefore, agriculture would tend to concentrate in more rural areas where alternative economic activities are less viable.

Additionally, both the OLS and probit specifications that include the cost distance to Addis Ababa and the Euclidian distance to Addis Ababa as explanatory variables show a positive effect of Euclidian distance on agricultural land use. This is opposite of the effect found when Euclidian distance to Addis Ababa is included on its own. Therefore, separating the effect of distance on increasing the cost of travel to the capital, land farther away from the Addis Ababa is more likely agricultural. As with the direction of the coefficient on the interaction terms with Euclidian distance to Addis Ababa, this result can be explained by the benefits of agglomeration (Krugman, 1991) – a concentration of secondary and tertiary industries near the capital offer more economic alternatives to agriculture that reduce likelihood of farming regardless of the road network.

The coefficients on the control variables conform to expectation. Higher precipitation and soil quality have positive and significant effects on the likelihood of a land parcel being devoted to agriculture. Meanwhile, greater variation in elevation has a negative effect on the likelihood of agricultural land cover.

8.2 Expressway

In the second part, I estimate equation (8). Across all specifications, the results displayed in Table 12 show a statistically significant negative average treatment effect on the treated. That is, being in the treatment group (within an inner 20-km buffer of the expressway) is associated with a lower probability of agricultural land cover. Additionally, across groups, land parcels with higher soil quality and a higher neighboring concentration of agricultural activity are associated with a lower probability of agricultural land cover in the second (treatment) period.

These results are counterintuitive, and contradict the initial theory. However, they are consistent with the results from the cross-section that found positive, if insignificant, effects of an increase in distance to road on probability of agriculture. Additionally, when I re-estimate the cross-section using only land parcels within the 40-km buffer of the Addis Ababa-Adama expressway, I find that proximity to the capital and market access are negatively associated with agriculture. These are opposite effects from when the model is estimated using the whole sample of land parcels covering all of Ethiopia. This suggests that there is something unique about the land surrounding the expressway. A discussion of possible reasons for the unexpected results, including why land in near the expressway may respond differently to changes in transportation costs than other land in Ethiopia, follows.

As mentioned in the analysis of the cross-section, one possible explanation for these results is that agricultural land close to new roads (such as the expressway) is being transformed into residential or industrial uses. Table 6 disaggregates percentage of agriculture by second-level administrative region, and shows that the administrative region containing the core of Addis Ababa is assigned to 28-percent agriculture in 2009 and 25-percent agriculture in 2016. Therefore, likely some urban/industrial area is being captured in the non-agriculture category, which would influence the results. Perhaps there is a higher benefit to proximity to roads for urban/industrial land versus agricultural land and therefore agricultural land in close proximity to roads is converted to other uses after road construction.

Additionally, the section of road and the surrounding land chosen for this analysis is unique in several respects. The road is the only expressway in the country and connects the country's two largest cities, meaning that urban/industrial economic activity is more concentrated in this part of the country than in more rural regions. As shown in the cross section, Euclidian distance to Addis Ababa (the capital city which is included within the 40-km buffer of the expressway) is associated with smaller positive effects of market access on probability of agriculture and smaller negative effects of cost distance to market on probability of agriculture. As already discussed, the estimating the logit model for the cross-section using only land parcels within a 40-km buffer of the expressway produces results with the opposite sign as when using the entire sample. Therefore, the estimate treatment effect of road construction on agricultural land cover may be unique to the area of analysis and not generally applicable across Ethiopia.

Finally, Euclidian distance to road may be a poor measure of transportation costs to market, the true variable of interest. In the case of the expressway, distance to the road does not take into account where are the entry points onto the expressway or changes that may have occurred over the observation period in roads that connect to the expressway or other cities in the region. This means that being within an inner buffer of the expressway may not be a good indicator of treatment, if treatment is meant to measure a decline in transportation costs.

The results in Table 12 are only related to the change in the probability of agricultural land cover, and do not take into account which transitions are taking place. There four possible (non) transitions over the period: staying agriculture, staying non-agriculture, transitioning from agriculture to non-agriculture, and transitioning from non-agriculture to agriculture. In Table 13, I divide land parcels by their original classification in 2009, and look at how being in the treatment or control group affects the probability of transition. As shown in the table, proximity to the expressway results in a higher probability of transition both into and out of agriculture. Therefore, treatment is associated with changes in land cover/use, but not solely in one direction and overall out of agriculture.

Von Thünen's theory of agricultural land use, the basis for this paper, can be applied to these results. Von Thünen proposed that landholders maximize profits by allocating land to the most cost-effective product, balancing land costs (higher nearer to market) and transportation costs (lower nearer to market). This means that vegetables would be grown closer to the city center than grain because of faster spoiling. While Von Thünen's theory assumes that agriculture is the only economic activity outside of the city and that soil quality and climate are consistent everywhere, this is evidently not true in our real-life sample of land surrounding the Addis Ababa-Adama expressway. Therefore, a reduction in transportation costs changes the balance of costs and benefits for different land uses – why we see transitions in land use near the expressway –, but does not mean a transition towards agricultural activity in all cases.

The direction of the transition in land cover will depend on the relative value/cost of soil quality, transportation, and other unobserved factors to different land uses. Thus, reducing transportation costs can cause both an absolute increase in economic activity and a change in the allocation of different types of economic activity across space, whether towards agriculture or other uses. In this case, we see an increase in land cover transitions in proximity of the new Addis Ababa-Adama expressway and an overall decline in agricultural activity.

Why do we see this result? Firstly, the estimation results may be due to the unique character of land near the expressway. A re-analysis of the cross-section using only land parcels within 40-km of the expressway shows that proximity to Addis Ababa and market access are negatively associated with agricultural land cover, the opposite effect found when using the full sample. Likely the already highly urbanized nature of the land in this region impacts the response of landholders to declining transportation costs. We may be seeing an increase in urban/industrial activity after construction of the expressway that cannot be disaggregated from other non-agricultural land cover types using the methodology in this paper. Additionally, it is possible that my treatment variable is not well defined, and that proximity to the expressway is not a good indicator of declining transportation costs, the treatment of interest.

9. Conclusion

This study has shown that agriculture tends to be concentrated in regions with more access to market. Using a cross-section of land cover in Ethiopia in 2005/2006, I show that agricultural land use is more likely in areas with better access to market, after controlling for soil quality, elevation, latitude and longitude, Euclidian distance to the capital, and administrative zone. Additionally, I show that the effect of changes in cost distance is stronger for land further away from the primate capital city (Addis Ababa). Unlike previous studies, I do not find a significant effect on only distance to roads, ignoring market access.

Using panel data on land cover in a buffer of the Addis Ababa-Adama expressway, I show that proximity to the expressway increases the likelihood of transitions both into and out of agriculture. Additionally, I found a negative average treatment effect on land parcels within an inner buffer of the expressway during the treatment period (after the construction of the expressway). Proximity to the expressway is therefore associated with a decline in agricultural activity compared to with land parcels farther away from the new expressway. A re-analysis of the estimation from the cross-section using only the land parcels in within 40-km of the future expressway shows a negative effect of proximity to Addis Ababa and market access on probability of agricultural land cover. This confirming that a decline in transportation costs in this part of the country does not increase agricultural land cover on average.

The results indicate that reducing transportation costs/increasing market access can play an important role in spurring economic activity, including an expansion in agricultural land use. However, the effect is not the same everywhere: reducing travel costs to more rural areas – those farther away from the densely-populated capital region in Ethiopia – has a greater effect on expanding agricultural activity, as measured through land cover. While roads are an important means to reduce travel costs, I find that proximity to them, without taking into account other measures of market access, is in fact associated with a decline in agricultural land use. This effect is perhaps because of increases in urban/industrial activities near roads, or because of other unobserved factors.

This study adds to the literature by using a new measure of market access that takes into account cost-distance to all major markets, and by looking at a wider geographic area (the whole of Ethiopia) than previous studies. I demonstrate the feasibility of using newly-available satellite-derived land cover data, such as the European Space Agency dataset, to evaluate changes in the spatial allocation of economic activity. Additionally, I show that reducing transportation costs through road construction can be an effective way to grow Ethiopia's economy by spurring agricultural activity. However, effects of road construction on agricultural activity may not be the same across the entire country. Additionally, satellite data is most useful for analyzing changes in agricultural land cover, since urban/industrial land cover is difficult to classify and therefore typically under-estimated.

While the focus of this study is on Ethiopia, the same empirical results could be present in other primarily rural countries experiencing a significant road network expansion. An area of further research would be to compare the economic benefits of increasing agricultural and other types of economic activities with the costs of road construction.

Limitations of this study include the systematic underestimation of urban area classified from satellite imagery and lack of data due to the time-intensive nature of land cover classification when no pre-classified imagery is available. Future studies should enhance the accuracy of classification by ground-truthing and/or interviews with people local to the area. In addition, future studies should compare land cover change after the construction of roads in both urban and rural areas, in order to determine if different responses occur.

10. References

Literature:

Ai, C., & Norton, E.C. (2003). Interaction terms in logit and probit models. *Economic Letters, 30*, 123-129.

Allen, T. & Arkolakis, C. (2014). Trade and the topography of the spatial economy. *The Quarterly Journal of Economics, 129*(3), 1085-1139.

Alonso, W. (1964). *Location and land use: Toward a general theory of land rent*. Cambridge: Harvard University Press.

Baum-Snow, N. (2007). Do highways cause suburbanization? *The Quarterly Journal of Economics, 122*(2), 775-805.

Bicheron P., Defourny P., Brockmann C., Schouten L., Vancutsem C., Huc M., Bontemps S., Leroy M., Achard F., Herold M., Ranera F., Arino O. (2008). Globcover products description and validation report. Medias France, Toulouse, France. Available online at http://due.esrin.esa.int/files/GLOBCOVER_Products_Description_Validation_Report_I2.1.1.pdf

Chomitz, K.M. & Gray, D.A. (1996). Land use, and deforestation: A spatial model applied to Belize. *The World Bank Economic Review*, *10*(3), 487-512.

Dercon, 2004. Growth and shocks: evidence from rural Ethiopia. *Journal of Development Economics, 74*(2), 309-329

Dercon, S., Hoddinott, J., & Woldehanna, T. (2012). Growth and chronic poverty: Evidence from rural communities in Ethiopia. *Journal of Development Studies, 48*(2), 238–253.

Dercon, S. & Hill, R.V. (2009), Growth from agriculture in Ethiopia: identifying key constraints. Retrieved from: http://users.ox.ac.uk/~econstd/Ethiopia%20paper%203_v5.pdf

Donaldson, D. (in press). Railroads of the Raj: Estimating the Impact of Transportation Infrastructure. American Economic Association.

Donaldson, D., & Hornbeck, R. (2016). Railroads and American economic growth: A "market access" approach. *The Quarterly Journal of Economics, 131*(2), 799-858.

Dorosh, P., & Thurlow, J. (2013). Can cities or towns drive African development? Economywide analysis for Ethiopia and Uganda. *World Development, 63*, 113-123.

Eaton, J. & Kortum, S. (2002). Technology, geography, and trade. *Econometrica*, 70(5), 1741-1779.

Embassy of Ethiopia in Beligum (2014). *Ethiopia's first expressway nears completion*. Retrieved from: http://www.ethiopianembassy.be/en/2014/04/14/ethiopias-first-expressway-nears-completion/

Faber, B. (2014). Trade integration, market size, and industrialization: Evidence from China's national trunk highway system. *Review of Economic Studies, 81*, 1046-1070.

Federal Democratic Republic of Ethiopia. (2015). *The Second Growth and Transportation Plan*. Addis Ababa: National Planning Commission.

Fenta, K. (2014). Industry and industrialization in Ethiopia: Policy dynamics and spatial distributions. *European Journal of Business and Management, 6*(34), 326-344.

Fourie, E. (2015) 'China's example for Meles' Ethiopia: when development "models" land.' *The Journal of Modern African Studies, 53*(3), pp. 289–316.

Glaeser, E.L. (2008). *Cities, agglomeration and spatial equilibrium*. New York: Oxford University Press.

Fujita, M., Krugman, P., & Venables, A.J. (1999). *The spatial economy*. Cambridge: MIT Press.

Krugman, P. (1991). Increasing returns and economic geography. *Journal of Political Economy, 99*(3), 483-499.

Lavers, Tom. (2012) 'Land grab' as development strategy? The political economy of agricultural investment in Ethiopia. *The Journal of Peasant Studies*, 39(1), 105-132.

Li, B. (2011) The multinomial logit model revisited: A semi-parametric approach in discrete choice analysis. *Transportation Research Part B: Methodological*, 45(3), 461-473

Mills, E.S. (1972). *Urban economics*. Glenview, Illinois: Scott Foresman.

Muth, R.F. (1969). *Cities and housing*. Chicago: University of Chicago Press.

Natchergaele, F., van Velthuizen, H., Verelst, L., & Wilberg, D. *Harmonized World Soil Database (version 1.2)*. Rome, Italy: FAO, and Austria: IIASA.

Nelson, G.C. & Hellerstein, D. (1997) Do roads cause deforestation? Using satellite imagines in econometric analysis of land use. *American Journal of Agricultural Economics*, *79*(1), 80-88.

Pfaff, A.S.P. (1999). What drives deforestation in the Brazilian amazon? Evidence from satellite and socioeconomic data. *Journal of Environmental Economics and Management, 37*, 26-43

Puhani, P.A. (2012). The treatnment effect, the cross difference, and the interaction term in non-linear “difference-in-difference” models, *Economics Letters, 115*(1), 85-87.

Roberts, M., Deichmann, U., Fingleton, B. & Shi, T. (2012). Evaluating China’s road to prosperity: A new economic geography approach. *Regional Science and Urban Economics, 42*, 580-594.

Russel, C. (2014). Global land cover mapping: A review and uncertainty analysis. *Journal of Remote Sensing, 6(12)*, 12070-12093

Shiferaw, A., soderbom, M., Eyerusalem, S., & Alemu, G. (2015). Road infrastructure and enterprise dynamics in Ethiopia. *Journal of Development Studies, 51*(11), 1541-1558.

USDA Foreign Agriculture Service (2016). Ethiopia’s agriculture imports continue growing (Report No. ET1634). Retrieved from: https://www.fas.usda.gov/data/ethiopia-ethiopia-s-ag-imports-continue-growing

Worku, I. (2011). *Road sector development and economic growth in Ethiopia*. Addis Ababa: Ethiopian Development Research Institute.

World Bank. (2016). *Ethiopia’s great run: The growth acceleration and how to pace it*. Washington, DC: World Bank Group.

Wubneh, M. (2013). Addis Ababa, Ethiopia – Africa’s diplomatic capital. *Cities*, 35, 255-269.

11. Appendix A: Tables

Table 1: Descriptive statistics, 2005/2006 Ethiopia cross section

Variable	Obs	Mean	Std. Dev.	Min	Max
Land cover	1,147,556			1	3
Cost distance to capital	1,232,351	3.17E+08	1.99E+08	0	1.19E+09
Euclidian distance to capital	1,012,216	387823.8	146565	0	737151.3
Euclidian distance to road	1,176,008	13619.51	15902.84	0	124084.6
Market access	1,232,170	7.13E-09	3.07e-087	9.60E-11	2.93E-06
long run avg precipitation	1,232,351	816.4738	426.4613	126	1800
elevation stdev	1,232,351	14.32354	15.59316	0	256
elevation mean	1,232,351	1223.103	696.0951	-150	4338
topsoil organic carbon	1,220,520	0.9264244	0.7332208	0.17	33.87
Difference from pH =7	1,223,524	0.7433856	0.5245469	0	2.7
latitude	1,232,351	1032491	319945.43	98842.7	1772843
longitude	1,232,351	4378724	342087.4	3649582	5302582

Note: land cover is classified into three categories (0=vegetation, 1=agriculture, 3=urban). Water bodies are excluded.

Table 2: **Distribution of land cover by all classes, 2005/2006 Ethiopia cross section**

Land Cover	Frequency	Percent
Rainfed croplands	30,162	2.45
Mosaic cropland (50-70%)/vegetation (20-50%)	209,492	17
Mosaic vegetation (50-70%)/cropland (20-50%)	181,674	14.74
Closed to open >15% broadleaved evergreen or semi-deciduous forest (>5m)	13,673	1.11
Open (15-40%) broadleaved deciduous for	57,424	4.66
Mosaic forest or shrubland (50-70%)/grassland (20-50%)	258,933	21.01
Mosaic grassland (50-70%)/forest or shrubland (20-50%)	3,074	0.25
Closed to open (>15%) shrubland (<5m)	172,517	14
Closed to open (>15%) herbaceous vegetation	67,332	5.46
Sparse (<15%) vegetation	153,220	12.43
Closed to open (>15%) broadleaved forest regularly flooded	50	0
Closed to open (>15%) grassland or woody vegetation on regularly flooded or waterlogged soil	2,503	0.2
Urban >50%	137	0.01
Bare areas	74,429	6.04
Water bodies	7,731	0.63
Total	1,232,351	100

Table 3: Distribution of land cover by aggregated class, 2005/2006 Ethiopia cross section

Land Cover	Frequency	Percent
Vegetation	890,464	77.6
Cropland	256,951	22.39
Urban Area	141	0.01
	1,147,556	100

Note: Urban area represents >50% urban and cropland represents >50% crops. Vegetation encompasses all other categories except for water bodies, which are excluded.

Table 4: Descriptive statistics, expressway

Variable	Observations	Mean	Min	Max
Agriculture in 2009	487,551	0.7852	0	1
Agriculture in 2016	487,551	0.6767	0	1
If agriculture in 2009	157,606	0.6566	0	1
If non-agriculture in 2009	329,945	0.1534	0	1
Agriculture concentration	863,368	0.6873	0	1
Ideal topsoil pH	975,102	0.8094	0	1
Within 20km of expressway	975,102	0.389	0	1

Note: This table shows descriptive statistics on land cover and distance to road for land parcels within a 40km buffer of the Addis Ababa-Adama expressway. *Agriculture concentration* calculates the percentage of land parcels devoted to agriculture in 2009 within a 2.5-km buffer of every observation. All other variables are dummies.

Table 5: Descriptive statistics by distance to road, expressway

Variable	Observations	Mean	Min	Max
Outside 20-km buffer of expressway				
Agriculture in 2009	297,904	0.7151	0	1
Agriculture in 2016	297,904	0.6467	0	1
If agriculture in 2009	33,112	0.399	0	1
If non-agriculture in 2009	275,094	0.1742	0	1
Agriculture concentration	269,575	0.6637	0	1
Ideal topsoil pH	595,808	0.7524	0	1
Within 20km of expressway				
Agriculture in 2016	189,647	0.7239	0	1
If agriculture in 2009	189,647	0.7877	0	1
If non-agriculture in 2009	52,355	0.6882	0	1
Agriculture concentration	137,292	0.1744	0	1
Ideal topsoil pH	340,172	0.7454	0	1
Within 20km of expressway	379,294	0.8989	0	1

Note: This table shows descriptive statistics on land cover and distance to road for land parcels within a 40km buffer of the Addis Ababa-Adama expressway, divided by distance to expressway. *Agriculture concentration* calculates the percentage of land parcels devoted to agriculture in 2009 within a 2.5-km buffer of every observation. All other variables are dummies.

Table 6: Agriculture in 2009 and 2016 by administrative region, expressway

Administrative zone	Observations	Mean 2009	Mean 2016	Min	Max
13647	1,265	0.2751	0.253	0	1
13648	165	0.1758	0.103	0	1
13649	4,046	0.5974	0.6518	0	1
13650	11,793	0.6617	0.6984	0	1
13651	2,279	0.2694	0.5401	0	1
13652	1,723	0.2879	0.379	0	1
13653	4,657	0.6951	0.3769	0	1
13663	13,514	0.7612	0.8886	0	1
13677	64,994	0.7873	0.8816	0	1
13681	277,851	0.7192	0.805	0	1
13685	39,507	0.4588	0.6982	0	1
12687	65,757	0.541	0.7209	0	1

Note: See figure for 7 for a map of administrative regions within a 40-km buffer of the expressway.

Table 7: Multinomial logit estimates, Euclidian distance to capital as explanatory variable of land classification

	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se
Land Class	Rainfed croplands	Mosaic cropland (50-70%)/vegetation (20-50%)	Mosaic vegetation (50-70%)/cropland (20-50%)	Closed to open >15% broadleaved evergreen or semi-deciduous forest (>5m)	Open (15-40%) broadleaved deciduous forest/woodland (>5m)	Mosaic forest or shrubland (50-70%)/grassland (20-50%)	Mosaic grassland (50-70%)/forest or shrubland (20-50%)	Closed to open (>15%) shrubland (<5m)	Closed to open (>15%) herbaceous vegetation	Sparse (<15%) vegetation	Closed to open (>15%) broadleaved forest regularly flooded	Closed to open (>15%) grassland or woody vegetation on regularly flooded or waterlogged soil	Urban >50%	Bare areas	Water bodies
log Euclidian distance to capital (km)	-1.3057***	-0.3986***	1.0201***	0.7505***	0.1835***	(dropped)	-0.1261***	0.1791***	-2.7291***	0.4209***	-23.3441***	-5.9141***	-6.2141***	-2.4736***	-1.0331***
	(0.0129)	(0.0092)	(0.0152)	(0.0339)	(0.0155)		(0.0432)	(0.0103)	(0.0177)	(0.0338)	(2.0251)	(0.0792)	(0.2852)	(0.0182)	(0.0355)
longterm annual precip 1901-2005 (km)	-0.4585***	3.2916***	4.3160***	6.4938***	4.7105***		2.3410***	3.4219***	-7.3769***	-4.1004***	16.7542***	-2.6280***	1.1634	-6.1768***	3.4758***
	(0.0364)	(0.0200)	(0.0248)	(0.0548)	(0.0313)		(0.1208)	(0.0203)	(0.0811)	(0.0722)	(2.6036)	(0.1569)	(3.0658)	(0.0861)	(0.1125)
elevation std	-0.0254***	-0.0117***	-0.0072***	0.0136***	0.0117***		0.0336***	-0.0009***	-0.0099***	-0.0596***	0.0471	-0.4324***	-0.1470***	0.0012**	-1.6166***
	(0.0005)	(0.0002)	(0.0002)	(0.0005)	(0.0003)		(0.0007)	(0.0002)	(0.0005)	(0.0008)	(0.0477)	(0.0342)	(0.0374)	(0.0005)	(0.0596)
elevation mean (100m)	0.1047***	0.0349***	0.0557***	0.0309***	-0.1329***		0.1383***	-0.0512***	-0.1790***	-0.0904***	-3.9333***	-0.8463***	-0.3210***	-0.2216***	0.0007
	(0.0013)	(0.0009)	(0.0009)	(0.0024)	(0.0017)		(0.0039)	(0.0009)	(0.0021)	(0.0024)	(0.3221)	(0.0155)	(0.1018)	(0.0024)	(0.0056)
ideal topsoil pH	0.0997***	0.3846***	-0.2232***	0.3055***	0.2165***		0.1995***	0.2081***	-0.3891***	-0.2085***	-1.6105*	0.0205	0.0694	-0.2014***	-2.9908***
	(0.0152)	(0.0077)	(0.0077)	(0.0188)	(0.0110)		(0.0415)	(0.0074)	(0.0138)	(0.0135)	(0.8341)	(0.0450)	(0.2533)	(0.0132)	(0.0489)
Constant	11.3532***	2.1887***	-10.7390***	-5.7229***	-3.7845***			-3.0499***		-13.8452***		54.0737***		15.1240***	
	(0.2740)	(0.1520)	(0.2012)	(0.5865)	(0.2299)			(0.1469)		(0.4054)		(0.8098)		(0.4395)	
o._cons						(dropped)	-9.6033***		13.9732***		559.9576***		-75.5933***		6.7170***
							(0.9333)		(0.4180)		(92.7753)		(12.6222)		(0.6827)
Number of observations							1,012,215								

note: .01 - ***; .05 - **; .1 - *;

Note: The dependent variable is a categorical variable representing sixteen types of land cover, with the largest category selected as the comparison group: mosaic forest or shrubland (50-70%)/grassland (20-50%). The explanatory variable is log Euclidian distance to capital. The model controls for precipitation, soil quality and elevation (shown) and latitude and longitude (not shown).

Table 8: Multinomial logit estimates, cost distance to capital as explanatory variable of land classification

	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se
Land Class	Rainfed croplands	Mosaic cropland (50-70%)/vegetation (20-50%)	Mosaic vegetation (50-70%)/cropland (20-50%)	Closed to open >15% broadleaved evergreen or semi-deciduous forest (>5m)	Open (15-40%) broadleaved deciduous forest/woodland (>5m)	Mosaic forest or shrubland (50-70%)/grassland (20-50%)	Mosaic grassland (50-70%)/forest or shrubland (20-50%)	Closed to open (>15%) shrubland (<5m)	Closed to open (>15%) herbaceous vegetation	Sparse (<15%) vegetation	Closed to open (>15%) broadleaved forest regularly flooded	Closed to open (>15%) grassland or woody vegetation on regularly flooded or waterlogged soil	Urban >50%	Bare areas	Water bodies
log cost distance to capital	-1.9033***	-1.7919***	-0.8148***	-0.2199***	-0.2562***	(dropped)	-0.8073***	-0.6730***	-2.2230***	-0.9221***	67.6332***	-6.8924***	-3.0515***	-3.1523***	-5.6442***
	(0.0318)	(0.0173)	(0.0167)	(0.0448)	(0.0261)		(0.0806)	(0.0173)	(0.0396)	(0.0352)	(10.1042)	(0.1377)	(0.5422)	(0.0384)	(0.1125)
log Euclidian distance to capital (km)	0.5575***	1.4102***	1.9654***	0.8211***	0.3758***		0.5909***	0.9216***	-0.5438***	1.4388***	-97.2959***	0.8835***	-2.5444***	0.7601***	4.5382***
	(0.0314)	(0.0170)	(0.0218)	(0.0510)	(0.0281)		(0.0832)	(0.0182)	(0.0430)	(0.0475)	(11.5265)	(0.1842)	(0.5517)	(0.0428)	(0.1184)
log distance to nearest road*log Euclidian distance to Addis	-0.0171***	-0.0358***	-0.0206***	0.0351***	0.0255***		0.0305***	-0.0209***	0.0362***	-0.0053***	-0.3831***	0.0122***	-0.1789***	0.0500***	0.0686***
	(0.0015)	(0.0007)	(0.0007)	(0.0021)	(0.0011)		(0.0041)	(0.0006)	(0.0012)	(0.0009)	(0.0395)	(0.0038)	(0.0361)	(0.0011)	(0.0041)
longterm annual precip 1901-2005 (km)	0.0581	3.7298***	4.7644***	7.0176***	4.9501***		2.8754***	3.7709***	-6.8785***	-3.6692***	6.3859***	-0.8475***	-3.0352	-5.2055***	3.8423***
	(0.0386)	(0.0208)	(0.0265)	(0.0561)	(0.0320)		(0.1256)	(0.0213)	(0.0771)	(0.0762)	(1.5763)	(0.1996)	(2.8119)	(0.0769)	(0.1159)
elevation std	-0.0212***	-0.0068***	-0.0053***	0.0116***	0.0104***		0.0338***	0.0005**	-0.0083***	-0.0570***	0.0997***	-0.3457***	-0.0802***	0.0026***	-1.4763***
	(0.0006)	(0.0003)	(0.0003)	(0.0005)	(0.0003)		(0.0008)	(0.0002)	(0.0006)	(0.0008)	(0.0292)	(0.0309)	(0.0299)	(0.0005)	(0.0595)
elevation mean (100m)	0.0629***	-0.0125***	0.0266***	0.0225***	-0.1243***		0.1129***	-0.0774***	-0.2160***	-0.1272***	-11.7633***	-1.0139***	-0.1851**	-0.2659***	-0.0733***
	(0.0014)	(0.0009)	(0.0010)	(0.0024)	(0.0018)		(0.0037)	(0.0010)	(0.0024)	(0.0029)	(1.1040)	(0.0198)	(0.0760)	(0.0027)	(0.0063)
ideal topsoil pH	-0.0746***	0.2091***	-0.3443***	0.2622***	0.1944***		0.1091**	0.1116***	-0.5488***	-0.2925***	-1.3929**	-0.4095***	-0.1819	-0.3856***	-3.1694***
	(0.0161)	(0.0081)	(0.0081)	(0.0202)	(0.0114)		(0.0431)	(0.0078)	(0.0142)	(0.0143)	(0.6531)	(0.0448)	(0.3229)	(0.0136)	(0.0495)
Constant	10.6161***	1.2185***	-13.4796***	-6.9541***	-3.9182***			-4.6977***		-15.8004***		49.6585***		16.5321***	
	(0.2871)	(0.1608)	(0.2127)	(0.5659)	(0.2319)			(0.1529)		(0.4286)		(1.0765)		(0.3379)	
o._cons						(dropped)	-10.4104***		15.9246***		520.4494***		-58.4392***		10.8948***
							(0.9578)		(0.3724)		(47.3131)		(10.1595)		(0.7041)
Number of observations							949,436								

note: .01 - ***; .05 - **; .1 - *;

Note: The dependent variable is a categorical variable representing sixteen types of land cover, with the largest category selected as the comparison group: mosaic forest or shrubland (50-70%)/grassland (20-50%). The explanatory variable is log cost distance to capital. The model controls for precipitation, soil quality and elevation (shown) and latitude and longitude (not shown).

Table 9: Multinomial estimates, Euclidian distance to road as explanatory variable of land classification

	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se
Land Class	Rainfed croplands	Mosaic cropland (50-70%)/vegetation (20-50%)	Mosaic vegetation (50-70%)/cropland (20-50%)	Closed to open >15% broadleaved evergreen or semi-deciduous forest (>5m)	Open (15-40%) broadleaved deciduous forest/woodland (>5m)	Mosaic forest or shrubland (50-70%)/grassland (20-50%)	Mosaic grassland (50-70%)/forest or shrubland (20-50%)	Closed to open (>15%) shrubland (<5m)	Closed to open (>15%) herbaceous vegetation	Sparse (<15%) vegetation	Closed to open (>15%) broadleaved forest regularly flooded	Closed to open (>15%) grassland or woody vegetation on regularly flooded or waterlogged soil	Urban >50%	Bare areas	Water bodies
log Euclidian distance to road (km)	3.6343***	3.2258***	1.3232***	2.9574***	2.5024***	(dropped)	2.6969***	2.3807***	3.8104***	1.7323***	-96.8919***	7.7214***	8.6257***	5.5475***	10.3366***
	(0.0734)	(0.0437)	(0.0452)	(0.1238)	(0.0617)		(0.2085)	(0.0415)	(0.0794)	(0.0813)	(13.3510)	(0.2536)	(1.2461)	(0.0860)	(0.2773)
log Euclidian distance to capital (km)	-0.6040***	0.2961***	1.4377***	1.1501***	0.5618***		0.2946***	0.6925***	-2.0517***	0.7883***	-27.3514***	-4.4446***	-4.5872***	-1.2648***	1.0853***
	(0.0160)	(0.0101)	(0.0180)	(0.0437)	(0.0204)		(0.0612)	(0.0122)	(0.0236)	(0.0440)	(3.3468)	(0.0947)	(0.3469)	(0.0290)	(0.0864)
log cost distance to Addis*log Euclidian distance to Addis	-0.4934***	-0.4508***	-0.1830***	-0.3426***	-0.2890***		-0.3187***	-0.3141***	-0.4578***	-0.2216***	11.6276***	-1.0150***	-1.4609***	-0.6736***	-1.3144***
	(0.0096)	(0.0056)	(0.0056)	(0.0158)	(0.0077)		(0.0273)	(0.0051)	(0.0097)	(0.0096)	(1.6188)	(0.0319)	(0.2310)	(0.0105)	(0.0347)
longterm annual precip 1901-2005 (km)	-0.3193***	3.4514***	4.5771***	6.6955***	4.7755***		2.6297***	3.6087***	-7.4637***	-3.9325***	12.7669***	-2.3027***	-1.2363	-6.0020***	3.1992***
	(0.0377)	(0.0205)	(0.0261)	(0.0555)	(0.0314)		(0.1256)	(0.0209)	(0.0800)	(0.0764)	(0.8683)	(0.1687)	(2.7913)	(0.0818)	(0.1104)
elevation std	-0.0237***	-0.0092***	-0.0064***	0.0110***	0.0093***		0.0321***	-0.0008***	-0.0117***	-0.0598***	0.0753	-0.3718***	-0.0898***	-0.0007	-1.4732***
	(0.0006)	(0.0003)	(0.0003)	(0.0005)	(0.0003)		(0.0008)	(0.0002)	(0.0006)	(0.0008)	(0.0675)	(0.0330)	(0.0310)	(0.0005)	(0.0605)
elevation mean (100m)	0.0781***	0.0032***	0.0386***	0.0267***	-0.1243***		0.1203***	-0.0715***	-0.1808***	-0.1077***	-6.6287***	-0.8634***	-0.2245***	-0.2282***	-0.0177***
	(0.0014)	(0.0009)	(0.0010)	(0.0025)	(0.0018)		(0.0036)	(0.0010)	(0.0023)	(0.0027)	(0.8638)	(0.0178)	(0.0818)	(0.0025)	(0.0057)
ideal topsoil pH	-0.0409**	0.2509***	-0.3303***	0.2035***	0.1425***		0.0954**	0.0871***	-0.5176***	-0.2796***	-1.4496**	-0.2603***	-0.3689	-0.3488***	-3.0378***
	(0.0161)	(0.0081)	(0.0081)	(0.0200)	(0.0114)		(0.0431)	(0.0078)	(0.0142)	(0.0140)	(0.6919)	(0.0467)	(0.3138)	(0.0136)	(0.0487)
Constant	4.9171***	-4.2054***	-15.5780***	-9.9967***	-7.2524***			-8.2014***		-17.7161***		43.0325***		7.3370***	
	(0.2898)	(0.1569)	(0.2243)	(0.6191)	(0.2528)			(0.1596)		(0.4674)		(0.9349)		(0.3831)	
o._cons						(dropped)	-14.0042***		10.3192***		459.2591***		-78.9016***		-7.9151***
							(0.9992)		(0.3704)		(56.5711)		(11.6881)		(0.9060)
Number of observations								949,436							

note: .01 - ***; .05 - **; .1 - *;

Note: The dependent variable is a categorical variable representing sixteen types of land cover, with the largest category selected as the comparison group: mosaic forest or shrubland (50-70%)/grassland (20-50%). The explanatory variable is Euclidian distance to road. The model controls for precipitation, soil quality and elevation (shown) and latitude and longitude (not shown).

Table 10: Multinomial logit estimates, Market access as explanatory variable of land classification

	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se
Land Class	Rainfed croplands	Mosaic cropland (50-70%)/vegetation (20-50%)	Mosaic vegetation (50-70%)/cropland (20-50%)	Closed to open >15% broadleaved evergreen or semi-deciduous forest (>5m)	Open (15-40%) broadleaved deciduous forest/woodland (>5m)	Mosaic forest or shrubland (50-70%)/grassland (20-50%)	Mosaic grassland (50-70%)/forest or shrubland (20-50%)	Closed to open (>15%) shrubland (<5m)	Closed to open (>15%) herbaceous vegetation	Sparse (<15%) vegetation	Closed to open (>15%) broadleaved forest regularly flooded	Closed to open (>15%) grassland or woody vegetation on regularly flooded or waterlogged soil	Urban >50%	Bare areas	Water bodies
log market access	0.6928***	0.5779***	0.4357***	0.2533***	0.3106***	(dropped)	0.5958***	0.2654***	0.5748***	0.8707***	-54.0692***	1.8175***	1.7335***	0.6750***	1.5844***
	(0.0155)	(0.0104)	(0.0111)	(0.0281)	(0.0183)		(0.0520)	(0.0113)	(0.0231)	(0.0204)	(8.3919)	(0.0421)	(0.1327)	(0.0227)	(0.0338)
log Euclidian distance to capital (km)	-0.8576***	0.0460***	1.4321***	0.7680***	0.2774***		0.1146**	0.4396***	-2.4963***	1.1407***	-66.3339***	-4.3963***	-5.0234***	-2.1549***	0.0910**
	(0.0148)	(0.0102)	(0.0168)	(0.0349)	(0.0181)		(0.0473)	(0.0118)	(0.0223)	(0.0378)	(5.8380)	(0.0976)	(0.3020)	(0.0226)	(0.0417)
log market access*log Euclidian to Addis	0.0503***	0.0834***	0.0353***	-0.0559***	-0.0467***		-0.0677***	0.0438***	-0.0311***	0.0016	0.6050***	0.0432***	0.3155***	-0.0328***	0.0010
	(0.0028)	(0.0013)	(0.0013)	(0.0040)	(0.0020)		(0.0086)	(0.0012)	(0.0020)	(0.0015)	(0.0500)	(0.0056)	(0.0644)	(0.0019)	(0.0053)
longterm annual precip 1901-2005 (km)	-0.0462	3.6055***	4.6891***	6.9044***	4.8851***		2.7960***	3.7005***	-7.4056***	-3.3519***	15.4827***	-2.0079***	-2.7650	-6.1166***	3.4779***
	(0.0391)	(0.0211)	(0.0260)	(0.0560)	(0.0319)		(0.1263)	(0.0214)	(0.0818)	(0.0755)	(1.3525)	(0.1493)	(2.5624)	(0.0869)	(0.1139)
elevation std	-0.0219***	-0.0079***	-0.0058***	0.0118***	0.0105***		0.0336***	-0.0000	-0.0103***	-0.0583***	0.0788***	-0.3811***	-0.0849***	0.0010**	-1.5762***
	(0.0006)	(0.0003)	(0.0003)	(0.0005)	(0.0003)		(0.0008)	(0.0002)	(0.0005)	(0.0008)	(0.0300)	(0.0341)	(0.0299)	(0.0005)	(0.0605)
elevation mean (100m)	0.0577***	-0.0136***	0.0227***	0.0186***	-0.1303***		0.1109***	-0.0790***	-0.1993***	-0.1489***	-9.0362***	-0.9211***	-0.2518***	-0.2473***	-0.0625***
	(0.0015)	(0.0010)	(0.0010)	(0.0025)	(0.0019)		(0.0037)	(0.0011)	(0.0025)	(0.0028)	(0.7094)	(0.0172)	(0.0695)	(0.0029)	(0.0060)
ideal topsoil pH	-0.0254	0.2597***	-0.3353***	0.2559***	0.1974***		0.1268***	0.1259***	-0.4522***	-0.2751***	-1.2634	-0.1982***	-0.0329	-0.2617***	-3.2338***
	(0.0161)	(0.0081)	(0.0081)	(0.0199)	(0.0115)		(0.0432)	(0.0078)	(0.0141)	(0.0139)	(0.7945)	(0.0478)	(0.3248)	(0.0135)	(0.0511)
Constant	8.7978***	-0.2699*	-14.1895***	-7.0492***	-3.8803***			-5.3151***		-18.7335***		47.2034***		15.4715***	
	(0.2941)	(0.1613)	(0.2131)	(0.5643)	(0.2315)			(0.1536)		(0.4278)		(0.9349)		(0.4324)	
o._cons						(dropped)	-10.6462***		14.9901***		598.9548***		-75.9837***		4.0852***
							(0.9692)		(0.4185)		(48.6330)		(9.4955)		(0.7245)
Number of observations							949,369								

note: .01 - ***; .05 - **; .1 - *;

Note: The dependent variable is a categorical variable representing sixteen types of land cover, with the largest category selected as the comparison group: mosaic forest or shrubland (50-70%)/grassland (20-50%). The explanatory variable is market access. The model controls for precipitation, soil quality and elevation (shown) and latitude and longitude (not shown).

Table 11: Logit marginal effect estimates for the effect of distance to road/market on probability of agricultural land cover

	(1) coef/se	(2) coef/se	(3) coef/se	(4) coef/se
log Euclidian distance to capital (km)	-0.117***	0.011***	-0.107***	-0.087***
	(0.002)	(0.003)	(0.003)	(0.003)
log cost distance to capital		-0.147***		
		(0.002)		
log cost distance to Addis*log Euclidian distance to Addis		0.010***		
		(0.003)		
log Euclidian distance to road (km)			-0.015***	
			(0.005)	
log distance to nearest road*log Euclidian distance to Addis			0.005	
			(0.006)	
log market access				0.053***
				(0.001)
log market access*log Euclidian to Addis				-0.026***
				(0.001)
longterm annual precip 1901-2005 (km)	0.110***	0.080***	0.103***	0.078***
	(0.003)	(0.003)	(0.003)	(0.003)
elevation std	-0.001***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
elevation mean (100m)	0.008***	0.004***	0.005***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
ideal topsoil pH	0.019***	0.011***	0.015***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)
Number of observations	929,918	869,330	869,330	869,265

note: .01 - ***; .05 - **; .1 - *;

Note: This table shows the probit marginal effect estimates of land cover type with respect to five estimates of distance to road or market. The dependent variable in all models is a binary variable for vegetation or agriculture (0=vegetation, 1=agriculture). The explanatory variable is distance to road or market, through five different measures as shown in the table. Models 2-4 all include an interaction term with the Euclidian distance to the capital (Addis Ababa), the explanatory variable in model 1. Additionally, all regressions include administrative zone fixed effects and controls for elevation, soil quality, precipitation, and latitude and longitude. The marginal effects for the interaction term are calculated using the algorithm derived in Ai and Norton (2003).

Table 12: Logit marginal effect estimates for difference-in-difference model

	(1) coef/se	(1) coef/se	(1) coef/se
Post	0.217***	0.380***	0.399***
	(0.002)	(0.004)	(0.005)
Post*Treatment	-0.519***	-0.437***	-0.343**
	(0.011)	(0.011)	(0.012)
Post*Soil pH		-0.163***	-0.170***
		(0.003)	(0.003)
Post*Agricultural area			-0.011***
			(0.003)
Number of observations	308184	308184	262208

note: .01 - ***; .05 - **; .1 - *;

Note: This table represents the change in agriculture from 2009 (pre-expressway) to 2016 (post-expressway) comparing treatment and control groups of land parcels. The interaction term Post*Treatment measures the difference-in-difference between the two groups. The treated land parcels are those within an inner (20-km) buffer of the expressway and the control land parcels are those within an outer (40-km) buffer of the expressway. I allow the trend in quantity of agricultural land cover to vary with treatment, the quality of the soil based on pH (soil pH is a dummy for good or bad quality soil), and the nearby concentration of agriculture (percentage of agricultural land parcels in a 2.5-km buffer of each observation/land parcel).

The model used is a logit model with fixed effects, so it controls for constant heterogeneity. Marginal effects for difference-difference estimators are calculated using the algorithm derived in Puhani (2012). All other marginal effects for interaction terms are calculated using the algorithm derived in Ai and Norton (2003).

Table 13: Logit marginal effect estimates for the effect of distance to the expressway on probability of transitioning land cover type 2009 to 2016

	(1) coef/se	(2) coef/se
Treat	0.042***	0.013***
	(0.002)	(0.001)
Soil pH	0.145***	0.121***
	-0.003	(0.002)
Agricultural area	0.072***	-0.087***
	(0.003)	(0.001)
Number of observations	135,782	295,902

note: .01 - ***; .05 - **; .1 - *;

Note: The first specification, (1), examines the probability of transition from non-agriculture to agriculture over the period 2009 (pre-expressway) to 2016 (post-expressway). The second specification, (2), examines the probability of transition from agriculture to non-agriculture over the same period. Soil pH is a dummy variable for good (1) or bad (0) quality soil, based on pH level. Agricultural area is a variable that measures the percentage of agricultural land parcels in a 2.5-km buffer of each observation/land parcel.

Table 14: Logit marginal effect estimates for the effect of distance to road/market on probability of agricultural land cover for land parcels within 40-km of the Addis-Ababa Adama expressway

	(1) coef/se	(2) coef/se	(3) coef/se	(4) coef/se
log Euclidian distance to capital (km)	0.128***	0.083**	0.108***	0.093***
	(0.025)	(0.033)	(0.029)	(0.030)
log cost distance to capital		0.006		
		(0.021)		
log cost distance to Addis*log Euclidian distance to Addis		0.002		
		(-0.008)		
log Euclidian distance to road (km)			0.190***	
			(0.054)	
log distance to nearest road*log Euclidian distance to Addis			-0.086*	
			(0.046)	
log market access				0.003
				(0.012)
log market access*log Euclidian to Addis				0.002
				(0.010)
longterm annual precip 1901-2005 (km)	-0.647***	-0.672***	-0.688***	-0.678***
	(0.074)	(0.080)	(0.080)	(0.080)
elevation std	-0.004***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
elevation mean (100m)	0.059***	0.060***	0.060***	0.061***
	(0.003)	(0.003)	(0.003)	(0.003)
ideal topsoil pH	0.068***	0.078***	0.071***	0.078***
	(0.012)	(0.013)	(0.013)	(0.013)
Number of observations	10,774	9,124	9,124	9,117

note: .01 - ***; .05 - **; .1 - *;

Note: This table shows the probit marginal effect estimates of land cover type with respect to five estimates of distance to road or market. The dependent variable in all models is a binary variable for vegetation or agriculture (0=vegetation, 1=agriculture). The explanatory variable is distance to road or market, through five different measures as shown in the table. Models 2-4 all include an interaction term with the Euclidian distance to the capital (Addis Ababa), the explanatory variable in model 1. Additionally, all regressions include administrative zone fixed effects and controls for precipitation, elevation, soil quality, latitude, and longitude. The marginal effects for the interaction term are calculated using the algorithm derived in Ai and Norton (2003).

12. Appendix B: Figures

Figure 1: Ethiopia road network 2005 (ESA)

Figure 2: Ethiopia travel cost raster

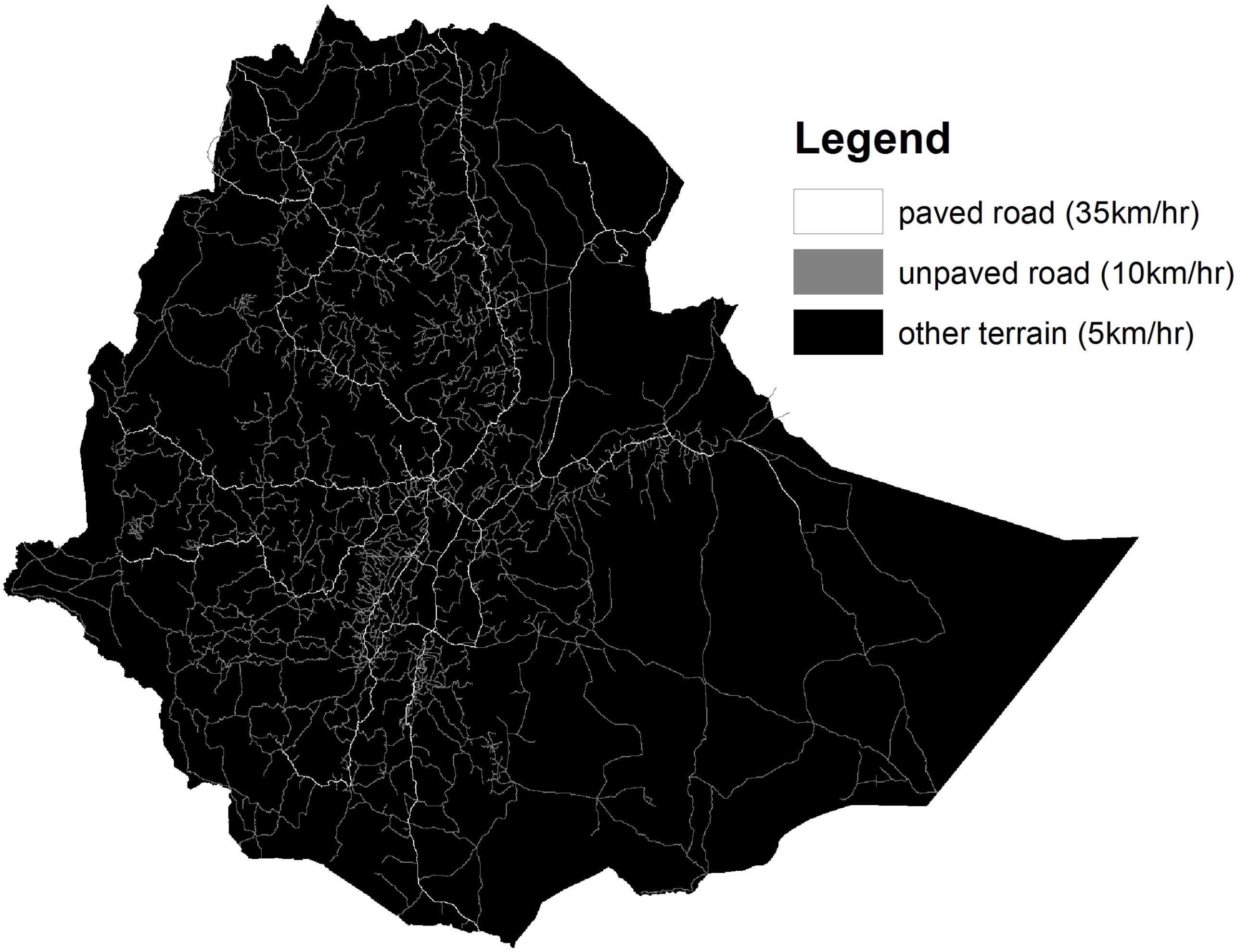


Figure 3: Ethiopian woreda and major cities and towns

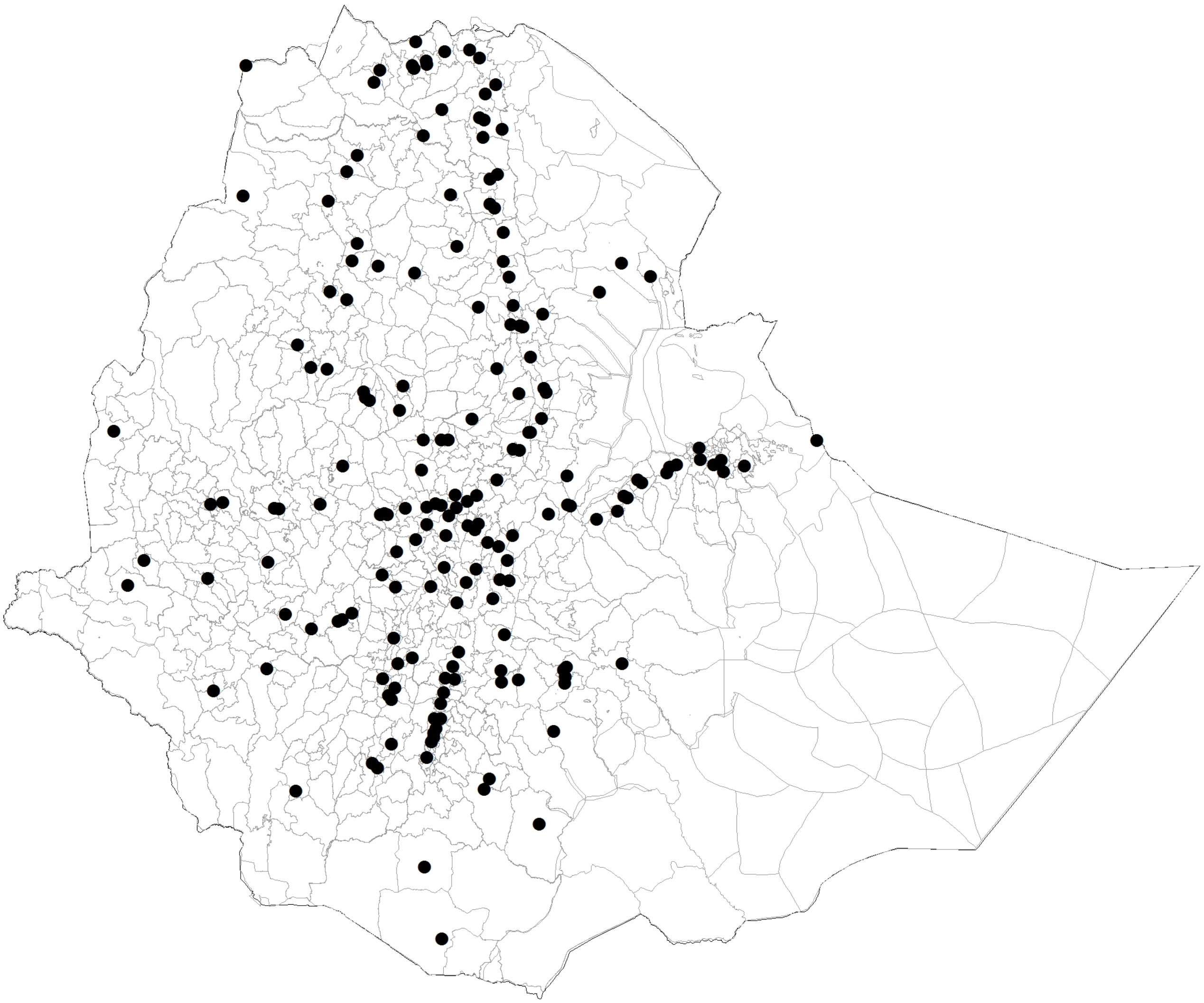


Figure 4: Cost distance to Addis Ababa

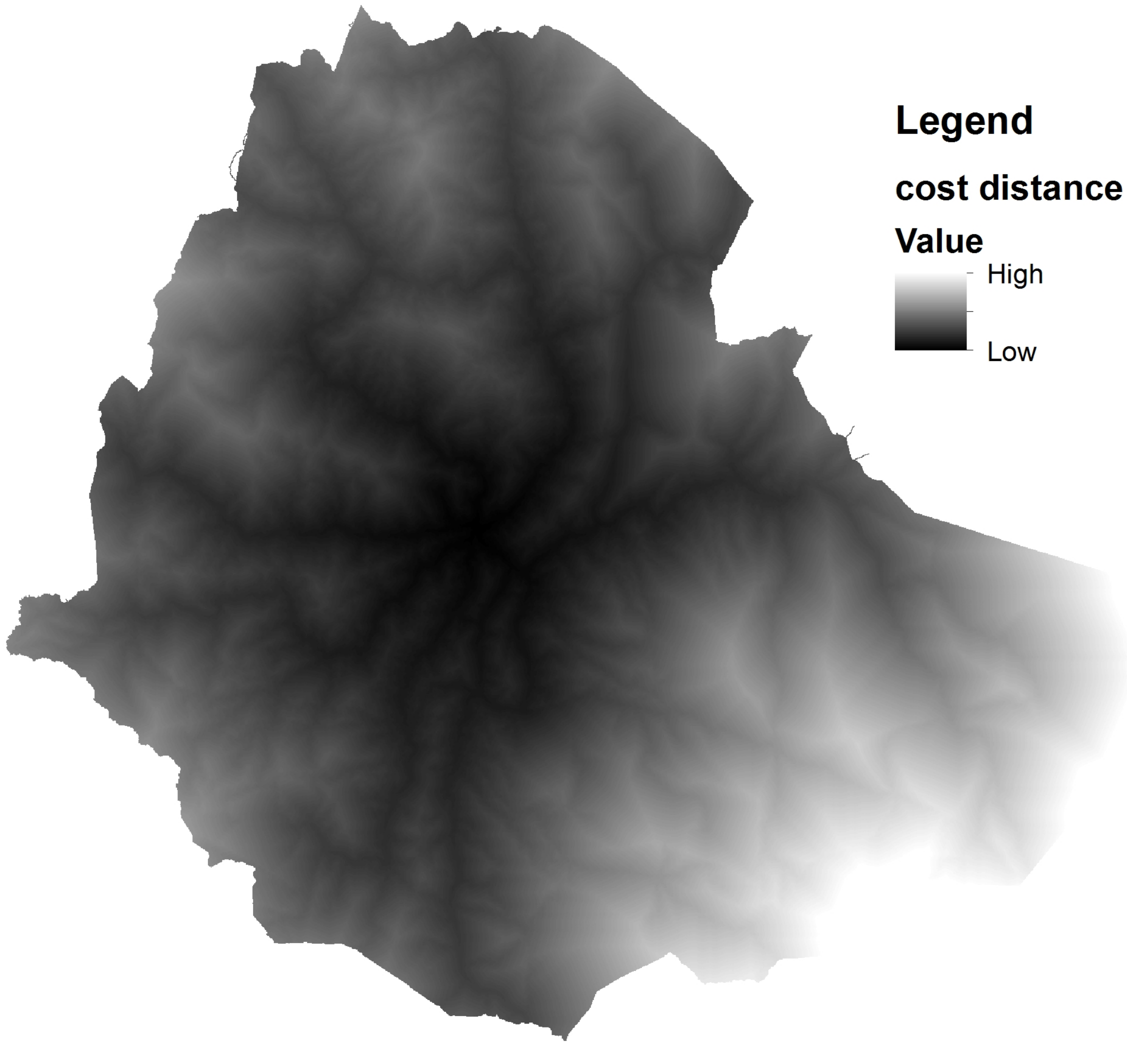
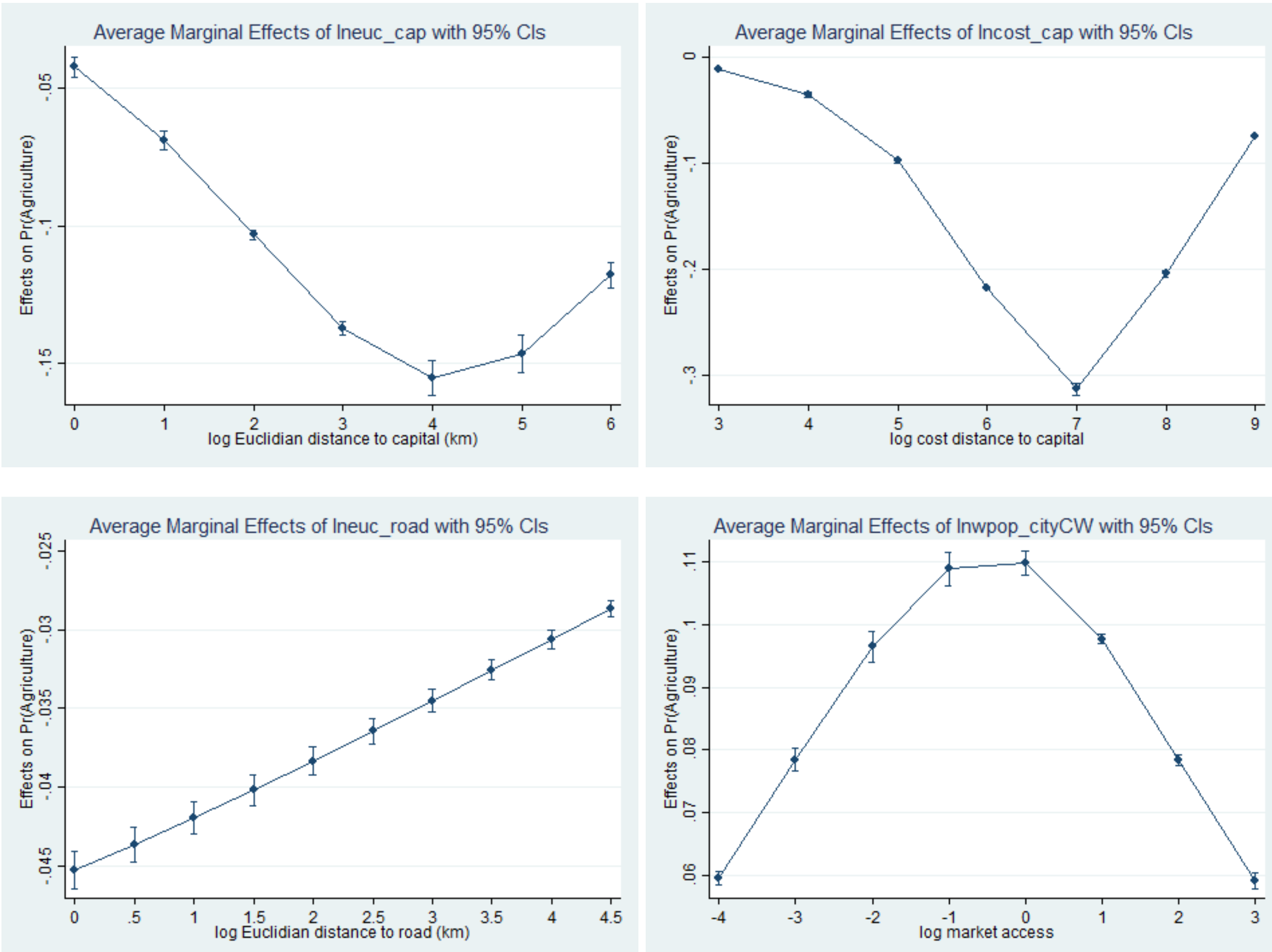
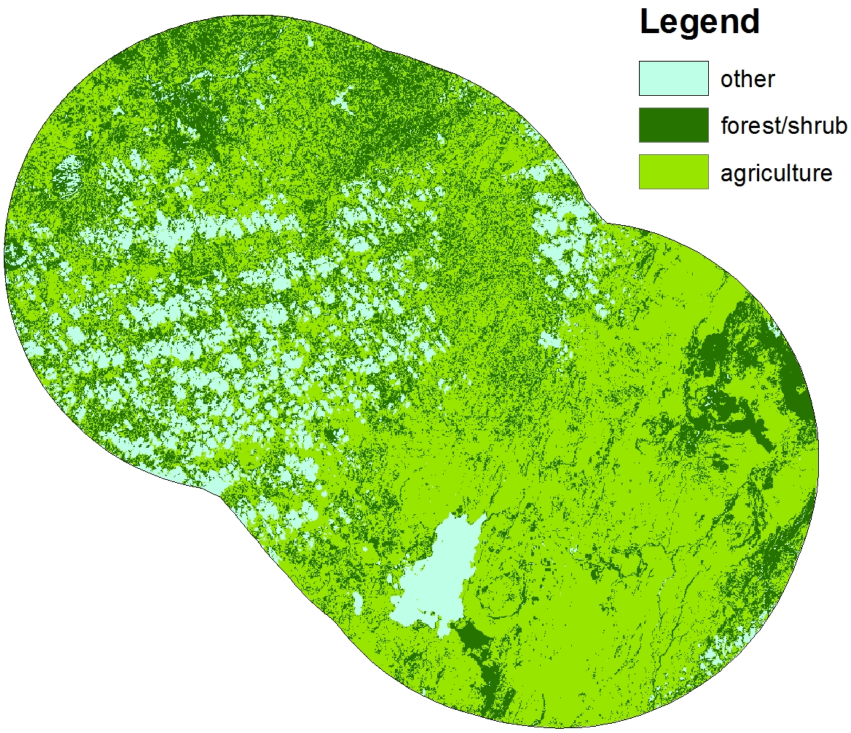


Figure 4: Logit average marginal effects of explanatory variables on probability of agricultural land cover for different specifications

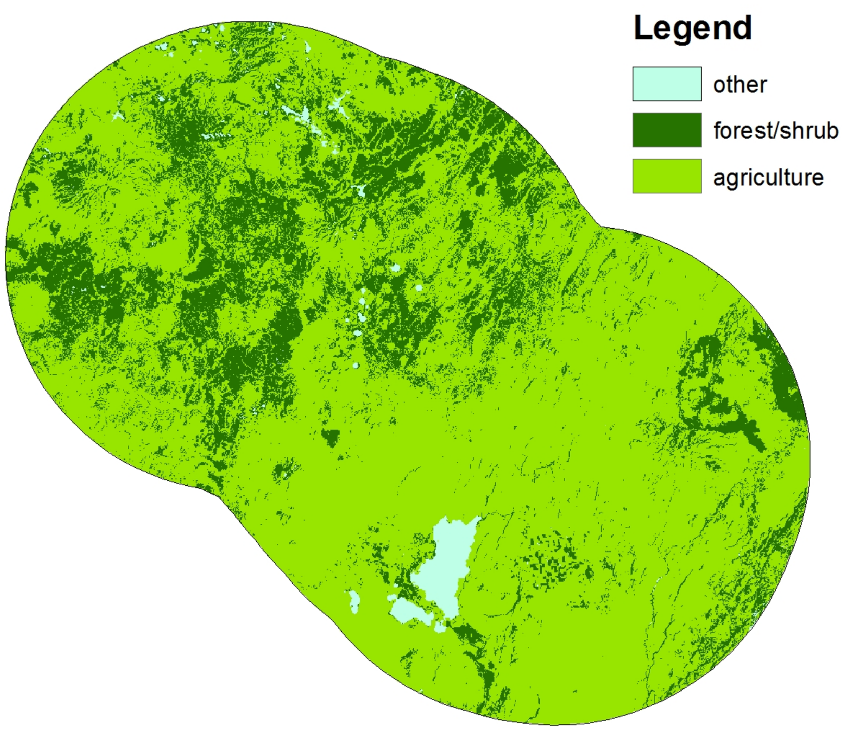


Note: All specifications have agricultural land cover as the dependent variable and include controls for administrative region, precipitation, elevation, soil quality, latitude, and longitude. Except for the specification where Euclidian distance to capital is the explanatory variable of interest, this variable is also included as a control.

Figure 5: Land cover classification in 2009 and 2016 within 40-km buffer of expressway



Year = 2009



Year = 2016

Figure 6: Road network and major cities in a 40-km buffer of the Addis Ababa-Adama expressway

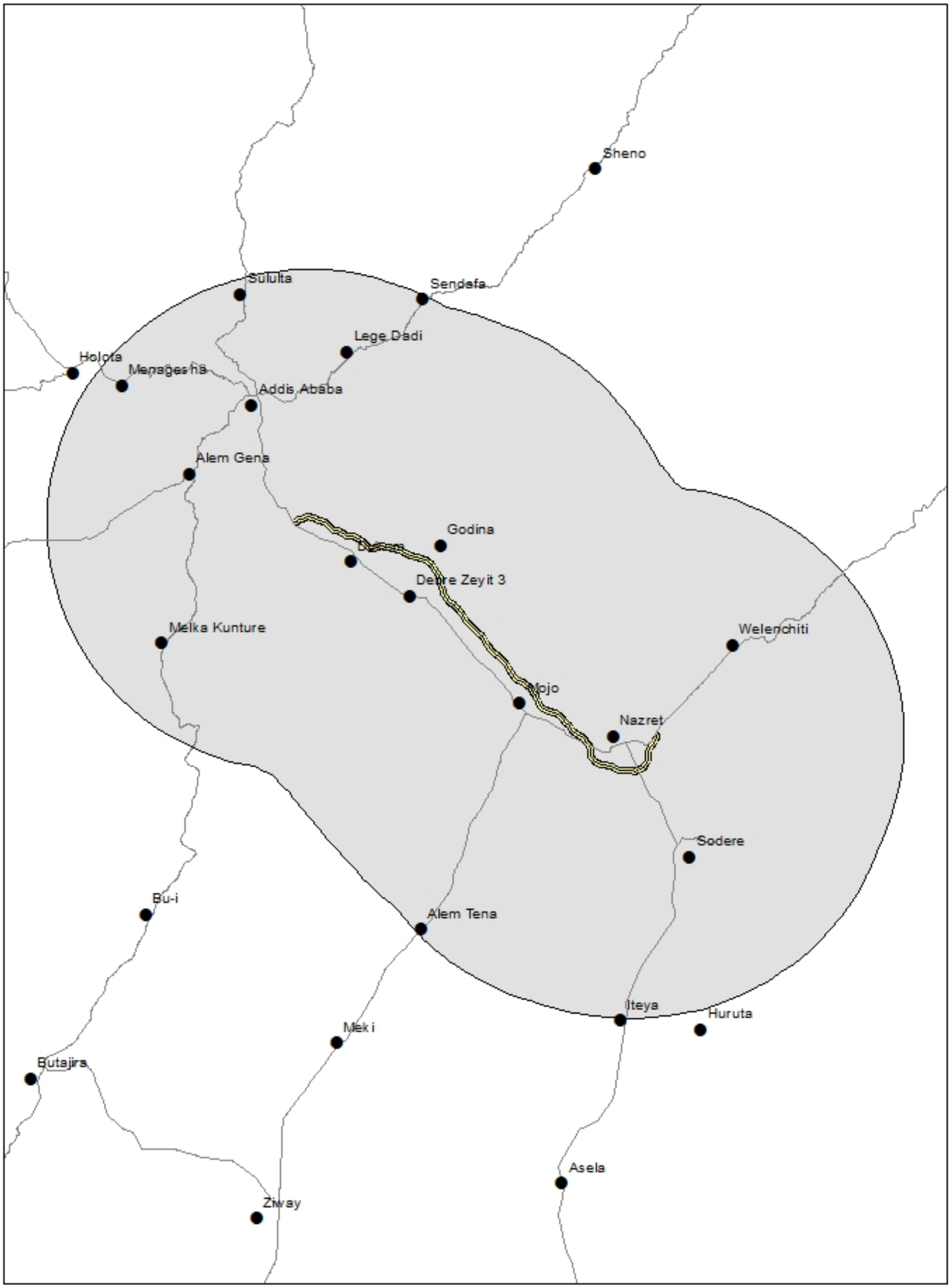


Figure 7: Second-level administrative units in a 40-km buffer of the Addis Ababa-Adama expressway