

**The gains from market integration:
The welfare effects of new rural roads in Ethiopia***

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Abstract

The welfare effects of new rural roads is complicated because the roads affect both the production and consumption decisions of the farmers and these decisions are intertwined. In this paper, I develop a Ricardian trade model to explain how rural roads affect welfare in agricultural villages. The model captures two contrasting effects of rural roads on welfare. On one hand, decreases in trade costs lead to reallocation of village farmland to its comparative advantage crops and enable farmers to obtain higher prices for these crops. On the other hand, as these crops constitute significant part of the household consumption basket, the increase in prices decreases welfare. I take these predictions of the model to a very rich micro data on agricultural production and crop prices from Ethiopia. I use a large-scale rural road expansion program called Universal Rural Road Access Program (URRAP) as a source of variation to trade costs. To address endogeneity of road placement, I use road network predicted from land gradient and location of rivers and lakes to construct instrumental variable. I show that, following decreases in trade costs, villages reallocate more farmland towards their comparative advantage crops and receive higher prices for these crops. These resulted in significant welfare gain. The size of the welfare gain varies across villages depending on the crop composition of village consumption vis-a-vis production. E.g., cash-crop villages gain more than cereal producing villages because the latter face increases in their consumption costs while the former experience the exact opposite.

Keywords: Market Integration, Ricardian Trade Models, Rural Development, Rural Roads, Trade Costs. JEL Codes: F11, H54, O13, O18, Q12, R12, R42

1 Introduction

A common feature of rural areas in developing countries is that they lack all-weather roads interconnecting the villages or connecting the villages to market centers in towns and cities. This

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makes villages isolated economies operating in a near-autarky environment. As a result, product markets are too thin for farmers to rely on, and farmers adopt subsistence farming where they self-produce most of the crops they need for consumption, instead of specializing in few crops and buying the rest from market.¹ This implies significant efficiency loss in land utilization compared to a scenario where villages specialize in fewer crops to which their agro-climatic condition is most suited.

The welfare effects of road infrastructure that decreases trade costs in rural villages is complicated because the production and consumption decisions of farm households are intertwined, and roads affect both of these decisions. In this paper, I study how construction of new roads affect village welfare. To understand the key mechanisms through which decreases in trade costs affect welfare in rural economies, I develop a multi-crop multi-location Ricardian model of trade with heterogeneous land quality within and across villages. On the demand side, a village maximizes utility by choosing optimal quantities of each crop to consume, given local crop prices. On the production side, the village makes a decision on how to optimally allocate its limited farmland across the potential crops, given local crop prices and the productivity of its village in different crops. Villages also engage in costly trade among each other, very similar to how countries trade in [Eaton and Kortum \(2002\)](#).

The model provides a number of sharp predictions on the mechanisms through which improvement in road infrastructure affects village welfare. First, decreases in trade costs lead to increases in the relative prices of the villages' comparative advantage crops (CA-crops). Second, decreases in trade costs lead to reallocation of farmland from a village's comparative disadvantage crops (CD-crops) towards the village's CA-crops. Third, the size of welfare gain from roads depends on the crop composition of the village's consumption basket vis-a-vis the fraction of village land allocated to these crops. For example, the model predicts that a village that has CA in cash-crops should benefit more from decreases in trade costs than a village that has CA in cereals because the latter faces significant increase in the relative costs of its consumption basket following decreases in trade costs.

Next, I use the model structure to derive a sufficient statistic for the welfare effect of new roads which enables me to quantify how much of the total welfare gain from roads estimated from a reduced-form regression is explained by the mechanisms suggested in the model. This

¹A manifestation of this is that a farm household in a developing country usually grows several crops, even though the average land holding of a household is less than two hectares. In Ethiopia for instance, the median land holding is about a hectare and a median farmers grows 5 crops.

sufficient statistic resembles the sufficient statistic for welfare gain from decreases in international trade costs in workhorse trade models, e.g., [Arkolakis et al. \(2012\)](#), and [Eaton and Kortum \(2002\)](#), with a straightforward modification to account for geographic variation in productivity of land in crops in my model. Interestingly, however, no trade flow data is required to construct the empirical measure of the sufficient statistic – it can be inferred from the villages’ land allocations across crops and the model parameters.

The predictions of the model can be tested easily given panel data on village level land utilization, crop prices, and a shock to transport infrastructure – which I obtain from Ethiopia. Ethiopia provides a unique setting to study the welfare effects of rural roads. First, almost all of the rural villages were not accessible by modern transport as recently as in 2010. Second, to alter this fact, the Ethiopian government launched a large-scale rural road expansion project called Universal Rural Road Access Program (URRAP), which planned to connect all rural villages by all-weather roads in just five years between 2011 and 2015.² The program led to doubling of the total road length in the country by 2015. Third, unlike most Sub-Saharan African countries, Ethiopia collects a very rich micro data on agricultural production and crop prices. My agricultural data covers about 2,000 nationally representative rural villages (locally named as *Kebeles*, which are the lowest administrative units) and all crops. The price data covers about 500 nationally representative rural villages and over 100 nationally representative urban centers, and almost all agricultural products and inputs. About half of my sample villages in each of agricultural and price data got road connection under this URRAP. To address the potential endogeneity of road placements (selection of villages for the URRAP program), I use road network predicted solely based on cost considerations (land gradient, and location of rivers and lakes) to construct an instrumental variable for the actual road network.

At the core of my empirical exercises is defining a village’s comparative advantage crop(s). This requires information on yield estimate for each crop in each village. My agricultural survey data includes village level crop yield estimated by trained enumerators.³ As a robustness check, I use FAO-GAEZ data on agro-climatically attainable yield of crops in each village. This data uses a number of agro-ecological, soil and climatic factors, and sophisticated agronomic models to provide yield estimate at 5 arc-minute resolution. Given the yield estimates, I define a village’s

²While the URRAP program was launched in 2011, the first year was spent on capacity building and most of the road constructions were not commenced until 2012.

³The enumerators use a method called *crop cut* where they take a sample of plots (each with area of 4 square meter) and conduct crop cut to obtain estimate of yield.

comparative advantage crops using the following procedure. First, I calculate a village's yield relative to national average for each crop. Next, I rank crops, within each village, based on their yield relative to national average. I define crops in the top 20% of ranking based on relative yield as my baseline comparative advantage crops. I relax this baseline threshold to top 30%, top 40%, etc. to see sensitivity of my results.

There are three main results in this paper. First, the road expansion led to increases in the relative prices of CA-crops by 1.62% for a village with average increase in market access. Second, the road expansion led to reallocation of farmland towards a village's CA-crops – the fraction of land allocated to CA-crops increased by about 3% for a village with average increase in market access. Finally, I estimate a total welfare gain of 14% from the road expansion between 2012-2016 for a village with average increase in market access, and using the sufficient statistic derived from the model, I show that 7.5% out of the total 14% welfare gain is attributed to the mechanisms suggested in the trade model (reallocation of farmland towards CA-crops, higher prices for CA-crops, and cheaper prices of non-local crops). These results are robust to an alternative methods of addressing endogeneity of road placement, a matching-based DID strategy. The result is also robust to different set of crops considered: all crops, non-tree crops only, or crops for which FAO-GAEZ yield measure is available.

This paper's novel contribution is that it uses micro data on agricultural production and crop prices to provide an in-depth analysis of the underlying mechanisms through which roads affect village welfare, particularly how the new roads change the relative prices of crops and lead to reallocation of farmlands across these crops. Moreover, the paper studies the welfare effect of low-cost gravel roads connecting rural villages (that were previously inaccessible by modern means of transport system) to the nearest market centers. Previous studies on the welfare effect of roads focused on trunk roads, high-ways, and railroads which connect different regions of a country and are much more expensive to build.

An emerging literature studies the gains from intra-national market integration, particularly in the agricultural sector, using many-location many-good Ricardian trade models with heterogeneous factors of production ([Costinot and Donaldson 2016](#), [Donaldson 2018](#), [Sotelo 2018](#), [Allen and Atkin 2018](#), and [Adamopoulos 2018](#)). The most closely related papers to the current paper are [Adamopoulos \(2018\)](#), [Donaldson \(2018\)](#), and [Sotelo \(2018\)](#). [Adamopoulos \(2018\)](#) finds 13.6% increase in aggregate agricultural yield following road expansion and upgrading that reduced trade costs between Ethiopian districts and location of national grain market centers. The main

difference with the current paper is that the current paper focuses on the effect of *rural* roads that connect village centers to district capitals, instead of a decrease in trade cost between district capitals and Addis Ababa or other major urban centers. [Donaldson \(2018\)](#) develops a multi-sector multi-region Ricardian model in which land is treated as homogeneous within a region to study the gains from the railway expansion in colonial India. [Sotelo \(2018\)](#) introduces heterogeneous land quality to study how falling trade costs due to (counter-factual) paving of roads increases agricultural productivity and welfare in Peru. The current paper builds on these two papers for the theoretical part and contribute to this literature by estimating the effect of low cost rural road construction on crop prices, land allocation, and welfare.

This paper also relates to broad literature in development economics on how rural roads improve livelihood of households in developing countries ([Gebresilasse 2018](#), [Shamdasani 2018](#), [Shrestha 2018](#), and [Asher and Novosad 2019](#)). [Asher and Novosad \(2019\)](#) exploit strict implementation rule of India’s massive rural road expansion project called Pradhan Mantri Gram Sadak Yojana (Prime Minister’s Village Road Program, or PMGSY) to identify the program’s causal effect using fuzzy regression discontinuity design. They find that the roads’ main effect is to facilitate the movement of people out of agriculture, with little or no effect on agricultural income and consumption. However, the paper relies on proxies, instead of direct measures, for agricultural outcomes due to lack of data at fine geographic level. The current paper uses large household-level agricultural survey and price surveys at detailed geography to construct real agricultural income and consumption. [Shamdasani \(2018\)](#) studies the effect of large road-building program in India and finds that remote farmers who got access to road diversified their crop portfolio by starting to produce non-cereal hybrids, adopted complementary inputs and improved technologies, and hired more labor. [Gebresilasse \(2018\)](#) studies how rural roads complement with agricultural extension program, a program that trains farmers on how to use best agricultural practices and technology adoption, to increase farm productivity in Ethiopia. [Shrestha \(2018\)](#) finds that a 1% decrease in distance to roads due to expansion of highways resulted 0.1–0.25% increase in the value of agricultural land in Nepal. The current paper uses a theoretical model structure to identify the mechanisms through which rural roads affect welfare in village economies.

The rest of the paper is organized as follows. In section 2, I present the data, identification issues, and give some descriptive statistics that motivate the model presented in Section 3. Sections 4 takes the key predictions of the model to the data. Section 5 presents estimation of

key model parameters and the welfare gain. Section 6 concludes the paper.

2 Data

2.1 Sources

Agricultural production data: I primarily use the Agricultural Sample Survey (AgSS), which is the largest annual agricultural survey in the country covering over 40,000 farm households in about 2200 villages. While this dataset goes back as far as 1995, villages were resampled every year until 2010 which makes tracking a village overtime difficult. Starting from 2010, Central Statistical Agency (CSA) kept the sample of villages fixed but took a random sample of about 20 farmers per village every year. This dataset includes detailed production information: areas of land covered by each crop, application of fertilizer and other inputs, and quantities of harvest. Moreover, every three-year starting from the year 2009/2010, CSA also gathered crop utilization information, i.e., the fraction of crop production used for own consumption, the fraction sold, the fraction used to pay wages, the fraction used for seeds, etc, for all crops.

Consumption data: To estimate some preference parameters of the model (the elasticity of substitution between crops), I need consumption information. I use Ethiopian Socioeconomic Survey (ESS) data which is an exceptionally detailed panel data of about 4,000 nationally representative farm households for the years 2011, 2013 and 2015. The main advantage of the ESS dataset is it includes consumption information disaggregated by crops.⁴ A big caveat of this data set is that it covers households in only about 330 villages.

Price data: The main price data is the Agricultural Producer Price Survey (AgPPS), which is a monthly survey of farm-gate prices at a detailed geography (villages) for almost all crops and many other agricultural produces.⁵ This data covers over 500 representative villages which can be tracked over period since 2010. I also use the Retail Price Survey (RPS), which is a monthly survey of prices of almost all crops and non-agricultural commodities in major urban centers throughout the country. This dataset covers over 100 urban centers across all administrative

⁴The consumption information is based on a seven-day recall of basic consumption items, which are predominantly crops. However, household's crop utilization information also gives how much of each crops produced is consumed within the household.

⁵CSA claims that the prices in this survey can be considered as *farm-gate* price because they are collected at the lowest market channel where the sellers are the producers themselves, i.e., no intermediaries involved.

zones of the country. Importantly, the agricultural products covered in both datasets overlap almost fully.

Rainfall and agro-climatic data: I use FAO/GAEZ agro-climatically attainable yield for low/intermediate input use to construct villages' crop suitability, as a robustness check to yield measures in AgSS data. This data covers about 19 crops. However, it misses some of the endemic crops that are widely grown in Ethiopia such as Enset and Teff. As a result, I use this data only for robustness exercise. The rainfall data comes from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), which provides rainfall dataset starting from 1981. CHIRPS incorporates 0.05° resolution satellite imagery with station data to create gridded rainfall time series for trend analysis and seasonal drought monitoring. It is widely used to monitor drought in East Africa ([Funk et al., 2015](#)).

Road data: I use administrative data on the entire road-network in the country. This data includes the attributes of the roads (such as surface type), the role of the road (trunk road, link road, etc), and ownership (federal government, regional government, etc). In this paper I use a large scale rural road expansion under URRAP as a source of variation to villages' access to road/market. Over the period 2011-2015, the Ethiopian government gave exclusive focus to the URRAP and constructed over 62,413 kms of new all-weather roads connecting village centers to the nearest road or the nearest town, whichever is shorter. [Figure 1](#) shows map of the road network before and after URRAP.

The main objective of the URRAP was to improve villages' access to product and input markets. The program increased the overall road density per 1000 square-km from 44.4 in 2010 to 100.4 in 2015 ([Ethiopian Road Authority, 2016](#)). Though the URRAP was launched in 2011, very few roads were commenced in the year 2011, which is officially considered as capacity building year. Almost all the rural roads constructed under this program were started and completed between 2013-2015.

2.2 Identification of the effect of roads

There are two main issues that have to be dealt with to identify the causal effect of roads on village outcomes. The first is heterogeneity in treatment intensity and potential spillover effects. That is, villages that get connected to a dense network may gain more from the road than those that get connected to sparse network. Moreover, road connection in a village may have spillover

effects to other villages that are not directly connected. When a village is connected to the preexisting road network or to the nearest urban center, all its neighbors also have improved access to market via the connected village. As a result, non-connected villages may not serve as a control group in identification of the effects of road connection. The second concern is selection bias – villages are selected for the road program based on some demographic, geographic, social, and economic factors. In particular, due to limited budget, officials might prioritize villages that would gain more from the road when deciding which villages to connect.⁶

To address the heterogeneity in treatment intensity and spillover effects, I use market access measure derived from general equilibrium trade models (see Donaldson and Hornbeck 2016) that are calculated using the entire road network and the distribution of population across Ethiopian villages. Change in market access captures treatment benefit from both direct and indirect road connection, and it accounts for the density of the network to which a village is connected. See Appendix A for details on the construction of market access measure.

I address the potential endogeneity of road placement using Instrumental Variable (IV) estimation strategy. To construct the IV, I first obtain road network predicted based solely on construction costs. The road construction cost is a function of land gradient and location of rivers and lakes. Next, I construct market access measure for each village based on the predicted road network – *predicted* market access measure. I use this *predicted* market access measure as an instrument for the *actual* market access measure. See Appendix B for the details on construction of the IV. Because the *predicted* market access is based on a road network that is predicted based solely on exogenous cost factors (without taking into account potential benefits of the roads or population settlements), it is a valid IV for the *actual* market access measure.

Table 1 reports descriptive statistics on the market access measure. The first column shows that the market access measure increased by 45.6%, on average, between 2012 and 2016. Column 2 shows that the market access measure increased more for villages that are directly connected compared to villages that are not directly connected by 42%. Finally, the last column reports the first stage regression result. Market access measure constructed from the *predicted* road network is strongly correlated with the market access measure constructed based the *actual* road network. The estimate in the column 3 shows that the correlation between within village

⁶Unfortunately there was no official guideline as to which villages should be selected for the URRAP in a given year. Even though the project was fully funded by the federal government, implementation of URRAP was completely decentralized to regional governments. Within each regional government, districts propose list of villages that should get a road during a particular year and the regional governments approve villages based the available regional budget.

changes in predicted and actual market access measures is 0.56, with a standard error of 0.024. As a result, the first-stage F-stat in all specifications is above about 1000.

To check sensitivity of my results, I use a Matching-Based Difference-in-Differences (MB-DID) estimation as an alternative strategy to address endogeneity. That is, I first obtain a matched sample of treated and non-treated villages based on their pre-URRAP observable characteristics that might be relevant for selection of villages for URRAP. I then conduct DID estimation based on these matched sample of treated and non-treated villages. Combining matching with DID strategy is a powerful approach to address the selection problem. The matching step enables me to compare treated villages with non-treated villages that have similar observed characteristics and hence similar treatment probability. The DID strategy on these matched samples helps me to washout unobserved time-invariant village characteristics that may confound the treatment effect. See Appendix E for details.

2.3 Evidences on improvement in market integration

In this subsection, I present some evidences on how the road construction under URRAP improved market integration among rural villages.

Farmers face considerable barrier to trade: ESS data includes direct questions about transport costs. I use this survey to obtain estimation of transport costs. The ad valorem trade cost (transport cost per value of transaction) on vehicle is very high (the median is 6.5% and the mean is 11.4%). The size of this cost is comparable to international trade costs estimated by [Hummels \(2007\)](#) for US and New Zealand import, although in my data the distance traveled is just 12 kilometers.

URRAP decreased trade costs: The main objective of URRAP roads was to integrate rural villages to market centers ([Ethiopian Road Authority, 2016](#)). If URRAP roads really integrated rural villages to local market centers, we would see the price gap between the rural villages and the market centers decreasing for villages that got road connection relative to villages that did not get roads. I test this by looking at the difference in crop prices between zone capitals and the villages within the zones using the two rich price surveys, AgPPS and

RPS. I run the following regression:

$$\ln P_{zmt}^k - \ln P_{zvm}^k = \alpha_1 Post_t + \alpha_2 (Post_t * URRAP_v) + \gamma_v + \gamma_m^k + \gamma_t + \varepsilon_{zvm}^k$$

where k denotes crop, v is village, z is zone capital, m is month, t is year, $Post$ equals zero for all month-years before URRAP and one for all month-years after URRAP; $URRAP_v$ is a dummy variable representing whether a village got URRAP road between 2012 and 2015; and γ_m^k is crop-month fixed effect which captures possible seasonality of crop prices.

The result is reported in Table 2. It shows that road connection significantly decreased the urban-rural price gap. The first column pools all 56 crops for which data is available on both urban and rural prices. It shows that trade cost, as proxied by the ratio of urban to rural prices, decreased by about 3% for villages that got road connection, relative to villages that did not get road connection. In column 2, the estimation is restricted to perishable products, vegetables and fruits. The estimated decrease in trade cost for these products is more than twice the estimate for all crops: trade cost for vegetables and fruits decreased by about 8%. This is not surprising because trading such products is difficult when there is no road passable by vehicle connecting a village to the urban center due to their perishability. In the last column, the sample is restricted to observations in which urban prices are higher than rural prices, which is what one would expect if villages are net exporters of crops to urban centers.⁷ The gap between these two prices are plausibly capturing trade costs, which decreased by about 2.4%.

URRAP decreases the correlation between local prices and yields: One good indicator of an integrated market is that local prices are less sensitive to local supply. Under autarky, prices are relatively lower (higher) for the goods in which a region has a comparative advantage (disadvantage). Market integration weakens this inverse relationship between local prices and local comparative advantage. I run the following generalized difference-in-differences regression to investigate this:

$$\begin{aligned} \ln P_{vt}^k &= \alpha_1 \ln A_v^k + \alpha_2 (Post_t * URRAP_v) + \alpha_3 (\ln A_v^k * Post_t * URRAP_v) \\ &+ \gamma_v + \gamma_k + \gamma_t + \varepsilon_{vt}^k \end{aligned}$$

⁷Note that about 80% of observations (67,147 out of 82,944) conform with this expectation.

where P_{vt}^k is price of crop k in village v , A_v^k is a village's productivity in crop k which is proxied by GAEZ potential yield for the crop.

The result is presented in table 3. Panel A uses binary treatment dummy. The first column shows that there is a negative relationship between local prices of a crop and local yield of the crops. Column 3 shows that this negative relationship is significantly weakened when a village gets road connection. The elasticity of village price to village yield is 2.7% for a village with no road connection and a road connection decreases this estimate to 1.8%.⁸ Panel B of table 3 reports the corresponding estimation result using market access measure. The result clearly shows that in villages that see an increase in their market access, the negative correlation between crop price and yield becomes significantly weaker.

Informed by these evidences on the effect of roads on market integration, in the next section, I develop a multi-sector multi-village Ricardian trade model to analyze the mechanisms through which road constructions affect village welfare.

3 Theoretical framework

The model builds on Donaldson (2018) and Sotelo (2018). Consider an economy composed of V villages indexed by $v = 1, \dots, V$, each village represented by a representative household. A village derives utility from consumption of K homogeneous crops indexed by $k = 1, \dots, K$ that can be potentially produced or purchased.

Preferences: The village spends all its income on crops and its preference over different crops is given by

$$U_v = \left(\sum_k (q_v^k)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

where σ is elasticity of substitution between crops, U_v is utility in village v , and q_v^k is the quantity of crop k consumed by the village.

Technology: Similar to Sotelo (2018) and Allen and Atkin (2018), I assume that the farmer's technology is constant returns to scale. I also assume, for simplicity of exposition, that land is

⁸Alternatively, a positive α_3 would imply that road connectivity increases the prices of crops in which a village has a comparative advantage.

the only input.⁹ Each village has L_v amount of land, which is divided into a continuum of plots of size one indexed by $\omega \in \Omega_v$, where Ω_v is the set of plots in village v such that $\int_{\Omega_v} \omega d\omega = L_v$. Each of the plot is potentially different in how well it is suited to growing different crops, which I denote as $z_v^k(\omega)$. Assuming that a given plot can only be used to grow one crop at a time (plots cannot be divided), the production function is given as:

$$y_v^k(\omega) = z_v^k(\omega)$$

where $y_v^k(\omega)$ is quantity of crop k per unit of plot.

A representative farmer in each village draws $z_v^k(\omega)$ independently for each plot-crop from a Fréchet distribution with the following cumulative distribution function:

$$F_v^k(z) = Pr(Z_v^k < z) = \exp(-(A_v^k)^\theta z^{-\theta})$$

where A_v^k is the location parameter for the distribution of crop-suitability of land across the set of plots in village v , Ω_v . A_v^k can be interpreted as the average productivity of village v in crop k . For villages with agro-climatic conditions that are impossible to produce crop k , A_v^k is set to zero. θ is the (inverse) measure of dispersion in the productivity of land in a village, and it is constant across villages and crops.

Trade: Villages operate in a perfectly competitive crop market. There is an iceberg trade cost of $\tau_{vv'}^k \geq 1$ between villages v and v' in crop k . Motivated by the result in table 2, which shows that spatial price variation differs across crops, trade costs are assumed to vary across crops to reflect that some crops, such as vegetables, are more costly to trade (e.g., perishable) than others such as cereals. I assume that $\tau_{vv}^k = 1, \forall k$, and impose the standard assumption of triangle inequality in trade costs, $\tau_{vv'}^k \times \tau_{v'v''}^k \geq \tau_{vv''}^k, \forall k$.

I assume no arbitrage condition, so that for any two villages v and v' equilibrium crop prices satisfy $p_{vv'}^k = \tau_{vv'}^k p_{vv}^k$ where $p_{vv'}^k$ is price in village v' of crop k originating from village v , p_{vv}^k is price in village v of crop k originating from the same village v .

Distribution of prices: Let r_v is the rental rate of plots in village v , which is determined in equilibrium. The unit cost of production of crop k in village v is $c_v^k = \frac{r_v}{Z_v^k}$, which is stochastic

⁹The model can easily be extended to include labor without altering any of the analysis in this section but at a cost of introducing new notations. Hence, I abstract from introducing labor in this section.

because it is a function of stochastic productivity Z_v^k . As a result, the price at which village v supplies crop k to village v' , $p_{vv'}^k = \frac{r_v}{Z_v^k} \tau_{vv'}^k$, is stochastic.

Using the distribution of Z_v^k , we obtain the following distribution of the prices of crop k that village v' is offered by another village v :

$$G_{vv'}^k(p) = 1 - \exp(- (A_v^k)^\theta (r_v \tau_{vv'}^k)^{-\theta} p^\theta)$$

Because crops supplied by different villages are homogeneous, village v' buys each crop k from the village that supplies the crop at the lowest price. Thus, the distribution of the price of crop k that is actually paid in village v' is the distribution of the lowest prices across all other villages and is given by:

$$\begin{aligned} G_{v'}^k(p) &= 1 - \prod_{v=1}^V (1 - G_{vv'}^k(p)) \\ &= 1 - \exp(- p^\theta \sum_{v=1}^V (A_v^k)^\theta (r_v \tau_{vv'}^k)^{-\theta}) \end{aligned} \quad (1)$$

The probability that village v is the cheapest supplier of crop k to village v' (the probability that village v 's productivity draw, adjusted for trade costs and rental rates, is the highest compared to all other potential villages trading with v') is:

$$\begin{aligned} \pi_{vv'}^k &= \Pr[p_{vv'}^k \leq \min_n \{p_{nv'}^k\}] \\ &= \frac{(A_v^k)^\theta (r_v \tau_{vv'}^k)^{-\theta}}{\sum_v (A_v^k)^\theta (r_v \tau_{vv'}^k)^{-\theta}} \end{aligned}$$

which is increasing in the average productivity of village v in crop k , A_v^k , and decreasing in the trade cost $\tau_{vv'}^k$ and the rental rate in village v , r_v , relative to other villages.

The probability that a village will be the cheapest supplier of a crop to itself is

$$\begin{aligned} \pi_{vv}^k &= \Pr[p_{vv}^k \leq \min_{\{n \neq v\}} \{P_{nv}^k\}] \\ &= \frac{(A_v^k)^\theta r_v^{-\theta}}{\sum_n (A_n^k)^\theta (r_n \tau_{nv}^k)^{-\theta}} \end{aligned}$$

A village is more likely to self-produce crop k if the village is more productive in the crop relative to other villages and/or if there is high trade costs between the village and other villages.

Following Donaldson (2018), we can obtain the expected value of the price distribution:

$$p_v^k = \Gamma \left(\sum_{v'=1}^I (A_{v'}^k)^\theta (r_{v'} \tau_{v'}^k)^{-\theta} \right)^{\frac{-1}{\theta}} \quad (2)$$

where Γ is a gamma function $\Gamma(1 + 1/\theta)$. I assume that farmers in village v make their production and consumption decisions based on this expected price. Given the CES preferences, the price index faced by village v is given by:

$$P_v = \left(\sum_k p_v^k \right)^{\frac{1}{1-\sigma}} \quad (3)$$

where p_v^k is given by equation 2.

Equilibrium land allocation: I assume that there is a competitive land rental market. Each village decides how to allocate its farmland across different crops given prices p_v^k and the suitability of the village land for various crops. Revenue maximization implies that each plot of land is allocated to a crop that yields the highest return:

$$R_v(\omega) = \max_k \{p_v^k z_v^k(\omega)\} \quad (4)$$

where $R_v(\omega)$ is revenue from plot ω . Together with the Fréchet distribution, this implies the following land allocation rule:

$$\eta_v^k = \frac{(p_v^k A_v^k)^\theta}{(\Phi_v)^\theta}, \quad \text{where } \Phi_v = \left(\sum_{l=1}^K (p_v^l A_v^l)^\theta \right)^{\frac{1}{\theta}} \quad (5)$$

where η_v^k is the fraction of land in village v allocated to crop k . It increases with the price of the crop and the average productivity of the the village in the crop, relative to all other crops. The following proposition summarizes the key mechanism through which roads affect village welfare in this model:

Proposition 1. *Decreases in trade costs lead to reallocation of farmland to a village's comparative advantage crops, resulting in more specialization of villages.*

Proof. The elasticity of land share of a crop in a village to the village's productivity is given as $\frac{d \ln \eta_v^k}{d \ln A_v^k} = \theta(1 - \eta_v^k)$. Differentiating with respect to trade costs, we obtain $\frac{d^2 \ln \eta_v^k}{d \tau_{vv'}^k d \ln A_v^k} = -\theta \frac{d \eta_v^k}{d p_v^k} \frac{d p_v^k}{d \tau_{vv'}^k}$. The term $\frac{d \eta_v^k}{d p_v^k}$ is always positive (see equation 5). Consider two villages v and v' and suppose

the price of crop k in village v' is normalized, so that the price in village v is defined relative to the price in village v' . This implies that $p_v^k = \tau_{vv'}^k$ if k is CD-crop in village v (i.e., $p_v^k > p_{v'}^k = 1$) or $p_v^k = \frac{1}{\tau_{vv'}^k}$ if k is CA-crop in village v (i.e., $p_v^k < p_{v'}^k = 1$). Thus the term $\frac{dp_v^k}{d\tau_{vv'}^k}$ has a positive sign if crop k is a CD-crop in the village and a negative sign otherwise.¹⁰ This implies that as trade costs decrease, villages reallocate more land to their CA-crops. \square

The intuition is simple. As trade costs decrease, a village's CA-crops ('export' crops) become relatively more expensive and CD-crops ('import' crops) become relatively cheaper at local markets. This makes growing CA-crops relatively more attractive and growing CD-crops relatively less attractive, which induces reallocation of land to these CA-crops.

Revenue per plot and equilibrium rental rate: In appendix C, I derive the conditional distribution of land productivity $\mathcal{Q}_v^k(z) \equiv \mathcal{P}(Z_v^k(\omega) < z | \omega \in \Omega_v^k)$, i.e., the distribution of productivity of a plot conditional on the plot being used for crop k , which gives the following distribution function:

$$\mathcal{Q}_v^k(z) = \exp\left(-\left(\frac{\Phi_v}{p_v^k}\right)^\theta z^{-\theta}\right)$$

which is Fréchet with the expected value of $\frac{\Phi_v}{p_v^k}$.

Suppose crop k is the crop that maximizes revenue from plot ω so that optimal revenue from plot ω is given by $R_v(\omega) \equiv p_v^k q_v^k(\omega) = p_v^k z_v^k(\omega)$. The conditional distribution of revenue from a plot conditional on the plot being used for crop k , $\mathcal{P}(R_v(\omega) < R | \omega \in \Omega_v^k)$, is also Fréchet with the expected value of Φ_v because revenue is just the productivity term multiplied by a non-stochastic price p_v^k . Moreover, given the assumption of competitive land rental market, rental rate per plot is equal to revenue per plot. Thus, the conditional distribution of rental rate per plot is the same as the conditional distribution of revenue per plot (note from equation 4 that $r_v(\omega) | \omega \in \Omega_v^k = p_v^k z_v^k(\omega)$ which has a Fréchet distribution with parameter Φ_v).

A sufficient statistic for the welfare gain: Because land is the only factor of production in the model, average real rental rate per plot, which is also equal to average real revenue per plot, can be used as a measure of village welfare: $W_v \equiv \frac{r_v}{P_v} = \frac{R_v}{P_v}$ where r_v is average rental rate per plot, R_v is average revenue per plot, and P_v is the village price index. Given data on

¹⁰Recall that, from the no-arbitrage and $\tau_{vv'}^k \geq 1$ conditions, $p_v^k = p_{v'}^k \tau_{vv'}^k$, if $p_v^k > p_{v'}^k$, or $p_v^k = p_{v'}^k / \tau_{vv'}^k$, if $p_v^k < p_{v'}^k$.

quantities of each crop produced in a village, village prices, and model parameters needed to construct village price index, one can construct village real revenue $\frac{R_v}{P_v}$ and compare its changes over time in villages that get new road connection against villages whose road status did not change in a difference-in-differences strategy. However, this DID estimate does not tell us how much of the change in welfare due to roads is explained by the mechanism suggested in this model. The simplicity of the current trade model allows me to derive a sufficient statistic for the welfare gain from road. This sufficient statistic is crucial to shed light on how much of the welfare gain from road obtained in the reduced-form DID estimation is attributed to the mechanism that our trade model captures.

Recall that the probability that village v is the cheapest supplier of crop k to village v' is equal to $\pi_{vv'}^k = (A_v^k)^\theta (r_v \tau_{vv'}^k)^{-\theta} (p_{v'}^k)^\theta$. Evaluating this expression at $v = v'$ and solving for p_v^k we obtain $p_v^k = r_v (A_v^k)^{-1} \pi_{vv}^k^{1/\theta}$. Plugging this into CES price index we obtain $P_v = r_v [\sum_k ((A_v^k)^{-1} (\pi_{vv}^k)^{\frac{1}{\theta}})^{1-\sigma}]^{\frac{1}{1-\sigma}}$ which implies:

$$\ln \Lambda_v \equiv \ln \frac{r_v}{P_v} = \frac{1}{\sigma - 1} \ln \sum_k A_v^{k\sigma-1} \pi_{vv}^k \frac{1-\sigma}{\theta} \quad (6)$$

where Λ_v denotes the sufficient statistic for the welfare effects of roads. This expression is similar to the sufficient statistic expressions for welfare gain from a decrease in trade cost given in [Arkolakis et al. \(2012\)](#), except that the expenditure share on own product π_{vv}^k is weighted by local productivity of crops. This modification is due to the assumption that the productivity distribution is allowed to vary across locations for each crop (compared to the same technology parameters assumed for all goods in [Arkolakis et al. \(2012\)](#)).

The main result in this model that enables me to construct an empirical measure of the sufficient statistic of welfare gain without observing any trade flows between villages is [Proposition 2](#).

Proposition 2. *The probability that a village is the cheapest supplier of crop k to itself, π_{vv}^k , is proportional to the fraction of the village farmland allocated to the crop, i.e., $\pi_{vv}^k = \kappa \eta_v^k$.*

Proof. The proof is straight forward. Recall that the probability that village v is the cheapest supplier of crop k to village v' is given by $\pi_{vv'}^k = \kappa (A_v^k)^\theta (r_v \tau_{vv'}^k)^{-\theta} (p_{v'}^k)^\theta$. Evaluating this expression at $v = v'$ we obtain $\pi_{vv}^k = (A_v^k)^\theta (r_v)^{-\theta} (p_v^k)^\theta$, which can be rearranged to give $\pi_{vv}^k = \kappa \frac{(A_v^k p_v^k)^\theta}{r_v^\theta} = \kappa \frac{(A_v^k p_v^k)^\theta}{\sum_l (A_v^l p_v^l)^\theta} = \kappa \eta_v^k$, where the second equality uses the expression for the average rent from the distribution of equilibrium rent, $r_v = \Phi_v$. $\kappa = \Gamma(1 + 1/\theta)^{-\theta}$, where $\Gamma(\cdot)$ is

a gamma function. □

Proposition 3. *The size of the welfare gain from road depends on the fraction of land allocated to different crops in a village vis-a-vis the consumption composition of the village.*

Recall that welfare is given by $\frac{r_v}{P_v} = \left(\sum_{k=1}^K (p_v^k A_v^k)^\theta \right)^{\frac{1}{\theta}} / \left(\sum_k p_v^k \right)^{\frac{1}{1-\sigma}}$. Taking logs and differentiating this with respect to p_v^k gives:

$$d \ln W_v = \sum_k (\eta_v^k - s_v^k) d \ln p_v^k \quad (7)$$

This equation implies that a decrease in trade costs of CA-crop increases village welfare by a larger magnitude if $\eta_v^k \gg s_v^k$. A testable implication of this proposition is that a village that specializes in cereals gains less from road connection compared to a village that specializes in cash-crops. This is because, while both groups of villages gain from the increase in the prices of their CA-crops, the villages specializing in cereals experience an increase in their consumption expenses relative to the villages that specialize in non-cereals.

4 Testing the model predictions

4.1 New roads and reallocation of farmland

The theoretical results in section 3 suggest that decreases in trade costs would lead to reallocation of farmland towards a village's CA-crops. I test this directly. In order to identify a village's CA-crop(s), I primarily use village level crop yield estimates provided in AgSS. This yield estimate is conducted by trained enumerators using a method called *crop cut* where they take sample plot of area of 4 square meters and conduct crop cut to obtain yield estimate. However, there are two caveats to this yield estimate. First, yield estimates are provided only for the crops that are actually produced in the village. Second, such yield estimates are influenced by seasonal fluctuations in climatic factors such as rainfall and crop diseases. I overcome the second problem by averaging yield estimates across pre-URRAP years within a village. As for the first problem, I assume a yield of zero for crops that are not produced in a village.

As a robustness check, I use FAO-GAEZ data on agro-climatically attainable yield of crops in each village. This data uses a number of agro-ecological, soil and climatic factors, and sophisticated agronomic models to provide yield estimate at 5 arc-minute resolution under three scenarios of intensity of input usage (low, medium, and high input intensity). I use yield

estimates under the low input intensity as that is more likely to reflect the reality in Ethiopia. While the FAO-GAEZ data overcomes the above two problems with the yield estimates provided in AgSS data, it covers only a partial list of crops produced in Ethiopia. In particular, it misses some of widely grown endemic crops in Ethiopia such as Enset and Teff. Nevertheless, I use this alternative yield estimate for a robustness check. The correlation between the FAO-GAEZ yield estimates and the AgSS yield estimates, based on crops that exist in both datasets, is about 0.8, and all my results are robust across the alternative yield estimates used.

Given the yield estimates A_v^k , I define a village's comparative advantage crops using the following procedure. First, I calculate a village's yield relative to national average for each crop, $\frac{A_v^k}{A^k}$. Next, I rank crops, within each village, based on their yield relative to national average. I define crops in the top 20% of ranking as my baseline comparative advantage crops. I relax this baseline threshold to top 30%, top 40%, etc. to see sensitivity of my results. One issue is some villages grow only a handful of the major crops considered for analysis, and using the above procedure would end up classifying all or most of the crops grown in the village as CA-crops in these villages.¹¹ For instance, if a village grows only 5 of, say, 25 crops in the data and we define CA crops as top 20% in relative yield, all the 5 crops grown in the village would be classified as CA crops. As a result, we would not discern any land reallocation because we are defining the set of all crops grown in the village as CA-crops. To overcome this problem, I keep only crops that are grown in a village in at least one of pre- or post-URRAP years and rank these crops in their relative productivity $\frac{A_v^k}{A^k}$ within the village. In this approach, for a village that grows only 5 of the 25 crops, the CA-crop is the crop that is at the top in ranking of $\frac{A_v^k}{A^k}$ within the village.

I estimate the following regression at a village level:

$$\eta_{vt}^k = \alpha_1(Post_t * URRAP_v) + \alpha_2 CA_v^k + \alpha_3(Post_t * Road_v * CA_v^k) + \beta \mathbf{X} + \gamma^k + \gamma_v + \gamma_t + \varepsilon_{vt}^k$$

where η_{vt}^k denotes the share of land allocated to crop k in village v in year t . $Post$ equals zero for the period before URRAP and one for the period after. $URRAP$ equals one for villages that got road under URRP and zero for other villages. CA_v^k is dummy variable indicating whether crop k is among the village's CA-crops, and X is a vector of village characteristics such as the population density and rainfall. I also include crop fixed effects to account for mean variation

¹¹About 4% of the villages grow five or less crops and the maximum number of crops grown in a given village is 19, out of the 25 major crops.

in land intensity across crops. The regression includes village fixed effect to account for time invariant village characteristics that may confound our result and year fixed effect to account for any year specific factor shared across villages.

To address the problems associated with binary treatment measure, I also estimate similar regression by using log market access derived from general equilibrium trade model.

$$\eta_{vt}^k = \alpha_1 \ln MA_{vt} + \alpha_2 CA_v^k + \alpha_3 (\ln MA_{vt} * CA_v^k) + \beta \mathbf{X} \quad (8)$$

$$+ \gamma^k + \gamma_v + \gamma_t + \varepsilon_{vt}^k \quad (9)$$

where $\ln MA$ is log market access. I estimate using both OLS and IV strategies using predicted market access as an IV.

For the main analysis, I drop tree-crops and crops that are very rarely produced and have insignificant land share. The issue with tree-crops such as coffee, banana, orange, etc. is that farmers are unlikely to switch between these crops and others in the short and medium run due to their long gestation period. This brings down the number of crops in the analysis to 25. However, I show that my results are robust to including all crops.

Table 4 presents the results. Panel A uses binary treatment dummy. The first column shows that area of land allocated to the top 20% crops (in relative yield rankings) increased by about 3.8% (0.006/0.159), between 2012 and 2016, following road connection. As the definition of CA-crops is extended to top 30%, top 40% and top 50% in the next three columns, the estimated effect of road slightly decreases because as we relax the cutoff for definition of CA-crops we classify more and more crops as CA-crops even if the village is not strongly more productive in those crops relative to national average. Panel B shows similar results using market access measure. We see that the fraction of land allocated to CA-crops increases significantly for villages that have seen an increase in their market access, and that this effect becomes weaker as we relax the cutoff for CA-crop definition. The estimate in the first column shows that the fraction of land allocated to CA-crops increased by about 2.5% for a village with average increase in market access of 45%.¹² Columns 2-4 of Panel B clearly shows that the estimated increase in fraction of land reallocated to CA-crops decreases steadily as we relax the definition of CA-crops to top 30%, top 40%, etc. Panel C reports the IV result. Clearly the IV results are very similar

¹²To obtain this percentage change, take partial derivative of equation 8 with respect to $\ln MA$ to obtain $-0.004 + 0.013 * CA\text{-crop}$. For $CA\text{-crop}=1$, this equals 0.009. Multiply this by average change in market access of 0.45, and to obtain percentage change divide it by land share of CA-crops in 2012 given in the next to last row of table 4 and multiply by 100: $\frac{0.009 * 0.45}{0.159} * 100 = 2.5\%$.

to the OLS result in Panel B. In particular, the estimates for the interaction term $\ln MA * CA_v^k$ are identical to those in Panel B. This is because the regression is basically triple difference (Panel A makes this clear) and that identification comes from variation across crops (CA-crops vs CD-crops). Under such specification, endogeneity of MA is not a problem and OLS and IV results will be very similar. This is not the case in specifications that do not include triple interaction below. Overall, the results in table 4 show that the road expansion led to modest reallocation of farmland towards villages' CA-crops.

I explore a number of robustness exercises. First, I include all the 45 crops reported in AgSS data for which complete information is available. Table A.1 shows the estimation result. The implied increase in the share of land allocated CA-crops, based on estimates in Panel A, is 6.2%. The estimated increase in land share of CA-crops based on Panel B and Panel C are 2.8% and 3.2% respectively. Overall, the results in table A.1 are comparable to those those in table 4, implying that the results are not sensitive to the selection of crops.

In the second robustness exercise, I use FAO-GAEZ yield measure. This data includes only 19 crops. Some of these crops are rarely produced. Only 11 of the 19 crops are produced across many villages which significantly reduces the variation in the data and the precision of the estimates. Nevertheless the results in table A.2 are comparable to those in table 4 in magnitude.

In a third robustness exercise, I use a matching-based DID estimation strategy (see appendix E) to deal with potential bias in selection of villages for the URRAP program. That is, I first obtain a matched sample of treated and non-treated villages based on a set of observed village characteristics that might affect selection of villages for the program before conducting DID estimation. The results are reported in table A.6. The estimates in both Panel A and Panel B are very similar to their counterparts in table 4. This implies that our results are robust to alternative methods used to account for potential selection bias.

4.2 New roads and crop prices

As trade costs between a village and its trading partners decrease due to new road construction, the relative prices of the village's CA-crops increase (or the relative prices of the village's CD-crops decrease). This prediction of the model can be directly tested, given data on village level prices of crops before and after the program and our CA-crop definition from the previous

subsection. I use the following regression to test this prediction:

$$\begin{aligned} \ln p_{vmt}^k &= \alpha_1 (Post_t * URRAP_v) + \alpha_2 CA_v^k + \alpha_3 (Post_t * URRAP_v * CA_v^k) \\ &+ \gamma^k + \gamma_v + \gamma_{mt} + \varepsilon_{vt}^k \end{aligned}$$

where $\ln p_{vmt}^k$ denotes the log price of crop k in village v in month m of year t . CA_v^k is dummy variable indicating whether crop k is among the village's CA-crops. I include crop-month fixed effects to account for seasonal fluctuation in crop prices. I also run similar regression using log market access instead of binary treatment dummy:

$$\begin{aligned} \ln p_{vmt}^k &= \alpha_1 \ln MA_{vt} + \alpha_2 CA_v^k + \alpha_3 (\ln MA_{vt} * CA_v^k) + \beta \mathbf{X} \\ &+ \gamma^k + \gamma_v + \gamma_{mt} + \varepsilon_{vt}^k \end{aligned}$$

I use the AgPPS data for the same 25 major non-tree crops in the main analysis. This data covers about 450 villages (after cleaning for missing information). The results are reported in table 5. While the estimates in the Panel A based on binary treatment are statistically insignificant, those in Panel B and Panel C are statistically and economically significant. Focusing on the results in Panel C, the estimates in column 1 imply that the prices of CA-crops (relative to prices of CD-crops) increased by 0.036 between 2012 and 2016 following 1 log unit increase in market access, implying 1.62% increase in prices of CA-crops (relative to CD-crops) for a village with average (45%) increase in market access.¹³ However, this estimate significantly drops as we relax the cut-off for the definition of CA-crops, eventually becoming statistically insignificant in columns 3 and 4 of Panel C.

I explore similar robustness exercises as in the previous subsection. First, I include all the 45 crops for which price data is available. The results are reported in table A.3. Clearly the results are very similar to those in table 5. Second, I use GAEZ data to define CA-crops. The result is reported in table A.4. The estimated increases in prices of CA-crops is significantly larger in table A.4 compared to tables A.3 and 5. This is partly driven by difference in the composition of crops across the specifications. Finally, I use the matching-based DID estimation to address endogeneity of road placement. Results are reported in table A.7 and they are very similar to those in the main specification, table 5.

¹³Note that this interpretation ignores the coefficients of $\ln MA$ which are statistically insignificant and close to zero in both Panel B and Panel C.

Overall, these results indicate that relative prices of CA-crops increased significantly following increases in market access.

Next, I explore the effect of increases in market access on village price index, which is computed using equation 3 and the elasticity of substitution estimated in section 5. The results in table 6 show that the village price index did not change much. This is not surprising given that village price index is a CES aggregate of prices of CA-crops and CD-crops, which move in the opposite direction when market access improves.

5 Estimation of parameters and welfare gain

In order to construct the empirical measure of sufficient statistic for welfare gain from roads, we need to obtain estimates for the parameters of the model: the elasticity of substitution σ , and the measure of homogeneity of plots in a village θ .

5.1 Estimation of model parameters

Estimation of σ : I use the expression for the expenditure share of a crop and ESS data on household consumption disaggregated by crops to estimate the σ . I estimate the following equation:

$$\ln s_{it}^k = \alpha_0 - (\sigma - 1) \ln p_{it}^k + \delta_1 E_{it} + \delta_2 H_{it} + \gamma_t + \gamma_r^k + \gamma_z + \varepsilon_{it}^k \quad (10)$$

where s_{it}^k is the share of crop k in household expenditure and p_{it}^k is the price of crop k . This equation is CES expenditure share equation augmented by including household annual expenditure E (a proxy for income), household size H_{it} , year fixed effects γ_t , region-crop fixed effects γ_r^k to account for regional variation in crop tastes, and a set of dummy variables for agro-ecological zones.

There is a well known endogeneity concern in estimation of equation 10 because unobserved factors could be correlated with both prices and the expenditure share of crops or measurement error in price could attenuate the coefficient of price. To address this, I use GAEZ yield measure to instrument for prices. GAEZ yield measure is a valid instrument because locations that have higher crop productivity have lower prices for the crop. The first-stage F-stat is 24.6. I obtain the coefficient of price of -0.3 (s.e. 0.07), which implies $\hat{\sigma}$ of 1.3. While this estimate looks too small at first glance, it is in fact in line with other studies estimating the elasticity of substitution

across food varieties in low income countries. For instance, [Behrman and Deolalikar \(1989\)](#) find $\hat{\sigma} \approx 1.2$. But other studies such as [Sotelo \(2018\)](#) find larger estimate of about 2.3 using data from Peru.¹⁴

Estimation of θ : I follow [Sotelo \(2018\)](#) in the estimation of θ . I rely on AgSS village level crop yield estimate that is constructed based on a random sample of crop cut. To purge out the noise in yield estimate and fluctuations due to whether conditions, I take the average across all years (2010-2016) to obtain a time invariant measure of yield for a crop in a village. I assume that the true crop productivity in a village A_v^k is related to the AgSS's village yield measure Y_v^k in the following equation:

$$A_v^k = \delta^k Y_v^k \exp(-u_v^k)$$

where $\exp(-u_v^k)$ is a random noise, and δ^k is crop-specific constant. Plugging this for A_v^k in equation 5 and taking logs gives:

$$\ln(P_v^k Y_v^k) = \frac{1}{\theta} \eta_v^k + \ln \Phi_v - \ln \delta^k + u_v^k$$

The empirical counterpart of this is:

$$\ln(P_{vt}^k Y_v^k) = \frac{1}{\theta} \eta_{vt}^k + \gamma_v + \gamma^k + \gamma_t + u_{vt}^k$$

where γ_v and γ^k are village and crop fixed effects respectively.

I obtain a value of $\hat{\theta} = 2.7$ for productivity dispersion. This is larger than the estimate of [Sotelo \(2018\)](#) which is around 1.7, but smaller than that of [Donaldson \(2018\)](#) who reports a mean of about 7.5 across the 17 crops in his data. However, [Donaldson \(2018\)](#) estimates θ from a gravity equation using data on trade flows between regions in colonial India.

5.2 Estimation of welfare gain

Recall that the measure of welfare W_{vt} in the model is real revenue per hectare $\frac{R_{vt}}{P_{vt}}$, which is also equal to real rental rate $\frac{r_{vt}}{P_{vt}}$. Given data on crop production and prices before and after the program, I can directly construct village revenue as $R_{vt} = \sum_k p_{vt}^k y_{vt}^k$. However, my price data

¹⁴[Sotelo \(2018\)](#) argues that his estimate of σ is the upper bound when compared to similar studies from developing countries.

(AgPPS data) does not cover all the villages for which agricultural production data is available (AgSS villages). I impute missing prices as follows. For each village in AgSS data that got road connection under URRAP, I find the nearest village in AgPPS data that also got road under URRAP. Similarly, for each village in AgSS data that did not get road under URRAP, I find the nearest village in the AgPPS data that did not get road under URRAP. I use these imputed prices to calculate village revenue. The price index is also calculated using the same data and the elasticity of substitution estimated in the previous subsection: $P_{vt} = (\sum_k p_{vt}^k)^{\frac{1}{1-\sigma}}$.

To estimate the welfare gain from road connectivity, I run the following regression:

$$\ln W_{vt} = \alpha_1(\text{Post}_t * \text{URRAP}_v) + \alpha_2 \text{Post}_t + \delta \mathbf{X} + \gamma_v + \varepsilon_{vt} \quad (11)$$

where X includes a vector of village characteristics such as rainfall. I also run similar regression using market access measure instead of binary treatment using both OLS and IV estimation:

$$\ln W_{vt} = \gamma_1 \ln \text{MA}_{vt} + \delta \mathbf{X} + \gamma_v + \gamma_t + \varepsilon_{vt} \quad (12)$$

Finally, in order to estimate how much of the estimated welfare gain in the above reduced-form estimation is attributed to the trade mechanism suggested in the model, I use the sufficient statistics derived from model and mediation analysis. First, I construct the sufficient statistics using equation 6 and proposition 2 as $\ln \Lambda_{vt} = \frac{1}{\sigma-1} \ln \sum_k A_v^{k\sigma-1} \eta_{vt}^k \frac{1-\sigma}{\theta}$, given data on village yield A_v^k and land share of crop η_{vt}^k , and the values of parameters θ and σ estimated in the previous subsection. Then, I rerun equations 11 and 12 by including $\ln \Lambda_{vt}$ on the right-hand side:

$$\ln W_{vt} = \beta_1(\text{Post}_t * \text{URRAP}_v) + \beta_2 \ln \Lambda_{vt} + \beta_3 \text{Post}_t + \delta \mathbf{X} + \gamma_v + \varepsilon_{vt} \quad (13)$$

$$\ln W_{vt} = \psi_1 \ln \text{MA}_{vt} + \psi_2 \ln \Lambda_{vt} + \delta \mathbf{X} + \gamma_v + \gamma_t + \varepsilon_{vt} \quad (14)$$

The logic behind this mediation analysis is as follows. Because $\ln \Lambda_{vt}$ captures the welfare gain from road that is mediated through the trade mechanism suggested in our model, once this term is included on the right-hand side of equations 13 and 14 the coefficient of road access (β_1 in equation 13 and ψ_1 in equation 14) capture only the welfare effect of roads that is mediated through non-trade mechanisms. Thus, comparing equations 11 and 13 α_1 captures the total welfare gain from road, β_1 captures part of this welfare gain that is attributed to non-trade mechanisms, and the difference $\alpha_1 - \beta_1$ captures the welfare gain attributed to the

trade mechanism. And analogous argument holds for equations 12 and 14.¹⁵ If roads affected real revenue *only* through the mechanism suggested in the model, then β_1 in equation 13 should be small and statistically insignificant. If instead, β_1 is statistically significant but significantly smaller than α_1 , then the trade mechanism captures only a portion of the effect of roads on real revenue. And similar argument holds in the specifications using market access.

Table 7 reports the estimation results. Panel A reports results for binary treatment approach while Panel B and Panel C report OLS and IV results using market access approach. From panel A, the first column shows that real agricultural income per a hectare of land (a measure of welfare) increased by 16.9% for treated villages compared to non-treated villages over the period of 2012 to 2016. This is the total welfare gain from URRAP roads, which can be attributed to a number of mechanisms. From column 2, we see that the sufficient statistic measure of welfare derived from the model ($\ln\Lambda_{vt}$) increases by 26.4% for the treated villages compared to non-treated villages. This is important for the validity of the mediation analysis because it proves that the roads significantly increase measure of welfare in the model. Column 3 reports estimation result for equation 13. Once the model predicted welfare $\ln\Lambda_{vt}$ is included in the right-hand side, the coefficient of $Post_t * URRAP_v$ decreases to 0.05 and loses its significance. Comparing the coefficient of $Post_t * URRAP_v$ in columns 1 and 3 implies that 11.9% (16.9%-0.05%), out of the total 16.9% welfare gain, is attributed to the trade mechanism.

Panel B and Panel C tell similar story using market access approach. I will focus on Panel C (the IV estimation) for discussion of the results. Column 1 implies that welfare increased by 14.1% for a village with average increase in market access.¹⁶ Column 2 implies that the sufficient statistic measure of welfare increased by 15.4% for a village with average increase in market access. Column 3 shows that, once the sufficient statistic measure is included in the right-hand side, the coefficient of log market access decreases by a half compared to column 1 and loses its statistical significance, similar to the binary treatment specification of Panel A. Comparing the estimates in Columns 1 and 3 implies that at least half of the 14.1% welfare gain in a village with average increase in market access is attributed to the trade mechanism suggested in the model.

In table A.8, I explore robustness of the above results to alternative way of addressing the endogeneity of roads – matching-based DID strategy. Panel A reports the results for binary

¹⁵See this excellent note on how mediation analysis works and the procedures to implement it http://web.pdx.edu/~newsomj/semclass/ho_mediation.pdf.

¹⁶This value is obtained by multiplying the estimated elasticity by average increase in market access: $0.313 * 0.45$.

treatment while Panel B report the results for market access approach. While the estimated welfare gains are slightly smaller than those in the main specification (table 7), the qualitative conclusion is the same. That is, the road expansion led to 12.5% increase in village welfare (by 7.7% for a village with average increase in market access in Panel B), and over half of this is attributed the mechanism suggested in the trade model.

Overall, the results in tables 7 and A.8 show that the URRAP roads have led to significant increases in village welfare. At least half of these welfare gain estimates are attributed to reallocation of farmland towards villages' CA-crops and higher prices received for these crops following improvement in market access. In the next subsection, I explore heterogeneity in the size of welfare gain across villages.

5.3 Heterogeneity in welfare gain: cereal vs. non-cereal villages

One of the key testable implications from the model is that the welfare gain from roads is heterogeneous and depends on the fraction of land allocated to different crops in a village vis-a-vis the expenditure share of these crops in village consumption. In particular, villages that specialize in cereals should gain less from roads because they experience an increase in the prices of their consumption baskets while non-cereal producing villages experience the opposite. That is, while both the cereal and non-cereal (cash-crop) villages obtain better prices for their CA-crops following improvement in market access, they experience different outcomes on the cost of their consumption baskets. The cereal villages experience increases in the costs of their consumption baskets because cereals (which account for 23% of CPI in Ethiopia, [Durevall et al. \(2013\)](#)) become more expensive locally. The cash-crop villages experience the opposite because cereals can now be imported at relatively cheaper prices and an increase in the prices of cash-crops has little effect on consumption costs because cash-crops have insignificant weight in consumption baskets.

Table 8 presents the empirical evidence supporting this result. I interact the fraction of village farmland allocated to cereals in the year 2011 with the treatment and post dummies (in the first column) and with the market access measure (in columns 2 and 3). To facilitate interpretation, the land share of cereal is standardized. The table shows that the welfare gain from roads is decreasing in the fraction of land allocated cereals, i.e., villages that allocate higher fraction of land to cereal gain significantly less than those that allocate lower fraction of land to cereals. The estimates in column 1 imply that villages with one standard deviation higher

fraction of farm land allocated to cereals compared to the average gain 9.3% lower in welfare compared to the average welfare gain of 16.5%. The estimates based on market access approach imply less dramatic heterogeneity between cereal and cash-crop villages in terms of welfare gain. For instance, the IV specification in column 3 implies 15% welfare gain for a village with average increase in market access and average cereal share of land. Villages with two standard deviation higher in the share of land allocated to cereals, compared to the average, experience only slightly smaller welfare gain of 14%.

5.4 Remoteness and welfare gain from new roads

An important policy question is how the gain from infrastructure expansion, such road connection, is distributed among villages of different characteristics. Would remote villages gain significantly more or less compared to villages that are located near roads or population centers? Theoretically, the answer is ambiguous. On one hand, non-remote villages gain less from road expansion because they would face competition from remote villages that may now have improved access to market centers. On the other hand, the decrease in trade costs might not be large enough for remote villages to engage in trade with distant markets but significant enough for villages near markets to engage in trade. In this subsection, I use villages' distance from nearest town (population center with more than 20,000 population), distance to major trunk roads which are considered as main trade routes (trunk roads include inter-state roads, roads connecting the Zone capitals to Addis Ababa and roads that connect to neighboring countries), and distance to pre-URRAP road networks as measure of remoteness.

Table 9 reports the estimation result. To facilitate interpretation, the distance measures are standardized so that the coefficients are interpreted as the effect of one standard deviation increase in distance relative to average. Panel A reports results using the binary treatment indicator, Panel B reports OLS estimates based on market access approach, and Panel C reports the corresponding IV results. Across all the three panels, remoteness is associated with lower welfare gain from road expansion. Focusing on the IV results in Panel C, column 1 implies that villages that are one standard deviation further from population center (compared to a village with average distance) gain about 15% less in welfare. Columns 2 implies that villages that are one standard deviation further from trunk roads (compared to a village with average distance) gain 11% less in welfare. Columns 3 implies that villages that are one standard deviation further from pre-URRAP roads (compared to a village with average distance) gain less than half of the

welfare gain by a village with average distance. To sum up, remote villages gain much less in welfare compared to non-remote villages suggesting that authorities may also have economic reason to prioritize non-remote villages in road infrastructure, in addition to the obvious technical reason of connecting the near villages to facilitate access to the remote ones.

6 Conclusions

In this paper, I estimate the welfare gain from a massive rural road expansion in Ethiopia. I develop a Ricardian trade model with multi-crop multi-location feature where land productivity is allowed to vary both within and across villages to study the key mechanisms through which roads affect village welfare. On the demand side, a representative farmer in each village maximizes utility by choosing optimal quantities of crops to consume, given prices. On the production side, the representative farmer decides how to allocate its limited farmland across potential crops, given local prices and local productivity of crops. A village also engages in costly trade with other villages.

The model gives sharp predictions about the effects of decreases in trade costs on village land allocation across crops and village prices of crops. However, the model implies that the size of welfare gain from roads could vary across villages. While a decrease in trade cost leads to increases in village income by inducing reallocation of crops towards village CA-crops and enables farmers receive better prices for these crops, it also leads to increase in the cost of consumption baskets for the villagers. The size of net welfare gain depends on the strength of these two contrasting forces, which in turn depends on the composition of the villages' CA-crops vis-a-vis their consumption baskets.

I directly test the model's predictions using micro data on agricultural production, crop prices, and geospatial data on the entire road network before and after the road expansion program. To address the potential endogeneity of road placements, I use road network predicted solely based on cost considerations (land gradient, and location of rivers and lakes) to construct an instrumental variable for the actual road network. First, the road expansion led to significant increases in the relative prices of CA-crops by 1.62% for a village with average increase in market access. Second, the road expansion led to reallocation of farmland towards a village's CA-crops – the fraction of land allocated to CA-crops increased by about 3% for a village with average increase in market access.

Finally, I estimate the welfare gain from the road expansion in a reduced-form regression and decompose the estimated total welfare gain from road into the trade mechanism captured in my model and other potential mechanisms not in the model. To do so, I derive a sufficient statistic for the welfare effect of roads from the model. This sufficient statistic is similar to those in workhorse Ricardian trade models, but it can be inferred only from data on land allocation and the model parameters which I directly estimate. I estimate a total welfare gain of 14% from the road expansion between 2012-2016 for a village with average increase in market access, and 7.5% of this is attributed to the mechanisms suggested in the trade model (reallocation of farmland towards CA-crops, obtaining higher prices for CA-crops, and cheaper prices of non-local crops).

While the paper is silent on what accounts for the remaining welfare gains, several other mechanisms through which roads can improve welfare can be imagined. In particular, future studies may explore how road connectivity might affect accessibility of health services and agricultural inputs, such as fertilizer and extension services, which are critical for agricultural productivity. Anecdotal reports show that construction of rural roads have significantly improved maternal and child health by facilitating faster access to health stations using modern transport.

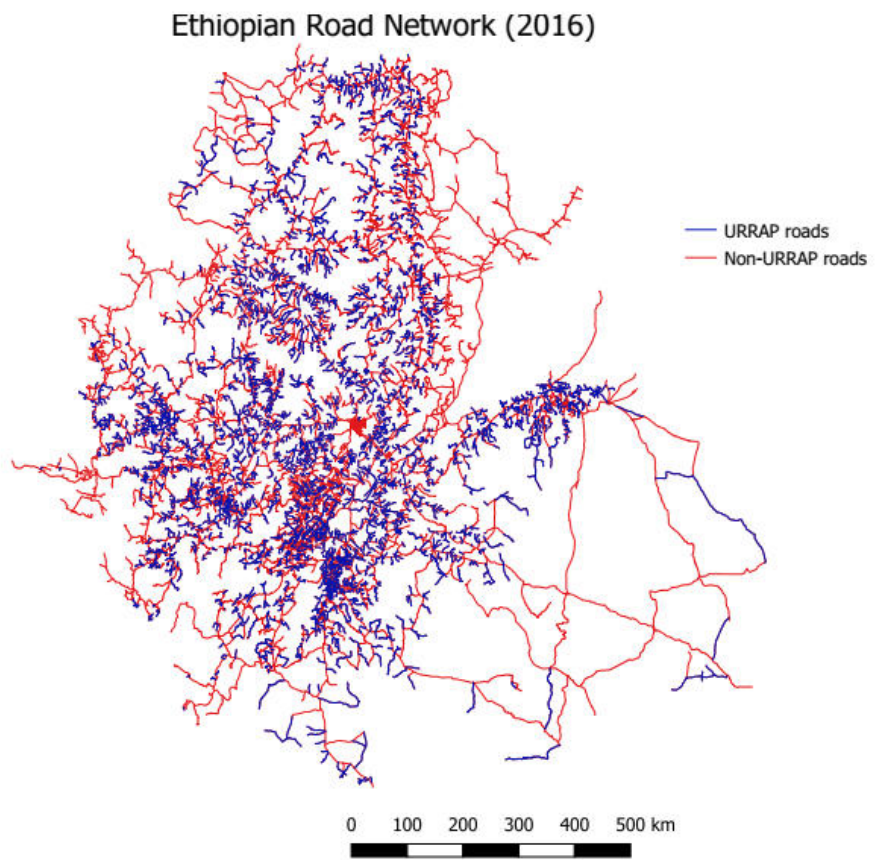


Figure 1: Rural road expansion under URRAP

Figure 2: Completed URRAP roads (pictures are taken from Oromia Roads Authority).



Table 1: Market access measure and first-stage regression

	Dependent Variable: log actual market access		
	(1)	(2)	(3)
Post	0.456*** (0.009)	0.252*** (0.006)	-0.130*** (0.022)
URRAP			
Post*URRAP		0.420*** (0.015)	
LogPredictedMarketAccess			0.560*** (0.024)
<i>N</i>	4332	4332	4332
<i>R</i> ²	0.937	0.954	0.957

Notes: Robust standard errors in parenthesis. All regressions include village fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: URRAP road access and trade costs

	Dependent Variable: log(Price in Zone Capital/Price in village)		
	All crops	Vegetables and Fruits	Cases where dep. var >0
Post*URRAP	-0.031** (0.016)	-0.079* (0.044)	-0.024* (0.013)
<i>N</i>	82944	24468	67147
<i>R</i> ²	0.378	0.360	0.493

Notes: Standard errors are clustered at village level. This table is based on AgPPS and RPS datasets. The regression includes 422 villages, 57 urban centers, and 56 crops. All regressions include village, crop-month, and year fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Rural roads and the link between local prices and local yield: the dependent variable is crop-village level prices in 2012 and 2015.

	(1)	(2)	(3)
Panel A: Binary Treatment			
LogYield	-0.036*** (0.003)		-0.027*** (0.003)
Post*URRAP		0.017 (0.023)	-0.083*** (0.023)
LogYield*Post*URRAP			0.009*** (0.003)
<i>N</i>	59270	59270	59270
<i>R</i> ²	0.752	0.739	0.776
Panel B: Market access approach			
LogYield	-0.036*** (0.003)		-0.099*** (0.026)
LogMarketAccess		-0.026** (0.012)	-0.043** (0.020)
LogYield*LogMarketAccess			0.006** (0.003)
<i>N</i>	59270	59270	59270
<i>R</i> ²	0.790	0.780	0.795

Notes: Standard errors are clustered at village level. The regression includes 277 villages, and 20 crops. All regressions include crop and year fixed effects, and log rainfall as a control. The last column includes village fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Road construction and reallocation of farmland towards CA-crops

	Definition of CA-crops:			
	Top 20%	Top 30%	Top 40%	Top 50%
Panel A: Binary treatment				
CA-crop	0.042*** (0.003)	0.050*** (0.003)	0.056*** (0.002)	0.055*** (0.002)
Post*URRAP	-0.003** (0.002)	-0.004** (0.002)	-0.004** (0.002)	-0.005** (0.002)
CA-crop*Post*URRAPs	0.009** (0.005)	0.008** (0.004)	0.006* (0.004)	0.007** (0.003)
<i>N</i>	34839	34839	34839	34839
adj. R^2	0.340	0.347	0.353	0.352
Panel B: Market access approach – OLS				
CA-crop	-0.080** (0.034)	-0.054* (0.030)	-0.015 (0.028)	-0.007 (0.027)
LogMarketAccess	-0.004** (0.002)	-0.005** (0.002)	-0.005** (0.002)	-0.005** (0.002)
CA-crop*LogMarketAccess	0.013*** (0.003)	0.011*** (0.003)	0.007** (0.003)	0.007** (0.003)
<i>N</i>	34839	34839	34839	34839
adj. R^2	0.340	0.348	0.353	0.352
Panel C: Market access approach – IV				
CA-crop	-0.082** (0.033)	-0.054* (0.029)	-0.014 (0.027)	-0.009 (0.026)
LogMarketAccess	-0.005 (0.003)	-0.005* (0.003)	-0.005 (0.003)	-0.005 (0.003)
CA-crop*LogMarketAccess	0.013*** (0.003)	0.011*** (0.003)	0.007*** (0.003)	0.007** (0.003)
<i>N</i>	34815	34815	34815	34815
adj. R^2	0.278	0.286	0.292	0.291
Mean land share (CA-crops) in 2012	0.159	0.162	0.160	0.153
Mean land share (all) in 2012	0.118	0.118	0.118	0.118

Notes: Standard errors are clustered at village level. These regressions include 25 major non-tree crops. Each column represents different cutoff for definition of CA-crops. In column 1, CA-crops are crops in the top 20% of within village ranking of crops based on yield relative to national average. In column 2 CA-crops are top 30% in the ranking, and so forth. All regressions include village, crop and year fixed effects. Panel A uses binary treatment dummy. Panel B uses market access measure constructed from the entire road network before and after the program, and pre-program spatial population distribution. Panel C uses market access measure constructed from *predicted* road network using land gradient and location of rivers and lakes as an instrument for market access measure constructed from *actual* road network. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: New road construction and prices of CA-crops

	Definition of CA-crops:			
	Top 20%	Top 30%	Top 40%	Top 50%
Panel A: Binary treatment				
CA-crop	-0.023** (0.011)	-0.029*** (0.011)	-0.038*** (0.011)	-0.048*** (0.013)
Post*URRAP	0.013 (0.019)	0.022 (0.020)	0.023 (0.021)	0.029 (0.023)
Post*URRAP*CA-crop	0.017 (0.022)	-0.009 (0.020)	-0.009 (0.021)	-0.016 (0.021)
<i>N</i>	31737	31737	31737	31737
adj. R^2	0.800	0.800	0.800	0.801
Panel B: Market access approach – OLS				
CA-crop	-0.303** (0.125)	-0.305** (0.122)	-0.293** (0.134)	-0.306** (0.149)
LogMarketAccess	0.001 (0.025)	-0.003 (0.024)	-0.005 (0.024)	-0.008 (0.025)
LogMarketAccess * CA-crop	0.029** (0.012)	0.028** (0.012)	0.026* (0.013)	0.026* (0.015)
<i>N</i>	31737	31737	31737	31737
adj. R^2	0.800	0.800	0.801	0.801
Panel C: Market access approach – IV				
CA-crop	-0.369*** (0.134)	-0.318** (0.131)	-0.253* (0.133)	-0.234 (0.146)
LogMarketAccess	-0.028 (0.051)	-0.030 (0.050)	-0.030 (0.050)	-0.028 (0.050)
LogMarketAccess * CA-crop	0.036*** (0.013)	0.029** (0.013)	0.022 (0.013)	0.018 (0.015)
<i>N</i>	31737	31737	31737	31737
adj. R^2	0.728	0.728	0.728	0.729

Notes: Standard errors are clustered at village level. The dependent variable is log village crop price. The analysis includes 25 major non-tree crops and over 450 nationally representative rural villages. Each column represents different cutoff for definition of CA-crops. In column 1, CA-crops are crops in the top 20% of within village ranking of crops based on yield relative to national average. In column 2 CA-crops are top 30% in the ranking, and so forth. All regressions include village, crop-month and year fixed effects. Panel A uses binary treatment dummy. Panel B uses market access measure constructed from the entire road network before and after the program, and pre-program spatial population distribution. Panel C uses market access measure constructed from *predicted* road network using land gradient and location of rivers and lakes as an instrument for market access measure constructed from *actual* road network. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: New road construction and village price index

	Binary treatment	Market access – OLS	Market access – IV
Post	0.208*** (0.019)	0.232*** (0.020)	0.207*** (0.032)
Post * URRAP	0.057** (0.026)		
LogMarketAccess		0.005 (0.035)	0.075 (0.070)
N	9041	9041	9041
adj. R^2	0.907	0.907	0.785

Notes: Robust standard errors in parenthesis. The regression includes 450 villages. The price index is computed from the 25 major non-tree crops in the main analysis and using elasticity of substitution estimated in section 5. All regressions include village and month fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: The welfare gains from new rural roads

	lnW	ln Λ	lnW
Panel A: Binary treatment			
Post*URRAP	0.169*** (0.060)	0.264*** (0.087)	0.050 (0.046)
Sufficient Statistic			0.453*** (0.013)
N	4148	4148	4148
R^2	0.886	0.835	0.936
Panel B: Market access approach – OLS			
LogMarketAccess	0.209*** (0.075)	0.229** (0.101)	0.105* (0.055)
Sufficient Statistic			0.453*** (0.013)
N	4148	4148	4148
R^2	0.886	0.835	0.936
Panel C: Market access approach – IV			
LogMarketAccess	0.313** (0.128)	0.343* (0.186)	0.157 (0.096)
Sufficient Statistic			0.453*** (0.011)
N	4148	4148	4148
R^2	0.003	0.007	0.438

Notes: Robust standard errors in parenthesis. All regressions include year and village fixed effects. The estimation is based on 25 non-tree crops for which full information on prices and quantities of production is available. Panel A uses binary treatment dummy. Panel B uses market access measure constructed from the entire road network before and after the program, and pre-program spatial population distribution. Panel C uses market access measure constructed from *predicted* road network using land gradient and location of rivers and lakes as an instrument for market access measure constructed from *actual* road network. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Welfare gain: cereal vs non-cereal villages

	The dependent variable is log real revenue per hectare $\ln W$		
	Binary treatment	Market access: OLS	Market access: IV
Post*URRAP	0.165*** (0.060)		
Post*URRAP*CerealShare	-0.093** (0.045)		
LogMarketAccess		0.224*** (0.074)	0.333*** (0.127)
LogMarketAccess*CerealShare		-0.009*** (0.002)	-0.009*** (0.002)
N	4128	4128	4128
adj. R^2	0.770	0.771	0.01

Notes: Robust standard errors in parenthesis. The first column reports results based on binary treatment dummy. The second column reports OLS results based on market access approach. The third column reports IV results where market access from *predicted* road network is used as an IV for market access measure based on *actual* road network. All regressions include year and village fixed effects. The estimation is based on 25 non-tree crops for which full information on prices and quantities of production is available. *CerealShare* is the share of farmland allocated to cereal crops in a village in the year 2011. Cereal crops include: Barley, Wheat, Maize, Teff, Sorghum, Millet, and Enset. Non-cereal crops include all vegetables, legumes and cash-crops which are predominantly produced for market. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Remoteness and welfare gain from new roads

The dependent variable is log real revenue per hectare $\ln W$			
	Distance to town	Distance to trunk roads	Distance to pre-URRAP roads
Panel A: Binary treatment			
Post*URRAP	0.091 (0.062)	0.113* (0.062)	0.113* (0.062)
Post*URRAP*Distance	-0.145*** (0.056)	-0.061 (0.050)	-0.026 (0.049)
N	3914	3914	3914
adj. R^2	0.747	0.746	0.746
Panel B: Market access approach – OLS			
LogMarketAccess	0.090 (0.080)	0.217*** (0.080)	0.196** (0.080)
LogMarketAccess * Distance	-0.217*** (0.082)	-0.198*** (0.061)	-0.125** (0.057)
N	3914	3914	3914
adj. R^2	0.747	0.747	0.747
Panel C: Market access approach – IV			
LogMarketAccess	0.127 (0.135)	0.409*** (0.142)	0.379*** (0.145)
LogMarketAccess * Distance	-0.345*** (0.103)	-0.241*** (0.076)	-0.158** (0.068)
N	3914	3914	3914

Notes: Robust standard errors in parenthesis. Distance measure is standardized so that the coefficients are interpreted as the effect of one standard deviation increase in distance. The first column uses distance to the nearest town with above 20,000 population. The second column uses distance to the nearest trunk road (inter-state roads and roads connecting zone capitals to the center). The third column uses distance to pre-existing road network. All regressions include year and village fixed effects. The estimation is based on 25 non-tree crops for which full information on prices and quantities of production is available. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendices

A Construction of market access measure

I follow [Donaldson and Hornbeck \(2016\)](#) to construct market access measure for each village derived from general equilibrium trade models. I use spatial distribution of population before the road program, and pre- and post-program entire road network of the country to construct the market access measure.

$$MarketAccess_{ot} = \sum_d \tau_{odt}^{-\theta} Population_d \quad (15)$$

where $Population_d$ is destination village population from the 2007 census (before the onset of the URRAP program). Using pre-URRAP population distribution is necessary because population distribution is likely to respond to improvement in road infrastructure. θ is the inverse land heterogeneity parameter (which governs trade elasticity), which I estimate in section 5.

τ_{odt} is the freight costs of transporting one ton of cargo from origin village o to destination village d along the least cost path, before ($t = 0$) and after ($t = 1$) the construction of URRAP roads.¹⁷ I use the following procedure to estimate τ_{odt} for each year. First, I construct a link from each village centroid to the nearest available road in year t . Next, I use data on costs of moving weight (in USD per ton-kilometer) for five different road quality levels: asphalt, major gravel, cobbled road, minor gravel, and earth road. Because there is no similar cost estimates along the link roads, I scale up the costs along earth road by the factor of $\frac{Cost\ along\ earth\ road}{Cost\ along\ minor\ gravel}$ to obtain estimate of cost along the links.¹⁸ After assigning each road type (including the links) with the estimated costs in USD per ton-kilometer, I use Network Analysis tool in ArcGIS to calculate the costs (in USD) of moving a ton of weight from origin o to destination d along the least cost path, in each year. I use these estimates as τ_{odt} . As can be seen in equation 15, a change to a village's market access comes only from changes in τ_{odt} , which in turn comes from construction of new roads.

¹⁷Alternatively, I use travel time along the least (time) cost path, instead of freight costs. The market access measures are strongly correlated (correlation of 0.92).

¹⁸I show that the results are robust to using alternative scales that are half or twice of the baseline scale $\frac{Cost\ along\ earth\ road}{Cost\ along\ minor\ gravel}$.

B Construction of the instrumental variable

I use two main information to construct the predicted road network. The first is regional budget constraint, which is the total road length planned to be constructed in 2010 in each of the seven Ethiopian regions covered under the URRAP.¹⁹ The second is a cost raster. I combine land gradient, location of rivers, and location of lakes data to obtain the cost raster, which gives me the costs of road construction in every 30meter-by-30meter grid cell. Given the cost raster and regional budget constraint, I use the following algorithm to obtain the predicted road network. First, I start by connecting villages that are adjacent to the pre-URRAP road network. Next, I connect villages that neighbor the first group to either the pre-URRAP road or to the roads constructed in step-1 (whichever option is less costly). I iterate this procedure until the regional budget is exhausted. For two of the seven regions (Oromia and Harari), the regional budget constraint is not binding. That is, I was able to connect all villages in those regions before exhausting the respective regional budgets. This is because the planned road lengths take into account several other factors than just construction costs, and as a result tend to be longer than the predicted roads based only on construction costs.

Once I get the predicted road network, I follow exactly the same procedure as in appendix A to construct market access measure based on the predicted roads. I assume freight cost on all the predicted roads is equal to that of minor gravel roads (almost all the URRAP roads are minor gravel roads).

C Derivation of the conditional distribution of productivity and rental rate

Because the distribution of rental rate of a plot depends on the distribution of productivity of land, we need to first derive the distribution of land productivity conditional on the land being used for crop k , i.e., $z_i^k(\omega)|\omega \in \Omega_i^k$, which I denote as $G_i^k(t)$. This derivation of conditional

¹⁹While the initial URRAP plan included all the nine Ethiopian regions, two regions (Afar and Somali) were dropped from the project later.

distribution of land quality is similar to [Sotelo \(2018\)](#):

$$\begin{aligned}
G_i^k(t) &= \mathcal{P}[z_i^k(\omega) < t | p_i^k z_i^k(\omega) = \max_l p_i^l z_i^l(\omega)] \\
&= \frac{\mathcal{P}[z_i^k(\omega) < t \wedge p_i^k z_i^k(\omega) = \max_l p_i^l z_i^l(\omega)]}{\mathcal{P}[p_i^k z_i^k(\omega) = \max_l p_i^l z_i^l(\omega)]} \\
&= \frac{1}{\eta_i^k} \mathcal{P}[z_i^k(\omega) < t \wedge p_i^l z_i^l(\omega) < p_i^k z_i^k(\omega), \quad \forall l] \\
&= \frac{1}{\eta_i^k} \mathcal{P}[\frac{p_i^l}{p_i^k} z_i^l(\omega) < z_i^k(\omega) < t, \quad \forall l] \\
&= \frac{1}{\eta_i^k} \int_0^t \Pi_{l \neq k} \mathcal{P}[\frac{p_i^l}{p_i^k} z_i^l(\omega) < v] f_i^k(v) dv
\end{aligned}$$

Using the distribution of $z_i^k(\omega)$:

$$\begin{aligned}
G_i^k(t) &= \frac{1}{\eta_i^k} \int_0^t \Pi_{l \neq k} \exp((-A_i^l)^\theta (\frac{p_i^k}{p_i^l} v)^{-\theta}) \quad \theta (A_i^k)^\theta v^{-\theta-1} \exp(-(A_i^k)^\theta v^{-\theta}) dv \\
&= \frac{1}{\eta_i^k} \int_0^t \exp(- (p_i^k v)^{-\theta} \sum_{l \neq k} (A_i^l p_i^l)^\theta) \exp(-(A_i^k)^\theta v^{-\theta}) \quad \theta (A_i^k)^\theta v^{-\theta-1} dv \\
&= \frac{1}{\eta_i^k} \int_0^t \exp(- (p_i^k v)^{-\theta} \sum_l (A_i^l p_i^l)^\theta) \quad \theta (A_i^k)^\theta v^{-\theta-1} dv \\
&= \int_0^t \exp(- (p_i^k v)^{-\theta} \Phi_i^\theta) \quad \theta \Phi_i^\theta (p_i^k)^{-\theta} v^{-\theta-1} dv \\
&= \exp\left(- \left(\frac{\Phi_i}{p_i^k}\right)^\theta t^{-\theta}\right)
\end{aligned}$$

Thus, the distribution of productivity of the set plots in village i 's which are covered by crop k is a Fréchet with the parameters $\frac{\Phi_i}{p_i^k}$ and θ . Notice that the average productivity of land covered with a crop decreases with the crop price. Intuitively, more and more land is allocated to a crop with higher price which leads to a decrease in the average quality of land allocated to the crop.

Recall that the rental rate on plot ω , conditional on ω being used for crop k , is given by $r(\omega) = \max_k \{p_i^k z_i^k(\omega)\}$. Thus the conditional distribution of rental rate $r(\omega) | \omega \in \Omega_i^k$ is Fréchet with parameters Φ_i and θ . That is, the rental rate of plots covered with different crops have the same distribution regardless of which crops are planted. This result follows from the property of the Fréchet distribution and the fact that $r(\omega)$ is homogeneous of degree one in crop prices.

D Appendix Tables

Table A.1: Road construction and reallocation of farmland towards CA-crops: all crops

	Definition of CA-crops:			
	Top 20%	Top 30%	Top 40%	Top 50%
Panel A: Binary treatment				
CA-crop	0.021*** (0.002)	0.027*** (0.002)	0.031*** (0.001)	0.030*** (0.001)
Road Access	-0.002** (0.001)	-0.004*** (0.001)	-0.003** (0.001)	-0.003** (0.001)
CA-crop*Road Access	0.008*** (0.003)	0.009*** (0.002)	0.005** (0.002)	0.004** (0.002)
<i>N</i>	56211	56211	56211	56211
adj. <i>R</i> ²	0.359	0.363	0.366	0.365
Panel B: Market access approach – OLS				
CA-crop	-0.060*** (0.020)	-0.041** (0.017)	-0.036** (0.016)	-0.018 (0.015)
LogMarketAccess	-0.003** (0.001)	-0.003*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)
CA-crop*LogMarketAccess	0.009*** (0.002)	0.007*** (0.002)	0.007*** (0.002)	0.005*** (0.002)
<i>N</i>	56211	56211	56211	56211
adj. <i>R</i> ²	0.359	0.364	0.366	0.365
Panel C: Market access approach – IV				
CA-crop	-0.068*** (0.020)	-0.045*** (0.017)	-0.041** (0.016)	-0.024 (0.015)
LogMarketAccess	-0.002 (0.002)	-0.003 (0.002)	-0.004** (0.002)	-0.003* (0.002)
CA-crop*LogMarketAccess	0.009*** (0.002)	0.008*** (0.002)	0.007*** (0.002)	0.006*** (0.002)
<i>N</i>	56211	56211	56211	56211
adj. <i>R</i> ²	0.306	0.312	0.314	0.313
Mean land share (CA-crops) in 2012	0.097	0.101	0.101	0.096
Mean land share (all) in 2012	0.073	0.073	0.073	0.073

Notes: Standard errors are clustered at village level. The analysis includes 45 crops. Each column represents different cutoff for definition of CA-crops. In column 1, CA-crops are crops in the top 20% of within village ranking of crops based on yield relative to national average. In column 2 CA-crops are top 30% in the ranking, and so forth. All regressions include village, crop and year fixed effects. Panel A uses binary treatment dummy. Panel B uses market access measure constructed from the entire road network before and after the program, and pre-program spatial population distribution. Panel C uses market access measure constructed from *predicted* road network using land gradient and location of rivers and lakes as an instrument for market access measure constructed from *actual* road network. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Road construction and reallocation of farmland towards CA-crops: based on GAEZ yield measure

	Definition of CA-crops:			
	Top 20%	Top 30%	Top 40%	Top 50%
Panel A: Binary treatment				
CA-crop	0.062*** (0.005)	0.071*** (0.004)	0.076*** (0.004)	0.077*** (0.004)
Post*URRAP	-0.002 (0.003)	-0.000 (0.004)	0.001 (0.004)	-0.002 (0.004)
CA-crop*Post*URRAP	0.015* (0.008)	0.009 (0.007)	0.006 (0.007)	0.008 (0.006)
<i>N</i>	22466	22466	22466	22466
adj. <i>R</i> ²	0.322	0.330	0.335	0.336
Panel B: Market access approach – OLS				
CA-crop	0.012 (0.057)	0.054 (0.052)	0.082 (0.050)	0.099** (0.048)
LogMarketAccess	-0.002 (0.004)	0.001 (0.004)	0.003 (0.004)	0.003 (0.005)
CA-crop*LogMarketAccess	0.006 (0.006)	0.002 (0.005)	-0.000 (0.005)	-0.002 (0.005)
<i>N</i>	22466	22466	22466	22466
adj. <i>R</i> ²	0.322	0.330	0.335	0.336
Panel C: Market access approach – IV				
CA-crop	-0.025 (0.058)	0.033 (0.052)	0.068 (0.050)	0.087* (0.048)
LogMarketAccess	-0.008 (0.007)	-0.004 (0.007)	-0.002 (0.007)	-0.002 (0.007)
CA-crop*LogMarketAccess	0.009 (0.006)	0.004 (0.005)	0.001 (0.005)	-0.001 (0.005)
<i>N</i>	22466	22466	22466	22466
adj. <i>R</i> ²	0.300	0.308	0.313	0.314
Mean land share (CA-crops) in 2012	0.198	0.207	0.209	0.2015
Mean land share (all) in 2012	0.176	0.176	0.176	0.176

Notes: Standard errors are clustered at village level. The analysis includes 19 GAEZ crops. Each column represents different cutoff for definition of CA-crops. In column 1, CA-crops are crops in the top 20% of within village ranking of crops based on yield relative to national average. In column 2 CA-crops are top 30% in the ranking, and so forth. All regressions include village, crop and year fixed effects. Panel A uses binary treatment dummy. Panel B uses market access measure constructed from the entire road network before and after the program, and pre-program spatial population distribution. Panel C uses market access measure constructed from *predicted* road network using land gradient and location of rivers and lakes as an instrument for market access measure constructed from *actual* road network. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: New road construction and prices of CA-crops: all crops

	Definition of CA-crops:			
	Top 20%	Top 30%	Top 40%	Top 50%
Panel A: Binary treatment				
CA-crop	-0.040*** (0.013)	-0.041*** (0.011)	-0.046*** (0.011)	-0.038*** (0.011)
Post* URRAP	0.028 (0.018)	0.025 (0.019)	0.027 (0.019)	0.044** (0.021)
Post*URRAP*CA-crop	0.041* (0.021)	0.027 (0.018)	0.022 (0.017)	-0.009 (0.018)
<i>N</i>	41930	41930	41930	41930
adj. <i>R</i> ²	0.798	0.785	0.799	0.799
Panel B: Market access approach – OLS				
CA-crop	-0.389*** (0.129)	-0.234** (0.113)	-0.249** (0.109)	-0.188 (0.119)
LogMarketAccess	0.009 (0.026)	0.010 (0.026)	0.006 (0.027)	0.007 (0.028)
LogMarketAccess * CA-crop	0.036*** (0.013)	0.020* (0.011)	0.021* (0.011)	0.015 (0.012)
<i>N</i>	41930	41930	41930	41930
adj. <i>R</i> ²	0.798	0.799	0.799	0.799
Panel C: Market access approach – IV				
CA-crop	-0.398*** (0.139)	-0.260** (0.122)	-0.267** (0.118)	-0.156 (0.125)
LogMarketAccess	-0.040 (0.050)	-0.040 (0.050)	-0.043 (0.050)	-0.039 (0.051)
LogMarketAccess * CA-crop	0.037*** (0.014)	0.023* (0.012)	0.023* (0.012)	0.012 (0.013)
<i>N</i>	41928	41928	41928	41928
adj. <i>R</i> ²	0.740	0.740	0.741	0.740

Notes: Standard errors are clustered at village level. The dependent variable is log village crop price. The analysis includes 45 crops and over 450 nationally representative rural villages. Each column represents different cutoff for definition of CA-crops. In column 1, CA-crops are crops in the top 20% of within village ranking of crops based on yield relative to national average. In column 2 CA-crops are top 30% in the ranking, and so forth. All regressions include village, crop-month and year fixed effects. Panel A uses binary treatment dummy. Panel B uses market access measure constructed from the entire road network before and after the program, and pre-program spatial population distribution. Panel C uses market access measure constructed from *predicted* road network using land gradient and location of rivers and lakes as an instrument for market access measure constructed from *actual* road network. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Road construction and prices of CA-crops: based on GAEZ yield measure

	Definition of CA-crops:			
	Top 20%	Top 30%	Top 40%	Top 50%
Panel A: Binary treatment				
CA-crop	-0.089*** (0.018)	-0.093*** (0.018)	-0.097*** (0.018)	-0.074*** (0.017)
Post*URRAP	-0.006 (0.021)	-0.030 (0.022)	-0.043* (0.023)	-0.046* (0.025)
CA-crop*Post*URRAP	0.090*** (0.022)	0.121*** (0.022)	0.128*** (0.025)	0.118*** (0.026)
<i>N</i>	21428	21428	21428	21428
adj. R^2	0.761	0.762	0.762	0.761
Panel B: Market access approach – OLS				
CA-crop	-0.591*** (0.179)	-0.506*** (0.195)	-0.415** (0.199)	-0.294 (0.196)
LogMarketAccess	0.014 (0.032)	0.010 (0.032)	0.012 (0.032)	0.015 (0.033)
LogMarketAccess * CA-crop	0.053*** (0.018)	0.045** (0.020)	0.036* (0.020)	0.025 (0.020)
<i>N</i>	21428	21428	21428	21428
adj. R^2	0.761	0.760	0.760	0.760
Panel C: Market access approach – IV				
CA-crop	-1.018*** (0.186)	-0.879*** (0.204)	-0.771*** (0.212)	-0.665*** (0.211)
LogMarketAccess	-0.038 (0.058)	-0.041 (0.057)	-0.038 (0.058)	-0.043 (0.059)
LogMarketAccess * CA-crop	0.096*** (0.019)	0.083*** (0.021)	0.072*** (0.021)	0.063*** (0.021)
<i>N</i>	21423	21423	21423	21423
adj. R^2	0.686	0.686	0.686	0.685

Notes: Standard errors are clustered at village level. The dependent variable is log price of crop. This regression analysis includes 19 crops for which GAEZ yield measure is available. Each column represents different cutoff for definition of CA-crops. In column 1, CA-crops are crops in the top 20% of within village ranking of crops based on yield relative to national average. In column 2 CA-crops are top 30% in the ranking, and so forth. All regressions include village, year and crop-month fixed effects. Panel A uses binary treatment dummy. Panel B uses market access measure constructed from the entire road network before and after the program, and pre-program spatial population distribution. Panel C uses market access measure constructed from *predicted* road network using land gradient and location of rivers and lakes as an instrument for market access measure constructed from *actual* road network. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E Robustness: Matching-Based Difference-in-Differences

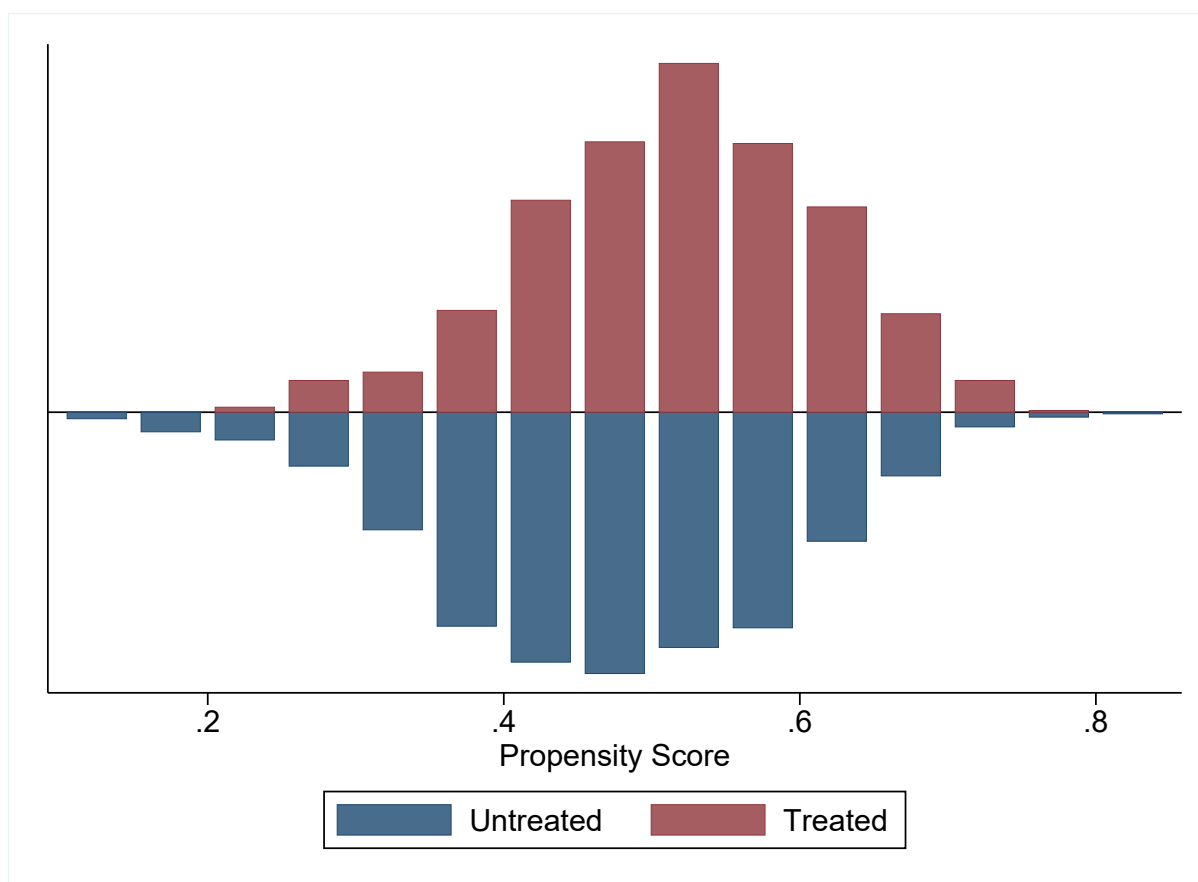
As a further robustness exercise, I also use a Matching-Based Difference-in-Differences (MB-DID) strategy to address endogeneity of road placement. That is, I first obtain a matched sample of treated and non-treated villages based on their observable characteristics that might be relevant for selection of villages for URRAP. I then conduct DID estimation using the matched sample. Combining matching with DID strategy is a powerful approach to address the selection problem. The matching step enables me to compare treated villages with non-treated villages that have similar observed characteristics and hence have similar treatment probability. The DID strategy on these matched sample helps me to washout unobserved time-invariant village characteristics that may confound the treatment effect.

To identify relevant village characteristics for matching treated and non-treated villages, I use information from officials at Ethiopian Roads Authority (ERA). They suggest that the main factors determining whether a village would be selected for URRAP in a particular year are: (1) the village's distance to preexisting road network, (2) population density of the village, and (3) the terrain and landscape of the village. Distance to preexisting roads is crucial because movement of machineries and other construction materials to the construction sites, by itself, requires roads that are passable by vehicles. Population density is relevant both for political consideration and the project's labor input requirements.²⁰ Finally, terrain and landscape significantly affects the road construction costs. Villages that require many bridge constructions or cutting and digging of hills are usually less favorable due to cost considerations. Based on these insights from the officials, I use the following list of variables to match treated and non-treated villages: distance to nearest town, distance to preexisting road network, population size, average slope of land in the village, average elevation in the village, and average rainfall over 1990-2010 period. I use Digital Elevation Model (DEM) data and ArcGIS tools to calculate average slope and elevation of each village.

Given these set of village characteristics, I use the *gmatch* command in STATA (for its handiness in panel data setting) to match treated and non-treated villages. For each treated village, the *gmatch* algorithm finds, non-treated village(s) that has/have the closest observed characteristics or propensity score. I conduct a DID estimation on these matched samples of treated and non-treated villages. Figure A.1 shows the histogram of propensity score by

²⁰Most of the labor input for the URRAP roads are contributed by local residents, about three-quarters of which is a free labor.

Figure A.1: Common support of propensity score matching



treatment status. The figure clearly shows that the region of common support is large as very few non-treated villages lie outside the common support. Table A.5 reports the balancing of the matching variables. All the t-statistics are insignificant and the bias percentage is small.

Table A.5: Balancing of variables for Average Treatment Effect on Treated (ATT)

	Treated	Control	% bias	t-stat	p-value
Distance to nearest town (meters)	10596	10417	2.2	0.57	0.571
Distance to nearest trunk road (meters)	4551.8	4280.5	6.2	1.47	0.143
Distance to preexisting road network (meters)	1320.5	1221.5	3.6	0.93	0.351
Population	5340.9	5458.1	-3.1	-0.63	0.528
Average slope (degrees)	9.9697	10.018	-0.9	-0.20	0.840
Average altitude (meters)	1946.2	1959.1	-2.3	-0.54	0.587
Rainfall (mm)	1183	1161.1	6.6	1.50	0.133

Notes: Population and rainfall correspond to the period before URRAP.

Table A.6: Road construction and reallocation of farmland towards CA-crops: Matching-Based DID estimation

	Definition of CA-crops:			
	Top 20%	Top 30%	Top 40%	Top 50%
Panel A: Binary treatment				
CA-crop	0.041*** (0.003)	0.049*** (0.003)	0.055*** (0.003)	0.056*** (0.003)
Post*URRAP	-0.004** (0.002)	-0.005** (0.002)	-0.006*** (0.002)	-0.005** (0.002)
CA-crop*Post*URRAP	0.010** (0.005)	0.010** (0.004)	0.010** (0.004)	0.007** (0.004)
<i>N</i>	28030	28030	28030	28030
adj. R^2	0.310	0.318	0.324	0.324
Panel B: Market access approach				
CA-crop	-0.100** (0.040)	-0.091** (0.035)	-0.053 (0.033)	-0.014 (0.031)
LogMarketAccess	-0.005*** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)	-0.006** (0.003)
CA-crop*LogMarketAccess	0.015*** (0.004)	0.014*** (0.004)	0.011*** (0.003)	0.007** (0.003)
<i>N</i>	28030	28030	28030	28030
adj. R^2	0.310	0.318	0.325	0.324
Mean land share (CA-crops) in 2012	0.159	0.162	0.160	0.153
Mean land share (all) in 2012	0.118	0.118	0.118	0.118

Notes: Standard errors are clustered at village level. This regression analysis includes 25 major non-tree crops. Each column represents different cutoff for definition of CA-crops. In column 1, CA-crops are crops in the top 20% of within village ranking of crops based on yield relative to national average. In column 2 CA-crops are top 30% in the ranking, and so forth. All regressions include village, crop and year fixed effects. Panel A uses binary treatment dummy. Panel B uses market access measure constructed from the entire road network before and after the program and pre-program spatial population distribution. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: New road construction and prices of CA-crops: Matching-Based DID estimation

	Definition of CA-crops:			
	Top 20%	Top 30%	Top 40%	Top 50%
Panel A: Binary treatment				
CA-crop	-0.028** (0.011)	-0.033*** (0.011)	-0.040*** (0.012)	-0.047*** (0.013)
Post*URRAP	0.009 (0.020)	0.019 (0.021)	0.022 (0.023)	0.032 (0.025)
Post*URRAP*CA-crop	0.021 (0.024)	-0.008 (0.021)	-0.013 (0.022)	-0.026 (0.023)
<i>N</i>	26786	26786	26786	26786
adj. <i>R</i> ²	0.797	0.797	0.797	0.797
Panel B: Market access approach				
CA-crop	-0.388** (0.151)	-0.387*** (0.141)	-0.382** (0.161)	-0.355* (0.181)
LogMarketAccess	-0.001 (0.026)	-0.006 (0.025)	-0.010 (0.026)	-0.011 (0.026)
LogMarketAccess * CA-crop	0.037** (0.015)	0.036** (0.014)	0.034** (0.016)	0.031* (0.018)
<i>N</i>	26786	26786	26786	26786
adj. <i>R</i> ²	0.797	0.797	0.797	0.798

Notes: Standard errors are clustered at village level. The dependent variable is log village crop price. The analysis includes 25 major non-tree crops and over 450 nationally representative rural villages. Each column represents different cutoff for definition of CA-crops. In column 1, CA-crops are crops in the top 20% of within village ranking of crops based on yield relative to national average. In column 2 CA-crops are top 30% in the ranking, and so forth. All regressions include village, crop-month and year fixed effects. Panel A uses binary treatment dummy. Panel B uses market access measure constructed from the entire road network before and after the program and pre-program spatial population distribution. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: The welfare gains from new rural roads: Matching-Based DID estimation

	lnW	lnΛ	lnW
Panel A: Binary treatment			
Post*URRAP	0.125* (0.067)	0.162* (0.096)	0.050 (0.050)
Sufficient Statistic			0.461*** (0.016)
<i>N</i>	3268	3268	3268
<i>R</i> ²	0.863	0.814	0.923
Panel B: Market access approach			
LogMarketAccess	0.172** (0.082)	0.161 (0.110)	0.098 (0.060)
Sufficient Statistic			0.461*** (0.015)
<i>N</i>	3268	3268	3268
<i>R</i> ²	0.863	0.814	0.923

Notes: Robust standard errors in parenthesis. All regressions include year and village fixed effects. The estimation is based on 25 non-tree crops for which full information on prices and quantities of production is available. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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