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RURAL ROADS, POVERTY, AND RESILIENCE

EVIDENCE FROM ETHIOPIA

Shohei Nakamura
Tom Bundervoet
Mohammed Nuru

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ABSTRACT

This study analyzes the impacts of the recent rural road development in Ethiopia on welfare and economic outcomes. The identification of the impacts relies on a difference-in-differences matching approach, taking advantage of the nationally representative household survey and the original road database, both of which are panel data spanning between 2012 and 2016. The results of the econometric analysis overall suggest that Ethiopia's recent rural road development has substantially increased household welfare and supported households in coping with the recent severe droughts. This study estimates that rural roads increased, on average, household consumption by 16.1 percent between 2012 and 2016 (or 3.8 percent per year). The effects of rural road development were largest in the most remote communities, as it increased household consumption by 27.9 percent. Furthermore, in the communities most affected by the El Niño drought, the likelihood of falling into poverty was 14.4 percent lower between 2012 and 2016 if the community was connected by a rural road. Taken together, the results suggest that, by connecting remote communities to markets, rural roads have substantially increased the welfare and resilience of rural households in shock-prone environments.

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Rural Roads, Poverty, and Resilience: Evidence from Ethiopia[1]

Shohei Nakamura, World Bank[2]

Tom Bundervoet, World Bank

Mohammed Nuru, World Bank

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[2] Corresponding author: snakamura2@worldbank.org.

1. Introduction

Transport development is widely considered as a key to economic growth and poverty reduction in the developing world (Berge et al. 2017). As global poverty is increasingly concentrated in Sub-Saharan Africa (World Bank 2018a) and the majority of the extreme poor live in rural Africa, it is imperative to ensure their access to markets. The provision of access to all-weather feeder roads, or rural roads, is expected to raise living standards in poor rural areas by reducing transport costs between villages and markets and thereby generating market activity, affecting input and output prices, and enhancing agricultural production through the increased use of modern technologies and the changes in crop choice (Hine et al. 2016). Moreover, rural roads potentially promote structural transformation by facilitating non-farm employment.

With such expectations of its fundamental role in economic growth and poverty reduction, a large amount of money has been invested in the development of rural roads in developing countries. Ethiopia is not an exception; the government has put considerable efforts into rural road development. In particular, under the umbrella of the Growth and Transformation Program, the government launched an ambitious program, the Universal Rural Road Access Program (URRAP), in 2010 to promote construction and upgrading of more than 70,000km of rural roads in the country (World Bank 2018b). The program aims to ensure all rural communities of the country have all-weather connections. The program implementation for the first five years cost 28 billion Ethiopian birr, or US$1.4 billion.

Despite the scale of the investment in developing countries and general consensus on the importance of rural roads, empirical evidence on the impacts of rural road development has been scarce. Among various methodological challenges in the impact evaluation of rural road programs, endogeneity problems stemming from the non-random placement of rural roads are particularly difficult to deal with (van de Walle 2009; Blimpo, Harding, and Wantchekon 2013; Burgess et al. 2015; Lehne, Shapiro, and Eynde 2018).[3] Some recent studies focus on India's nationwide rural road program (Pradhan Mantri Gram Sadak Yojana, or PMGSY) (Asher and Novosad 2018; Shamdasani 2016; Aggarwal 2018). They exploit the program's clear criteria for selecting villages, such as population thresholds, in identifying the impacts on agriculture and other outcomes. Unfortunately, such identification strategy cannot be applied to other rural road developments that are not strictly enforced based on objective criteria as in Ethiopia's URRAP.

This study attempts to assess welfare and economic impacts of recent rural road development in Ethiopia by addressing the aforementioned challenges with rich data sets. The analysis focuses on the short-term impacts, within six years from the road development at the longest, yet its study period from 2010 to 2016 covers recent severe droughts, which helps to examine the role of rural roads amid such weather shocks. This study examines the following key questions. First, to what extent has the development of rural roads contributed to the improvements in household welfare and economic activities in rural Ethiopia? Second, who (and which areas) have better/less benefited from the rural road developments? Of particular interest is whether those who are the least connected with markets have gained from the rural road investments. Finally, this study also

[3] Moreover, it is often hard to keep track of the rural road development across time and space if the program covers the entire area of a country. It is becoming common to rely on satellite imageries in economic studies (Donaldson and Storeygard 2017), though rural roads—which are community roads—and their changes in quality are hard to identify with such an approach because of their narrow and short paths.

examines whether the development of rural roads mitigated the welfare shocks from recent severe droughts.

The primary empirical approach is difference-in-differences (DID) matching based on road network and household panel data sets. A panel road network database is constructed for multiple years so that changes over time in rural roads and various welfare and economic outcomes can be compared. For the outcome measures, this study relies on the three waves of a panel household survey—the Ethiopian Socioeconomic Survey (ESS)—which were carried out in 2012, 2014, and 2016. The timing of the data collection was ideal to access the short- and medium-term impacts of rural roads that have been developed under the URRAP since 2010. In addition, the ESS represents a large part of rural Ethiopia, which allows this study to explore locational heterogeneity in the impacts of rural road development. Combining the road database and the ESS data, this study aims to estimate causal impacts by dealing with endogeneity due to nonrandom placement of rural roads. The primary strategy is a DID matching approach (Smith and Todd 2005), as used for the impact analysis of rural road access by Lokshin and Yemtsov (2005) and Mu and van de Walle (2011). Finally, this study analyzes one of the most relevant outcomes from a poverty reduction perspective: household consumption as a welfare measure.

The results of the econometric analysis suggest that Ethiopia's recent rural road development has substantially increased household welfare, supporting households amid the recent severe droughts. It is estimated that rural roads increased household consumption by 16.1 percent between 2012 and 2016. In other words, thanks to the rural roads, households in connected communities increased consumption by 3.8 percent each year during the period. Moreover, households were less likely to fall into or remain in poverty when connected by all-weather roads in drought areas, indicating the mitigating role of rural roads for drought shocks. The study also finds the effects of rural road developments for agriculture and non-agriculture work in communities farther away from towns. More farmers have come to sell their crops once connected to rural roads. In addition, more households—particularly women and the youth—have engaged in wage jobs in remote communities. By connecting to markets, rural roads have widened the economic base in otherwise physically and economically isolated communities.

This study contributes to the literature on the impacts of rural road development. There is a small number of previous studies that evaluate the impacts of rural road development in the developing world.[4] Khandker, Bakht, and Koolwal (2009) examined the impact of road investments on poverty in Bangladesh, finding the overall effect of road improvement on household consumption to be about 8–10 percent in the project areas. By contrast, a recent study of India's PMGSY program by Asher and Novosad (2018) finds no clear impact on household consumption and agricultural outcomes in connected villages.[5] Several studies investigate rural roads in Ethiopia. Dercon et al. (2009), using panel household surveys collected in selected villages between 1994 and 2004, found that access to all-weather roads reduced poverty by 6.9 percent and increased consumption growth

[4] There are some other studies investigating the impacts of rural road access in the developing world. Jalan and Ravallion (2002) find positive impacts of rural roads on consumption growth in China. A study of Vietnam by Mu and van de Walle (2011) found positive impacts of rural road rehabilitation on local market development. Damania et al. (2016) found that transport cost reduction encourages farmers to adopt modern technologies in Nigeria.

[5] Aggarwal (2018) finds lower prices, increased availability of non-local goods, increased use of agricultural technologies, and increased school enrollment among younger children in districts where the PMGSY program was implemented. Another study of the PMGSY by Shamdasani (2016) finds crop diversification among farmers in connected villages.

by 16 percentage points. The findings of a study by Minten, Korn, and Stifel (2013) for northwestern Ethiopia point to the link between higher transport costs and agricultural input prices. Another study by Stifel, Minten, and Koru (2016) suggests that rural feeder roads have internal rates of return of 12–35 percent.

Another collection of literature to which this study is related is about the impacts of disaster shocks on welfare and poverty, and the role that better connectivity can play in alleviating these impacts. As an agrarian economy dependent on smallholder rain-fed agriculture—located in one of the world's most drought-prone regions—Ethiopia has been historically susceptible to drought and, despite recent economic growth, well-being remains highly vulnerable to drought. Several previous studies have analyzed the impacts of droughts on consumption (Gao and Mills 2018; Dercon, Hoddinott, and Woldehanna 2005; Fuje 2017), poverty trap (Carter et al. 2007), long-term nutrition outcomes (Dercon and Porter 2014), and asset and wealth and inequality (Little et al. 2006; Thiede 2014). Recently, research focusing on Ethiopia has also shown that better connectivity can help alleviate the negative effects of drought. Hill and Fuje (2018) examine the effects of droughts on grain prices in Ethiopia, and find that this effect was substantially weaker in the post-2007 period compared to earlier periods, a finding that can partly be explained by better market access through road investments. Focusing on the 2015/16 El Niño drought, Hirvonen et al. (2017) find that the drought negatively affected child nutrition in places that were poorly connected, but not in better-connected places. This study contributes to this line of literature by shedding new light on the role of rural connectivity in potentially alleviating the impact of adverse weather droughts.

The rest of this report is structured as follows. Section 2 reviews the recent placement of rural roads in Ethiopia. Section 3 describes the data: the Ethiopia road database and the ESS. Section 4 explains the empirical strategy to identify and estimate impacts of rural road developments on welfare and other outcomes. Section 5 reports the estimation results of DID matching models. Finally, Section 6 concludes with a brief summary of the findings and discussion.

2. Recent rural road development in Ethiopia

Among several programs that have contributed to recent rural road developments in Ethiopia, the URRAP has provided all-weather connections to rural communities (or kebeles) at the largest scale since 2010.[6] Through the upgrading of existing fair-weather access roads or unimproved tracks, URRAP brings those unclassified roads into the classified network. With 100% funding from the central government and technical support from regional and zonal governments, woredas identify project areas by prioritizing based on population, traffic, and facilities served. However, actual practice of prioritization is unclear and varies regionally. URRAP road construction work is partly the responsibility of the beneficiary communities. Communities in principle carry out site clearance and preliminary earth work as a contribution in kind, yet actual practice differs by regions. On

[6] A 'kebele' is a subdivision of woreda and the smallest administrative unit in Ethiopia. It is similar to a ward, a neighborhood, or parish in other countries. We refer to it as community in the remaining part of this paper. Woreda is an administrative unit of one level higher than kebele.

completion of the community works, a URRAP contractor engaged by the woreda carries out the remainder of the construction.[7]

We focus on rural roads developed between 2010 and 2014. During the initial four years of the URRAP program, the Ethiopian government developed rural roads in about 4,000 communities, reaching nearly 20,000 km in total (Table 1). The number of communities in which any segment of newly developed or upgraded roads was 1,850 (or 13 percent of the total number of rural communities) between 2010 and 2012 and 2,205 (15 percent) between 2012 and 2014.[8] Among the nine regions analyzed, Oromia has the largest number of communities (around 2,500) that received rural roads between 2010 and 2014. The total length of the rural roads developed in Oromia during the period was about 13,000 km, accounting for 64 percent of the total length in the nine regions.

A recent report (World Bank 2018b) shows that connectivity and accessibility of rural Ethiopians have substantially improved since 2010. The average travel time to the nearest town decreased by nearly 30 minutes between 2010 and 2016. An additional 6 percent of rural Ethiopians were connected to rural roads during the same period, as the rural accessibility index (RAI) increased from 46 in 2010 to 52 in 2016.[9] As a result, market accessibility improved except for some lagging regions.[10]

Although a glance of Figure 1 gives the impression that rural road development has taken place all around the country, a comparison of baseline community characteristics illustrates that recent rural road development occurred in communities that were already relatively well connected prior to the placement (Table 2). For example, the communities that have received rural roads (i.e., treated communities) since 2010 were located closer to the nearest towns (91 minutes), compared to the other communities (i.e., untreated communities, 196 minutes). The length of rural roads was already longer in treated communities as of 2010. In addition, treated communities were located in woredas with higher population density. On the other hand, treated communities (or woredas they belong to) were not necessarily better-off in terms of poverty, educational level, and infrastructure and basic services. Nevertheless, this comparison clearly indicates the need to take account of the nonrandom placement in evaluating the impact of rural road development (discussed more in Section 3).

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[7] In addition to the URRAP, the Productive Safety Net Program (PSNP)—a large social protection project providing transfers to food insecure areas—also has a component of rural road construction. Those roads are generally earth roads for very low traffic levels, connecting watersheds to kebeles and other service centers. Some feeder roads were constructed under the Agricultural Growth Program (AGP), which is a program focusing on increasing sustainable agriculture growth in potentially rich, but underdeveloped woredas of the country. See World Bank (2018) for a comprehensive review of Ethiopia's rural road programs.

[8] The identification of URRAP and other rural roads is based on the Ethiopia road database. The total length of those roads does not necessarily correspond to the official records. Somali region and a part of Amhara and Oromia regions are not included for this study due to data availability.

[9] The RAI was measured by the share of population in each community who lives within 2km from any all-weather road. The calculated RAI differs from World Bank (2016) due to the definitions of all-weather roads, as well as the coverages of roads and geographic areas.

[10] Market accessibility index (MAI) was calculated for each community as the sum of the population in the other communities within a certain travel time, as in Donaldson and Hornbeck (2016) and Berge, Blankespoor, and Selod (2016).

3. Data

The road network data in the Ethiopia road database were collected from different sources. Federal Road Network data were obtained from the Ethiopian Roads Authority, the main agency in the Road Sector Development Program (RSDP) and Growth and Transformation Plan (GTP); and district- and woreda-level road data were collected from the Regional Road Authorities. The collected information includes years of new construction, upgrading, and rehabilitation, as well as the volume and distribution of the network in the country. It is important to note that the database includes rural roads that were motorable at the time of the national road inventory carried out in 2015−16. Rural roads in some parts of Oromia and Amhara regions were not covered due to missing bridges, as well as Somali region for security reasons.

In analyzing household-level impacts of the recent rural road development, this study primarily relies on the ESS. The ESS, part of the World Bank supported Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA), started as the Ethiopian Rural Socio-economic Survey (ERSS) in 2012. A sample of about 3,470 households were interviewed in rural areas and re-interviewed in 2014 and 2016. Among the rural communities covered by the ESS, this study focuses on the communities that received rural roads between 2010 and 2014 (i.e., treated group) and the other communities that did not receive rural roads between 2010 and 2016 (i.e., control group). This results in 204 communities, including 59 communities in Amhara, 46 communities in Oromia, 37 communities in SNNPR, 26 communities in Tigray, and 36 communities in the other regions.

The recipient indicator used for the econometric analysis in this study is a binary indicator about whether a rural road passes by within the community's boundary regardless of the road length.[11] How to define households and areas affected by the rural road development is methodologically important. Given the nature of rural roads, this study considers that households in the communities in which rural roads were developed have been affected.[12] Among the 204 communities analyzed for this study, 72 communities had URRAP or other types of rural roads developed between 2010 and 2014. The total length of the segment of the roads within the analyzed communities has reached 400 km.

The main welfare outcome to be considered in this study is household consumption. The consumption aggregate in the ESS includes expenditures on and own-consumption of food (with a recall period of 7 days) and also includes spending on a selection of important nonfood items, including education. Health spending is not included in the aggregate to avoid that large expenses incurred following adverse health shocks would signal an increase in household welfare. This study adjusts the consumption aggregate in the three waves of the ESS in 2016 prices. In addition, spatial adjustments are also made to account for differences in living cost across regions. To convert the nominal consumption into a spatially adjusted real consumption, the consumer price index (CPI) is used to perform temporal adjustment (that is, convert all consumption values into 2016 prices) and the Fisher spatial price index is used for spatial adjustment. For the analysis of poverty, the poverty

[11] Development of non-rural roads, such as regional corridors, is not considered as the treatment. Iimi et al. (2018) is an example that analyzes the impacts of road access by distinguishing rural roads and regional corridors in Ethiopia.

[12] No spatial spillover is a key assumption for the identification of the impacts of rural roads (stable unit treatment value assumption, or SUTVA).

line is set to Br 4,360 (in 2016 prices), which corresponded to the 40th percentile of consumption expenditure distribution in 2016.[13] Households that earn less than Br 4,360 per adult equivalent per year (in 2016 prices) are considered as poor households in each wave.

According to the recent three waves of the ESS, household consumption has been dropping in many regions. Among the untreated group of communities, the average per adult-equivalent annual consumption (expressed in 2016 prices) has steadily decreased from 6,347 birr in 2012 to 6,030 birr in 2014 and 5,383 birr in 2016 (Table 3). In tandem, the share of population in poverty, or poverty rates have been rising in those communities, reaching 43.7 percent in 2016. By contrast, the mean consumption level and poverty rates have been relatively stable in treated communities during the period.

This study employs an objective indicator of drought exposure. The 2015/16 drought is thought to be one of Ethiopia's worst droughts in the past five decades. About 10.2 million people in Ethiopia needed assistance. The drought was a result of rain failure during both *Meher* (the main harvest) and *Belg* (spring harvest) seasons in 2015. In order to identify communities that were affected by the recent droughts, an objective measure is prepared.[14] The normalized difference vegetation index (NDVI) is a commonly used measure of vegetation, and its deviation in the period of the droughts in 2015/16 from the long-term average score—which is calculated as the z-score— indicates the effect of the drought for agricultural production:

$$Z_{jm}^{y} = \frac{(X_{jm}^{y} - \bar{X}_{jm})}{SD(X_{jm})} \qquad (1)$$

where X_{jm}^{y} indicates the monthly value of NDVI in community *j* in year *y*; $\bar{X}_{jm}$ is the mean value over each month for the years 2000 to 2016; and $SD(X_{jm})$ is the standard deviation over the period.[15] Negative z-scores mean that the vegetation during the drought period was worse than the long-term average. Thus, households in the communities with z-scores below zero are identified as exposed to drought shock, accounting for 37.5 percent of households in the treated communities and 41.0 percent in the control group.

4. Empirical strategy

The primary approach of the econometric analysis in this study is a DID matching approach (Smith and Todd 2005), which combines DID and propensity score matching. In the impact analysis of rural road development, endogeneity problems arise when initial conditions influence project placement and the subsequent growth paths and prospects of the communities. While either DID or household fixed-effects-panel regression models can statistically control for time-invariant factors,

[13] Official poverty lines are developed for HICES, which is a different household expenditure survey from the ESS. Thus, poverty estimates in this paper are not comparable with the official poverty statistics.
[14] In the ESS data, a lot of households reported that they had been affected by drought during the last 12 months. In the study area, 29 percent of the households were affected by drought in 2015/16. However, such measure of drought exposure reported by households—and even by communities—can be susceptible to measurement errors, and the errors can be correlated with the respondents' income levels if lower-income households are more likely to overstate the drought impact and/or higher-income households tend to understate the impact.
[15] NDVI was calculated based on the MODIS Terra satellite data.

either observed and unobserved in the data, it is still necessary to deal with time-varying factors to obtain unbiased estimates. This study estimates a DID model for households in the communities that are matched based on propensity scores; that is, the predicted probability of the communities receiving rural road development (Rosenbaum and Rubin 1983; Imbens and Rubin 2016). The propensity score matching approach rests on the assumption of conditional independence; that is, the method is valid as long as the selection bias is conditional on the observed covariates. Unobservables affecting both the placement of rural roads and outcomes can create a bias in estimating the impacts (discussed below).

The first step is to estimate propensity scores. The propensity score is estimated using a probit model at the community level, defined as follows:

$$\Pr(Road_j = 1) = F(Connectivity_j, Demography_j, Infrastructure_j, Agroecological\ zone_j) \qquad (2)$$

where the probability of community j receiving rural roads between 2010 and 2014, Pr ($Road_j$ = 1), depends on the community's prior characteristics about connectivity (such as length of all-weather roads in 2010 and the natural logarithm of travel time to the nearest town in 2010), demography (such as population density in 2007, poverty rates in 2007, and the share of adults with no education), and infrastructure (such as the share of households with public piped water and the share of households with electricity). We also add dummy indicators about agroecological zones to control for agricultural potentials.[16] The estimation results of the propensity score model are presented in Table 4. Predicted probabilities of having a rural road based on the results are the propensity scores.[17]

Then, kernel matching is performed to make communities in the treated and control groups comparable. In the kernel matching method, observations in the control group are assigned weights according to a kernel function of the predicted propensity scores (Heckman, Ichimura, and Todd 1997). We check covariate balancing to ensure the quality of matching. The comparison of mean values of covariates between the treated group and the control group in Table 5 shows that their differences were sufficiently reduced after matching. The mean difference in the length of all-weather roads between the treated and control groups is reduced by 104 percent. Other connectivity measures also show a profound reduction; for example, a 74 percent reduction for the log of travel time to the nearest town. Also, among the matched sample, the mean difference between the treated and control groups is not statistically significant in all the covariates.[18] Alternative matching methods are also tested as a robustness check.

We then estimate the following standard DID model for households in the matched sample:

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[16] Agro-ecological zones include tropic-warm/arid zone, tropic-warm/semiarid zone, tropic-warm/subhumid zone, tropic-cool/subhumid zone, tropic-cool/semiarid zone, and tropic-cool/humid zone (HarvestChoice and IFPRI 2016).

[17] Panel (A) of Figure A1 in the Appendix shows the distribution of propensity scores for both treated and control groups. It is visually clear that communities in the treated group are concentrated in higher scores, whereas many communities in the control group are in lower scores. Panel (B) of Figure A1 shows propensity scores for the matched households.

[18] The mean difference of the share of adults with no education slightly increased after matching since it has a very small difference prior to the matching (Table 5). Nevertheless, their mean values are not statistically significant among the matched sample.

$$y_{ijt} = \alpha + \beta_1 \text{ROAD}_j + \beta_2 \text{POST}_t + \beta_3 (\text{ROAD} \times \text{POST})_{jt} + \beta_4 X_{it} + \varepsilon_{it} \quad (3)$$

where y_{ijt} is a vector of outcomes, such as the natural logarithm of per adult-equivalent annual consumption, for household i in community j at year t; ROAD_j is an indicator about the community's recipient status of rural road development; POST_t indicates the year when the outcome is measured (2014 or 2016); X_{it} includes various time-variant household characteristics (listed in Table A1); ε_{it} is an error term; and β_3 is the parameter that indicates the effect of rural road development for the outcome Y.[19] In estimating the models above, cluster robust standard errors are estimated to account for the clustering of households at the community level.

It is crucial to know whether households in remote communities and/or exposed to the recent droughts have benefited from recently developed rural roads. To explore such heterogeneity in the impacts of rural roads across those communities, this study introduces interaction terms to Equation (3). In case of remote communities, which is expressed by a dummy indicator *REMOTE* (1 if the community is located more than 120 minutes away from the nearest town; otherwise 0), the model is as follows:[20]

$$y_{ijt} = \alpha + \beta_1 \text{ROAD}_j + \beta_2 \text{REMOTE}_j + \beta_3 \text{POST}_t + \beta_4 (\text{ROAD} \times \text{REMOTE})_j + \beta_5 (\text{ROAD} \times \text{POST})_{jt} + \beta_6 (\text{REMOTE} \times \text{POST})_{jt} + \beta_7 (\text{ROAD} \times \text{REMOTE} \times \text{POST})_{jt} + \beta_8 X_{it} + \varepsilon_{it} \quad (4)$$

where β_5 indicates the impact estimate for households in the communities closer to towns (that is, REMOTE = 1) and ($\beta_5 + \beta_7$) indicates the impacts in communities more than 120 minutes away from the nearest towns.

The DID matching method above cannot perfectly rule out endogeneity in estimating the impacts of rural road development since unobserved factors may have critically affected the placement and outcome changes. Political capital is such a factor as reported in some previous studies in India (Lehne, Shapiro, and Eynde 2018) and Kenya (Burges et al. 2015). Communities with a strong relationship with local politicians might have been more likely to receive rural roads, and residents in the communities may also have received various supports that are not observed in our data. While we control for some assistance received by each household, such as the Productive Safety Nets Program (PSNP) and the amount of transfer received, based on the ESS data, community-level political capital is not included there and thus creates room for endogeneity bias.

[19] Among the covariates are the controls for assistance, including the dummy indicator about whether the household received a cash transfer from the PSNP during the last 12 months; the dummy indicator whether any member of the household participated in the PSNP labor work during the last 12 months; and the natural logarithm of the amount of transfer received by the household during the last 12 months. All these variables are based on self-reports in the ESS.

[20] Travel time to the nearest town is calculated by assuming different travel speeds for various road types in the Ethiopia road database. Foot-based speed is used for the path from the centroid of the community to the nearest road.

5. Results

5-1. Welfare impacts

Table 6 reports the estimation results of the DID model in Equation (3) with the natural logarithm of household consumption as the outcome variable. We first look at the results based on the unmatched sample (columns 1 to 4). The coefficient estimate for the interaction term between the dummy variable about the rural road indicator and the year dummy indicates the impacts of rural road development on household consumption between 2012 and 2016. The baseline result with no control variable in column 1 indicates that the mean consumption in the treated communities is 14.5 percent higher than that in the control communities. The coefficient estimate remains at the similar level when additional control variables are added, such as drought shocks (column 2), assistance (column 3), and household characteristics (column 4).

Compared to the results based on the unmatched sample above, the results for the matched sample show slightly larger impacts. The specification with full controls in column 8 suggests that households in the treated group increased household consumption by 16.1 percent between 2012 and 2016 thanks to the rural road development. In other words, rural roads increased household consumption by, on average, 3.8 percent each year during the period. This impact is larger than what Dercon et al. (2009) report for the impact of the access to all-weather roads on household consumption in rural Ethiopia: 16 percent increase between 1994 and 2004 or 1.5 percent annual increase.

Households in areas farther away from towns and/or affected by droughts have clearly benefited from rural road development. Interacting the rural road indicators with the baseline travel time to the nearest town (as in Equation 4), the analysis suggests that households in communities with travel time to the nearest town greater than 120 minutes more clearly benefited (row A in Table 7). The estimated impact in such remote areas is 27.9 percent between 2012 and 2016 (column 6). Also, we find that rural roads mitigated the drought impacts on household consumption. Without rural roads, household consumption levels would have been 16.9 percent lower in drought-hit areas between 2014 and 2016 (column 4).

Recent rural road development has also supported rural households from falling into or remaining in poverty—particularly in areas hit by the droughts. The results summarized in row (B) in Table 7 suggest that when connected to rural roads, rural residents were about 10.4 percent less likely to fall into or remain in poverty between 2012 and 2016 (column 5). In other words, without the rural roads 10 percent more households would have been poor by 2016. The examination of heterogeneity implies that people in remote areas have also benefited (21.1 percent lower chance of poverty between 2012 and 2014, column 2). Moreover, rural roads mitigated households exposed to the 2015/16 drought by lowering their chance of becoming poor by around 14.4 percent (column 7).

5-2. Economic impacts

Rural farmers in remote areas sold more crops when connected to rural roads. Table 8 reports the results for the four different outcomes: the binary indicator about whether the household sold any crop (row A), the natural logarithm of the amount of crop sold (row B), the share of harvested crops sold (row C), and the binary indicator about whether the household used fertilizer (row D).

As shown in column 1, rural households in the treated communities were 18.2 percent more likely to sell crops (row A) and sold a 32.2 percent larger amount or crops (row B)—or 6.5 percentage points larger share of crops (row C)—between 2012 and 2014. The increased crop sales, however, tapered off between 2014 and 2016 and resulted in no clear impacts between 2012 and 2016 (column 5). Nevertheless, agricultural impacts are clear in remote areas. As column 7 shows, among the households in remote areas, those with a connection to rural roads were 16.1 percent more likely to sell crops between 2012 and 2016. These results demonstrate that rural road developments have influenced agricultural outcomes of farmers in remote areas by providing better access to markets.

However, it is not clear whether rural farmers connected to rural roads have increased the use of fertilizer (row D in Table 8). Rural households were 3.6 percent more likely to use fertilizer in kebeles with rural roads between 2012 and 2016 (column 5). However, this estimate is very marginal and not statistically significant. This finding contradicts the expectation that lower transport costs lower input costs and facilitate the adaptation of modern technologies among farmers, as demonstrated by recent empirical studies, such as Minten, Korn, & Stifel (2013) for Ethiopia, Damania et al. (2016) for Nigeria, and Aggarwal (2018) for India.

Some of the recently connected households started to engage in wage jobs. Table 9 summarizes the results of DID matching with the share of household members who engaged in wage jobs as the outcome. The impact is not clear when all household members are analyzed (row A in column 5). However, among communities that were exposed to droughts during 2014 and 2016, rural roads increased the share of household members with wage jobs by 2.8 percentage points (column 4). The impacts were particularly large among women and the youth in remote areas. The development of rural roads there resulted in the increase in the share of female and young members with wage jobs by 2.6 percentage points (row B) and 7.5 percentage points (row C), respectively. Given the very small share of wage workers in the sample (Table 3), this impact is by no means marginal.

5-3. Robustness check

The estimated welfare impacts are robust against the choice of household consumption measures (Table 10). The rural road impacts on household consumption above are measured as the percent change in consumption based on the natural logarithm of consumption values (reported again in row A for the sake of comparison). Estimating the impacts as the changes in the level of consumption (using the non-log real consumption values as the outcome variable) in row B shows that rural roads increased annual household consumption by 1,132 birr between 2012 and 2016. In addition, the estimation results with the log of nominal consumption show that the estimated impacts are robust against the price adjustment (row C). Focusing on only food consumption does not substantially change the impact estimate (a 17.8 percent increase between 2012 and 2016, row D).

As opposed to household consumption, the effects of rural roads for reducing food insecurity are less clear (except for remote communities). The ESS asked whether the household had a situation in which they did not have enough food to feed the household during the last 12 months. The results of the matching DID analysis for the all rural kebeles do not show any clear effects (row E in Table 10). However, further analysis of heterogeneity suggest that rural road developments profoundly reduced the chance of facing food insecurity in remote areas.[21]

The estimated welfare impacts of rural roads are robust against the measure of drought shock. How to identify households/areas affected by droughts is not straightforward. As explained, this study uses an NDVI-based drought exposure indicator. As a robustness check, six dummy variables are created based on different thresholds (z-scores lower than 0, −0.5, or −1.0) and interacted with rural road indicators in estimating the DID matching models to assess how the impacts of rural roads on household consumption change, depending on the degree of abnormalities in vegetation. Except for the extreme threshold (−1.0), the estimated impacts of rural roads on household consumption are not substantially different from the baseline with the threshold being zero (Table A2 in the Appendix).

Moreover, the estimated impacts above do not substantially change when other matching methods are applied. Table A3 in the Appendix summarizes the results based on nearest neighbor matching (one-to-one matching). Overall, the estimated impacts on household consumption are larger than those based on kernel matching. Regardless of setting caliper (row A) or not (row B), the results demonstrate that rural roads increased household consumption by about 20 percent between 2012 and 2016.

6. Conclusion

This study attempts to assess the impacts of recently developed rural roads on household welfare and economic activities. The panel data sets of both household surveys, which include detailed household consumption information, and transport networks make it possible to relate the development of rural roads to welfare changes across space and over time. Moreover, the study period between 2010 and 2016 incorporates both the launching and development of a large-scale rural road development program (URRAP) and historically severe droughts, which allows it to analyze the contribution of rural roads to resilience against disaster shocks.

The study finds that recently developed rural roads have brought significant welfare and economic impacts for rural Ethiopians who would have otherwise been physically and economically isolated. Amid the recent severe droughts, rural roads played a fundamental role in reducing poverty and enhancing resilience against shocks by providing rural populations access to markets.

Rural roads supported household welfare amid the recent severe drought shocks. The econometric analysis of this study suggests that recent rural road development contributed to household welfare, which is measured by household consumption. Rural roads increased household consumption by 3.8 percent each year between 2012 and 2016. In other words, without the rural roads, the average household consumption would have been 16.1 percent lower between 2012 and 2016. The estimated impacts mainly come from rural households who were affected by the recent severe droughts, which indicates the contribution of rural roads to reducing vulnerability and enhancing resilience against disaster shocks. Rural households in the most remote communities benefited most from rural road development. Importantly, poorer people gained more from recently developed rural roads: without rural roads, 10 percent more households would have been poor.

[21] Not reported. Results available upon request. Recipient indicators for PSNP and other transfers are added as controls.

Rural roads particularly prevented people in drought areas from falling into poverty or helped them to get out of poverty.

By connecting rural communities to markets, rural road developments have also influenced how rural households—particularly those in remote areas—engaged in agricultural and non-agricultural work. In communities that used to be more than 120 minutes away from the nearest towns, connected households were about 16 percent more likely to sell crops—and sold a larger share of harvested crops—between 2012 and 2016. In addition, rural roads have contributed to widening the economic base of rural communities. The share of wage workers increased by 2.8 percentage points in communities exposed to droughts between 2014 and 2016. Importantly, more women (2.6 percentage points) and the youth (7.5 percentage points) took wage jobs in remote communities when connected to rural roads. These results demonstrate the fundamental economic role of rural roads in providing rural populations access to markets.

The findings above highlight that rural road development contributed significantly to the welfare of rural households, and increased households' resilience to adverse weather shocks. Despite the welfare and economic impacts observed in this report, the implementation of the URRAP has been slowing down due to, among other factors, the lack of financial resources. In light of the results, it will be important to connect the remaining kebeles, particularly in remote areas, to accelerate poverty reduction and enhance the resilience of rural populations against shocks.

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Tables

Table 1. Recently developed rural roads in Ethiopia, 2010−2014

	Number of communities		Share of communities (%)		Length (km)	
	2010-12	2012-14	2010-12	2012-14	2010-12	2012-14
Oromia	1273	1229	21	20	5944	6724
Amhara	465	680	15	23	1821	3267
SNNPR	61	10	2	0	170	24
Tigray	23	225	4	37	116	1304
Benishangul Gumuz	18	52	4	13	104	268
Dire Dawa	0	1	0	3	0	8
Harar	5	2	26	11	23	1
Afar	3	1	1	0	6	0
Gambella	2	5	1	3	1	11
Total	1850	2205	13	15	8186	11607

Source: The Ethiopia road database.

Table 2. Baseline community characteristics with and without rural road developments

	Rural road received			
	Yes	No	Difference	%
Length of all-weather road 2010 (km)	5.721	2.298	2.973	129.4
Travel time to town 2010 (minutes)	91.35	196.2	-104.8	-53.6
Log(MAI) 2010	12.44	11.41	1.028	9.0
Length of all-weather road 2010 at woreda (km)	116.2	98.93	17.27	17.2
RAI 2010 at woreda (%)	50.37	39.15	11.22	46.1
Population density 2010 at woreda (per km2)	202.6	160.2	42.40	26.9
Poverty rate 2011 at woreda (%)	30.57	30.61	-0.040	-0.0
Average age 2007	21.24	21.24	0.000	0.0
Share of no education 2007 (%)	70.39	73.58	-3.190	-4.3
Share of public tap 2007 (%)	16.24	13.09	3.150	23.7
Share of no toilet 2007 (%)	73.34	75.95	-2.610	-3.6
Share of electricity for lighting 2007 (%)	2.151	2.369	-0.218	-8.3
Agro-ecological zone: Tropic-warm/semiarid at woreda (%)	2.112	7.361	-5.249	-71.6
Agro-ecological zone: Tropic-warm/subhumid at woreda (%)	4.240	9.456	-5.216	-55.8
Agro-ecological zone: Tropic-cool/subhumid at woreda (%)	55.97	46.66	9.310	20.0
Agro-ecological zone: Tropic-cool/semiarid at woreda (%)	19.52	20.73	-1.210	-5.8
Agro-ecological zone: Tropic-cool/humid at woreda (%)	18.16	15.79	2.370	15.2

Note: The unit of observations is rural communities (kebeles) in the Ethiopia road database.

Table 3. Outcome and key variables 2012-2016

	Treated			Control		
	2012	2014	2016	2012	2014	2016
More than 2 hours away from the nearest town (1 = yes; 0 = no)	0.769	0.769	0.769	0.590	0.590	0.590
Exposed to droughts between 2014 and 2016 (1 if z-score of NDVI < 0; otherwise 0)	0.375	0.375	0.375	0.410	0.410	0.410
Per adult equivalent annual consumption (2016 Birr)	6049	6184	5979	6347	6030	5383
Poor (1 if consumption < 4360; otherwise 0)	0.369	0.347	0.377	0.334	0.375	0.437
Whether the household sold any crop this season (1 = yes; 0 = no)	0.436	0.623	0.702	0.574	0.578	0.762
Amount of crops sold by the household this season	271.5	768.9	1409.8	282.1	533.0	1375
Share of crops sold by the households among the harvested crops this season (%)	4.881	7.882	13.18	10.52	7.454	16.93
Fertilizer used during the last 12 months (1 = yes; 0 = no)	0.778	0.837	0.842	0.714	0.753	0.758
Share of household members engaged in wage job during the last 12 months (%)	6.136	5.706	4.645	6.066	5.184	4.396
Share of female household members engaged in wage job during the last 12 months (%)	1.918	2.317	1.774	2.768	2.260	1.757
Share of young household members engaged in wage job during the last 12 months (%)	4.306	3.188	2.447	6.378	3.324	1.685

Note: The unit of observations are rural households in the ESS.

Table 4. Estimation results of propensity score model

	Whether rural roads received
Length of all-weather road 2010	0.121***
	(0.007)
ln(Travel time to town 2010)	-0.321***
	(0.019)
Road × ln(Travel time to town)	0.018***
	(0.003)
ln(MAI 2010)	-0.026***
	(0.006)
ln(Length of all-weather road 2010 in Woreda)	0.869***
	(0.286)
RAI 2010 in Woreda	0.934***
	(0.090)
ln(Population density 2007 in Woreda)	0.014
	(0.021)
Poverty rate 2011 in Woreda	0.998***
	(0.349)
Poverty rate squared	-1.060**
	(0.452)
Share of adults with no education	-0.048
	(0.067)
Share of households with public piped water	-0.056
	(0.052)
Share of households with electricity	-1.070***
	(0.140)
Constant	-2.289***
	(0.157)
Agro-ecological zone FE	Yes
Prob > chi2	0.000
Obs.	13928

Note: The unit of observations is rural communities (kebeles) in the Ethiopia road database. The probit model includes the binary indicator about whether the community received rural roads after 2010 as the dependent variable. *, **, and *** indicate significance level of estimated impacts at 10%, 5%, and 1% levels.

Table 5. Balancing of covariates before and after matching

	Unmatched			Matched			% |bias|	t-test	
	Treated	Control	% bias	Treated	Control	% bias	reduction	t-value	p > |t|
Length of all-weather roads (km)	9.065	4.416	105.3	8.677	8.872	-2.2	97.9	-0.11	0.913
ln(Travel time to town in minutes)	3.816	4.381	-12.9	3.872	3.856	0.4	96.9	0.10	0.919
ln(MAI)	12.66	11.76	7.7	12.54	12.50	0.3	96.1	0.10	0.924
ln(Length of all-weather roads in woreda)	4.688	4.281	9.5	4.616	4.533	1.8	81.1	0.61	0.541
RAI at woreda	43.94	40.34	8.9	44.39	45.81	-3.1	65.2	-0.42	0.673
ln(Population density of woreda)	4.902	4.707	4.1	4.811	4.725	1.8	56.1	0.46	0.647
Poverty rate at woreda (%)	33.74	30.97	8.9	33.74	31.24	8.0	10.1	1.04	0.301
Share of no education (%)	74.60	73.01	2.2	74.40	72.75	2.3	-4.5	0.60	0.550
Share of public tap (%)	20.32	15.31	32.7	20.21	18.15	-11.3	65.4	0.52	0.602
Share of electricity (%)	46.30	31.82	45.5	19.72	24.08	-18.1	60.2	-0.52	0.603

Note: The unit of analysis is rural households in the ESS. Matched sample was created by kernel matching method based on propensity scores (estimated based on the propensity score model in Table 4). Standard errors in t-test were clustered at the community-level.

Table 6. Impact of rural road development on household consumption 2012-2016

	Unmatched				Matched			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Road	-0.018	-0.033	-0.028	-0.065	-0.066	-0.074	-0.067	-0.098
	(0.053)	(0.051)	(0.051)	(0.048)	(0.059)	(0.058)	(0.058)	(0.053)
Post	-0.180***	-0.188***	-0.180***	-0.173***	-0.205***	-0.192***	-0.183***	-0.185***
	(0.037)	(0.044)	(0.045)	(0.045)	(0.049)	(0.055)	(0.056)	(0.052)
Road × Post	0.145**	0.155**	0.141**	0.153**	0.164**	0.168**	0.153**	0.161**
	(0.060)	(0.061)	(0.061)	(0.060)	(0.069)	(0.070)	(0.070)	(0.068)
Weather shocks	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Assistance	No	No	Yes	Yes	No	No	Yes	Yes
Household characteristics	No	No	No	Yes	No	No	No	Yes
Treated (clusters)	1584 (72)	1584 (72)	1584 (72)	1574 (72)	1447 (67)	1447 (67)	1447 (67)	1437 (67)
Observations (clusters)	4342 (196)	4342 (196)	4322 (196)	4293 (195)	4030 (194)	4030 (194)	4010 (194)	3981 (194)

Note: The unit of observations is rural households in the 2012 and 2016 ESS. Matched sample was created by kernel matching method based on propensity scores (estimated based on the propensity score model in Table 4). The DID model in Equation 2 was estimated with the natural logarithm of per adult equivalent household annual consumption as the outcome variable. 'Road' is a dummy indicating the treatment status (1=treated; 0=control). 'Post' is a dummy indicating post-treatment year (1=2016; 0=2012). The coefficient estimate for (Road×Post) indicates the impact of rural roads on household consumption between 2012 and 2016. Weather shock controls include indicators about drought exposure based on NDVI. Assistance controls include the amount of transfer received, PSNP assistance, and PSNP labor. Household characteristic controls include the number of adult equivalent, household head's age, sex, education level, marital status, and religion. See Table A1 for the descriptions of these controls. Cluster robust standard errors in parentheses. *, **, and *** indicate significance level of estimated impacts at 10%, 5%, and 1% levels.

Table 7. Impact of rural road development on household consumption and poverty

	2012-14		2014-16		2012-16		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(A) Log of household consumption							
Road × Post	0.106**	0.302***	0.060	0.169**	0.161**	0.279**	0.217**
	(0.050)	(0.086)	(0.064)	(0.079)	(0.068)	(0.133)	(0.089)
Road × Post × Remote		-0.254**				-0.158	
		(0.103)				(0.154)	
Road × Post × Drought				-0.303**			-0.143
				(0.082)			(0.141)
(B) Poverty							
Road × Post	-0.072*	-0.211***	-0.033	-0.104	-0.103*	-0.117	-0.144**
	(0.040)	(0.071)	(0.058)	(0.075)	(0.053)	(0.106)	(0.068)
Road × Post × Remote		0.180**				0.020	
		(0.085)				(0.120)	
Road × Post × Drought				0.208**			0.111
				(0.078)			(0.105)

Note: The unit of observations is rural households in the ESS, matched by kernel matching method based on propensity scores (estimated based on the propensity score model in Table 4). The DID models in Equations 2 and 4 were estimated with (A) the natural logarithm of per adult equivalent household annual consumption and (B) a binary indicator whether the household's consumption is below 4,360 as the outcome variable. 'Road' is a dummy indicating the treatment status (1=treated; 0=control). 'Post' is a dummy indicating post-treatment year (1=2016; 0=2012). 'Remote' is a dummy indicating whether the household lives in a community more than 2 hours away from the nearest town (1) or not (0). 'Drought' indicates whether the household's community was exposed to drought between 2014 and 2016 (1) or not (0). Weather shocks, assistance, and household characteristics are controlled. See Table A1 for the descriptions of the variables. Cluster robust standard errors in parentheses. *, **, and *** indicate significance level of estimated impacts at 10%, 5%, and 1% levels.

Table 8. Impact of rural road development on agriculture

	2012-14		2014-16		2012-16		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(A) Whether the household sold any crop							
Road × Post	0.182**	0.245*	-0.135**	-0.226***	0.046	0.178*	-0.045
	(0.074)	(0.145)	(0.061)	(0.076)	(0.055)	(0.093)	(0.066)
Road × Post × Remote		-0.078				-0.164	
		(0.168)				(0.113)	
Road × Post × Drought				0.216*			0.231*
				(0.121)			(0.121)
(B) Log of the amount of crop sold							
Road × Post	1.322**	1.552	-0.885**	-1.659***	0.387	1.222	-0.307
	(0.512)	(1.027)	(0.436)	(0.542)	(0.405)	(0.761)	(0.458)
Road × Post × Remote		-0.283				-1.065	
		(1.158)				(0.876)	
Road × Post × Drought				1.882**			1.783**
				(0.834)			(0.887)
(C) Share of crop sold							
Road × Post	0.065**	0.103**	-0.042*	-0.059*	0.019	0.082*	-0.005
	(0.028)	(0.049)	(0.024)	(0.032)	(0.023)	(0.043)	(0.021)
Road × Post × Remote		-0.048				-0.081*	
		(0.056)				(0.048)	
Road × Post × Drought				0.044			0.060
				(0.045)			(0.055)
(D) Fertilizer use							
Road × Post	0.040	0.103	-0.004	-0.016	0.036	0.027	0.036
	(0.041)	(0.082)	(0.030)	(0.039)	(0.039)	(0.090)	(0.040)
Road × Post × Remote		-0.078				0.013	
		(0.092)				(0.096)	
Road × Post × Drought				0.033			-0.003
				(0.059)			(0.079)

Note: The unit of observations is rural households in the ESS, matched by kernel matching method based on propensity scores (estimated based on the propensity score model in Table 4). The DID models in Equations 2 and 4 were estimated with the following outcome variables: (A) whether the household sold any crop (1) or not (0), (B) the natural logarithm of the amount of crops sold by the households, (C) the share of harvested crops sold by the household, and (D) whether the household used fertilizer (1) or not (0). 'Road' is a dummy indicating the treatment status (1=treated; 0=control). 'Post' is a dummy indicating post-treatment year (1=2016; 0=2012). 'Remote' is a dummy indicating whether the household lives in a community more than 2 hours away from the nearest town (1) or not (0). 'Drought' indicates whether the household's community was exposed to drought between 2014 and 2016 (1) or not (0). Weather shocks, assistance, and household characteristics are controlled. See Table A1 for the descriptions of the variables. Cluster robust standard errors in parentheses. *, **, and *** indicate significance level of estimated impacts at 10%, 5%, and 1% levels.

Table 9. Impact of rural road development on wage jobs

	2012-14		2014-16		2012-16		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(A) Share of HH members with wage jobs							
Road × Post	0.005	-0.022	0.008	0.028***	0.009	0.007	0.021*
	(0013)	(0.021)	(0.009)	(0.010)	(0.011)	(0.016)	(0.011)
Road × Post × Remote		0.033				0.001	
		(0.026)				(0.020)	
Road × Post × Drought				-0.056***			-0.038*
				(0.018)			(0.022)
(B) Share of HH members with wage jobs							
Road × Post	-0.001	-0.001	0.006	0.018*	0.004	0.026***	0.007
	(0.009)	(0.010)	(0.007)	(0.010)	(0.007)	(0.008)	(0.008)
Road × Post × Remote		0.000				-0.028**	
		(0.015)				(0.012)	
Road × Post × Drought				-0.031**			-0.010
				(0.014)			(0.014)
(C) Share of HH members with wage jobs							
Road × Post	0.028*	0.022	0.009	0.024	0.037**	0.075**	0.034*
	(0.016)	(0.019)	(0.014)	(0.015)	(0.018)	(0.029)	(0.018)
Road × Post × Remote		0.011				-0.050	
		(0.027)				(0.035)	
Road × Post × Drought				-0.044			0.004
				(0.039)			(0.040)

Note: The unit of observations is rural households in the ESS, matched by kernel matching method based on propensity scores (estimated based on the propensity score model in Table 4). The DID models in Equations 2 and 4 were estimated with the following outcome variables: (A) the share of household members who engaged in wage jobs (%), (B) the share of female household members who engaged in wage jobs (%), and (C) the share of young household members who engaged in wage jobs (%). 'Road' is a dummy indicating the treatment status (1=treated; 0=control). 'Post' is a dummy indicating post-treatment year (1=2016; 0=2012). 'Remote' is a dummy indicating whether the household lives in a community more than 2 hours away from the nearest town (1) or not (0). 'Drought' indicates whether the household's community was exposed to drought between 2014 and 2016 (1) or not (0). Weather shocks, assistance, and household characteristics are controlled. See Table A1 for the descriptions of the variables. Cluster robust standard errors in parentheses. *, **, and *** indicate significance level of estimated impacts at 10%, 5%, and 1% levels.

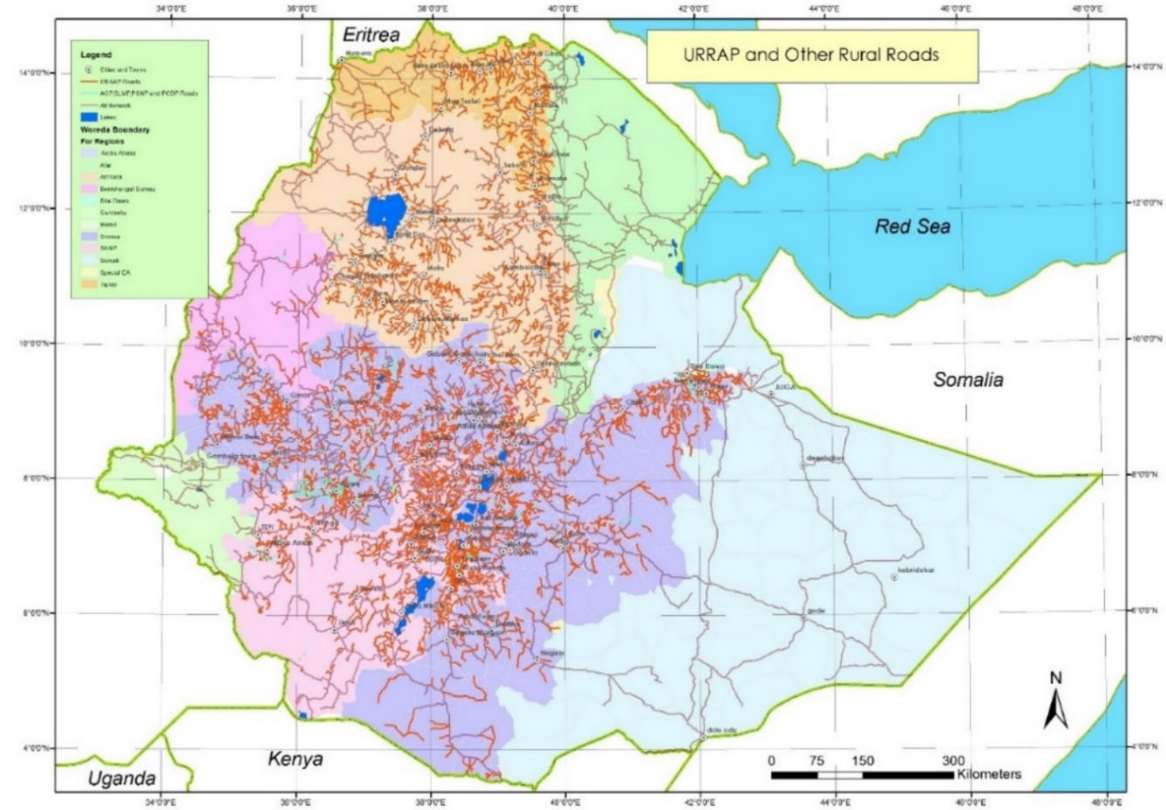
Table 10. Impact of rural road development on alternative welfare indicators

	2012−14	2014−16	2012−16
	(1)	(2)	(3)
(A) Log of real consumption	0.106**	0.060	0.161**
	(0.050)	(0.064)	(0.068)
(B) Real consumption	736.2*	404.9	1132**
	(379.3)	(400.5)	(494.1)
(C) Log of nominal consumption	0.131**	0.054	0.180***
	(0.051)	(0.061)	(0.067)
(D) Log of real food consumption	0.102*	0.083	0.178**
	(0.060)	(0.073)	(0.076)
(E) Food insecurity	-0.086	0.067	-0.015
	(0.061)	(0.056)	(0.050)

Note: The unit of observations is rural households in the ESS, matched by kernel matching method based on propensity scores (estimated based on the propensity score model in Table 4). The DID models in Equations 2 was estimated with the following outcome variables: (A) the natural logarithm of per adult equivalent real total (i.e., food and non-food) consumption, (B) (non-log) real total consumption, (C) the natural logarithm of nominal total consumption, (D) the natural logarithm of real food consumption, and (E) whether the household experienced food shortage during the last 12 months (1) or not (0). Weather shocks, assistance, and household characteristics are controlled. See Table A1 for the descriptions of the variables. Only the coefficient estimates for (Road × Post) in Equation 2 are reported in the table above. Cluster robust standard errors in parentheses. *, **, and *** indicate significance level of estimated impacts at 10%, 5%, and 1% levels.

Figures

Figure 1. Recently developed rural roads in Ethiopia



Source: The Ethiopia road database.

Appendix A.

Table A1. List of variables

Name	Description	Data source
Consumption	Per adult-equivalent annual consumption in 2016 prices	ESS
Poor	1 if per adult-equivalent annual consumption is lower than Br. 4,360 (in 2016 prices); otherwise 0	ESS
Food insecurity	1 if the household experienced a situation in which they did not have food enough to feed the members during the last 12 months; otherwise 0	ESS
Share of crop for sale	Share of harvested crop for sale	ESS
Fertilizer use	1 if the household used fertilizer during the season; otherwise 0	ESS
Wage job	1 if any household member engaged in wage job during the last 12 months; otherwise 0	ESS
Rural road developed between 2010 and 2014	1 if any all-weather roads developed within the boundary of the community between 2010 and 2014; otherwise 0	The Ethiopia road database
Length of rural road (Kebele/Woreda)	Length of all-weather roads in the community/woreda	The Ethiopia road database
Travel time to town (Kebele)	Travel time from the geometric center of the kebele to the nearest town (in minutes)	The Ethiopia road database
RAI (Woreda)	Share of population within 2km from any all-weather road in the kebele/woreda	The Ethiopia road database, WorldPop
MAI (Kebele)	Sum of the population within 200 minutes from the Kebele center discounted by travel time	The Ethiopia road database, WorldPop
Road density (Woreda)	Length of all-weather roads per population at the Woreda in which the household resides (kilometer per population)	The Ethiopia road database WorldPop
Number of adult equivalent	Number of adult equivalent in the household	ESS
Age of household head	Age of the household head (in years)	ESS
Female-headed household	1 if the household head is female; otherwise 0	ESS
Education level of household head	The highest level of education achieved by the household head: no education, incomplete primary, complete primary, incomplete secondary, complete secondary, post-secondary, adult education	ESS
Marital status of household head	Marital status of the household head: never married, married (monogamous), married (polygamous), divorced, separated, widowed	ESS
Religion of household head	Religion of the household head: orthodox, catholic, protestant, Muslim, traditional, pagan, wakifata, other	ESS
Drought (Kebele)	1 if z-score of NDVI < 0; otherwise 0.	ESS
Log of transfer received	Amount of transfer received by the household during the last 12 months (in 2016 prices)	ESS
PSNP assistance	1 if the household received PSNP assistance during the last 12 months	ESS
PSNP labor	1 if the household participated in PSNP labor activity during the last 12 months	ESS
Population density (Woreda)	Population density in the woreda	Census
Poverty rate (Woreda)	Poverty headcount ratio at the woreda	HICES
No education (Kebele)	Share of adults with no education in the kebele	Census
Share of public piped water (Kebele)	Share of households with access to public piped water in the kebele	Census
Share of electricity (Kebele)	Share of households with access to electricity for lighting in the kebele	Census
Agro-climate zone (Woreda)	Agro-ecological zones: tropic-warm/arid, tropic-warm/semiarid, tropic-warm/subhumid, tropic-cool/subhumid, tropic-cool/semiarid, tropic-cool/humid	HarvestChoice/IFPRI
Region	Region in which the household resides: SNNPR, Amhara; Oromia, Tigray, B/Gumuz, D/Dawa, Harar, Gambella, Afar	ESS

Table A2. Impact of rural road development on alternative poverty indicators 2014-2016

	NDVI < 0 (1)	NDVI < -0.5 (2)	NDVI < -1.0 (6)
Road × Post	0.169**	0.193*	0.364**
	(0.079)	(0.101)	(0.157)
Road × Post × Drought	-0.303**	-0.188	-0.351**
	(0.129)	(0.130)	(0.171)

Note: The unit of observations is rural households in the ESS 2014 and 2016, matched by kernel matching method based on propensity scores (estimated based on the propensity score model in Table 4). The DID models in Equations 2 was estimated with the natural logarithm of per adult equivalent real consumption as the outcome variable. 'Road' is a dummy indicating the treatment status (1=treated; 0=control). 'Post' is a dummy indicating post-treatment year (1=2016; 0=2012). 'Drought' indicates whether the household's community was exposed to drought between 2014 and 2016 (1) or not (0) based on the following thresholds in NDVI: 0 in column 1, -0.5 in column 2, and -1.0 in column 3. Assistance and household characteristics are controlled. See Table A1 for the descriptions of the variables. Cluster robust standard errors in parentheses. *, **, and *** indicate significance level of estimated impacts at 10%, 5%, and 1% levels.

Table A3. Welfare impacts based on nearest neighbor matching

	2012-14 (1)	2014-16 (2)	2012-16 (3)
(A) Without caliper			
Road × Post	0.096*	0.105*	0.196***
	(0.052)	(0.062)	(0.067)
Treated	1420	1454	1437
Obs.	2809	2871	2852
(B) With caliper			
Road × Post	0.099*	0.103	0.200***
	(0.056)	(0.064)	(0.073)
Treated	1228	1256	1242
Obs.	2440	2496	2480

Note: The unit of observations is rural households in the ESS 2014 and 2016, matched by nearest neighbor matching (one-to-one matching). Caliper was used (0.1) for the matching in row (B). The DID models in Equations 2 was estimated with the natural logarithm of per adult equivalent real consumption as the outcome variable. 'Road' is a dummy indicating the treatment status (1=treated; 0=control). 'Post' is a dummy indicating post-treatment year (1=2016; 0=2012). Weather shocks, assistance and household characteristics are controlled. See Table A1 for the descriptions of the variables. Cluster robust standard errors in parentheses. *, **, and *** indicate significance level of estimated impacts at 10%, 5%, and 1% levels.

Figure A1. Estimated propensity scores

Note: The unit of observations is rural households in the ESS, matched by kernel matching method based on propensity scores (estimated based on the propensity score model in Table 4).