Agriculture Production and Transport Connectivity: Evidence from Mozambique

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ABSTRACT Despite relative richness of the existing literature, it remains a challenge to consistently estimate the impacts of transport connectivity on agricultural production. The paper constructs pseudo-panel data with transport infrastructure defined at high resolution in two periods of time and examines spatially heterogeneous impacts of improved transport connectivity. The paper takes advantage of the unique circumstances in Mozambique where the Government invested intensively in road infrastructure during a relatively short period of time in the 2010s. Combining the highly disaggregated location-specific fixed effects with the instrumental variable method, the paper controls for the endogeneity to show that the improved road connectivity increased agricultural production significantly. Rural connectivity and domestic market accessibility are found to be of particular importance, but substantial heterogeneity exists across regions. The northern provinces, where transport connectivity is limited, have the potential for agricultural growth, exhibiting increasing returns to scale.

KEYWORDS: Agriculture production; spatial data; transport infrastructure

JEL CLASSIFICATION: H54; H41; Q12; C21

1. Introduction

Transport connectivity is one of the most important constraints on agricultural growth in the developing world. The literature supports a wide range of positive impacts of improved transport connectivity (for example, Bell & van Dillen, 2012; Dorosh, Wang, You, & Schmidt, 2012; Edmeades, Phaneuf, Smale, & Renkow, 2008; Escobal & Ponce, 2002; Dercon, Gilligan, Hoddinott, & Woldehanna, 2009; Khandker, Bakht, & Koolwal, 2009). Despite the relative rich literature, it remains a challenge to examine the impacts of transport connectivity on economic outcomes. The current paper aims to develop new spatial datasets and use them to estimate unbiased impacts of transport connectivity on agricultural productivity. Transport connectivity is measured at different levels. The paper also casts light on the importance of regional heterogeneity in the infrastructure-growth nexus. Transport connectivity normally differs across regions. Furthermore, the levels of market orientation of the agricultural sector are also different. The paper shows that different types of accessibility are needed to promote agricultural growth. Rural accessibility is always important, but port access is an important
consideration mainly where there is substantial potential for export crops. The northern provinces are found to have the highest returns to scale, indicating its agricultural growth potential.

From the empirical point of view, one of the most important challenges is endogeneity caused by transport infrastructure placement. Many unobservables potentially affect both infrastructure investment and economic growth, thus generating an omitted-variable-based endogeneity bias (for example, Datta, 2012; Donaldson, 2018; Banerjee, Duflo, & Qian, 2020; Jedwab & Moradi, 2012). Another empirical challenge is that transport data is generally scarce. Granular, time-series data is rarely available. Thus, it is difficult to observe changes in the transport infrastructure for a relatively short research period. Some studies in the literature look into a 5- to 10-year period of time (for example, Dercon, Gilligan, Hoddinott, & Woldehanna, 2009; Mu & van de Walle, 2011).

The current paper generates pseudo-panel data with transport infrastructure defined at high resolution in two periods of time and estimates the unbiased impacts of improved transport connectivity. In the literature, one of the approaches to deal with the endogeneity is the instrumental variable (IV) method (Donaldson, 2018; Jedwab & Moradi, 2012). Quasi-random (or quasi-exogenous) factors, such as geographic conditions, physical nature of infrastructure and historical events, are often used. These factors are less relevant to current economic outcomes but may have influenced subsequent infrastructure developments. Datta (2012) argues that if a highway connects two cities, other places between them also benefit ‘unintentionally’. In Banerjee et al. (2020), it is argued that the transport infrastructure placement in China was historically determined by proximity to old cities and treaty ports, which were used to construct valid IVs. The current paper applies a similar approach based on the historic port and rail development in the colonial era.

The paper takes advantage of a historically unique opportunity in Mozambique where detailed road network data exists and substantial road investment was made during a relatively short period in the 2010s. This circumstance allows for development of spatially disaggregated data on transport connectivity and combination of them with the IV method and the location-specific fixed effects in the empirical models. This approach is found to be effective in solving the potential infrastructure endogeneity problem.

Unlike existing studies, the paper considers different types of connectivity. The literature often ignores that different types of connectivity cause different impacts. The treatment of road improvement is usually defined in a binary manner (for example, 2 km from a road) (for example, Dercon, Gilligan, Hoddinott, & Woldehanna, 2009; Khandker et al., 2009). However, this may not be true in reality. Roads constitute a network. Thus, road connectivity is beneficial regardless of distance. This paper will show that farmers in Mozambique benefit differently from local market accessibility versus other long-distance accessibility, such as port access.

In the development context, agricultural growth is an important policy agenda. Although it is simply a classic structural transformation that the agricultural sector is reduced in relative terms, about 330 million people or 53 per cent of the working age population still engage in agricultural production in Africa. The potential exists in the region but has not been fully explored yet.1 The poor transport connectivity often impedes farmers’ access to input and output markets.2 Using spatial data, Dorosh et al. (2012) find that transport accessibility to a large city is highly related to agricultural production in Africa. Still, causality remains unclear. With the potential endogeneity controlled, the current paper attempts to have an unbiased estimate of the impact of transport connectivity on agricultural production.

The remaining sections are organised as follows: Section 2 provides an overall country context. Section 3 develops an empirical model. Section 4 describes our data. Section 5 presents our main estimation results and discusses some policy implications. Section 6 concludes.

2. Country context

Mozambique has a wide range of economic potentials, such as agriculture, agrobusiness, light manufacturing, and mining. During the first half of the 2010s, the average economic growth
rate reached approximately 7 per cent per year, with particularly strong growth performance by the nonmanufacturing industry (10 per cent growth) and the service sector (9 per cent). Although the national poverty rate improved considerably, it remained persistently high in rural areas. Though the poverty rate was reduced from 58 per cent in 2008/2009 (World Bank, 2020), approximately 12.3 million people or 48 per cent still lived below the poverty line in 2014/2015. The growing literature suggests that regional inequality has been widening in Mozambique. Poverty remains systematically high in the northern and central regions. One reason for the increasing inequality is the skewed distribution of benefits from the emerging non-subsistence sectors, such as mining (Gradín & Tarp, 2019). Another reason may be misallocation of public investment biased towards urban areas (World Bank, 2019). Although some resource-dependent growth led by liquefied natural gas projects is expected in the short term, it may not be sustainable or inclusive. Many poor, rural residents in remote areas are left behind.

Agriculture is an important economic sector in Mozambique, employing approximately 80 per cent of the country’s workforce and generating 30 per cent of GDP. Mozambique produces approximately US$3 billion in agricultural crops. Domestic food crops such as cassava (US$1 billion), bananas (US$132 million), and maize (US$125 million) are predominant. In addition, Mozambique is a traditional exporter of cash crops such as tobacco, sugar, and cotton. Tobacco and cotton exports value US$200 million and US$40 million per year, respectively. Agricultural productivity is low because production is based on subsistence farming, with few advanced inputs, such as fertiliser, irrigation, and improved seeds, used. Cereal yield in Mozambique averaged approximately 0.8 tons per hectare from 1996 to 2016, which is approximately 10 per cent to 20 per cent of the world average yield and among the lowest even in Africa (Zavale et al., 2020). With few other job opportunities, most poor people in rural areas depend on agriculture.

From the agroclimatic point of view, Mozambique has significant untapped agricultural potential. Geographically, production areas are concentrated in Nampula and Zambezia provinces and in coastal areas of the southern provinces. The country is estimated to currently produce about US$3 billion of crops per year (Figure 1). According to IFPRI’s Spatial Production Allocation Model (SPAM) (see You & Wood, 2006); however, it has an agricultural potential of more than US$500 billion (Figure 2). The government of Mozambique has been trying to modernise and commercialise the agricultural sector. The goal of its 10-year development plan was to double productivity by promoting adoption of more advanced inputs, such as fertilisers and improved seeds, and improving rural infrastructure, including the road network and storage facilities. The implementation of the plan seems to have lagged, with only 3.8 per cent of smallholder farmers using fertilisers, 3.4 per cent using pesticides, and 5.2 per cent using improved seeds in 2014/2015 (Zavale et al., 2020). These figures do not seem to be very different from the situation in the early 2000s, when only 7 per cent of smallholder farmers used fertilisers, animal traction, or small-scale irrigation (Mucavele, 2009). Agricultural productivity growth has been particularly stagnant in the southern provinces, which is evident in their high food import-dependency on South Africa and weak north-south transport linkages (Pauw, Thurlow, Uaiene, & Mazunda, 2012).

Transport connectivity is an important constraint for Mozambiquan farmers. Only 10 per cent of arable land is in use, of which 90 per cent is used for small-scale subsistence farming. Low fertiliser adoption is partly attributed to high transportation costs for farmers to access input and output markets (Zavale et al., 2020). The expansion of all-year road access to areas with high productive potential is identified as a key strategy to achieve an annual agricultural growth of 7 per cent (Ministry of Agriculture, 2010).

Historically, Mozambique’s north-south connectivity has been limited. Since the late nineteenth century, three east-west rail systems have been developed, all of which connect inland areas to major seaports on the Indian Ocean, such as Nacala in the north, Beira in the central region and Maputo in the south. In 2006, the Government of Mozambique embarked upon the
Road Sector Strategy 2007–2014, allocating significant public resources to road rehabilitation and upgrading works in the first half of the 2010s (3), particularly focusing on National Road 1 (N1), a main north-south corridor (Figure 4). The share of classified roads in good or fair condition was increased from 59 per cent in 2006 to 70 per cent in 2011 (Ministry of Public Works and Housing, 2015; National Roads Administration, 2006). Although primary paved roads are relatively well maintained, some national and rural roads are in poor condition, particularly where climate vulnerability is high, for instance, the Cabo Delgado, Nampula, Niassa, and Zambezia provinces. About 44 per cent of rural (unpaved) roads were in poor condition in 2017, increasing from 42 per cent in 2010.

Because of the recent intensive road investments, transport connectivity is expected to have improved. The impact however may vary across locations. The degree to which the connectivity was improved may differ across locations. It also varies depending on type of connectivity. Using the detailed road condition data, three types of connectivity are considered (see Supplementary Materials for a detailed explanation about how our connectivity variables are constructed).

First, rural accessibility is considered. Rural accessibility can be measured by the Rural Access Index (RAI), which is defined by the proportion of people who have access to an all-season road within an approximate walking distance of 2 km or a walking time of 25 minutes (World Bank, 2016). This is one of the global indicators in the transport sector and was adopted as one of the Sustainable Development Goals (SDGs) Indicators 9.1.1. In Mozambique, the national RAI deteriorated from 27 per cent in 2006 to 20.4 per cent in 2010 and then to 19.3 per cent in 2015. There is a marked heterogeneity across areas. RAI is
estimated by administrative post (which is the lowest administrative boundary in Mozambique) to be less than 10 per cent in many rural areas. In urban areas close to megacities, such as Maputo and Nampula, it is estimated to be over 60 per cent (Figure 5).

Second, domestic market accessibility is measured by the potential market that can be reached from a given location (Figure 6). While Mozambique has several large markets, such as Maputo and Beira, there are also many other small local markets at the district and village levels. Since there is no presumption about which markets are destined for, all these markets need to be

**Figure 2.** Agricultural production potential ($mil).
*Source: IFPRI SPAM Update.*

**Figure 3.** Road sector spending (constant 2010 MZN million).
captured. To this end, the geographic area that is reachable in 5 hours is considered. With the road conditions taken into account, the number of people who live in this area is calculated. In general, the road improvement allows for faster driving, thus, resulting in increased market accessibility, which stimulates agricultural production. The areas along good national highways and peri-urban areas seem to have the advantage of proximity to consumption areas. In remote areas, on the other hand, farmers may be faced with more difficulties accessing agricultural input and output markets.

Finally, the accessibility to global and regional markets is measured by computing the transport cost of bringing one ton of goods to the nearest port. The transport costs are dependent on underlying road condition and surface type. The poor quality of roads increases vehicle operating costs and transport costs. Three regional hub ports at Maputo, Beira, and Nacala are considered as a proxy of the global market. Because of the investment in the southern part of N1, the accessibility to Ports Maputo and Nacala seems to have been improved between 2010 and 2015 (Figure 7). This may have a positive impact on agricultural production of export crops, such as cotton and cashew nuts. However, the northern provinces, such as Tete and Gaza, remain disconnected from the ports, let alone the global market, despite recent major road improvements. In the following analysis, we take advantage of these intertemporal changes in transport connectivity to identify the potential impact on agricultural production.

3. Empirical model

To measure the impacts of transport connectivity and other factors, a conventional production function approach is adopted (see, for instance, Gyimah-Brempong (1987) and
Bravo-Ortega & Lederman (2004) for literature reviews, and Dorosh et al. (2012)). Suppose that household $i$ at location $j$ produces a total value of crops, $v$, at time $t$, using various inputs $X$. Then, the following simple specification is considered:

$$\ln v_{ijt} = \beta_0 + \beta_TR\ln TR_{jt} + X'_{ijt}\beta_X + Z'_{ijt}\beta_Z + c_j + c_t + \varepsilon_{ijt}$$  \hspace{1cm} (1)
The dependent variable is the total value of crops produced. The advantage of aggregating all crops is that we can avoid extreme values in production of each crop. Although the production patterns remained broadly the same over the surveyed period, there were certain changes in crops produced by sampled households (see Supplementary Materials). By using the total value of crops, the dependent variable is expected to be less noisy, mitigating potential noise in the data. Transport connectivity at $i$’s location $j$ is denoted by $TR$, which can affect agricultural productivity. Note that $TR$ is time-variant. Our estimation exploits such a variation over time,
apart from the location-specific fixed effects, $c_j$. $Z$ is a set of household characteristics to control for heterogeneity among households. $c_t$ represents the time-specific fixed effects. $\epsilon$ is an idiosyncratic error.

For production inputs $X$, five inputs are considered in this paper: labour ($L$), land ($H$), fertiliser ($F$), pesticide ($P$), and employed labour ($N$). In the literature, commonly considered production factors are labour, land, fertiliser, and irrigation. Irrigation is not included because its use is still minimal in Mozambique.\(^4\) In general, fertiliser and other advanced inputs are critical to

Figure 7. Transport costs to a major port.

Source: Author’s calculation based on data provided by National Roads Administration (ANE)
increasing agricultural production, although the statistical significance varies across studies (Bravo-Ortega & Lederman, 2004). In the African context, for instance, it is shown that timely availability of fertiliser could increase maize yields by 11 per cent (Xu, Guan, Jayne, & Black, 2009).

To avoid taking the logarithm of zero, the inverse hyperbolic sine transformation (or arcsinh) is used: $x = \text{arcsinh}(x) = \ln(x + \sqrt{x^2 + 1})$. Bellemare and Wichman (2020) show that the inverse hyperbolic sine transformation to a variable is a good approximate of the natural logarithm of that variable and allows retaining zero-valued observations. In our data, for instance, fertiliser or pesticide is not often used. Given our loglinear-arcsinh specification, the output elasticity with respect to production factor $x$ can be estimated by:

$$\eta_{vx} = \beta_x \frac{x}{\sqrt{x^2 + 1}}$$

In our model, the hyperbolic sine transformation is applied to fertiliser, pesticide, and employed labour, which have zero values in many observations. The same transformation is also used for some of the household characteristics, such as the number of household members who are self-employed or engaged in employed activities.

For transport connectivity, it is important to account for different types of connectivity required for different crops. The literature indicates that transport connectivity is generally an important determinant of agricultural productivity. Better market access can reduce input prices. Khandker et al. (2009) find that farm-gate fertiliser prices were lowered by rural road investment in Bangladesh. Improved transport infrastructure can also provide more opportunities for farmers to engage in cash crop production and market transactions. Khandker et al. (2009) shows that agriculture output prices increased by 2 per cent, and the volume of production was boosted by 22 per cent. However, the examined connectivity seems to be different. For instance, access to the road network is of foremost importance for farmers and anyone. Access to domestic markets is also essential for farmers to not only sell their produce but also purchase necessary inputs and equipment. When agriculture is more advanced and commercialised, access to ports may also be important for export crop producers. Mozambique produces tobacco, cotton, and cashew nuts, which are historically important export commodities of the country. To capture the heterogenous impacts of connectivity discussed in the previous section, three variables are constructed: Rural Access Index ($TR_{RAI}$), domestic market accessibility ($TR_{MKT}$) and access to global or regional markets (which are proxied by the ports) ($TR_{PORT}$).

One of the most important empirical issues to estimate Equation (1) is endogeneity of transport connectivity. The Government’s decision on infrastructure investment is often affected by various tangible and intangible factors. Unfortunately, econometricians cannot observe all of them. Therefore, there would likely be endogeneity due to omitted-variable bias. For example, agricultural productivity is inherently high where agroclimatic potential already exists for meteorological and geological reasons. More people tend to live in such areas. Policymakers may invest more in public infrastructure where many people live. As the result, high road density can coexist with high agricultural productivity regardless of their actual impact. If this is the case, the ordinary least squares estimator is likely to be upwardly biased (for example, Banerjee et al., 2020; Chandra & Thompson, 2000).

To mitigate this risk, the current paper combines two approaches. First, it takes advantage of the narrowly defined location-specific fixed effects ($c_j$) to control for unobservables. If panel data were available, their unobserved time-invariant characteristics could be removed. However, our agricultural sample survey data is not panel but composed of two rounds of cross-sectional data in 2012 and 2015. The farmers’ locations are only identifiable at the postos level. Postos are the smallest administrative unit in Mozambique. The country has 10 provinces, which are divided into 128 divisions. Each division has one to seven postos, the lowest administrative boundary in Mozambique. In most cases, there are two or three postos in each
division. In total, Mozambique has 405 postos, which on average about 53,000 people live in each. By using the postos-specific fixed effects, we can control substantially for location-specific unobservables, such as agroclimatic potential.

Second, the paper also takes advantage of the instrumental variable (IV) technique. Following the literature (for example, Banerjee et al., 2020; Datta, 2012), two instrumental variables are constructed based on the history of transport infrastructure development in Mozambique. They are expected to allow for some exogenous variation in data. The first instrument is the straight-line distance from each posto to the existing rail lines. In the colonial era, many rail lines were developed based on political and military motivation in Africa (for example, Amin, Duncan, & Alastair, 1986). Their placement is often irrelevant to economic outcomes that are observed at present (Jedwab & Moradi, 2012). In the case of Mozambique, some economic motives may have existed. The rail lines aimed to connect resource-rich inland areas, such as Northern Rhodesia (now Zambia) and Southern Rhodesia (now Zimbabwe), to the Indian Ocean. But the railway construction in Mozambique seems to have been less relevant to agricultural productivity. However, the established rail infrastructure has clearly been affecting the country’s road transport development since then. Therefore, it is clearly relevant to our transport connectivity variables.

Another instrument is constructed using a historical map including eight landing sites (ports) that already existed in the 1860s (Gräf (186-?)). The logic behind it is the same as the above. The historic ports may have been ‘discovered’ perhaps because of their topological conditions and less likely to be related to agricultural productivity. Thus, the straight-line distance from each posto to the nearest historical landing site is likely to be related more to the current transport connectivity and less to agricultural productivity. To allow time-series variations, the fuel prices are used. No households are individually capable of influencing the fuel prices (for example, Storeygard, 2016). The instruments are multiplied by the pump prices. which were US$1.58 and US$0.65 in 2010 and 2015, respectively. Note that the validity of these instruments will ex post be tested empirically with actual data.

It is important to note that our transport connectivity variables are time-variant. The underlying road condition data, based on which our transport variables are constructed, are available for 2010 and 2015. There is considerable variation in our three constructed variables (Table 1), presumably because of the Government’s intensive investments in the road network during the first half of the 2010s. In the postos where the sample data were collected, rural accessibility increased from 22 per cent to 23.1 per cent. The change is statistically significant according to the t-test. The reachable market size also increased by an average 10,000 people because of the improved road conditions. The difference is statistically significant at the 1 per cent level, though it varies substantially across locations. The transportation costs to the nearest port declined by US$3.20 on average.

The observed changes look different by region. The transport connectivity improved most in the southern region, followed by the northern region. The improvements are modest in the central region (Table 2). The paper exploits these time and locational variations to quantify the impact of transport connectivity.

Table 1. Changes in transport variables between 2010 and 2015

| Variable | 2010 | 2015 | Difference |
|----------|------|------|------------|
|          | Obs  | Mean | Standard error | Obs  | Mean | Standard error | Mean | Standard error |
| TRRAI    | 12,064 | 0.220 (0.002) | | 12,626 | 0.231 (0.002) | 0.010 (0.002)** | |
| TRMKT    | 12,064 | 28,670.7 (1188.4) | | 12,626 | 38,866.1 (1777.3) | 10,195.4 (2157.6)** | |
| TRPORT   | 11,984 | 24.657 (0.115) | | 12,626 | 21.396 (0.109) | –3.261 (0.159)*** | |
4. Data

Our crop production data come from the agricultural sample surveys in 2012 and 2015, each of which is comprised of about 13,000 households nationwide in Mozambique. With the observations containing missing data excluded, the following analysis uses about 24,000 observations. The data covers 43 food crops and vegetables. To aggregate different types of crops, the median values of local market prices from the surveys are used. See Supplementary Materials for a full list of prices that are used for the conversion.

Summary statistics are shown in Table 3. An average farmer produces about US$5000 of crops per annum. This is the total production value evaluated at market prices. Note that some of the crops produced may be self-consumed. The potentially reachable market size varies significantly from nearly zero to over 3 million people, with an average of 34,000. In Manica, Niassa and Tete Provinces, there are some inland areas where domestic markets are very far. Rural accessibility is on average 23 per cent. The average cost of transporting goods to the nearest port is about US$23 per ton, with a wide range from nearly zero to US$73.

The vast majority of households surveyed by the studies are small-scale farmers, owning less than 1.5 ha of land. The distribution of land is heavily skewed with a wide variation from 0.0001 ha to 57 ha. Fertiliser use is generally limited. The average land area is about 2 ha. Regarding the use of advanced agricultural inputs, about 5 per cent of households use chemical or organic fertiliser in their production system. The average amount of fertiliser used is merely 11.8 kg. Similarly, there are only a few households that use pesticides. About 5.7 per cent of households use pesticides, with an average amount of 2.1 kg. In the sample data about 3 per cent of the households rely on irrigation. However, this variable turns out to be highly correlated with the use of fertiliser and pesticides and thus was omitted from our model.

5. Estimation results and policy implications

The OLS regression is first performed with the location-specific fixed effects included. Although the estimates are potentially biased because of the uncontrolled infrastructure endogeneity, it is confirmed that the estimated coefficients are broadly consistent with prior expectations. The location-specific fixed-effect model control for a large part of unobservables. All the production inputs included in the model seem to be productive, but the implied elasticities vary. Land has the highest elasticity, followed by labour. The full results are included in Supplementary Materials.

Still, there remains a concern about the infrastructure endogeneity. To address this issue, the instrumental variable (IV) method is combined with the location-specific fixed effects model. The main results are shown in Table 4. Since we have only two instruments, the impact of transport connectivity must be assessed separately among the RAI, market access, and port accessibility. First of all, endogeneity matters. Our proposed IV approach is found to be valid from the statistical point of view. The endogeneity test statistics indicate that the exogeneity hypothesis can be rejected in all cases. The test statistics are estimated at 65.8 to 78.7.

| Table 2. Changes in transport variables by region |
|-----------------------------------------------|
| Region: | North | Central | South |
| variable | Mean | Standard error | Mean | Standard error | Mean | Standard error |
| \( y \) | 16,474 (756) *** | 5105 (567) *** | 5882 (853) *** |
| \( TR_{RAI} \) | 0.012 (0.003) *** | -0.003 (0.003) | 0.014 (0.005) *** |
| \( TR_{MKT} \) | 8003 (3143) *** | -9211 (2486) *** | 38,037 (5439) *** |
| \( TR_{PORT} \) | -2.16 (0.34) *** | -0.08 (0.23) | -8.31 (0.19) *** |

***Statistical significance at the 1 per cent level.
Depending on specification. Thus, our transport variables are likely to be endogenous, implying the endogenous infrastructure placement. The first stage F statistics are fairly large, meaning that the employed instruments are relevant to the transport variables. Finally, Sargan’s test for over identifying restrictions cannot be rejected. The test statistics are estimated at 0.17, 0.19, and 0.99, respectively. Therefore, the proposed instruments are not correlated to with the error term and properly excluded from the equation, ensuring the validity of our IV regression outcomes.

32. The IV results indicate that agricultural production increases with rural accessibility and access to domestic markets. The coefficient of RAI is estimated at 7.00. Thus, rural accessibility is important to promote agricultural growth in Mozambique. This is very basic accessibility at the local level. Recall that the RAI is measured by accessibility to an all-season road within a walking distance of 2 km. The coefficient of TR_{MKT} is also found to be significant and positive at 0.41, meaning that if a farmer has better access to the market, he or she produces more agricultural produce. The estimated elasticity looks relatively high compared with earlier studies in the literature, which show a range between 0.05 and 0.15 (see, for example, Donaldson, 2018; Iimi, You, & Wood-Sichra, 2020; Khandker et al., 2009). Therefore in Mozambique, it is

### Table 3. Summary statistics

| Variable | Abb. | Obs. | Mean | Standard deviation | Min. | Max. |
|----------|------|------|------|--------------------|------|------|
| Total value of crops produced by each household (US$) | v | 24,690 | 5110 | 34,359 | 0.04 | 1,944,825 |
| Rural Access Index at postos level (0 to 1) | TR_{RAI} | 24,690 | 0.23 | 0.19 | 0.00 | 0.98 |
| Potentially reachable market size measured by the number of people who live in 5 h | TR_{MKT} | 24,690 | 33884 | 169,546 | 0.35 | 3,186,671 |
| Transport cost to the nearest port (US$ per ton) | TR_{PORT} | 24,610 | 22.98 | 12.54 | 0.00 | 73.01 |
| Number of household members working on crop production | L | 24,690 | 2.57 | 1.49 | 0.50 | 26.50 |
| Land area cultivated (ha) | H | 24,690 | 2.03 | 2.24 | 0 | 57 |
| Fertiliser use (kg) | F | 24,690 | 11.81 | 353.78 | 0 | 36,700 |
| Pesticide use (kg) | P | 24,690 | 2.10 | 56.60 | 0 | 5000 |
| Outside labour employed | N | 24,690 | 0.10 | 0.98 | 0 | 40 |
| Household head sex (male = 1) | D_{male} | 24,690 | 0.73 | 0.44 | 0 | 1 |
| Household head age | Age | 24,690 | 44.99 | 15.60 | 13 | 99 |
| Household head education attainment | Edu | 24,690 | 4.10 | 3.28 | 1 | 14 |
| Household size | Size | 24,690 | 5.37 | 2.93 | 1 | 56 |
| Dummy for households receiving agriculture training | D_{training} | 24,690 | 0.02 | 0.15 | 0 | 1 |
| Dummy for household receiving agriculture extension services in last 12 months | D_{extension} | 24,690 | 0.07 | 0.25 | 0 | 1 |
| Dummy for animal traction use | D_{animal} | 24,690 | 0.22 | 0.41 | 0 | 1 |
| Number of household members engaged in employed activities | Employed | 24,690 | 0.50 | 0.85 | 0 | 10 |
| Number of household members engaged in self-employment activities | SelfEmp | 24,690 | 0.65 | 0.86 | 0 | 9 |
| Year 2012 | | 24,690 | 0.49 | 0.50 | 0 | 1 |
| Year 2015 | | 24,690 | 0.51 | 0.50 | 0 | 1 |
| Instruments: | | | | | | |
| Straight distance from the rail line (km) | KM_{rail} | 24,690 | 126.85 | 101.76 | 0.24 | 440.25 |
| Straight distance from the nearest historic port city (km) | KM_{port} | 24,690 | 189.54 | 140.50 | 0.77 | 622.35 |

*a* A part-time worker counts for 0.5 of a full-time equivalent.

*b* Categorically ordered from one for no education, 2 to 13 for formal education grades, and to 14 for the most advanced education.
important to not only improve rural accessibility, which is always a fundamental prerequisite for development, but also connect farmers to domestic markets. One of the unexpected results may be a positive coefficient for $TR_{PORT}$, which is statistically significant. Note that the current paper ignores the importance of Mozambique’s road network connecting its neighbouring landlocked countries, such as Malawi and Zambia, to regional hub ports. This is outside the scope of the current analysis; however, it is of course important from the regional integration point of view. The result seems to be affected by potential heterogeneity across regions. Mozambique is a large and geographically diverse country with a land area of 786,000 km$^2$, with a stretch of over 2000 km from north to south and about 1000 km from east to west. The transport connectivity is generally better in the south. On the other hand, the northern and central provinces are more fertile than the southern provinces, which are more urbanised (Figures 1 and 2). The levels of agricultural development and market orientation also differ across regions. Market opportunities for farmers are much more limited in the north, where transport connectivity is generally low. Agriculture in the southern region is more focused on cash crops. The region is also highly dependent on food imports from South Africa. Note that as shown in Figure 7, transport connectivity between the north and the south is weak in Mozambique. Therefore, agricultural growth has historically been stagnant in the northern and southern provinces (Pauw et al., 2012).

### Table 4. IV regression with location-specific fixed effects

|                | Coef.       | Standard error | Coef.       | Standard error | Coef.       | Standard error |
|----------------|-------------|----------------|-------------|----------------|-------------|----------------|
| $\ln TR_{RAI}$ | 7.000       | (1.457)***     |             |                |             |                |
| $\ln TR_{MKT}$| 0.413       | (0.055)***     |             |                | 1.733       | (0.219)***     |
| $\ln L$       | 0.186       | (0.044)***     | 0.181       | (0.030)***     | 0.181       | (0.029)***     |
| $\ln H$       | 0.531       | (0.023)***     | 0.596       | (0.014)***     | 0.595       | (0.014)***     |
| arcsinh $F$    | 0.164       | (0.019)***     | 0.144       | (0.011)***     | 0.143       | (0.010)***     |
| arcsinh $P$    | 0.120       | (0.032)***     | 0.084       | (0.017)***     | 0.083       | (0.017)***     |
| arcsinh $N$    | 0.266       | (0.056)***     | 0.172       | (0.035)***     | 0.169       | (0.034)***     |
| $D_{male}$     | 0.038       | (0.039)        | 0.053       | (0.027)**      | 0.058       | (0.025)**      |
| $\ln Age$     | 0.203       | (0.051)***     | 0.239       | (0.032)***     | 0.260       | (0.031)**      |
| $\ln Edu$     | 0.072       | (0.019)***     | 0.076       | (0.013)**      | 0.079       | (0.013)**      |
| $\ln Size$    | 0.033       | (0.037)        | 0.055       | (0.025)**      | 0.050       | (0.024)**      |
| $D_{training}$| -0.068      | (0.124)        | 0.116       | (0.081)        | 0.089       | (0.078)        |
| $D_{extension}$| 0.465       | (0.066)***     | 0.319       | (0.046)***     | 0.320       | (0.045)***     |
| $D_{animal}$  | 0.165       | (0.043)***     | 0.179       | (0.038)***     | 0.162       | (0.035)***     |
| arcsinh $Employed$ | -0.164     | (0.033)***   | -0.068      | (0.019)***     | -0.048      | (0.018)***     |
| arcsinh $SelfEmp$ | 0.054       | (0.029)*      | 0.096       | (0.019)***     | 0.103       | (0.018)***     |
| $t$           | -0.950      | (0.042)***     | -0.800      | (0.024)***     | -0.436      | (0.044)***     |
| constant      | 16.047      | (2.248)***     | 2.337       | (0.424)***     | -1.751      | (0.901)*       |
| Obs.           | 23,502      | 24,690         | 24,636      |                |             |                |
| No. of postos |             |                |             |                |             |                |
| dummy variables|             |                |             |                |             |                |
|               | 353         | 379            | 377         |                |             |                |
| R-squared     |             | 20.404         | 30.301      |                |             |                |
| Wald chi2     | 8023.6      | 11,187         | 11,772      |                |             |                |
| Exogeneity test chi2 stat. | 78.777***     | 65.822***     | 66.692***   |                |             |                |
| First stage F-stat. | 18.88***     | 429.77***     | 783.69***   |                |             |                |
| Sargan overidentifying restrictions chi2 | 0.173 | 0.193 | 0.997 |                |             |                |

Notes: The dependent variable is the total value of crop production of each household. Robust standard errors are shown in parentheses. *, **, and *** indicate the statistical significance at the 10, 5, and 1 per cent level, respectively.
The data is separated into 3 regions: North including Niassa, Cabo Delgado, and Nampula Provinces; Central including Zambezia, Tete, Manica, and Sofala; and South including Inhambane, Gaza, and Maputo. It is found that there are significant differences in the estimated transport connectivity impacts across the regions (Table 5). While the northern provinces still have a weakly positive coefficient for $TR_{\text{PORT}}$, the coefficients for the central and southern provinces turned out to be negative. Thus, port accessibility is important for agricultural growth in the latter. This is consistent with recent agrobusiness developments in these areas, notably, along the Beira corridor. It is consistent with the literature, which is supportive of the importance of port access in African countries (for example, Iimi, Adamtei, Markland, & Tsehaye, 2019). In the northern areas, however, farmers are still disconnected from the global market, which is also consistent with the current crop production patterns. In northern Mozambique, subsistence farming is predominant, producing domestic food crops, such as cassava and maize. In the southern provinces, more cash crops, such as beans and potatoes, are produced.

The rural accessibility has a consistently positive impact on agriculture production. The better rural access, the larger crop production. This looks consistent to the literature. It is normally found that the proximity to rural road projects is important to stimulate agricultural productivity (for example, Dercon et al., 2009; Khandker et al., 2009). The domestic market accessibility is also found to be of particular importance in the northern and central regions. It seems less important to the southern area where urbanisation is high. The negative coefficient may be interpreted to mean low agricultural production where the market accessibility is high and thus highly urbanised.

In sum, among other factors, transport connectivity is generally important to promote agricultural growth in Mozambique. The rural road accessibility is fundamental. As measured by RAI, it is important to rehabilitate and maintain rural roads. It is also important to connect farmers to the domestic markets. The impacts of port accessibility, or access to the global market, are heterogeneous across regions. It is particularly important to the central provinces, where agrobusinesses have been agglomerated.

Apart from transport connectivity, the estimated production functions indicate that the current agricultural system in Mozambique is highly land intensive. The highest elasticity is found for land (Table 6). It is estimated at about 0.53 to 0.59. This is consistent with the fact that Mozambique’s agriculture remains extensive, with little use of non-factor inputs. The elasticity of production with respect to labour input is relatively low, suggesting abundant labour in rural areas. A 10 per cent increase of labour input would result in a 1.8 per cent increase in production. The impacts of fertiliser and pesticides are also found productive. Recall that when the inverse hyperbolic sine transformation is applied, the implied elasticity needs to be calculated based on Equation (2). The elasticities with respect to fertiliser and pesticide are 0.14 and 0.07, respectively.

While agricultural training may not be effective, extension services are found to have an important role to play in increasing agricultural production. The coefficient is always found to be significantly positive, indicating the importance of complementary policy interventions.

### Table 5. Implied elasticity based on IV regression by region

| Transport var. included | $\ln TR_{\text{RAI}}$ Elasticity (Standard error) | $\ln TR_{\text{MKT}}$ Elasticity (Standard error) | $\ln TR_{\text{PORT}}$ Elasticity (Standard error) |
|-------------------------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|
| North                   | 3.098 (0.303)**                                 | 1.496 (0.217)**                                 | 1.214 (0.646)*                                  |
| Central                 | 1.010 (0.599)*                                  | 0.368 (0.091)**                                 | -13.366 (3.127)**                               |
| South                   | 6.505 (1.500)**                                 | -0.156 (0.033)**                                | -0.647 (0.133)**                                |

* and *** indicate statistical significance at the 10 and 1 percent level, respectively.
This includes not only hard infrastructure, such as road connectivity, but also soft issues, such as technical knowledge transfers.

One may wonder whether the underlying production systems are systematically different across regions. When the data is separated into three regions, the implied elasticities are different (Table 7). The table presents the elasticities based on the specification including $TR_{MKT}$ (see the full results in Supplementary Materials). The northern and central provinces are found to be more land and labour intensive. The elasticities associated with land and labour is particularly high in the northern provinces. The elasticities for other production factors, such as fertiliser and pesticide, are commonly low. This is consistent with the fact that subsistence farming is dominant in the country.

Based on the estimated production functions, the degree of returns to scale in agricultural production is estimated. With all data, it is about one; however, there is significant heterogeneity across regions. With the pooled data, the sum of the coefficients of the five agricultural inputs, that is, $L$, $H$, $F$, $P$, and $N$, is estimated at 1.01 with a standard error of 0.03 to 0.05 (see Table 6). Regardless of specification, the hypothesis that the degree of homogeneity is equal to one cannot be rejected by the chi square test statistics using the delta method. Thus, the current production system is considered reasonably productive.

When the data are disaggregated to three regions, the degree of returns to scale is different from region to region. The highest returns are found in the northern provinces (Table 8). It ranges from 1.22 to 1.42, depending on specification. In all cases, the constant returns to scale can be rejected. This is consistent with the fact that northern Mozambique is very fertile from the agroclimatic point of view, but its potential remains underdeveloped because of poor transport connectivity. There are certain cases where the agricultural production exhibits economies
of scale in Africa. For instance, Izekor and Alufohai (2015) estimate the return to scale in agriculture at 1.43 in Nigeria. Agricultural growth remains an important growth agenda in the region, but perhaps, it must depend on location.

On the other hand, the southern provinces are found to be much less productive. The estimated degree of returns to scale ranges from 0.47 to 0.64. The hypothesis that the production system exhibits diminishing returns cannot be rejected. As discussed, this can be partly attributed to the southern areas in Mozambique being generally more urbanised and less fertile. It is also attributed to the fact that the majority of agricultural production systems in Mozambique, as in other African countries, are small-scale subsistence farming. There are no scale economies. The returns to scale in the central region are something between the two other regions. It is estimated at about 1.1, supporting the degree of homogeneity of production function.

From the policy point of view, it can be concluded that high priority areas for agricultural growth in Mozambique are the northern and central regions. Prioritisation is of importance from the public infrastructure investment point of view because available resources are always limited. While primary paved roads are relatively well maintained, rural roads are generally poor. About 44 per cent of rural roads were in poor condition in 2017. It is estimated that approximately US$400 million (about 2 per cent of GDP) are needed to maintain the current road network optimally (World Bank, 2021). However in recent years, only about US$200 million is available in the road sector. Therefore, strategic prioritisation of road investment and maintenance is essential.

6. Conclusion

Transport connectivity is one of the most important growth constraints in the developing world, where agriculture remains an important economic sector. The literature is supportive of a wide range of positive impacts of improved transport connectivity; however, it is still a challenge to estimate the impacts of transport connectivity on economic outcomes consistently. One difficulty is endogeneity caused by transport infrastructure placement. Another challenge is that transport data is often scarce. Granular, time-series data, specifically, is rarely available.

The paper constructed pseudo-panel data with transport infrastructure defined at high resolution in two periods of time and estimated the unbiased impacts of improved transport connectivity. Taking advantage of a unique opportunity in Mozambique where detailed road network data exists and substantial road investment was made during a relatively short period in the 2010s, the IV method is combined with the location-specific fixed effects.

The estimated results confirmed that the endogeneity of transport infrastructure placement matters, as expected. The exogeneity hypothesis can be rejected. Based on the standard test statistics, our proposed IV approach is found to be largely valid. This is one contribution to the literature. The same method may be applicable to other cases. It is also shown that agricultural production increases with rural accessibility and access to domestic markets. The estimated

### Table 8. Implied rate of return based on IV estimation by region

| Transport var. included | $\ln TR_{RAI}$ | Standard error | $\ln TR_{MKT}$ | Standard error | $\ln TR_{PORT}$ | Standard error |
|------------------------|----------------|----------------|----------------|----------------|----------------|----------------|
| North                  | 1.222 (0.086)** | 1.423 (0.089)** | 1.347 (0.069)** |
| Central                | 1.147 (0.048)** | 1.123 (0.048)** | 1.101 (0.049)** |
| South                  | 0.473 (0.090)** | 0.648 (0.065)** | 0.641 (0.064)** |

*** Statistical significance at the 1 percent level.
elasticities are relatively large, suggesting that the potential impacts of transport infrastructure investment are generally significant in Mozambique.

Although, the impacts of connectivity vary across different types of accessibility. Rural accessibility is consistently found to be important to agriculture production: The better rural access, the greater crop production. On the other hand, the estimated impact of port accessibility is much more heterogeneous among the regions. Port accessibility is important for agricultural growth in the central and southern regions, where agribusinesses have been developed, but not in the northern province, where subsistence farming of food crops is still predominant. Thus, different transport development projects are needed depending on the location and needs.

The significance of regional heterogeneity cannot also be underestimated from the public expenditure point of view. Fiscal space is limited in low-income countries, such as Mozambique. Among the three regions, the highest returns are found in the northern provinces where transport connectivity is relatively limited, but agricultural growth potential is high from the agroclimatic point of view. Strategic prioritisation is essential to stimulate the country’s agricultural growth.

Finally, it is reconfirmed that it is not only transport connectivity but also other soft issues that determine agricultural productivity. The analysis shows that extension services have an important role to play in increasing agricultural production. Education is also an important household characteristic to increase agricultural production. Complementary policy interventions, including not only hard infrastructure but also soft issues, such as technical knowledge transfers, are also important.

Notes

1. It is estimated that agricultural production, which currently generates US$31 billion or nearly half of the GDP of the region, could be increased to US$1 trillion by 2030 (World Bank, 2013). In West Africa, the ratios of potential to actual agricultural outputs are estimated at 1.5 for cassava, 1.9 for rice, 2.7 for maize, and 5 for wheat.
2. The limited use of fertiliser and other advanced inputs is a typical constraint (Bravo-Ortega & Lederman, 2004). In Zambia, farmers use 25 kg of nitrogen per hectare, about 20 per cent of the recommended amount of fertiliser (Xu et al., 2009). In Mali, it is shown that even small-scale irrigation can increase productivity and household income dramatically (Dillon, 2011).
3. Based on FAOSTAT.
4. Even if the irrigation use is included, the estimation results turned out unchanged, while the irrigation variable is statistically insignificant.
5. The northern region includes Niassa, Cabo Delgado, and Nampula Provinces, the central region includes Zambezia, Tete, Manica, and Sofala Provinces, and the southern region is composed of Inhambane, Gaza, and Maputo Provinces.
6. Delagoa Bay, Inhambane Port, Sofala Port, Luabo Port, Kalimane Port, Port Curro, Mozambique, and Ilha do Ibo Port.
7. According to the World Development Indicators.
8. The crop prices observed in the sample data have a huge variation across areas and households, depending on location and quantity sold. This creates significant noise in our dependent variable. To mitigate this problem, the median is used rather than the mean.
9. See Supplementary Materials for summary statistics by year and a correlation matrix of the variables.
10. See Supplementary Materials for the detailed results.
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