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How Large are the Contributions of Cities to the Development of Rural Communities? A Market Access Approach for a Quarter Century of Evidence from Chile

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¿Que tan importantes son los efectos de las ciudades en el desarrollo económico de las comunidades rurales? Un enfoque de acceso a mercados para un cuarto de siglo de evidencia en Chile

RESUMEN

Este articulo estima el impacto de las ciudades en el desarrollo economico de las comunidades rurales en Chile siguiendo un enfoque de acceso a mercados. El efecto de la proximidad a ciudades en el desarrollo de las comunidades rurales es analizado estimando el impacto del acceso a mercados en la poblacion, y empleo agricola y no-agricola de las comunidades rurales. Usando censos de poblacion y datos satelitales, encontramos que un 10% de mayor acceso a mercados indujo un crecimiento de un 10 a un 14% en la poblacion de las comunidades rurales. Adicionalmente, elasticidades de mayor magnitud fueron encontradas para el empleo no-agricola que en el caso del empleo agricola. Nuestros resultados apoyan la hipotesis de cambio estructural y diversificacion de la economia rural para comunidades rurales con mayor acceso a mercados.

Palabras clave: Desarrollo Económico Rural, Acceso a Mercados, Empleo Rural Agricola y No Agricola, Sistema Urbano

SUMMARY

This article estimates the impact of cities on the economic development of rural communities in Chile, following a market access approach. The effect of the proximity to cities on the development of rural communities is analyzed by estimating the impact of market access on the population, and farm and non-farm employment of rural communities. Using population censuses and remote sensing data, we find, in our preferred estimations, that a 10% higher market access induced a 10%–14% increase in the population of rural communities. Additionally, higher positive elasticities are found in the non-farm sector rather than in the agricultural one. Our results widely support the hypothesis of structural change and the diversification of the rural economy for rural communities with better access to markets.

Keywords: Rural Economic Development, Market Access, Farm and Non-Farm Rural Employment, Urban System

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INTRODUCTION

In an increasingly urbanized world, the idea of cities as engines of economic growth and development has gained an increasing number of supporters (Glaeser, 2011). Even for rural policies, the positive effects derived from the urban growth that spill over to rural areas are large enough to outweigh the negative effects, such as the rural-to-urban migration (Christiaensen et al., 2013; Christiaensen and Todo, 2013; Berdegue et al., 2015; Wu et al., 2016). The mechanisms that influence the development of rural areas by means of cities are called 'urban- rural linkages'. Nonetheless, data limitations mean that many arguments for such policies in the rural sector are based on limited rigorous empirical evidence, mostly oriented to the developed world (Partridge and Rickman, 2008).

'Urban-rural linkages' have been recognized as one of the main engines of economic development for rural households (Berdegue et al., 2014). However, the aggregate benefits of these linkages between cities and rural communities are not usually considered simultaneously in a framework (see Wu et al., 2016 for criticism on this point). Therefore, this article focuses on understanding how rural communities are influenced by the scope and intensity of their linkages with cities using a 'market access' approach. Market access is, as Harris (1954) suggests, 'an abstract index of the intensity of possible contact with markets,' and also a proxy for the different spillover effects or linkages between rural and urban areas (Chen and Partridge, 2013).

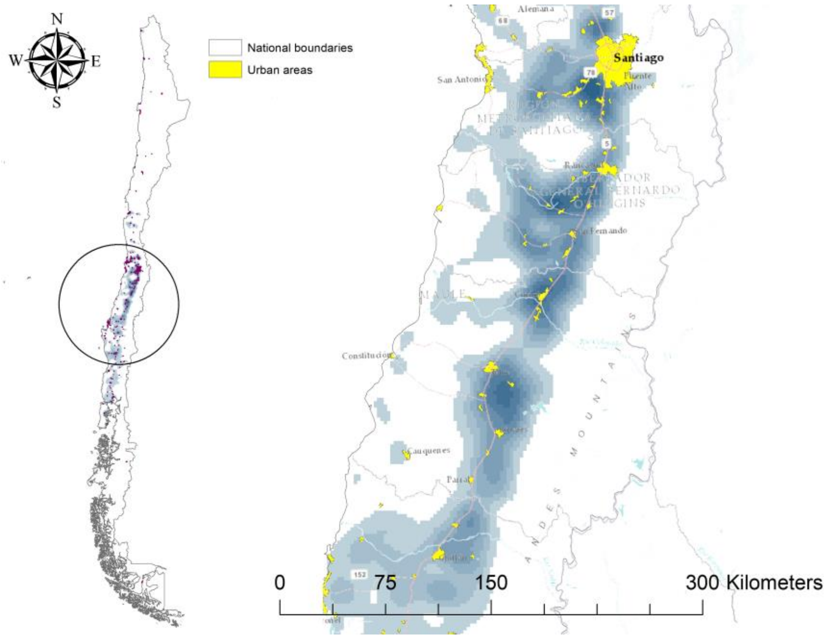
Using population censuses (1992, 2002 and 2017) and remote sensing data, we estimate the impact of market access on the changes in population and farm and non-farm employment for more than 500 rural communities in Chile over 25 years. The population growth, as well as the farm and non-farm employment growth, of rural communities describe the spatial variations in the localization incentives of both rural households and workers. Our results show a 25-year elasticity of market access for the population growth of rural communities of around 1.0 to 1.4 in our preferred estimations, and a positive significant effect in non-farm employment growth. These results are robust to different specifications for market access, including a city-size adjusted market access variable. This adjusted market access variable allows us to capture the greater potential that medium and small-sized cities (compared to large ones) may have for the development of rural communities (and also acknowledges recent contributions in the field, e.g., Christiaensen et al. 2013; Chen and Partridge 2013; Berdegue et al. 2015; Soto and Paredes 2016).

This paper contributes to the literature in four different ways. First, we present a framework that allows us to understand the aggregate effect of cities on the population, farm employment, and non-farm employment growth of rural communities.[1] Second, using a market access approach and following recent advances in measuring the impact of infrastructure on local economic development (Donaldson and Hornbeck, 2016; Jedwab et al., 2017), we present a methodology to estimate the impact of cities on the development of rural communities using population censuses and remote sensing data, following the recent increase in the use of satellite imagery data in the contexts of unavailable or less reliable official information (Henderson et al., 2012; Donaldson and Storeygard, 2016). Third, the unit of analysis of this work is also important. Usually, the units of analysis of empirical works that explore the relationships between cities and rural areas are counties, districts, or other aggregate spatial units (e.g., Chen and Partridge 2013; Berdegue et al. 2015; Veneri and Ruiz 2016). However, this could lead to biased results,

[1] Most empirical studies related to the impact of cities on the growth of rural areas are generalizations of the empirical partial adjustment models of Carlino and Mills (1987), which are usually not explicitly microfounded (e.g., Henry et al., 1999; Deller et al., 2001; Carruthers and Vias, 2005), with only few studies distinguishing between farm and non-farm rural employment.

as exemplified by (Briant et al., 2010).[2] For this reason, we adopt a more disaggregate spatial unit that leads to more precise estimations of the effect of cities on rural communities. Finally, we present evidence for a developing country, where scarce evidence is hitherto found at this analysis level.

FIGURE 1. Cities and Rural Communities in Chile

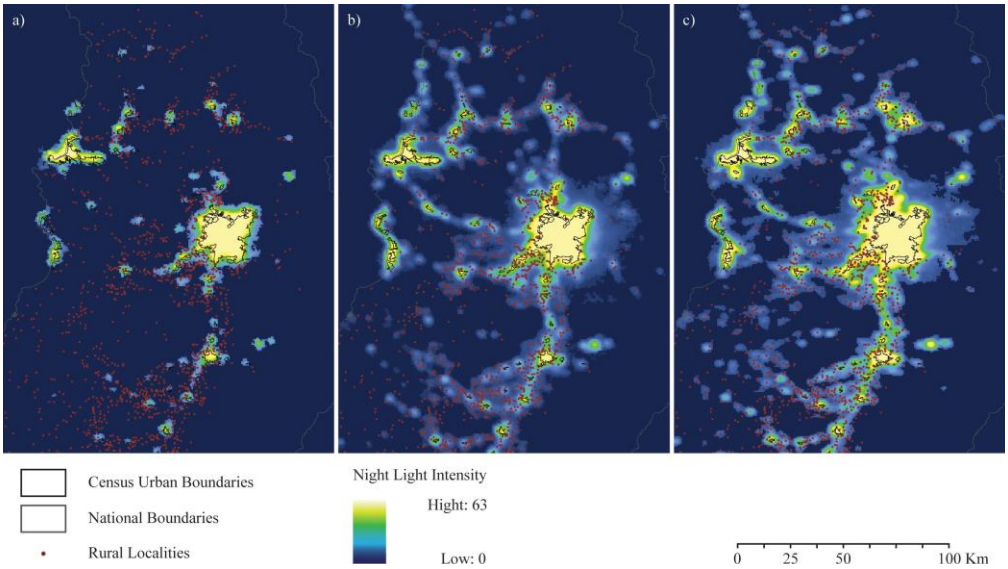


Note: The figure describes the spatial distribution of cities and rural communities in Chile. The yellow color represents urban areas using the administrative city borders at 2002. The blue scale represents the density of rural communities. Rural communities were defined as communities with less than 3,000 inhabitants. A spatial kernel density of the centroids of the rural communities weighted by their population in 2002 is used in the figure. The darker blue color represents more densely populated rural communities. Most of these rural communities are located in the central-south part of the country.

Chile is an interesting case study due to its particular geography. Fig. 1 shows the spatial distribution of rural communities and cities in the country. Chile is 4,700 km long and 450 km wide at its widest point. However, the land and climate conditions mean that most of the rural communities are located in the central-south part of the country, where the majority of the population is also concentrated as are the three most important cities in the country: the metropolitan areas of Santiago and Valparaiso—located at one and a half hours car-driving distance from each other—and Concepción—located on the coastal central south zone of Chile, at eight hours of car-driving distance from Santiago. In this area, between the cities Santiago-Valparaiso and Concepción, there are an important number of small- and medium-sized cities surrounded by a dense "green belt" of rural communities (represented by the blue-color gradient in the Fig. 1), where the majority of the rural population works and lives. The urban growth has been particularly concentrated in this area. The Fig. 2 compares the urban growth using nighttime lights between 1992, 2002 and 2013 (from left to right), near the metropolitan area of Santiago de Chile. Rural communities are represented by red points. The black lines are the census urban boundaries at 2002, and nighttime light intensity is represented by a color scale from dark-blue (low values) to light yellow (high values).

[2] Counties, districts, or municipalities are usually classified as rural when a large percentage of their population is living in rural communities. However, these spatial units are not usually entirely rural. As such, researchers cannot distinguish if growth is occurring only in rural communities, thus overestimating or underestimating the impact of cities on the growth of rural communities

FIGURE 2. Urban Growth and Rural Communities



Note: The figure describes the spatial distribution of rural communities (red points) near the metropolitan area of Santiago de Chile. Panel a) shows the image for 1992, panel b) for 2002 and panel c) for 2013. Urban boundaries (in black) are the official boundaries for the national census of 2002. The economic activity of urban areas was approximated for each year using nighttime light. Nighttime light intensity goes from zero (in dark-blue) to 63 (in light-yellow) and has a spatial resolution of one pixel per kilometer.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 presents the model. Section 4 details the econometric specifications. Section 5 describes the data and estimation issues. Section 6 shows the results and, finally, Section 7 summarizes main results and concludes the paper.

Cities and the Development of Rural Communities

The agricultural economics literature proposes multiple causal mechanisms to understand the relationship between cities and the economic development of rural communities.[3] First, rural communities close to and connected to a densely populated area are more likely to receive more gains of trade than remote ones. This is because cities represent large markets for the commercialization of agricultural goods produced in rural communities, which would raise the prices of these goods, increasing farmers profits from trade (Jacoby, 2000; Donaldson and Hornbeck, 2016). The trade between rural communities and cities could be one of the main channels for rural economic development (Fleming and Abler, 2013) and can contribute to its productive specialization, as well as to the diversification of its economy.

The economic specialization of rural communities tends to be concentrated toward agricultural products that require lower travel times from the production places to the market (Beckmann, 1972; Costinot and Donaldson, 2012). These could lead to higher wages in the agricultural sector, derived from the division of labor (Yang and Liu, 2012). Nonetheless, the increasing demand for jobs in activities auxiliary to agricultural production (e.g., transportation, manufacturing, or sales) could also lead to the economic diversification of rural communities through an increase in the number of non-farm activities (Foster and Rosenzweig, 2004). This diversification may also lead to higher wages in the non-farm sector (Berdegue et al., 2001). However, this is not the rule,

[3] For a good critical summary on this relationship, see Wu et al. (2016).

since some workers in non- farm jobs in rural or even urban areas may earn less than the average wage in the agricultural sector (Perloff, 1991; Lanjouw and Lanjouw, 2001).

The increase in rural non-farm employment could have two different origins. The first is the demand for jobs that are auxiliary to the agricultural sector due to the increasing number of non-farm activities in growing agricultural markets (Foster and Rosenzweig, 2004). The second is the demand for jobs in cities, which leads to the commuting of workers living in rural communities and working in cities (Renkow, 2003). Both causes are likely to be related to low-skill jobs from rural communities in proximity to cities (So et al., 2001). Moreover, rural workers may also be working in remote cities or highly productive extractive places by fly-in/fly-out or drive-in/drive-out commuting; however, this would typically be associated with medium-skill jobs (Paredes et al., 2017).

The number of amenities and employment opportunities in cities could also influence the localization incentives of rural households, causing important migration flows from rural areas to cities, which lead to the decline of the population in rural communities (Goetz and Debertin, 2001). However, in theory, this process may also have a positive effect on the labor productivity of the rural community of origin.[4] This is because rural-urban migration reduces the number of agricultural workers and, since the agricultural production is subject to constant returns to scale, it increases the marginal productivity of each worker in that agricultural area (Harris and Todaro, 1970), accompanying a process of structural change in the economy (Alvarez-Cuadrado and Poschke, 2011). Similarly, the migration of rural workers to cities could, at the same time, increase the amount of remittances that families in the rural community of origin receive (Banerjee, 1984).

Another impact of cities on the development of rural communities is the rent of land (Thunen, 1826). Rural households and landowners have access to lower consumer prices and land rent than city residents, allowing a lower cost of living (Kurre, 2003; Loveridge and Paredes, 2016), and consequently a higher quality of life (Roback, 1982; Deller et al., 2001), which is also due to natural amenities such as open spaces (Klaiber and Phaneuf, 2009) or the access to services that nearby cities offer. Such price advantages in rural communities are widely exploited in urban processes, such as the relocation of the manufacturing industry (Lonsdale and Browning, 1971) and suburbanization (Lopez et al., 1988; Burchfield et al., 2006). The price of the land in rural communities near cities may also be affected by these factors, leading to price increases as market access improves.

The above suggest that the positive effects derived from the trade between rural communities and cities may have a large spatial scope compared to the other mechanisms, which usually have a reduced spatial scope and ambiguous outcomes (Irwin et al., 2009; Castle et al., 2011).[5] Therefore, given that market access is a good proxy of trade flows, this article focuses on measuring and understanding its role in the economic development of rural communities.

A Model of Rural Development and Cities

For the empirical estimations, our analysis is based on a model of urbanization and structural change that follows the setting of Gollin et al. (2016). This model summarizes a large body of literature on structural change and agriculture (see Herrendorf et al., 2014 for a detailed survey). The logic is that urbanization is synonymous with positive income shocks that will move activities from the farm to the non-farm sector and also increase the demand for agricultural goods. Therefore, we assume that the preferences of individuals are represented

[4] This holds only in theory because the empirical findings on this topic are ambiguous at this point.

[5] In fact, empirical works relating cities to rural development found ambiguous results for the effect of this relationship on employment (e.g., Chen and Partridge, 2013 found a non-significant effect on employment in rural areas in China and a negative effect when only capital districts are considered), but also identified consistent positive effects on the population (Partridge et al., 2009). However, these results have to be carefully interpreted due to aggregation in their units of analysis (Briant et al., 2010).

by a log-linear utility function of three goods: food goods produced in rural communities (F), tradable goods produced in cities (NF), and non-tradable goods (S). Therefore, the utility function for a representative individual is

(1) $$U = \beta_F \ln(C_F - \bar{C}_F) + \beta_{NF} \ln(C_{NF}) + \beta_S \ln(C_S),$$

where β_F, β_{NF}, and β_S, $\in \{F, NF, S\}$, with β_j, $j \in \{F, NF, S\}$ representing the percent of income spent on each type of good, under the condition that $\beta_F + \beta_{NF} + \beta_S = 1$. The terms C_F, C_{NF}, and C_S describe the amount of consumption of each good, with $\bar{C}_F$ representing the subsistence food consumption. Individuals maximize their utility subject to a budget constraint given by $P_F^*(C_F - \bar{C}_F) + P_{NF}^* C_{NF} + P_S C_S = m - P_F^* \bar{C}_F$, where $m - P_F^* \bar{C}_F$ is the disposable income. P_F^* and P_{NF}^* are the prices of food and tradable goods, respectively, which are set exogenously. Non-tradable goods are produced only for domestic demand and their price P_S is endogenously determined. Therefore, for tradable ($j = NF$) and non-tradable goods ($j = S$), the condition that $P_j C_j = \beta_j (m - P_F^* \bar{C}_F)$ must be achieved, which for the case of agricultural goods is $P_F^* C_F = \beta_F (m - P_F^* \bar{C}_F) + P_F^* \bar{C}_F$.

On the production side, we assume a small open economy, composed by three productive sectors: agricultural sector (F), located in rural communities; non-agricultural sector (NF), which is tradable and located in cities[6]; and the non-tradable sector (S). For each sector, a representative firm produces one unit of good Y_j, with $j \in \{F, NF, S\}$. This requires an amount of labor L_j. Each economic sector is described by the following production function $Y_j = A_j L_j^{1-\alpha}$, where $A_j > 0$ is a parameter that represents the productivity of each sector. This parameter also considers the effects of capital, land, and agroclimatic conditions. Each economic sector is under perfect competition and the free mobility of workers between sectors is allowed. Therefore, the wage will be equalized across sectors as: $w = (1-\alpha) P_F^* A_F L_F^{-\alpha} = (1-\alpha) P_{NF}^* A_{NF} L_{NF}^{-\alpha} = (1-\alpha) P_S^* A_S L_S^{-\alpha}$. This mobility of labor across sector requires that:

$$\frac{L_{NF}}{L_F} = \left(\frac{P_F^* A_F}{P_{NF}^* A_{NF}}\right)^{\frac{1}{\alpha}}, \qquad \frac{L_{NF}}{L_S} = \left(\frac{P_S^* A_S}{P_{NF}^* A_{NF}}\right)^{\frac{1}{\alpha}}, \qquad \frac{L_F}{L_S} = \left(\frac{P_S^* A_S}{P_F^* A_F}\right)^{\frac{1}{\alpha}}$$

The amount of labor in each sector depends on the relative productivity between them. If the productivity in one sector increases, then the amount of labor increases in relation to other sectors. Therefore, the market clearing conditions to determine the amount of labor in each sector are going to be given by the following condition in the non-tradable sector: $\beta_S (m - P_F^* \bar{C}_F) L = P_S Y_S$. Tradable goods are produced for the domestic market, as well as for exporting. The market clearing conditions for tradable goods are given by:

(2) $$(\beta_F + \beta_{NF})(m - P_F^* \bar{C}_F) L = P_{NF}^* Y_{NF} + P_F^* Y_F - P_F^* \bar{C}_F$$

This means that the expenditure on foods and tradable goods must be equal to the total value of production in each sector. To determine the amount of labor in each sector, we use

(3) $$\frac{\beta_S}{(\beta_F + \beta_{NF})} = \frac{\frac{L_S}{(1-\alpha)}}{\frac{L_F}{(1-\alpha)} + \frac{L_{NF}}{(1-\alpha)} - \frac{P_F^* \bar{C}_F}{w}}.$$

Since $L_F + L_{NF} + L_S = 1$,

6 We can assume, without loss of generality, that a small proportion of non-farm workers produce manufactured goods while continuing to live in rural communities.

(4) $$L_S = \frac{\beta_S}{(1-\alpha)\beta_F + \beta_{NF}}\left(1 - \frac{P_F^* \bar{C}_F}{w}\right).$$

Further, the amount of labor in the agricultural sector is given by

(5) $$L_F = \frac{\beta_F + \beta_{NF}}{(1-\alpha)\beta_S}\left(L_S - L_{NF} - \frac{P_F^* \bar{C}_F}{w}\right).$$

From this setting and assuming that workers are indifferent to working in either sector and have free mobility, the farm employment of a rural community j depend on the way farm and non-farm workers substitute agricultural and manufactured goods. If the demand for agricultural goods is inelastic (as suggested by Tobin, 1950; Tolley et al., 1969; Van-Driel et al., 1997), any improvement in agricultural productivity could induce a movement of farm workers to the non-farm sector since an increase in agricultural productivity decreases the price of the agricultural good. However, since a proportion of non-farm employment is generated in rural communities, this migration from the farm to the non-farm sector does not always imply a reduction in the total employment level of the rural community.

Therefore, the relationship between rural communities and cities is likely to be influenced by the access of rural communities to urban markets. Hence, we assume that there exist k cities influencing nearby rural communities through potential demand. Market access is a measure that captures this potential demand. The market access of rural community j, located at a distance $d_{j,k}$ from a city with Y_k income, is given by $g_j = \sum_j Y_k e^{-\theta d_{j,k}}$ (Harris, 1954; Krugman, 1991; Hanson, 2005), where θ θ is a parameter that defines the shape of the distance discount over Y_k. Following the recent literature on interregional trade and considering that trade diminishes with distance and prices may vary across locations (Eaton and Kortum, 2002; Donaldson and Storeygard, 2016), we assume that the relationship between agricultural and manufactured goods is determined by market access. Consequently, we can set a direct relationship between market access and farm and non-farm employment in rural communities.

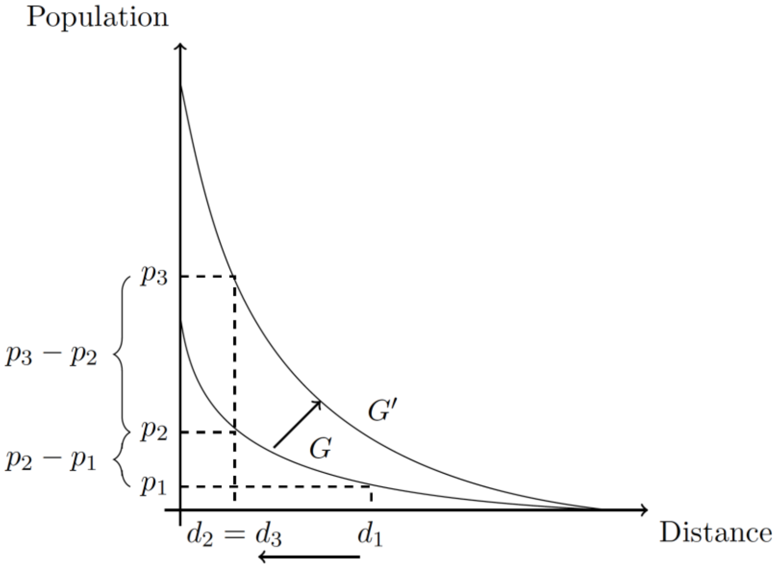
According to our framework, the effects of market access on farm and non- farm employment may be associated with two main mechanisms: the demand for agricultural goods and changes in agricultural productivity. Both of these mechanisms are captured by market access. On one hand, a higher access to urban markets is associated with a higher demand for agricultural products and, consequently, a higher employment in the farm sector and also in the non-farm sector but in activities auxiliary to agriculture, such as the commerce and transportation of agricultural goods. On the other hand, rural communities with increased market access may have more access to technology for agricultural production. This would increase the agricultural productivity of these rural communities, diminishing the price of agricultural goods in relation to manufactured goods, leading to a movement of workers from the farm to the non-farm sector. However, is likely that some non-farm jobs would be in activities that are auxiliary to agriculture.

The effects of market access on the non-farm employment of rural communities may also impact activities not related to agricultural production. For example, if the opportunity cost of producing agricultural goods is higher in the hinterland of cities due to the reallocation of some urban activities such as manufacturing production, this would lead to an increase in the employment of rural communities in the non-farm sector in activities not necessarily related to agricultural production. However, this effect is likely to be found only in the hinterland of cities.

The population of rural communities is an important indicator of their development and also determines total employment (Carlino and Mills, 1987; Henry et al., 1999; Partridge and Rickman, 2003; Hoogstra et al., 2011; Chen and Partridge, 2013; Olfert et al., 2014), considering both the number of workers in the farm and non-farm sector. Despite the migration effects of workers to cities, on average, this may be offset by the benefits of higher market access. From our setting, the expected effect of market access on the non-farm employment of rural communities is positive and, hence, a positive effect is also expected for the population of these communities. An increase in the non-farm employment, however, may also induce a decrease in the farm employment. Notwithstanding, this only would affect negatively the average population of rural communities if this migration is to urban areas.

The aggregate impact of market access over the population on rural communities is exemplified in Fig. 3. The figure compares the population of a rural community at an average distance $d_1$of k cities, with another rural community at an average distance $d_2$of the same cities. The distance decline effect is given by the G curve and the difference in population levels is given by $p_2 - p_1$. However, if cities were bigger (i.e., greater market access), the aggregate influence of these cities over the rural communities is given by the function G'. Consequently, the difference between two rural communities located at the same distance of two differently sized urban systems would be given by $p_3 - p_2$. Fig. 3 also characterizes a situation in which G describes the effect of big cities and G' the effect of medium- and small-sized cities, when the aggregate effect of the income of medium- and small-sized cities is more important for rural communities than that of a few big cities (i.e., a scenario of high spatial concentration). In such cases, the market access effect of second- and third-order cities will be higher than the effect of big cities.

FIGURE 3. Impact of Market Access on the Population of Rural Communities



Note: The figure compares the effect of the market access in the population of a rural community at an average distance d_1 of k k urban centers, with another rural community at a distance d_2 of the same cities. Were G is the distance decay market access function, that for each rural community j is defined by $g_j = \sum_j Y_k e^{-\theta d_{j,k}}$, where $d_{j,k}$ is the distance from a city with Y_k income. The figure also illustrates the case in which the aggregated effect of medium- and small-sized cities are more important in terms of income than big cities. In such cases, the market access effect of second- and third-order cities (G') would have a higher impact than the effect of big cities in the population of rural communities (G).

Estimation

We estimate the impact of market access by four different variables that are informative of the changes in the economic development of rural communities, namely changes in population, farm employment, non-farm employment, and agricultural productivity. The impact of market access on the changes in the population of rural communities is estimated by:

(6) $$\Delta \log(P_j) = \gamma_0 + \gamma_1 \log(g_{j,t-1}) + \sum_{r=2}^{R} \gamma_r X_{j,r} + \varepsilon_j,$$

where $\Delta \log(P_j)$ is the change in the log of the population of the rural community j; $\log(g_{j,t-1})$ is the log of market access at $t-1$; and $X_{j,r}$ is a vector of variables that includes the change in the log of farm employment $\Delta \log(L_j^F)$, the change in the log of non-farm employment $\Delta \log(L_j^{NF})$, a series of controls at $t-1$ such as the log of population, the percentage of the population with tertiary education and its change, percentage of young workers (between 18 and 29 years old) and its change, volume of precipitation in the driest month, distance to minor water sources (such as water springs and wells), and municipality fixed effects. ε_j is the random error term. Equivalently, to estimate the impact of market access in the farm-employment of rural communities, we estimate:

(7) $$\Delta \log(L_j^F) = \delta_0 + \delta_1 \log(g_{j,t-1}) + \sum_{h=2}^{H} \delta_h Z_{j,h} + \mu_j,$$

where $\Delta \log(L_j^F)$ is the change in the log of farm employment of the rural community j; $\log(g_{j,t-1})$ is the log of market access at $t-1$; and $Z_{j,h}$ is a vector of variables that includes the change in the log of of the population $\Delta \log(P_j)$, and a series of variables at $t-1$, such as the log of farm employment, percentage of male workers and its change, percentage of workers in the mining sector and its change, minimum temperature in the coldest month, distance to minor water sources, an index for the ruggedness of the land using terrain elevation data (Nunn and Puga, 2012), and fixed effects at municipality level. μ_j is the random error term. The impact of the market access on the non-farm employment of rural communities is estimated by:

(8) $$\Delta \log(L_j^{NF}) = \tau_0 + \tau_1 \log(g_{j,t-1}) + \sum_{k=2}^{K} \tau_h W_{j,k} + \eta_j,$$

where $\Delta \log(L_j^{NF})$ is the change in the log of non-farm employment of the rural community j; $\log(g_{j,t-1})$ is the log of market access at $t-1$; and $W_{j,k}$ is a vector of variables that includes the change in the log of of the population $\Delta \log(P_j)$, and other control variables at $t-1$, such as the log of non-farm employment, percentage of male workers and its change, percentage of the population with tertiary education, percentage of workers in the mining sector and its change, minimum temperature in the coldest month, an index of the ruggedness of the land, and municipality fixed effects. η_j is the random error component.

The market access variable, $g_j = \sum_j Y_k e^{-\theta d_{j,k}}$ is computed using stable satellite nighttime lights to approximate the values of Y_k, and the euclidean distance between the centroids of rural communities and cities were used to compute $d_{j,k}$. Since we are interested in estimating the impact of cities on the growth and development of rural communities, our relevant measure is the access to urban markets that each rural community has. Additionally, we are aware that the values of θ could affect the estimated elasticity of market access. Therefore, we follow a different approach to observe how the elasticity of market access can be affected by different values of θ and, since we do not have information on transportations costs and flows of goods between rural communities and cities, to an appropriate estimation of θ. Consequently, we operate under three different scenarios to check the robustness of our estimations.

Under the first scenario, we compute market access following Harris (1954). This is the baseline scenario, as the case in which $\theta = 1$ and the square of $d_{j,k}$ is used, which is also the most widely used empirical approximation for market access. For the second scenario, we rely on the literature om planning and transportation, based on the early works of Carrothers (1956), Hansen (1959), and Weibull (1976) and recently used for similar applications in agricultural economics by Binswanger-Mkhize et al. (2016) and Binswanger-Mkhize and Savastano (2017). In this scenario, we use a standard negative exponential distance decay function, in which $\theta = 1/2a^2$ and the square of $d_{j,k}$ is used, where a is a parameter that represents the distance to the point of inflection of the distance decay function. We estimate it by using a representative value for $a = 50$ and $a = 100$, as in Binswanger-Mkhize et al. (2016).

Under the last scenario for the computation of market access, we follow recent approaches in the literature on international trade (Donaldson and Hornbeck, 2016). Therefore, we estimate parameter θ of the market access function using non-linear least squares. Taking advantages of the flexibility of this approach, we compute an aggregate market access variable adjusted by using three different distance decay functions according to the size of cities (a similar approach has been explored by Halas et al., 2014). This allows us to account for the fact that the spatial distribution of medium- and small-sized cities is more spread and easier to access by the population of rural communities, together with the fact that large cities are usually more concentrated in some areas and have less spatial scope over the entire spatial distribution of rural communities.[7]

Additionally, for certain distances between rural communities and cities, the effects of market access on population and farm and non-farm employment are arguably endogenous. This endogeneity is associated with the proportion of workers in the non-farm sector that live in a rural community but work in a nearby city and with some urban activities that are performed in the hinterland, such as manufacturing production. However, only rural communities that are very close to cities are likely to be affected by this situation. Following a similar approach as Donaldson and Hornbeck (2016), we account for this issue by constructing buffers/polygons of 10 and 15 kilometers from the boundaries of cities and selecting those rural communities outside these areas. Farther away from these thresholds, the average effect of market access on the population and farm and non-farm employment of rural communities is expected to be positive. Moreover, we also estimate the results with and without small rural communities to observe the robustness of our results to different cut-off points for the inhabitants of rural communities.

Finally, we follow recent studies that use remote sensing data to measure the agricultural productivity of farms by computing vegetation indexes (Costinot and Donaldson, 2012; Donaldson and Storeygard, 2016; Costinot et al., 2016; Costinot and Donaldson, 2016; Burke and Lobell, 2017). Since true agricultural productivity is unobserved, both survey-based methods and remote sensing indicators represent limited but informative approximations of the agricultural productivity of farms (Burke and Lobell, 2017). Therefore, we also estimate the elasticities of the market access incorporating in the farm employment equation the vegetation index. We compute three different vegetation indexes for robustness check, namely the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Green Chlorophyll Vegetation Index (GCVI), as proxies of the agricultural productivity in rural communities.

Data

We use data from the Chilean censuses of population and housing of 1992, 2002 and 2017 (INE). The Chilean statistical office defines a rural community as any spatial entity with less than 3,000 inhabitants.[8] We select all those rural communities defined in 1992 with a population greater than 100 inhabitants for a total of 536 observations in each year. Additionally, we use remote sensing data to complement census information. For a proxy of the economic activity in cities, we use stable satellite nighttime light data, from the NASA Operational

[7] This stylized fact can be inferred from Fig. 1 and Fig. A1, and confirmed in Fig. A3 for the case of study.

[8] This definition was established in 1992. Since 2002, a rural community is defined a spatial entity with less than 5,000 inhabitants and more than 35% of the labor force working in the agricultural sector.

Line Scan Defense Meteorological Satellite Program (OLS-DMSP).[9] In the absence of economic data, the nighttime light satellite data was considered a good proxy of economic activity of the subnational units when used appropriately (Chen and Nordhaus, 2011; Henderson et al., 2012; Donaldson and Storeygard, 2016).[10] We process the nighttime light satellite images at one kilometer of spatial resolution for 1992 and 2002. For each year, we compute the sum of the nighttime light contained within the official urban boundaries defined for the census of 2002 and for areas considering buffers of 2km from the urban boundaries (for similar applications, see Binswanger-Mkhize and Savastano 2017; Henderson et al. 2017).[11]

The literature on remote sensing had identified two main problems related with the use of nighttime light data, namely the "blooming" and "saturation" effects (Imhoff et al., 1997). These effects are distortions in the satellite image due to the high intensity of light is some places. A simple analogy would be taking a photography with a source of light just in front of the camera. This would cause a saturation on the values of pixels from the direct source of light (saturation effect) and a light blurring to other pixels in the image (blooming effect). The main problem for our purposes is the blooming effect, due that overestimate the size of urban areas and, consequently, the sum of lights from cities. This is a problem that, until recent years, had been ignored in the applied economics literature using nighttime light data. Hence, we clean nighttime lights images following remote sensing literature, specifically Su et al. (2015).[12] The basic idea of this cleaning process is that allow us to identify thresholds in the distribution of nighttime lights and extract built-up urban areas.

Fig. 4 describes the spatial distribution of rural communities near the metropolitan area of Santiago de Chile and the cleaning process of nighttime lights for 2002. Rural communities are represented by red points that correspond to the centroid of the area. The black lines represent the urban boundaries in 2002. The nighttime light information of each pixel is represented by a color scale from dark-blue (low values) to light yellow (high values). The maximum nighttime light intensity is 63 and the minimum nighttime light intensity is 0. The image on the left displays nighttime lights without blooming correction and the image on the right is corrected. White lines are used to represent the urban buffers of 2, 5, 10 and 15km from the urban boundaries. Since rural communities do not have boundaries delineating their areas, the sum of the nighttime light cannot be accurately computed for rural communities.[13] The distances between rural communities and cities were computed using the Euclidean distance between the centroids of rural communities and the centroids of cities.

Additionally, we use NASA's Landsat-5 and Lansat-7 satellite data to com- pute the vegetation indexes, namely the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI) and Green Chlorophyll Vegetation Index (GCVI). Due to the satellite coverage of the NASA Landsat-5, these indexes cannot be computed for the entire country for almost the entire duration of the 1990s.[14] Consequently, we estimate the elasticities of market access for only 189 rural communities that have this information. The three vegetation indexes differ in the spectral bands of the sensors of the satellite used for their computations, the GCVI being the most accurate to capture the agricultural productivity of farms (for a detailed discussion of applicability of these indexes for similar purposes, see Burke and Lobell, 2017).[15] A cloud-free annual median of each pixel

[9] Chile, as many developing countries, does not provide data on the economic activity at city level.

[10] Some other applications are those of Beakley and Lin (2012); Michalopoulos and Papaioannou (2014); Storeygard (2016); Axbard (2016); Pinkovsky and Sala-Martin (2016); Henderson et al. (2017)

[11] We use the urban boundaries of 2002 to have a spatial unit that would be comparable in time (Briant et al., 2010). Results are also robust to buffers of 5, 10 and 15km from the urban boundaries for the sum of nighttime lights in cities.

[12] See Abrahams et al. (2018) for a more recent approach.

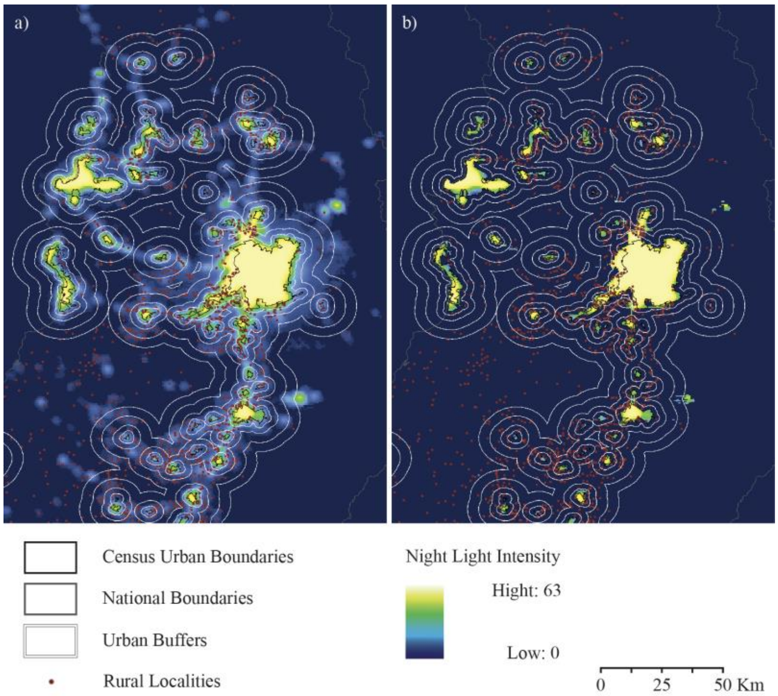
[13] We also extract the value of the pixel interpolated with surrounding pixels. This reaches an area of approximately two square kilometers (for a similar computation of interpolated values of satellite images, see Nunn and Puga, 2012). However, only 99 rural communities had nighttime light information in 1992 due to the low access to electricity in rural communities during that census.

[14] See Fig. A4 for a detailed map of the coverage of LandSat-5 and Landsat-7 during the census years in Chile.

[15] The NDVI is computed as $NDVI = (NIR - Red)/(NIR + Red)$, EVI is computed as $EVI = 2.5 * (NIR - Red)/(NIR + 6 * Red + 7 * Blue + 1)$, and GCVI as $GCVI = (NIR/Green) - 1$, where NIR is the Near Infrared Band and each color represents a different wavelength band of the satellite sensors.

at 30 meters of spatial resolution was used for each year to compute the vegetation indexes using Google Earth Engine (Gorelick et al., 2017). Subsequently, the resulting raster images of the vegetation indexes averaged to a spatial resolution of 500 meters per pixel were processed in ArcGIS and interpolated with surrounding pixels to impute a value of agricultural productivity considering a representative area of one square kilometer. Fig. 4 shows the GCVI index for 2015 in the hinterland of the metropolitan area of Santiago de Chile.

FIGURE 4. Nighttime Lights Image Correction

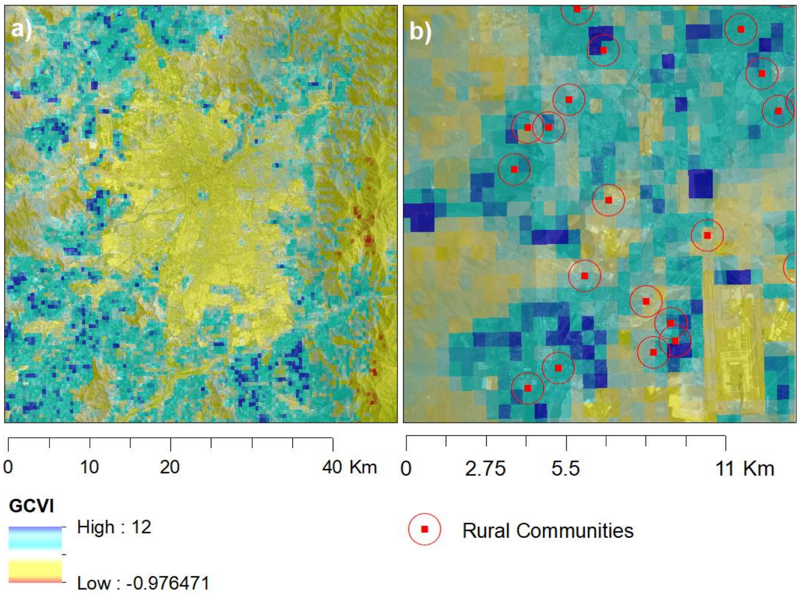


Note: The figure describes the nighttime lights image correction for the blooming effect. Both images display nighttime lights in the area surrounding the metropolitan area of Santiago de Chile in 2002. Panel a) displays the nighttime lights image without correction and Panel b) shows the image corrected. In addition, the figure describes urban buffers for 2, 5, 10 an 15 kilometers from 2002 the census urban boundaries.

Results

Table 1 reports the results of the impact of market access on the changes of the log of population, farm employment, and non-farm employment of rural communities. The table describes the baseline scenario, which assumes that parameter $\theta = 1$ (i.e., the market access variable used in these estimations) is similar to that of Harris (1954). We choose this as the baseline scenario because it is the most widely used measure of market access. All columns include controls at rural community level and fixed effects at municipality level. The first three columns of Table 1 show the ordinary least squares (OLS) estimations of the impact of market access on the changes of the log of population, farm employment, and non-farm employment of rural communities between 1992 and 2017 (Panel a), 1992 and 2002 (Panel b), and 2002 and 2017 (Panel c). The last three columns of the table present the three-stage least squares (3SLS) estimations to account for the simultaneity between the population and employment of rural communities (Partridge and Rickman, 2003; Hoogstra et al., 2011). The observations in this set of regressions are 536 rural communities with a population between 100 and 3,000 inhabitants at 1992.

FIGURE 5. Market Access and Agricultural Productivity



Note: The figure describes the agricultural productivity near the metropolitan area of Santiago de Chile in 2015. Agricultural productivity is represented with the GCVI, with a spatial resolution of 500 meters per pixel using data from the NASA Landsat-7. Panel a) shows the overall hinterland of the city of Santiago, where high values of the GCVI are displayed with more intense blue colors. Panel b) displays a zoomed image of the hinterland of the city, in which rural communities are represented by a red circle.

Across all 3SLS estimations in Table 1, the impact of the market access on the change of the population of rural communities is positive and statistically significant. The estimated 25-year elasticity in Column (4) suggests that a 10% more market access led to an increase of approximately 12% in the population of rural communities, while this effect is about 3% for the period between 1992 and 2002 (column 10), and approximately 10% between 2002 and 2017 (column 16). High elasticities should be common due to the small size of rural communities, as an example, double the population of the largest rural community according to the census definition at 1992 just would mean to reach almost 6,000 inhabitants. The impact of market access on the change of non-farm employment of rural communities is also positive and stronger than the effect on the rural population, with particularly high elasticities of around 2.4 and 2.9 for the 25-year period (column 6) and between 2002 and 2017 (column 18), respectively. And a still high elasticity of about 1.4 for the period between 1992 and 2002 (column 12). On the other hand the market access elasticity on farm employment is non-significant in all the periods. This higher elasticity of market access for non-farm employment relative to farm employment is robust across all estimations and is likely to be associated with the process of structural change in the rural economy (Irwin et al., 2009; Castle et al., 2011). A movement of workers from agriculture to non-farm sector in rural communities during the second period may explain the change in the market access effect on farm employment between the first and second period, and the higher elasticity in the non-farm employment during the second period. If this movement, in average, was inside rural communities would also explain a consistently positive market access effect in the population of rural communities across the different periods.

TABLE 1. Impact of Market Access on Population and Farm and Non-Farm Employment of Rural Communities (Baseline Scenario)

	Panel a): Long-Term Differences (1992-2017)					
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	3SLS	3SLS	3SLS
Log Market Access	-0.037	-0.153	0.209**	1.238***	-0.504	2.417***
	(0.072)	(0.129)	(0.085)	(0.263)	(0.403)	(0.412)
Observations	536	536	536	536	536	536
Adjusted R^2	0.680	0.641	0.835			
Chi-squared				1,037.895	747.548	1,181.231
	Panel b): First-Period Differences (1992-2002)					
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	OLS	OLS	3SLS	3SLS	3SLS
Log Market Access	-0.001	-0.116	0.204*	0.339*	0.450	1.361***
	(0.041)	(0.093)	(0.113)	(0.179)	(0.637)	(0.396)
Observations	536	536	536	536	536	536
Adjusted R^2	0.493	0.416	0.538			
Chi-squared				539.224	321.535	675.919
	Panel c): Second-Period Differences (2002-2017)					
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
	(13)	(14)	(15)	(16)	(17)	(18)
	OLS	OLS	OLS	3SLS	3SLS	3SLS
Log Market Access	-0.011	-0.083	0.086	0.969***	-0.643	2.918***
	(0.055)	(0.119)	(0.060)	(0.220)	(0.462)	(0.573)
Observations	536	536	536	536	536	536
Adjusted R^2	0.786	0.655	0.803			
Chi-squared				941.623	657.656	1,224.274

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All models include controls and municipality fixed effects.

In Tables 2 (1992–2017), 3 (1992–2002) and 4 (2002–2017), we focus on the robustness of our estimations to the specification of the market access variable and the selection of rural communities. Panel a) of Tables (2)–(4) presents the elasticities of the market access for the population, farm employment, and non-farm employment of rural communities under three different scenarios. All coefficients were estimated by 3SLS.[16] Columns (1)–(6) show the estimated elasticity of the market access for the population, farm employment, and non-farm employment of rural communities. This market access variable was computed using a negative exponential market access function, usually presented as an accessibility indicator in the literature on transportation economics (Bigman and Deichmann, 2000). The difference between this market access variable and others is that parameter θ takes a particularly low value, assuming high distance frictions, in columns (1)–(3) and a particularly high value, assuming low distance frictions, in columns (4)–(6). The results of this estimation give an elasticity of market access of approximately 0.3–0.8 in the population equation and a positive significant effect on the growth of non-farm employment of rural communities of about 0.4–1.1 for the overall period. Similar signs and lower magnitudes were founded for this two variables in sub-periods. For the farm-employment equation, the elasticity of market access is non-significant for the 25-year period but ranges between approximately 0.2 and 0.7. The differences between these and the previous estimations in Table 1 can be attributed to the assumptions of high and low distance frictions in the construction of the market access variable (Binswanger-Mkhize et al., 2016).

[16] The OLS and 3SLS extended results can be founded in the Appendix B section.

The assumption that rural communities face similar distance frictions to get to large and small size cities is difficult to maintain because infrastructure is usually better for accessing large cities. Therefore, columns (7)–(9) in Tables (2)–(4) present the results using a market access variable calculated to allow rural communities to face different distance frictions to reach different types of cities. Consequently, in this scenario, we do not assume a particular value of θ for the computation of the market access variable, but use different values of θ to adjust the market access variable for different distance decay functions (these functions are presented in Figure A3). The results show an elasticity of market access for the population of rural communities of about 1.2 for the 25-year period and approximately 0.3 and 1.1 for the first and second period, respectively. Market access elasticities for the non-farm employment are still high and about 1.4 and 1.1 for the 25-year and second period, but much lower for the first period (0.5). A similar pattern to the baseline scenario is found for the farm employment, with non-significant effects.

In addition, we show the robustness of our elasticities to the selection of rural communities (Panel b of Tables 2–4). On one hand, we observe how these elasticities change when only rural communities farther away from cities are selected. Columns (10)–(15) show the results for selecting those rural communities that are outside the 10 km and 15 km buffers from the city boundaries.[17] This is important because some rural communities located in the hinterland of a city can be widely influenced by the suburbanization process. The 25-year period results using a 10 km city-buffer show that a 10% more access to urban markets led to average increases of approximately 12% in the population and 10–12% in non-farm employment of rural communities. Notwithstanding, for sub-periods, elasticities for the market access on farm employment are positive and significant, of approximately 4–5% between 1992 and 2002, and 2–3% between 2002 and 2017. These elasticities for sub-periods, may also be a sign that the diversification of the rural community related to market access has a limited spatial scope. This is because, in this scenario, the elasticity of market access for non-farm employment and farm employment are more similar in magnitude. However, in the long-term the evidence support the diversification of the economy in rural communities.

On the other hand, Tables (2)–(4) also shows the robustness of our elasticities to the inclusion of small rural communities. Columns (16)–(18) present the effect of the estimation of the city-sized adjusted market access variable for the population, farm employment, and non-farm employment, by adding all small rural communities with a population between 50 and 100 inhabitants. This allows us to run this set of regressions with 878 rural communities with populations between 50 and 3,000 inhabitants in 1992. The 25-year elasticity of market access for the population is about 1.1 and 1.2 for non-farm employment. These elasticities are smaller for the sub-periods, and with non-significant effect in the farm employment.

Summarizing these results, the elasticity of market access for population is robust across all estimations and ranges from 0.3 to 1.2 for the 25-year period (Table 2). For the elasticity of market access in respect to farm employment the results are non-significant for the overall period. However, positive and significant for sub-periods when only more remote rural communities are considered. On the other hand, in the case of the non-farm employment the 25-year elasticity of market access in relation to the non-farm employment of rural communities ranges from 0.4 to 1.4 (Table 2), which is justifiable due to the growing importance of non-farm employment together with the fact that, across almost all estimations, the elasticity of market access in relation to non-farm employment is greater than in relation to the farm employment.[18]

[17] Buffers are equidistant areas delimited from the boundaries of cities, constructed using GIS tools. See Figure 4 for an illustration.

[18] See Fig. A2 for the trends between farm and non-farm employment in rural communities.

TABLE 2. Market Access Elasticities for Different Specifications (1992-2017)

Panel a):	Distance Decay Market Access Function with $a = 50$			Distance Decay Market Access Function with $a = 100$			City-size Adjusted Market Access Function		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
Log market access	0.259***	0.093	0.379***	0.802***	0.345	1.134***	1.230***	-0.059	1.438***
	(0.052)	(0.075)	(0.069)	(0.166)	(0.277)	(0.202)	(0.201)	(0.212)	(0.201)
Observations	536	536	536	536	536	536	536	536	536
Chi-squared	1,344.902	729.947	1,444.385	1,478.852	745.490	1,726.118	1,258.854	743.177	1,279.242
Panel b):	**City-Size Adjusted Market Access Function with 10 km City Buffer**			**City-Size Adjusted Market Access Function with 15 km City Buffer**			**City-Size Adjusted Market Access Function with Small Communities**		
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
Log market access	1.160***	0.290	0.928***	1.244***	0.224	1.195***	1.117***	-0.124	1.248***
	(0.213)	(0.233)	(0.148)	(0.212)	(0.211)	(0.184)	(0.183)	(0.187)	(0.180)
Observations	377	377	377	416	416	416	878	878	878
Chi-squared	1,399.597	603.309	1,778.101	1,268.798	751.972	1,309.351	2,643.669	814.926	1,754.971

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All models were estimated by 3SLS and include control variables and fixed effects at municipality level. In Panel a), columns (1)–(3) use the distance decay market access function with a parameter a = 50. Columns (4)–(6) use the distance decay market access function with a parameter a = 100. Columns (7)–(9) use market access with different parameters for θ by city-size, derived from a nonlinear least square estimation. In Panel b), columns (10)–(12) use only 416 rural communities selected from the original sample at a distance greater than 10 km of the boundaries of cities. Columns (13)–(15) use only 377 rural communities selected from the original sample at a distance greater than 15 km from the city boundaries. Columns (16)–(18) add to the original sample 342 small rural communities with a population between 50 and 100 inhabitants.

TABLE 3. Market Access Elasticities for Different Specifications (1992-2002)

Panel a):	Distance Decay Market Access Function with $a = 50$			Distance Decay Market Access Function with $a = 100$			City-size Adjusted Market Access Function		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
Log market access	0.069**	0.173*	0.167***	0.264***	0.650**	0.612***	0.317**	0.321	0.491***
	(0.029)	(0.094)	(0.056)	(0.098)	(0.327)	(0.175)	(0.127)	(0.269)	(0.161)
Observations	536	536	536	536	536	536	536	536	536
Chi-squared	589.162	274.984	789.094	613.124	284.024	817.477	639.672	303.728	821.273
Panel b):	City-Size Adjusted Market Access Function with 10 km City Buffer			City-Size Adjusted Market Access Function with 15 km City Buffer			City-Size Adjusted Market Access Function with Small Communities		
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
Log market access	0.388***	0.437*	0.602***	0.511***	0.480**	0.722***	0.388***	0.233	0.491***
	(0.135)	(0.251)	(0.166)	(0.138)	(0.228)	(0.171)	(0.133)	(0.159)	(0.141)
Observations	416	416	416	377	377	377	878	878	878
Chi-squared	561.081	300.775	628.584	478.314	406.216	661.398	1,017.578	624.004	937.264

Note: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. All models were estimated by 3SLS and include control variables and fixed effects at municipality level. In Panel a), columns (1)–(3) use the distance decay market access function with a parameter a = 50. Columns (4)–(6) use the distance decay market access function with a parameter a = 100. Columns (7)–(9) use market access with different parameters for θ by city-size, derived from a nonlinear least square estimation. In Panel b), columns (10)–(12) use only 416 rural communities selected from the original sample at a distance greater than 10 km of the boundaries of cities. Columns (13)–(15) use only 377 rural communities selected from the original sample at a distance greater than 15 km from the city boundaries. Columns (16)–(18) add to the original sample 342 small rural communities with a population between 50 and 100 inhabitants.

TABLE 4. Market Access Elasticities for Different Specifications (2002-2017)

Panel a):	Distance Decay Market Access Function with $a = 50$			Distance Decay Market Access Function with $a = 100$			City-size Adjusted Market Access Function		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
Log market access	0.038**	0.049	0.053***	0.189**	0.208	0.218***	1.084***	0.017	1.145***
	(0.016)	(0.032)	(0.020)	(0.076)	(0.137)	(0.076)	(0.202)	(0.236)	(0.181)
Observations	536	536	536	536	536	536	536	536	536
Chi-squared	1,379.982	812.918	1,309.649	1,620.084	775.461	1,296.424	1,104.561	673.739	1,040.838
Panel b):	**City-Size Adjusted Market Access Function with 10 km City Buffer**			**City-Size Adjusted Market Access Function with 15 km City Buffer**			**City-Size Adjusted Market Access Function with Small Communities**		
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
Log market access	0.265***	0.317***	0.168***	0.415***	0.221*	0.212***	0.128**	0.070	0.188***
	(0.087)	(0.112)	(0.062)	(0.134)	(0.121)	(0.063)	(0.053)	(0.077)	(0.068)
Observations	416	416	416	377	377	377	878	878	878
Chi-squared	1,441.773	674.462	1,253.708	1,465.673	705.068	1,518.722	1,994.984	1,119.316	2,334.111

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All models were estimated by 3SLS and include control variables and fixed effects at municipality level. In Panel a), columns (1)–(3) use the distance decay market access function with a parameter a = 50. Columns (4)–(6) use the distance decay market access function with a parameter a = 100. Columns (7)–(9) use market access with different parameters for θ by city-size, derived from a nonlinear least square estimation. In Panel b), columns (10)–(12) use only 416 rural communities selected from the original sample at a distance greater than 10 km of the boundaries of cities. Columns (13)–(15) use only 377 rural communities selected from the original sample at a distance greater than 15 km from the city boundaries. Columns (16)–(18) add to the original sample 342 small rural communities with a population between 50 and 100 inhabitants.

TABLE 5. Market Access Elasticities Including Agricultural Productivity

	Long-Term Differences (1992-2017)			First-Period Differences (1992-2002)			Second-Period Differences (2002-2017)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
1. Baseline Specification	1.344***	3.036***	1.818***	0.008	3.071**	0.807*	1.785***	2.450***	1.954***
	(0.465)	(0.907)	(0.507)	(0.156)	(1.449)	(0.480)	(0.411)	(0.577)	(0.453)
2. Distance Decay Market Access with $a = 50$	0.103	0.632***	0.531***	0.048*	1.287***	0.871***	0.076**	0.086**	0.085**
	(0.067)	(0.166)	(0.122)	(0.026)	(0.489)	(0.240)	(0.033)	(0.040)	(0.038)
3. Distance Decay Market Access with $a = 100$	0.421	2.431***	1.904***	0.178*	5.402***	3.546***	0.381***	0.347**	0.383***
	(0.266)	(0.671)	(0.463)	(0.098)	(2.058)	(1.009)	(0.144)	(0.161)	(0.141)
4. City-size Adjusted Market Access	1.885***	1.115**	1.010***	0.358***	1.733*	1.454**	1.405***	0.970***	0.891***
	(0.410)	(0.484)	(0.346)	(0.131)	(0.884)	(0.569)	(0.449)	(0.365)	(0.331)

Note: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All models were estimated by 3SLS and include control variables and fixed effects at municipality level. The GCVI is used as a proxy of agricultural productivity and included in the Farm Employment Equation. The GCVI was computed as $GCVI = (NIR/Green) - 1$, where NIR is the Near Infrared Band and Green represents a wavelength band of the satellite sensors. Images from LanSat L5 was used for 1992 and LanSat L7 for 2002. Due to spatial coverage of L5 this set of regression is estimated for 189 rural communities (see Fig. A4 for a visualization of the spatial coverage of daytime satellite images in years of censuses).

To provide more evidence on the mechanisms behind the growth of rural communities, Table 5 and A2 shows the regressions including our proxy of agricultural productivity in the farm employment equation. For this purpose, we use remote sensing data to construct a proxy of agricultural productivity, which as the evidence suggests, may be as informative as survey-based methods (Burke and Lobell, 2017). We estimate this relationship using three indexes. Namely, the NDVI, EVI, and GCVI. The different market access variables are used to show the robustness of the results. All equations in Table 5 use the GCI and are estimated by 3SLS and includes controls and fixed effects at municipality level (see Table A2 for results including EVI and NDVI). Due to the availability of daytime cloud-free satellite data for the entire country, the sample is reduced to 189 rural communities. Our estimations show significant positive elasticities of the market access for the population and farm and non-farm employment of rural communities and are robust across the different proxies of agricultural productivity. Is interesting to note that in many of these regressions the elasticities of the farm employment are higher that for the non-farm employment, probably due to the selection bias toward rural communities with information on the vegetation indexes. Therefore, is likely that rural communities highly specialized in agriculture, or at least with good agroecological conditions for the production of agriculture (probably captured by our vegetation indexes), continuing to specializing in the farm sector, taking large advantages of the access to urban markets with also a growth in the non-farm sector, probably in activities that are auxiliary to agriculture, such as the transportation of agricultural goods or commerce, rather than in activities that are not related to agriculture.

The elasticity of market access for the population is similar to that in the literature (Jedwab et al., 2017). However, the elasticity is particularly high for farm and non-farm employment, but not much other empirical evidence exists to compare with these results.[19] However, the distinction between farm and non-farm employment in rural communities is crucial. When no distinction is made and the elasticities of market access are computed for the total employment of the rural areas, the results may not be well understood, in the sense that, in many locations, particularly near cities, the behavior of farm employment and non-farm employment in rural communities may follows different patterns, leading to negative effects of market access on farm employment. This could also be the case in some articles that argue a negative or non-significant effect of market access on the total employment of rural areas but a positive and significant effect on the population, as in Chen and Partridge (2013) for China. The high values of the elasticities of market access for the non-farm employment of rural communities in relationship to the elasticities for the farm employment of rural communities are also indicative of the growing importance of the non-farm sector for rural areas, something that has been widely studied in agricultural economics (Berdegue et al., 2001). However, there is an important heterogeneity in rural communities, evidenced when our proxy of agricultural productivity was included in estimations. In any case, this paper provides additional evidence at a more disaggregate level.

Conclusions

To provide evidence on the dynamics of cities for rural communities, we follow a market access approach to develop a framework to better understand how cities influence the development of rural communities through market access and estimate the impact of cities on the development of rural communities. Consequently, we estimate the aggregate effect of cities on the development of rural communities as the effect of the market access on the population, farm employment, non-farm employment, and agricultural productivity of rural communities in Chile.

The results can be summarized by the following four main points. First, we found, in our preferred estimations, that a 10% higher market access led to an average 25-year increase of nearly 10—14% in the population of

[19] Most studies usually estimate one equation of the total employment of rural areas without distin- guishing between farm and non-farm employment.

rural communities in Chile. This elasticity is robust across all estimations. Second, a high access to urban markets is in the short-term generally associated with increasing both farm employment and non-farm employment in rural communities. Third, higher elasticities of market access were found for non-farm employment rather than in the farm sector. However, rural communities that are farther away from cities might benefit almost equally from increases in farm and non-farm employment. And, furthermore, rural communities more specialized in agriculture might experience higher levels of growth induced by cities in the farm employment rather than in the non-farm sector.

Various policy implications can be derived from this work. First, improvements in the infrastructure connecting rural communities and cities could lead to important effects in the growth and development of rural communities, thus accelerating the process of structural change for those rural communities nearby cities. Second, these improvements in infrastructure can be prioritized for rural communities that are near medium-sized cities, since they can reach a larger number of rural communities. Third, for rural communities that are farther away from cities, policies can be oriented to develop both the farm and non-farm sector, but should carefully consider the conditions for agricultural production in those areas. Finally, for rural communities highly specialized in agriculture, rural development policies may be created to provide farmers with a better comprehension of the products that are highly demanded in cities, together with increased access to farming technology.

More research could be conducted to better understand the dynamics of rural communities near the boundaries of cities. The effects associated with the changes in land use, rural non-farm employment that is generated in the city, and other commuting opportunities for rural inhabitants could be leading to different patterns of development for those rural communities located farther away from cities. Despite that, on average, the effect of cities is positive and significant for population, the dynamics of nearby communities could be playing an important role and there is limited evidence available in this respect.

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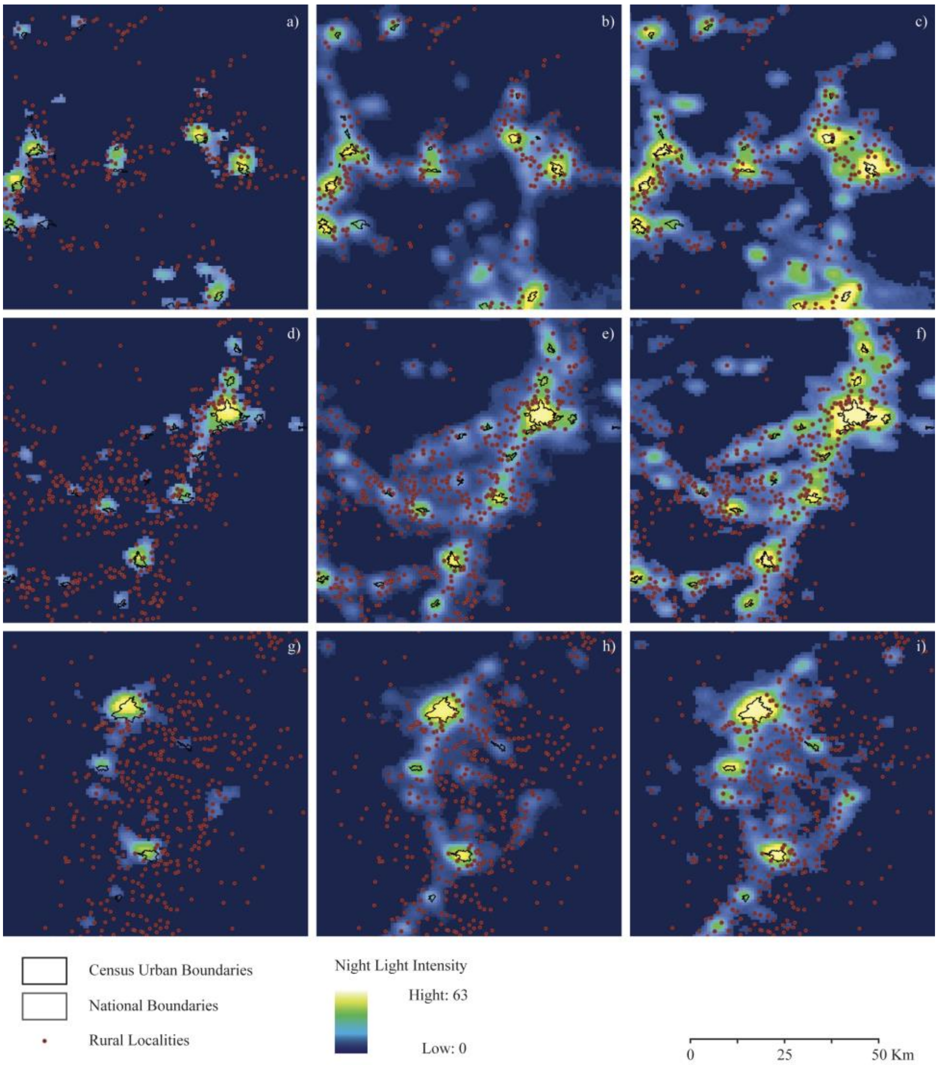
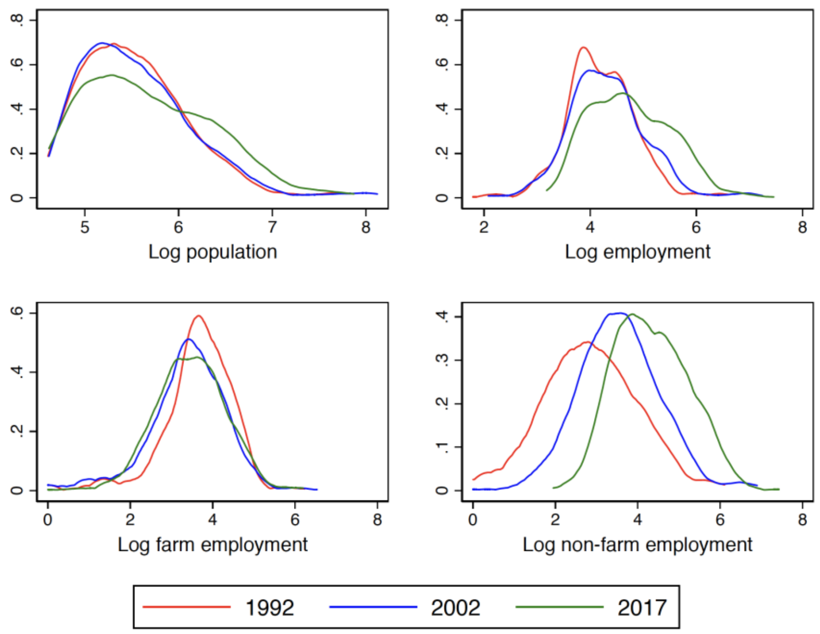
Appendix A

FIGURE A1. Medium-Sized City Growth and Rural Communities



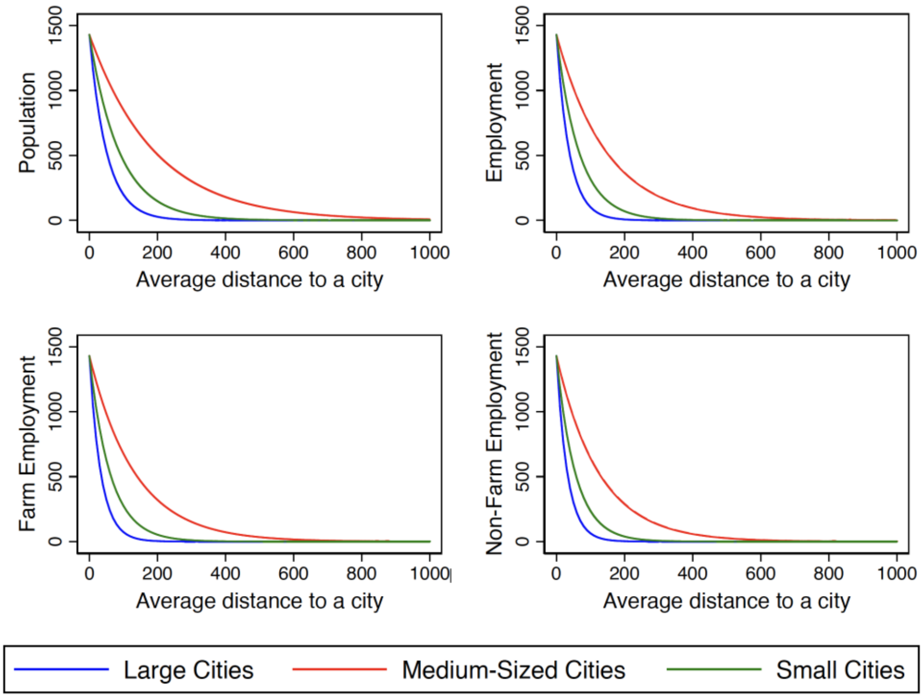
Note: The figures describes the spatial distribution of rural communities near medium-sized cities in Chile. The left-hand side panel of the figure shows the scenario for 1992, the center at 2002, and the right-hand side for 2013. Urban boundaries (in red), are the official boundaries delimited for the national census of 2002 by the Chilean National Statistical Office (INE).

FIGURE A2. Changes in Population and Employment in Rural Communities



Note: The figure shows the kernel (epanechnikov) density graphs for the log of population, employment, farm employment and non-farm employment in rural communities for 1992, 2002 and 2017.

FIGURE A3. Distance-Decay Market Access Functions by City-Size



Note: The figure shows the market access predictions for population, total employment, farm and non-farm employment by city-size at 1992 using non-linear least squares. The estimated parameters of these distance decay functions were used to construct the city-size adjusted market access variable. In all cases, there are larger effects of medium-sized cities (the red line) over rural population and employment. These effects are because the aggregate wealth of medium-sized cities is larger and they are more equally distributed in space, having a larger spatial scope of their positive effects, compared to big or small-sized cities.

FIGURE A4. Spatial Coverage of Day-Time Satellite Images

Note: Figure shows the spatial coverage of LandSat L5 and LandSat L7 day-time satellite images for the census years of 1992 and 2002. Information is missing for most of the area of the south of Chile until 1998. These images were used to compute the vegetation indexes (proxies of agricultural productivity).

TABLE A1. Data Description (GIS Variables)

Variable	Description	Primary Source
1. Baseline Market Access	$g_j = \sum_j Y_k e^{-d_{j,k}}$	NASA DMSP-OLS
2. Distance Decay Market Access with $a =$ 50	$g_j = \sum_j Y_k e^{-\frac{1}{2(50)^2} d_{j,k}}$	NASA DMSP-OLS
3. Distance Decay Market Access with $a =$ 100	$g_j = \sum_j Y_k e^{-\frac{1}{2(200)^2} d_{j,k}}$	NASA DMSP-OLS
4. City Size Adjusted Market Access (Population)	$g_j = \sum_j Y_k e^{-\theta_m d_{j,k}}$, $\theta_m =${0.0196(large-cities), 0.0052(medium-sized-cities), 0.0113(small-cities), 0.0095(towns)}	NASA DMSP-OLS
5. City Size Adjusted Market Access (Farm Employment)	$g_j = \sum_j Y_k e^{-\theta_m d_{j,k}}$, $\theta_m =${0.0310(large-cities), 0.0080(medium-sized-cities), 0.0179(small-cities), 0.0149(towns)}	NASA DMSP-OLS
6. City Size Adjusted Market Access (Non-Farm Employment)	$g_j = \sum_j Y_k e^{-\theta_m d_{j,k}}$, $\theta_m =${0.0296(large-cities), 0.0075(medium-sized-cities), 0.0164(small-cities), 0.0137(towns)}	NASA DMSP-OLS
7. Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{(NIR-Red)}{(NIR+Red)}$, pixel by pixel annual average at 500m spatial resolution	NASA/USGS LandSat L5 and L7
8. Enhanced Vegetation Index (EVI)	$EVI = \frac{2.5(NIR-Red)}{(NIR+6*Red+7*Blue+1)}$, pixel by pixel annual average at 500m spatial resolution	NASA/USGS LandSat L5 and L7
9. Green Chlorophyll Vegetation Index (GCVI)	$GCVI = \frac{NIR}{Green} - 1$, pixel by pixel annual average at 500m spatial resolution	NASA/USGS LandSat L5 and L7
10. Ruggedness	Average (interpolated) terrain ruggedness in a neighborhood of 2km from the centroid of the rural community using terrain elevation data	NASA SRTM 90m DEM
11. Precipitation of driest month	Average precipitation (≈1960-1990) of driest month	WorldClim v1.4
12. Min temperature in coldest month	Average (interpolated) minimum temperature (≈1960-1990) in coldest month	WorldClim v1.4
13. Distance to minor water sources	Euclidean distance between the centroid of the rural community and the nearest minor source of water (polyline shape with water springs and wells)	SIIT-BCN-Chile

Note: For 1–6, $d_{j,k}$ is the Euclidean distance between the centroid of a rural community j and the centroid of a city k, with Y_k sum of night-time light intensity. For 7–12, pixels were interpolated for an area of 2km from the centroid of each rural community.

TABLE A2. Robustness Checks using Alternative Proxies of Agricultural Productivity

	Long-Term Differences (1992-2017)			First-Period Differences (1992-2002)			Second-Period Differences (2002-2017)		
Panel a): Including EVI	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
1. Baseline Specification	1.183**	3.152***	1.959***	-0.060	2.938**	0.882*	1.844***	2.562***	1.995***
	(0.504)	(0.923)	(0.527)	(0.159)	(1.392)	(0.501)	(0.526)	(0.592)	(0.510)
2. Distance Decay Market Access with $a = 50$	0.140**	0.526***	0.458***	0.046*	1.036**	0.718***	0.077**	0.084**	0.085**
	(0.068)	(0.145)	(0.104)	(0.026)	(0.412)	(0.184)	(0.033)	(0.040)	(0.038)
3. Distance Decay Market Access with $a = 100$	0.583**	1.964***	1.579***	0.171*	4.305**	2.895***	0.383***	0.340**	0.383***
	(0.269)	(0.571)	(0.380)	(0.097)	(1.672)	(0.732)	(0.144)	(0.160)	(0.141)
4. City-size Adjusted Market Access	2.065***	1.101**	0.985***	0.367***	1.519**	1.278**	1.015**	1.204***	1.271***
	(0.432)	(0.464)	(0.317)	(0.133)	(0.752)	(0.546)	(0.416)	(0.370)	(0.383)
Panel b): Including NDVI	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
1. Baseline Specification	1.262**	3.108***	1.867***	-0.003	3.145**	0.833*	1.715***	2.491***	2.022***
	(0.494)	(0.943)	(0.536)	(0.156)	(1.482)	(0.483)	(0.396)	(0.585)	(0.462)
2. Distance Decay Market Access with $a = 50$	0.112*	0.606***	0.514***	0.049*	1.248***	0.868***	0.074**	0.084**	0.086**
	(0.068)	(0.161)	(0.118)	(0.026)	(0.484)	(0.243)	(0.032)	(0.041)	(0.039)
3. Distance Decay Market Access with $a = 100$	0.446*	2.339***	1.841***	0.179*	5.150***	3.496***	0.368***	0.341**	0.388***
	(0.268)	(0.649)	(0.447)	(0.098)	(1.987)	(1.005)	(0.142)	(0.163)	(0.145)
4. City-size Adjusted Market Access	1.941***	1.035**	0.949***	0.349***	1.690**	1.460***	1.090**	1.152***	1.196***
	(0.394)	(0.474)	(0.333)	(0.130)	(0.846)	(0.559)	(0.430)	(0.377)	(0.383)

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All models were estimated by 3SLS and include control variables and fixed effects at municipality level. The EVI (Panel a) and NDVI (Panel b) is used as a proxy of agricultural productivity and included in the Farm Employment Equation. The The EVI is computed as $EVI = 2.5 * (NIR - red)/(NIR + 6 * Red + 7 * Blue + 1)$, and NDVI is computed as $NDVI = (NIR - Red)/(NIR + Red)$, where NIR is the Near Infrared Band and each color represents a wavelength band of the satellite sensors. Images from LanSat L5 was used for 1992 and LanSat L7 for 2002. Due to spatial coverage of L5 this set of regression is estimated for 189 rural communities (see Fig. A4 for a visualization of the spatial coverage of daytime satellite images in years of censuses).

Appendix B

TABLE B1. Impact of Market Access on Population and Farm and Non-Farm Employment of Rural Communities (OLS Baseline Scenario)

Panel a): OLS estimation	Long-Term Differences (1992-2017)			First-Period Differences (1992-2002)			Second-Period Differences (2002-2017)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
Log market access	-0.037 (0.072)	-0.153 (0.129)	0.209** (0.085)	-0.001 (0.041)	-0.116 (0.093)	0.204* (0.113)	-0.011 (0.055)	-0.083 (0.119)	0.086 (0.060)
Log population	-0.120*** (0.043)			-0.078*** (0.024)			-0.077** (0.030)		
Diff log farm employment	0.284*** (0.034)			0.167*** (0.026)					
Diff log non-farm employment	0.324*** (0.032)			0.180*** (0.021)			0.493*** (0.031)		
% young workers	1.353 (0.869)			0.228 (0.577)			1.339** (0.654)		
Diff % young workers	0.946 (0.664)			0.017 (0.381)					
% workers with tertiary education	5.615*** (1.771)		1.184 (2.379)	4.077*** (1.137)		0.238 (2.664)	2.823*** (0.764)		0.876 (0.854)
Diff % workers with tertiary education	0.699 (0.544)			1.644** (0.704)					
Precipitation of driest month	0.000 (0.000)			-0.000 (0.000)			0.000 (0.000)		
Distance to minor water sources	-0.016 (0.021)	0.053 (0.037)		0.018 (0.012)	-0.068* (0.035)		-0.018 (0.016)	0.096*** (0.036)	
Log farm employment		-0.559*** (0.062)			-0.324*** (0.058)			-0.594*** (0.059)	
Diff log population		0.620*** (0.061)	0.826*** (0.047)		0.830*** (0.123)	1.049*** (0.106)			
Diff % male workers		1.549 (1.110)	-0.541 (0.816)		1.064 (1.167)	1.200 (0.932)			
% male workers		0.029 (1.292)	-2.572*** (0.938)		0.627 (1.201)	-1.226 (0.989)		0.630 (1.223)	-1.217 (0.749)
Diff % mining workers		-0.003 (0.009)	0.012* (0.007)		0.005 (0.007)	0.011 (0.009)			
% mining workers		-0.001 (0.008)	0.014*** (0.005)		0.012 (0.009)	0.011 (0.008)		0.002 (0.008)	0.007 (0.005)
Min temperature in coldest month		-0.000 (0.000)	0.000** (0.000)		-0.000 (0.000)	0.000 (0.000)		-0.000 (0.000)	0.000** (0.000)
Log ruggedness		-0.035 (0.035)	-0.023 (0.025)		-0.046 (0.036)	-0.029 (0.034)		-0.025 (0.034)	-0.004 (0.020)
Log non-farm employment			-0.588*** (0.027)			-0.410*** (0.037)			-0.363*** (0.029)
Diff log farm employment							0.200*** (0.024)		
Diff % young workers							0.362 (0.583)		
Diff % workers with tertiary education							0.350 (0.384)		
Diff log population								0.653*** (0.066)	0.905*** (0.040)
Diff % male workers								1.720 (1.244)	-0.202 (0.832)
Diff % mining workers								-0.001 (0.012)	0.006 (0.006)
Constant	-0.460 (1.333)	-0.291 (2.288)	7.378*** (1.530)	0.084 (0.736)	-0.865 (1.739)	5.734*** (2.004)	-0.102 (0.998)	0.775 (2.155)	3.583*** (1.119)
Adjusted R^2	0.680	0.641	0.835	0.493	0.416	0.538	0.786	0.655	0.803
AIC	345.877	904.703	523.916	-65.430	959.882	769.237	70.531	907.084	362.529
Observations	536	536	536	536	536	536	536	536	536

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE B2. Impact of Market Access on Population and Farm and Non-Farm Employment of Rural Communities (3SLS Baseline Scenario)

Panel a): OLS estimation	Long-Term Differences (1992-2017)			First-Period Differences (1992-2002)			Second-Period Differences (2002-2017)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
Log market access	1.238*** (0.263)	-0.504 (0.403)	2.417*** (0.412)	0.339* (0.179)	0.450 (0.637)	1.361*** (0.396)	0.969*** (0.220)	-0.643 (0.462)	2.918*** (0.573)
Log population	-0.582*** (0.063)			-0.293*** (0.024)			-0.406*** (0.048)		
Diff log farm employment	0.006 (0.017)			0.078** (0.032)					
Diff log non-farm employment	-0.117*** (0.040)			-0.121*** (0.020)			0.015 (0.046)		
% young workers	-0.376 (0.557)			0.104 (0.335)			-0.620 (0.512)		
Diff % young workers	-0.528 (0.616)			-0.044 (0.249)					
% workers with tertiary education	1.375 (2.086)		3.356 (3.840)	0.986 (1.088)		0.196 (2.764)	2.182*** (0.807)		6.986*** (2.392)
Diff % workers with tertiary education	-0.278 (0.203)			0.888* (0.506)					
Precipitation of driest month	0.000 (0.000)			-0.000 (0.000)			0.000 (0.000)		
Distance to minor water sources	0.010 (0.009)	0.057* (0.033)		0.016 (0.011)	-0.051 (0.043)		0.004 (0.005)	0.055 (0.036)	
Log farm employment		-0.842*** (0.061)			-0.693*** (0.091)			-0.902*** (0.061)	
Diff log population		-0.606*** (0.164)	-0.432** (0.172)		-1.901*** (0.641)	0.136 (0.304)			
Diff % male workers		1.085 (1.078)	0.941 (0.670)		0.965 (0.894)	1.356** (0.565)			
% male workers		1.000 (1.231)	0.561 (0.875)		2.583** (1.039)	0.018 (0.672)		1.096 (1.245)	0.628 (1.091)
Diff % mining workers		0.022** (0.011)	-0.009 (0.008)		0.000 (0.013)	0.002 (0.008)			
% mining workers		-0.002 (0.009)	-0.006 (0.007)		0.006 (0.013)	0.004 (0.007)		-0.015 (0.010)	0.002 (0.006)
Min temperature in coldest month		-0.000 (0.000)	0.000 (0.000)		-0.000 (0.000)	-0.000 (0.000)		0.000 (0.000)	0.000 (0.000)
Log ruggedness		-0.106*** (0.035)	0.022 (0.016)		-0.054 (0.040)	0.020 (0.026)		-0.125*** (0.040)	0.020 (0.017)
Log non-farm employment			-0.753*** (0.050)			-0.444*** (0.032)			-0.902*** (0.094)
Diff log farm employment							0.018** (0.008)		
Diff % young workers							-0.550 (0.507)		
Diff % workers with tertiary education							-0.375*** (0.142)		
Diff log population								-1.003*** (0.229)	-1.170*** (0.332)
Diff % male workers								0.498 (1.321)	1.102 (1.154)
Diff % mining workers								0.053*** (0.019)	-0.021 (0.022)
Constant	25.029*** (4.614)	-4.203 (6.986)	44.665*** (7.261)	7.155** (3.137)	9.094 (10.959)	24.627*** (6.746)	19.444*** (3.865)	-5.922 (7.876)	54.190*** (10.277)
Chi-squared	1037.895	747.548	1181.231	539.224	321.535	675.919	941.623	657.656	1224.274
Observations	536			536			536		

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE B3. Elasticities for Different Specifications of Market Access (1992-2017)

Panel a): OLS estimation	Distance Decay Market Access Function with $a = 50$			Distance Decay Market Access Function with $a = 100$			City-size Adjusted Market Access Function		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
Log market access	-0.006 (0.011)	0.020 (0.025)	0.025 (0.016)	-0.037 (0.046)	0.109 (0.105)	0.125* (0.069)	0.078 (0.074)	0.035 (0.087)	0.094 (0.066)
Log population	-0.119*** (0.042)			-0.118*** (0.042)			-0.124*** (0.043)		
diff_ln_farm_employment_all	0.286*** (0.034)			0.286*** (0.034)			0.282*** (0.035)		
diff_ln_nonfarm_employment_all	0.323*** (0.031)			0.324*** (0.031)			0.320*** (0.031)		
% young workers	1.336 (0.862)			1.345 (0.860)			1.210 (0.877)		
diff_edad_young_all	0.931 (0.665)			0.940 (0.662)			0.842 (0.683)		
% workers with tertiary education	5.726*** (1.757)		0.905 (2.427)	5.797*** (1.752)			5.484*** (1.762)		1.312 (2.405)
diff_tipo_educacion3_all	0.665 (0.539)			0.670 (0.537)			0.559 (0.567)		
Precipitation of driest month	0.000 (0.000)			0.000 (0.000)			0.000 (0.000)		
Distance to minor water sources	-0.016 (0.021)	0.054 (0.038)		-0.016 (0.021)	0.054 (0.037)		-0.014 (0.021)	0.054 (0.037)	
Log farm employment		-0.559*** (0.061)			-0.558*** (0.061)			-0.560*** (0.062)	
diff_ln_population_all		0.613*** (0.064)	0.825*** (0.047)		0.613*** (0.064)	0.827*** (0.047)		0.613*** (0.064)	0.820*** (0.048)
diff_man_all		1.672 (1.107)	-0.513 (0.833)		1.701 (1.103)	-0.518 (0.836)		1.646 (1.101)	-0.471 (0.840)
% male workers		0.151 (1.291)	-2.534*** (0.950)		0.190 (1.288)	-2.530*** (0.943)		0.140 (1.296)	-2.463** (0.963)
diff_rama_Min_all		-0.004 (0.008)	0.015** (0.007)		-0.003 (0.008)	0.014** (0.007)		-0.004 (0.008)	0.014** (0.007)
% mining workers		-0.002 (0.008)	0.012*** (0.004)		-0.002 (0.008)	0.012*** (0.004)		-0.001 (0.008)	0.012*** (0.004)
Min temperature in coldest month		-0.000 (0.000)	0.000* (0.000)		-0.000 (0.000)	0.000* (0.000)		-0.000 (0.000)	0.000* (0.000)
Log ruggedness		-0.024 (0.034)	-0.031 (0.025)		-0.022 (0.034)	-0.028 (0.025)		-0.024 (0.034)	-0.026 (0.025)
Log non-farm employment			-0.589*** (0.027)			-0.585*** (0.024)			-0.591*** (0.027)
Constant	0.061 (0.363)	2.579*** (0.923)	4.365*** (0.688)	0.001 (0.359)	2.633*** (0.904)	4.393*** (0.670)	0.574 (0.447)	2.417*** (0.927)	4.356*** (0.682)
Adjusted R^2	0.680	0.640	0.833	0.680	0.641	0.834	0.681	0.639	0.833
Observations	536	536	536	536	536	536	536	536	536
Panel b): 3SLS estimation	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
Log market access	0.259*** (0.052)	0.093 (0.075)	0.379*** (0.069)	0.802*** (0.166)	0.345 (0.277)	1.134*** (0.202)	1.230*** (0.201)	-0.059 (0.212)	1.438*** (0.201)
Log population	-0.645*** (0.062)			-0.661*** (0.058)			-0.620*** (0.057)		
diff_ln_farm_employment_all	0.029* (0.017)			0.036** (0.017)			0.021 (0.018)		
diff_ln_nonfarm_employment_all	-0.158*** (0.034)			-0.157*** (0.027)			-0.129*** (0.034)		
% young workers	-0.436 (0.530)			-0.440 (0.481)			-0.460 (0.512)		
diff_edad_young_all	-0.597 (0.585)			-0.608 (0.525)			-0.695 (0.562)		
% workers with tertiary education	-2.463 (2.023)		-2.921 (3.189)	-0.634 (0.686)			0.136 (1.840)		2.475 (3.155)
diff_tipo_educacion3_all	-0.286 (0.174)			-0.275* (0.159)			-0.019 (0.184)		
Precipitation of driest month	0.000 (0.000)			0.000 (0.000)			0.000 (0.000)		
Distance to minor water sources	0.009 (0.009)	0.050 (0.033)		0.008 (0.008)	0.045 (0.032)		0.010 (0.009)	0.058* (0.033)	
Log farm employment		-0.952*** (0.059)			-0.981*** (0.058)			-0.890*** (0.059)	
diff_ln_population_all		-0.842*** (0.167)	-0.200 (0.138)		-0.902*** (0.171)	-0.151 (0.120)		-0.677*** (0.162)	-0.311** (0.144)
diff_man_all		1.495 (1.043)	0.854 (0.543)		2.017** (1.012)	0.705 (0.483)		0.630 (1.069)	1.062* (0.588)
% male workers		2.075* (1.195)	0.316 (0.699)		2.871** (1.167)	0.077 (0.614)		0.685 (1.234)	0.855 (0.754)
diff_rama_Min_all		0.003 (0.010)	-0.002 (0.006)		-0.002 (0.010)	-0.001 (0.005)		0.009 (0.010)	-0.005 (0.007)
% mining workers		0.004 (0.009)	-0.008 (0.006)		-0.002 (0.009)	-0.006 (0.005)		0.009 (0.009)	-0.009 (0.006)
Min temperature in coldest month		-0.000 (0.000)	0.000 (0.000)		-0.000 (0.000)	0.000* (0.000)		-0.000 (0.000)	0.000 (0.000)
Log ruggedness		-0.044 (0.029)	-0.001 (0.011)		-0.046 (0.029)	-0.001 (0.010)		-0.100*** (0.033)	0.013 (0.014)
Log non-farm employment			-0.719*** (0.037)			-0.724*** (0.028)			-0.762*** (0.041)
Constant	9.154*** (1.235)	5.571*** (1.785)	10.633*** (1.621)	7.630*** (0.956)	5.020*** (1.591)	8.212*** (1.189)	8.896*** (1.014)	4.391*** (1.613)	11.739*** (1.530)
Chi-squared	1344.902	729.947	1444.385	1478.852	745.490	1726.118	1258.854	743.177	1279.242
Observations	536	536	536	536	536	536	536	536	536

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE B4. Elasticities for Different Selection of Rural Communities (1992-2017)

Panel a): OLS estimation	City-Size Adjusted Market Access Function with 10 km City Buffer			City-Size Adjusted Market Access Function with 15 km City Buffer			City-Size Adjusted Market Access Function with Small Communities		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
Log market access	0.037 (0.092)	0.076 (0.120)	0.083 (0.083)	0.007 (0.104)	-0.006 (0.143)	0.190* (0.097)	-0.003 (0.051)	-0.064 (0.064)	0.113** (0.054)
Log population	-0.152*** (0.054)			-0.165*** (0.054)			-0.073*** (0.022)		
diff_ln_farm_employment_all	0.255*** (0.042)			0.304*** (0.048)			0.301*** (0.019)		
diff_ln_nonfarm_employment_all	0.324*** (0.035)			0.296*** (0.042)			0.357*** (0.020)		
% young workers	1.223 (1.111)			1.279 (1.155)			1.523*** (0.498)		
diff_edad_young_all	1.419* (0.845)			1.363 (0.828)			0.821** (0.418)		
% workers with tertiary education	6.641*** (2.003)		1.656 (2.987)	5.035** (2.352)		2.407 (3.189)	4.285*** (0.938)		-5.281*** (1.450)
diff_tipo_educacion3_all	0.097 (0.704)			0.963 (0.704)			0.640** (0.318)		
Precipitation of driest month	0.000 (0.000)			0.000 (0.000)			-0.000 (0.000)		
Distance to minor water sources	-0.034 (0.033)	0.064 (0.050)		0.001 (0.025)	0.024 (0.060)		-0.032** (0.016)	0.090*** (0.027)	
Log farm employment		-0.577*** (0.075)			-0.528*** (0.090)			-0.481*** (0.041)	
diff_ln_population_all		0.587*** (0.083)	0.896*** (0.065)		0.593*** (0.091)	0.811*** (0.061)		0.707*** (0.045)	0.882*** (0.033)
diff_man_all		1.697 (1.445)	-0.647 (1.083)		2.602* (1.551)	-0.297 (1.175)		-0.135 (0.804)	-1.163* (0.601)
% male workers		0.395 (1.737)	-2.388** (1.194)		1.503 (1.800)	-1.580 (1.325)		-1.690* (0.867)	-2.998*** (0.735)
diff_rama_Min_all		-0.010 (0.010)	0.006 (0.008)		0.001 (0.010)	0.009 (0.007)		-0.002 (0.007)	0.014*** (0.005)
% mining workers		-0.001 (0.010)	0.004 (0.006)		0.018* (0.010)	0.012* (0.006)		0.001 (0.007)	0.017*** (0.005)
Min temperature in coldest month		-0.000 (0.000)	0.000*** (0.000)		-0.000** (0.000)	0.000*** (0.000)		-0.000 (0.000)	0.000*** (0.000)
Log ruggedness		-0.041 (0.046)	-0.054 (0.035)		0.007 (0.052)	-0.054 (0.038)		-0.040 (0.027)	-0.009 (0.022)
Log non-farm employment			-0.601*** (0.036)			-0.604*** (0.039)			-0.485*** (0.022)
Constant	0.599 (0.544)	2.856** (1.179)	4.620*** (0.903)	0.517 (0.582)	0.862 (1.248)	4.933*** (0.966)	-0.423 (0.282)	2.314*** (0.637)	4.717*** (0.576)
Adjusted R^2	0.709	0.642	0.833	0.703	0.627	0.834	0.734	0.622	0.791
Observations	416	416	416	377	377	377	878	878	878
Panel b): 3SLS estimation	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
Log market access	1.160*** (0.213)	0.290 (0.233)	0.928*** (0.148)	1.244*** (0.212)	0.224 (0.211)	1.195*** (0.184)	1.117*** (0.183)	-0.124 (0.187)	1.248*** (0.180)
Log population	-0.790*** (0.063)			-0.675*** (0.066)			-0.569*** (0.038)		
diff_ln_farm_employment_all	0.053** (0.023)			0.014 (0.023)			-0.010 (0.013)		
diff_ln_nonfarm_employment_all	-0.213*** (0.035)			-0.159*** (0.037)			-0.151*** (0.024)		
% young workers	-0.245 (0.590)			-0.558 (0.648)			-0.345 (0.360)		
diff_edad_young_all	-0.445 (0.671)			-0.564 (0.729)			-0.493 (0.406)		
% workers with tertiary education	-0.573 (1.970)		0.955 (2.377)	-0.114 (2.056)		2.078 (3.067)	-2.266* (1.181)		-2.569 (2.088)
diff_tipo_educacion3_all	0.065 (0.288)			-0.444* (0.263)			-0.454*** (0.134)		
Precipitation of driest month	0.000** (0.000)			0.000 (0.000)			0.000 (0.000)		
Distance to minor water sources	0.014 (0.014)	0.055 (0.052)		0.025** (0.012)	0.076* (0.043)		0.010 (0.006)	0.078*** (0.028)	
Log farm employment		-1.012*** (0.074)			-0.857*** (0.058)			-0.860*** (0.050)	
diff_ln_population_all		-0.872*** (0.199)	0.071 (0.113)		-0.685*** (0.187)	-0.141 (0.162)		-0.773*** (0.171)	-0.466*** (0.151)
diff_man_all		2.922** (1.173)	0.657* (0.388)		1.467 (1.105)	0.689 (0.453)		-0.564 (0.728)	0.737** (0.359)
% male workers		3.827*** (1.344)	0.101 (0.465)		1.943 (1.244)	0.394 (0.626)		-0.369 (0.896)	0.424 (0.541)
diff_rama_Min_all		-0.004 (0.012)	-0.000 (0.005)		0.001 (0.012)	-0.001 (0.008)		0.013 (0.011)	-0.006 (0.009)
% mining workers		0.001 (0.013)	-0.003 (0.006)		0.008 (0.011)	-0.010 (0.007)		0.008 (0.009)	-0.004 (0.006)
Min temperature in coldest month		0.000 (0.000)	0.000*** (0.000)		-0.000 (0.000)	0.000* (0.000)		-0.000 (0.000)	0.000 (0.000)
Log ruggedness		-0.014 (0.040)	-0.013 (0.013)		-0.104*** (0.037)	-0.001 (0.015)		-0.122*** (0.028)	0.023** (0.011)
Log non-farm employment			-0.707*** (0.031)			-0.739*** (0.040)			-0.718*** (0.034)
Constant	9.489*** (1.035)	4.544*** (1.749)	8.884*** (1.060)	9.314*** (1.031)	5.601*** (1.625)	10.489*** (1.403)	8.009*** (0.889)	3.775*** (1.367)	10.604*** (1.304)
Chi-squared	1399.597	603.309	1778.202	1268.798	751.972	1309.351	2643.669	814.926	1754.971
Observations	377	377	377	416	416	416	878	878	878

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE B5. Elasticities for Different Specifications of Market Access (1992-2002)

Panel a): OLS estimation	Distance Decay Market Access Function with $a = 50$			Distance Decay Market Access Function with $a = 100$			City-size Adjusted Market Access Function		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
Log market access	0.007 (0.008)	0.015 (0.045)	-0.002 (0.018)	0.028 (0.033)	0.054 (0.182)	0.027 (0.077)	0.076 (0.046)	-0.082 (0.103)	0.011 (0.072)
Log population	-0.078*** (0.024)			-0.079*** (0.024)			-0.079*** (0.023)		
Diff log farm employment	0.166*** (0.026)			0.166*** (0.026)			0.167*** (0.026)		
Diff log non-farm employment	0.179*** (0.021)			0.179*** (0.021)			0.178*** (0.021)		
% young workers	0.210 (0.577)			0.207 (0.578)			0.212 (0.577)		
Diff % young workers	0.012 (0.382)			0.006 (0.384)			0.030 (0.380)		
% workers with tertiary education	3.922*** (1.157)		0.495 (2.775)	3.913*** (1.160)			3.926*** (1.147)		0.430 (2.765)
Diff % workers with tertiary education	1.641** (0.705)			1.643** (0.705)			1.498** (0.725)		
Precipitation of driest month	-0.000 (0.000)			-0.000 (0.000)			-0.000 (0.000)		
Distance to minor water sources	0.019 (0.012)	-0.067* (0.036)		0.019 (0.012)	-0.067* (0.036)		0.019* (0.012)	-0.067* (0.036)	
Log farm employment		-0.325*** (0.056)			-0.325*** (0.057)			-0.326*** (0.057)	
Diff log population		0.815*** (0.126)	1.061*** (0.108)		0.816*** (0.126)	1.059*** (0.105)		0.833*** (0.125)	1.059*** (0.109)
Diff % male workers		1.059 (1.171)	1.193 (0.953)		1.070 (1.173)	1.182 (0.943)		0.976 (1.177)	1.201 (0.958)
% male workers		0.647 (1.198)	-1.246 (0.995)		0.658 (1.203)	-1.246 (0.993)		0.518 (1.199)	-1.232 (1.002)
Diff % mining workers		0.005 (0.007)	0.011 (0.009)		0.005 (0.008)	0.011 (0.009)		0.004 (0.007)	0.011 (0.009)
% mining workers		0.013 (0.009)	0.010 (0.008)		0.013 (0.009)	0.010 (0.007)		0.014 (0.009)	0.010 (0.007)
Min temperature in coldest month		-0.000 (0.000)	0.000 (0.000)		-0.000 (0.000)	0.000 (0.000)		-0.000 (0.000)	0.000 (0.000)
Log ruggedness		-0.038 (0.035)	-0.040 (0.034)		-0.037 (0.035)	-0.039 (0.034)		-0.047 (0.037)	-0.039 (0.034)
Log non-farm employment			-0.412*** (0.037)			-0.410*** (0.033)			-0.412*** (0.037)
Constant	0.245 (0.242)	1.344 (1.194)	2.300*** (0.783)	0.240 (0.237)	1.285 (1.101)	2.454*** (0.778)	0.434* (0.251)	0.657 (0.891)	2.391*** (0.791)
Adjusted R^2	0.494	0.415	0.531	0.494	0.415	0.533	0.497	0.417	0.531
Observations	536	536	536	536	536	536	536	536	536
Panel b): 3SLS estimation	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
Log market access	0.069** (0.029)	0.173* (0.094)	0.167*** (0.056)	0.264*** (0.098)	0.650** (0.327)	0.612*** (0.175)	0.317** (0.127)	0.321 (0.269)	0.491*** (0.161)
Log population	-0.303*** (0.024)			-0.308*** (0.024)			-0.324*** (0.025)		
Diff log farm employment	0.095*** (0.032)			0.090*** (0.030)			0.084*** (0.031)		
Diff log non-farm employment	-0.136*** (0.020)			-0.136*** (0.018)			-0.150*** (0.020)		
% young workers	-0.045 (0.311)			-0.068 (0.304)			-0.073 (0.314)		
Diff % young workers	-0.164 (0.239)			-0.185 (0.233)			-0.214 (0.243)		
% workers with tertiary education	0.227 (1.189)		-1.685 (2.828)	0.625 (0.875)			0.660 (1.120)		0.881 (2.472)
Diff % workers with tertiary education	0.561 (0.486)			0.455 (0.468)			0.482 (0.504)		
Precipitation of driest month	-0.000 (0.000)			-0.000 (0.000)			-0.000 (0.000)		
Distance to minor water sources	0.017 (0.011)	-0.046 (0.048)		0.016 (0.010)	-0.049 (0.046)		0.017 (0.011)	-0.047 (0.044)	
Log farm employment		-0.782*** (0.097)			-0.777*** (0.094)			-0.743*** (0.090)	
Diff log population		-2.474*** (0.686)	0.200 (0.279)		-2.421*** (0.669)	0.143 (0.255)		-2.128*** (0.638)	0.161 (0.274)
Diff % male workers		0.946 (0.984)	1.190** (0.506)		0.921 (0.967)	1.240** (0.488)		0.609 (0.959)	1.380*** (0.493)
% male workers		3.017*** (1.141)	-0.143 (0.601)		3.003*** (1.125)	-0.104 (0.579)		2.676** (1.125)	0.162 (0.591)
Diff % mining workers		0.003 (0.014)	0.005 (0.007)		0.002 (0.014)	0.006 (0.007)		0.001 (0.013)	0.004 (0.007)
% mining workers		0.009 (0.013)	-0.002 (0.006)		0.008 (0.012)	-0.001 (0.006)		0.009 (0.012)	-0.001 (0.006)
Min temperature in coldest month		-0.000 (0.000)	-0.000 (0.000)		-0.000 (0.000)	-0.000 (0.000)		-0.000 (0.000)	-0.000 (0.000)
Log ruggedness		-0.038 (0.035)	-0.018 (0.018)		-0.037 (0.035)	-0.015 (0.017)		-0.048 (0.038)	-0.009 (0.019)
Log non-farm employment			-0.444*** (0.029)			-0.455*** (0.024)			-0.457*** (0.029)
Constant	2.755*** (0.666)	4.629** (2.221)	4.954*** (1.259)	2.593*** (0.545)	4.083** (1.857)	4.321*** (0.978)	2.791*** (0.618)	3.501* (1.959)	4.410*** (1.082)
Chi-squared	589.162	274.984	789.094	613.124	284.024	817.477	639.672	303.728	821.273
Observations	536	536	536	536	536	536	536	536	536

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE B6. Elasticities for Different Selection of Rural Communities (1992-2002)

Panel a): OLS estimation	City-Size Adjusted Market Access Function with 10 km City Buffer			City-Size Adjusted Market Access Function with 15 km City Buffer			City-Size Adjusted Market Access Function with Small Communities		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
Log market access	0.022 (0.058)	0.000 (0.108)	0.099 (0.094)	0.017 (0.067)	-0.060 (0.135)	0.205* (0.113)	0.041 (0.037)	-0.077 (0.058)	0.066 (0.055)
Log population	-0.120*** (0.033)			-0.077** (0.030)			-0.061*** (0.017)		
Diff log farm employment	0.162*** (0.032)			0.150*** (0.037)			0.220*** (0.019)		
Diff log non-farm employment	0.182*** (0.027)			0.164*** (0.028)			0.202*** (0.015)		
% young workers	0.123 (0.794)			0.191 (0.814)			0.612 (0.377)		
Diff % young workers	0.040 (0.542)			0.081 (0.499)			0.519** (0.258)		
% workers with tertiary education	4.732*** (1.400)		-0.479 (3.459)	3.769** (1.486)		2.872 (3.014)	3.159*** (0.715)		-1.296 (1.702)
Diff % workers with tertiary education	1.312 (0.879)			2.090** (0.901)			0.505 (0.507)		
Precipitation of driest month	-0.000 (0.000)			-0.000 (0.000)			-0.000 (0.000)		
Distance to minor water sources	0.010 (0.019)	-0.057 (0.061)		0.021 (0.021)	-0.095 (0.076)		0.015 (0.011)	-0.043* (0.023)	
Log farm employment		-0.390*** (0.076)			-0.319*** (0.079)			-0.296*** (0.033)	
Diff log population		0.778*** (0.159)	1.070*** (0.139)		0.732*** (0.203)	1.036*** (0.153)		0.869*** (0.066)	0.956*** (0.078)
Diff % male workers		1.999 (1.609)	1.222 (1.405)		0.118 (1.665)	1.895 (1.237)		0.367 (0.706)	0.222 (0.711)
% male workers		1.617 (1.598)	-1.112 (1.325)		0.439 (1.640)	-0.475 (1.224)		-1.427* (0.774)	-1.960** (0.783)
Diff % mining workers		-0.002 (0.007)	0.007 (0.010)		0.003 (0.007)	0.017** (0.008)		-0.004 (0.007)	0.017* (0.010)
% mining workers		0.003 (0.009)	0.005 (0.011)		0.013 (0.009)	0.018** (0.009)		0.009 (0.006)	0.013** (0.006)
Min temperature in coldest month		-0.000 (0.000)	0.000*** (0.000)		-0.000 (0.000)	0.000*** (0.000)		0.000 (0.000)	0.000 (0.000)
Log ruggedness		-0.030 (0.050)	-0.052 (0.052)		-0.046 (0.053)	-0.047 (0.057)		-0.020 (0.026)	-0.039 (0.027)
Log non-farm employment			-0.416*** (0.048)			-0.434*** (0.051)			-0.360*** (0.027)
Constant	0.422 (0.317)	0.655 (1.117)	3.092*** (1.105)	0.178 (0.370)	0.883 (1.193)	3.350*** (1.100)	0.102 (0.197)	1.151* (0.593)	3.348*** (0.617)
Adjusted R^2	0.472	0.391	0.484	0.449	0.354	0.499	0.546	0.449	0.489
Observations	416	416	416	377	377	377	878	878	878
Panel b): 3SLS estimation	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
Log market access	0.388*** (0.135)	0.437* (0.251)	0.602*** (0.166)	0.511*** (0.138)	0.480** (0.228)	0.722*** (0.171)	0.388*** (0.133)	0.233 (0.159)	0.491*** (0.141)
Log population	-0.372*** (0.034)			-0.356*** (0.032)			-0.390*** (0.020)		
Diff log farm employment	0.060* (0.033)			0.019 (0.038)			0.006 (0.026)		
Diff log non-farm employment	-0.167*** (0.025)			-0.160*** (0.028)			-0.184*** (0.019)		
% young workers	-0.196 (0.349)			-0.034 (0.413)			0.060 (0.316)		
Diff % young workers	-0.310 (0.296)			-0.120 (0.303)			0.155 (0.304)		
% workers with tertiary education	0.705 (1.390)		0.297 (2.964)	1.470 (1.521)		2.788 (3.013)	0.899 (0.928)		1.122 (1.795)
Diff % workers with tertiary education	0.290 (0.562)			0.818 (0.667)			-0.217 (0.338)		
Precipitation of driest month	-0.000 (0.000)			0.000 (0.000)			-0.000 (0.000)		
Distance to minor water sources	0.014 (0.014)	-0.054 (0.056)		-0.002 (0.016)	-0.096* (0.053)		0.012 (0.010)	-0.038 (0.027)	
Log farm employment		-0.747*** (0.099)			-0.545*** (0.076)			-0.545*** (0.044)	
Diff log population		-1.797*** (0.641)	0.028 (0.303)		-0.983* (0.558)	0.033 (0.339)		-0.662** (0.318)	0.126 (0.228)
Diff % male workers		1.712 (1.151)	1.360** (0.601)		0.005 (0.967)	1.343** (0.568)		0.872* (0.530)	0.513 (0.374)
% male workers		3.732*** (1.208)	0.054 (0.629)		1.730 (1.079)	-0.012 (0.619)		0.351 (0.691)	-0.201 (0.520)
Diff % mining workers		-0.004 (0.013)	0.006 (0.007)		-0.006 (0.011)	0.008 (0.007)		-0.006 (0.011)	0.003 (0.008)
% mining workers		-0.001 (0.012)	-0.002 (0.006)		-0.005 (0.013)	0.003 (0.008)		0.001 (0.007)	0.001 (0.005)
Min temperature in coldest month		-0.000 (0.000)	0.000 (0.000)		-0.000 (0.000)	0.000* (0.000)		-0.000 (0.000)	-0.000 (0.000)
Log ruggedness		-0.016 (0.043)	-0.012 (0.022)		-0.012 (0.042)	-0.015 (0.024)		-0.007 (0.025)	-0.010 (0.017)
Log non-farm employment			-0.469*** (0.036)			-0.481*** (0.034)			-0.446*** (0.023)
Constant	3.346*** (0.646)	3.407* (1.880)	5.226*** (1.154)	3.745*** (0.664)	4.155*** (1.559)	6.064*** (1.126)	3.453*** (0.642)	2.968*** (1.131)	4.923*** (0.934)
Chi-squared	561.081	300.775	628.584	478.314	406.216	661.398	1017.578	624.004	937.264
Observations	416	416	416	377	377	377	878	878	878

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE B7. Elasticities for Different Specifications of Market Access (2002-2017)

Panel a): OLS estimation	Distance Decay Market Access Function with $a = 50$			Distance Decay Market Access Function with $a = 100$			City-size Adjusted Market Access Function		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
Log market access	-0.008 (0.010)	0.016 (0.027)	0.031** (0.012)	-0.040 (0.043)	0.098 (0.110)	0.130** (0.054)	-0.028 (0.058)	0.077 (0.083)	0.101* (0.054)
Log population	-0.075** (0.031)			-0.074** (0.031)			-0.076** (0.031)		
Diff log farm employment	0.201*** (0.024)			0.201*** (0.024)			0.201*** (0.024)		
Diff log non-farm employment	0.495*** (0.032)			0.495*** (0.031)			0.495*** (0.031)		
% young workers	1.368** (0.658)			1.379** (0.656)			1.343** (0.656)		
Diff % young workers	0.388 (0.589)			0.389 (0.588)			0.372 (0.584)		
% workers with tertiary education	2.855*** (0.762)		0.751 (0.824)	2.862*** (0.761)			2.859*** (0.767)		0.712 (0.828)
Diff % workers with tertiary education	0.361 (0.371)			0.364 (0.371)			0.365 (0.375)		
Precipitation of driest month	0.000 (0.000)			0.000 (0.000)			0.000 (0.000)		
Distance to minor water sources	-0.018 (0.015)	0.097*** (0.036)		-0.018 (0.015)	0.097*** (0.036)		-0.018 (0.015)	0.096*** (0.036)	
Log farm employment		-0.594*** (0.060)			-0.595*** (0.060)			-0.593*** (0.059)	
Diff log population		0.654*** (0.067)	0.904*** (0.040)		0.655*** (0.067)	0.909*** (0.039)		0.651*** (0.067)	0.900*** (0.040)
Diff % male workers		1.854 (1.244)	-0.076 (0.826)		1.892 (1.238)	-0.129 (0.834)		1.879 (1.242)	-0.118 (0.832)
% male workers		0.711 (1.209)	-1.142 (0.746)		0.755 (1.206)	-1.191 (0.750)		0.817 (1.208)	-1.059 (0.754)
Diff % mining workers		-0.002 (0.012)	0.006 (0.006)		-0.003 (0.012)	0.006 (0.006)		-0.003 (0.012)	0.005 (0.006)
% of mining workers		0.003 (0.008)	0.006 (0.004)		0.003 (0.008)	0.006 (0.004)		0.002 (0.008)	0.006 (0.005)
Min temperature in coldest month		-0.000 (0.000)	0.000** (0.000)		-0.000 (0.000)	0.000** (0.000)		-0.000 (0.000)	0.000** (0.000)
Log ruggedness		-0.019 (0.034)	-0.005 (0.020)		-0.017 (0.034)	-0.004 (0.020)		-0.014 (0.034)	-0.001 (0.019)
Log non-farm employment			-0.363*** (0.029)			-0.353*** (0.026)			-0.362*** (0.029)
Constant	-0.107 (0.293)	2.416** (0.955)	2.702*** (0.530)	-0.129 (0.283)	2.496*** (0.928)	2.672*** (0.518)	-0.047 (0.335)	2.496*** (0.964)	2.610*** (0.529)
Adjusted R^2	0.786	0.655	0.805	0.786	0.655	0.805	0.786	0.655	0.805
Observations	536	536	536	536	536	536	536	536	536
Panel b): 3SLS estimation	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
Log market access	0.038** (0.016)	0.049 (0.032)	0.053*** (0.020)	0.189** (0.076)	0.208 (0.137)	0.218*** (0.076)	1.084*** (0.202)	0.017 (0.236)	1.145*** (0.181)
Log population	-0.522*** (0.048)			-0.573*** (0.054)			-0.545*** (0.053)		
Diff log farm employment	0.035*** (0.011)			0.043*** (0.013)			0.037*** (0.012)		
Diff log non-farm employment	-0.190*** (0.032)			-0.308*** (0.033)			-0.205*** (0.045)		
% young workers	-0.534 (0.426)			-0.539 (0.468)			-0.795 (0.526)		
Diff % young workers	-0.439 (0.418)			-0.434 (0.460)			-0.617 (0.519)		
% workers with tertiary education	2.703*** (0.556)		4.528*** (0.924)	0.084 (0.351)			1.321 (0.808)		2.450* (1.327)
Diff % workers with tertiary education	-0.218** (0.108)			-0.196* (0.119)			-0.079 (0.143)		
Precipitation of driest month	0.000* (0.000)			0.000* (0.000)			0.000 (0.000)		
Distance to minor water sources	0.004 (0.006)	0.049 (0.030)		0.003 (0.007)	0.048 (0.032)		0.003 (0.007)	0.051 (0.035)	
Log farm employment		-0.986*** (0.052)			-1.012*** (0.055)			-0.973*** (0.060)	
Diff log population		-1.263*** (0.235)	-0.307** (0.152)		-1.310*** (0.243)	-0.125 (0.135)		-1.150*** (0.235)	-0.292 (0.181)
Diff % male workers		2.864*** (1.056)	0.434 (0.532)		2.988*** (1.110)	0.380 (0.482)		0.861 (1.256)	0.983 (0.657)
% male workers		3.497*** (0.995)	0.070 (0.500)		3.946*** (1.039)	-0.016 (0.453)		0.798 (1.212)	0.592 (0.612)
Diff % mining workers		-0.004 (0.016)	-0.005 (0.010)		-0.001 (0.017)	-0.006 (0.009)		0.035* (0.018)	-0.015 (0.012)
% of mining workers		-0.014* (0.008)	0.000 (0.003)		-0.010 (0.008)	-0.001 (0.003)		-0.007 (0.009)	-0.001 (0.004)
Min temperature in coldest month		0.000 (0.000)	0.000** (0.000)		0.000 (0.000)	0.000** (0.000)		0.000 (0.000)	0.000 (0.000)
Log ruggedness		-0.033 (0.025)	-0.003 (0.008)		-0.028 (0.027)	-0.003 (0.008)		-0.109*** (0.035)	0.012 (0.011)
Log non-farm employment			-0.607*** (0.035)			-0.524*** (0.029)			-0.621*** (0.048)
Constant	4.038*** (0.584)	4.203*** (1.327)	3.754*** (0.820)	4.543*** (0.643)	3.977*** (1.332)	3.500*** (0.725)	8.065*** (1.036)	5.686*** (1.750)	9.608*** (1.356)
Chi-squared	1379.982	812.918	1309.649	1620.084	775.461	1296.424	1104.561	673.739	1040.838
Observations	536	536	536	536	536	536	536	536	536

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

TABLE B8. Elasticities for Different Selection of Rural Communities (2002-2017)

Panel a): OLS estimation	City-Size Adjusted Market Access Function with 10 km City Buffer			City-Size Adjusted Market Access Function with 15 km City Buffer			City-Size Adjusted Market Access Function with Small Communities		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
Log market access	0.028 (0.076)	0.104 (0.114)	0.046 (0.073)	0.017 (0.091)	0.076 (0.139)	0.093 (0.084)	-0.056 (0.043)	-0.004 (0.059)	0.087** (0.044)
Log population	-0.067 (0.043)			-0.088* (0.044)			-0.051*** (0.018)		
Diff log farm employment	0.202*** (0.031)			0.207*** (0.034)			0.270*** (0.017)		
Diff log non-farm employment	0.456*** (0.038)			0.480*** (0.045)			0.474*** (0.022)		
% young workers	1.860** (0.803)			1.519* (0.885)			1.570*** (0.446)		
Diff % young workers	0.483 (0.743)			0.679 (0.759)			0.846** (0.355)		
% workers with tertiary education	2.406** (0.938)		1.785 (1.088)	2.424** (0.973)		1.195 (1.059)	2.614*** (0.498)		-0.850 (0.653)
Diff % workers with tertiary education	0.317 (0.532)			0.653 (0.431)			0.682*** (0.260)		
Precipitation of driest month	0.000 (0.000)			0.000 (0.000)			0.000 (0.000)		
Distance to minor water sources	-0.022 (0.025)	0.084* (0.048)		0.008 (0.024)	0.072 (0.058)		-0.027** (0.013)	0.126*** (0.026)	
Log farm employment		-0.600*** (0.075)			-0.567*** (0.083)			-0.479*** (0.040)	
Diff log population		0.671*** (0.085)	0.937*** (0.055)		0.638*** (0.096)	0.880*** (0.047)		0.726*** (0.043)	0.879*** (0.029)
Diff % male workers		2.651* (1.593)	-0.484 (1.094)		3.140* (1.753)	-0.056 (1.082)		0.646 (0.816)	-0.917 (0.627)
% male workers		1.255 (1.597)	-1.563 (0.985)		2.351 (1.679)	-1.297 (0.968)		-0.535 (0.881)	-1.589** (0.633)
Diff % mining workers		-0.016 (0.017)	-0.010 (0.007)		-0.003 (0.020)	-0.008 (0.007)		0.007 (0.008)	0.013*** (0.004)
% of mining workers		0.003 (0.008)	0.000 (0.004)		0.013 (0.011)	-0.001 (0.005)		-0.000 (0.007)	0.011** (0.005)
Min temperature in coldest month		-0.000 (0.000)	0.000 (0.000)		-0.000 (0.000)	0.000 (0.000)		-0.000** (0.000)	0.000 (0.000)
Log ruggedness		-0.039 (0.044)	-0.017 (0.027)		0.020 (0.051)	-0.023 (0.029)		-0.038 (0.027)	0.013 (0.018)
Log non-farm employment			-0.402*** (0.036)			-0.374*** (0.037)			-0.316*** (0.024)
Constant	0.128 (0.440)	2.766** (1.175)	2.805*** (0.705)	0.188 (0.501)	1.115 (1.247)	3.001*** (0.713)	-0.548** (0.245)	2.196*** (0.656)	2.600*** (0.465)
Adjusted R^2	0.789	0.656	0.805	0.798	0.641	0.818	0.801	0.621	0.762
Observations	416	416	416	377	377	377	878	878	878
Panel b): 3SLS estimation	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment	Change in Log Population	Change in Log Farm Employment	Change in Log Non-Farm Employment
Log market access	0.265*** (0.087)	0.317*** (0.112)	0.168*** (0.062)	0.415*** (0.134)	0.221* (0.121)	0.212*** (0.063)	0.128** (0.053)	0.070 (0.077)	0.188*** (0.068)
Log population	-0.593*** (0.055)			-0.826*** (0.050)			-0.396*** (0.024)		
Diff log farm employment	0.045*** (0.014)			0.055*** (0.019)			0.022*** (0.008)		
Diff log non-farm employment	-0.270*** (0.036)			-0.490*** (0.048)			-0.102*** (0.019)		
% young workers	-0.230 (0.623)			-0.366 (0.530)			-0.211 (0.233)		
Diff % young workers	-0.332 (0.522)			-0.346 (0.506)			-0.228 (0.222)		
% workers with tertiary education	2.904*** (0.683)		4.537*** (0.957)	2.661*** (0.928)		2.583*** (0.835)	1.595*** (0.352)		4.157*** (0.855)
Diff % workers with tertiary education	-0.367* (0.208)			-0.065 (0.202)			-0.235*** (0.073)		
Precipitation of driest month	0.000 (0.000)			0.000* (0.000)			0.000 (0.000)		
Distance to minor water sources	0.013 (0.010)	0.063 (0.045)		0.020 (0.015)	0.078 (0.049)		0.004 (0.004)	0.079*** (0.025)	
Log farm employment		-1.014*** (0.058)			-0.972*** (0.060)			-0.924*** (0.040)	
Diff log population		-1.369*** (0.287)	-0.093 (0.153)		-0.938*** (0.209)	0.174** (0.084)		-1.323*** (0.149)	-0.898*** (0.105)
Diff % male workers		3.584*** (1.123)	0.098 (0.377)		3.608*** (1.153)	0.370 (0.312)		1.682*** (0.629)	0.296 (0.294)
% male workers		4.535*** (1.206)	-0.208 (0.472)		4.689*** (1.149)	-0.025 (0.317)		2.035*** (0.684)	-0.035 (0.353)
Diff % mining workers		0.005 (0.020)	-0.009 (0.009)		0.005 (0.018)	-0.008 (0.007)		-0.002 (0.012)	-0.006 (0.008)
% of mining workers		-0.004 (0.010)	-0.002 (0.005)		-0.001 (0.010)	-0.001 (0.003)		-0.016** (0.007)	-0.000 (0.003)
Min temperature in coldest month		0.000 (0.000)	0.000** (0.000)		0.000 (0.000)	0.000** (0.000)		0.000 (0.000)	0.000 (0.000)
Log ruggedness		-0.057* (0.034)	-0.009 (0.010)		0.022 (0.034)	-0.017** (0.009)		-0.049** (0.021)	0.012 (0.008)
Log non-farm employment			-0.573*** (0.032)			-0.518*** (0.028)			-0.675*** (0.028)
Constant	4.749*** (0.631)	5.278*** (1.404)	3.771*** (0.712)	6.715*** (0.835)	3.112** (1.254)	3.782*** (0.567)	2.604*** (0.324)	3.297*** (0.914)	3.560*** (0.732)
Chi-squared	1441.773	674.462	1253.708	1465.673	705.068	1518.722	1994.984	1119.316	2334.111
Observations	416	416	416	377	377	377	878	878	878

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$