Local poverty reduction in Chile and Mexico: The role of food manufacturing growth[1]

Chiara Cazzuffi, Mariana Pereira López**, Isidro Soloaga**,*

**Rimisp - Latin American Center for Rural Development, Santiago, Chile*

**Universidad Iberoamericana, Mexico City, Mexico*

This paper analyzes the relationship between local poverty and food manufacturing growth in Chile and Mexico using propensity score matching, differences in differences and spatial econometrics methods. We focus on food manufacturing as a sector with a number of characteristics that make it potentially pro-poor, and whose incentives for spatial distribution may either strengthen or dampen its poverty reduction potential. The overall results indicate that i) geographically, food manufacturing locates in relatively poor areas, but not in the poorest; ii) food manufacturing tends to locate in municipalities with more availability of labor and raw materials and with better infrastructure; iii) controlling for other factors, food manufacturing growth contributes to local poverty reduction both in terms of magnitude and speed.

Keywords: poverty, poverty reduction, food manufacturing, difference in difference, propensity score matching, spatial analysis

JEL Classifications: I32, R11, R12

[1] This publication is a product of the program Territorial Cohesion for Development, coordinated by Rimisp – Latin American Centre for Rural Development and funded by the International Development Research Centre (IDRC, Canada). The content of this publication is of exclusive responsibility of its authors. We are grateful to Julio Berdegué, Félix Modrego, Eduardo Ramirez, Andrés Tomaselli and Antonio Yúnez-Naude for insightful comments to earlier drafts.

1. Introduction

Pro-poor growth and transfers are the two main instruments for poverty reduction (De Janvry and Sadoulet, 2010). While transfers are more expensive and politically difficult to implement and sustain over time, pro-poor growth poses the challenge of identifying what kind of growth leads to the best results in terms of poverty reduction. Both the sectoral composition and the spatial distribution of growth are important factors for poverty reduction. There is evidence that growth is especially pro-poor when it is based on labor-intensive sectors, in particular agriculture (among others, Ravallion and Datt, 1996 and 2002; Anríquez and Lopez, 2007; Suryahadi et al., 2009; De Janvry and Sadoulet, 2010; Loayza and Raddatz, 2010; Christiaensen, 2011). On the other hand, the spatial distribution of economic activity and growth may affect poverty reduction through at least two channels. First, theoretical and empirical evidence suggests that, beyond a certain income threshold, excessive spatial concentration of economic activity slows down aggregate economic growth (Brülhart and Sbergami, 2009; Mureddu and Cerina, 2009; Atienza and Aroca, 2013). Second, spatially concentrated economic growth tends to be less inclusive if most of the poor live in the geographic periphery of economic activity, because their lives are characterized by multiple market failures (including in credit and land markets) which hinder their ability to participate in the opportunities generated by economic growth, if these do not occur where they live (Dercon, 2009). Empirical evidence suggests that growth is especially pro-poor in non-metropolitan areas, in particular medium and small cities (Christiaensen and Todo, 2014).

This paper focuses on food manufacturing as a sector with a number of characteristics that make it potentially pro-poor, and whose incentives for spatial distribution may either strengthen or dampen its poverty reduction potential. We investigate empirically what is the average impact of food manufacturing growth on the reduction of local poverty rates in Chile and Mexico since the 1990s. We define this sector as the manufacturing of food, beverages and tobacco, according to codes 311 and 312 from the North American Industry Classification (NAICS), and focus on formal establishments. Throughout the paper, we use food manufacturing and agriprocessing as synonyms. Even though agriculture in the two countries accounts for a low and decreasing share of the economy (5% of GDP in Mexico and 6% in Chile according to De Ferranti et al., 2005), food manufacturing represents about 15% of GDP (Byerlee et al., 2005), suggesting significant implications of this sector for growth and poverty reduction.

The characteristics that, at least in theory, make of food manufacturing a pro-poor sector include its labor-intensive and low-tech nature, similar to agriculture (FAO, 2004; World Bank, 2008). Second, it provides a way for natural resource based economies to diversify and add value to their production structure and employment (Da Silva et al., 2013). Third, food manufacturing tends to increase formal employment, especially of unskilled labor and of women (Thorbecke and Jung, 1996; Barron and Rello, 2000; Valdes and Foster, 2003; Maertens and Swinnen, 2012). Moreover, diversification into higher value activities can stimulate broader economic development in lower income areas and establish a virtuous cycle whereby the creation of off-farm development and income earning opportunities result in higher perceived returns to higher schooling and faster accumulation of human capital. This, coupled with agriprocessing backward linkages with agriculture, and its potentially diverse forward linkages with other sectors (especially services), can have a multiplier effect on local employment and may generate positive agglomeration externalities, catalyzing faster growth and further poverty reduction (World Bank, 2008; Maertens et al., 2012).

However, the impact of food manufacturing on poverty reduction also depends on its spatial distribution vis-à-vis that of the poor. Theoretical and empirical evidence on the service and manufacturing sectors suggests that geographical proximity to other firms, within the same or from other sectors, increases a firm's productivity via positive externalities such as knowledge spillovers, deeper and more skilled labor pools and closeness to consumer markets and specialized services (Henderson et al., 1995; Glaeser and Gottlieb, 2009; Saito and Gopinath 2011; Almeida and Fernandes, 2013). This provides strong agglomeration incentives for firms. In fact, both Chile and Mexico are characterized by a spatially unequal and highly concentrated pattern of economic development, where the political and economic power concentrate around one or two important and high-performing metropolitan cities[2], while the majority of the poor are located outside the high-growth metropolitan areas (Escobal and Ponce, 2011; Berdegué and Modrego, 2012; World Bank, 2009). The spatial distribution of food manufacturing may either increase or reduce the sector's potential for poverty reduction. If agriprocessing shares the same agglomeration incentives as those of the service sector or of the rest of the manufacturing industry, predominant concentration in or around already flourishing metropolitan cities may dampen the sector's potential for poverty reduction. However, a spatially dispersed location pattern may also emerge for food manufacturing, due to the sector's dependence on raw materials and rural areas. This would bring activity and employment to areas characterized by a lower density of economic activity, thus increasing food manufacturing's potential for poverty reduction.

In this paper we address the question of how much of the change in local poverty rates we observe can be attributed to food manufacturing growth, in the midst of all the simultaneous changes to local conditions that occurred during the period of analysis. We compare poverty rate reduction outcomes between municipalities[3] which experienced growth in the number of formal food manufacturing establishments (excluding micro-enterprises with less than 10 employees), versus municipalities where the sector has remained absent over the observed period, controlling for the non-random location decision of firms and for initial conditions that may affect subsequent outcome trends, using a combination of difference-in-difference and propensity score matching methods, as in Jalan and Ravallion (1998), van de Walle and Mu (2008) and Khandker et al. (2009). We focus on growth in the number of establishments (instead of, for example, on employment growth), because we consider that this enables us to capture more clearly the local effect of the presence of food manufacturing.

This paper contributes to the literature on the poverty elasticity to sectoral growth by, first, offering a comparison of two middle-income countries over a period of profound change in their

[2] Throughout this paper, we define a metropolitan city as a conurbation with a population of at least 250 thousands inhabitants. Non-metropolitan areas include all urban and rural areas with less than 250 thousands inhabitants. We do not adopt a unified definition of "rural" and "urban", but rather adopt for each country its official definition.
[3] Due to limitations in the data, we use municipalities as spatial unit of analysis, and not, as may be preferable, integrated spatial units of economic activity. We use spatial econometric methods to address the problems which may arise from this.

structure of production, focusing on an industry that is particularly relevant for resource rich countries, and using a lower level of spatial aggregation compared to most existing studies, which tend to rely on cross-country analyses. Second, the literature on the poverty elasticity to sectoral growth usually assumes the existing spatial distribution of sectoral activities to be exogenous, while our evaluation methodology allows us to control for non-random firm location in a particular industry, and for local characteristics which may simultaneously determine both the local composition of growth and poverty outcomes.

The rest of the paper is organized as follows: section 2 presents the conceptual framework and section 3 details the evaluation methodology. Section 4 presents the data and descriptive statistics, section 5 discusses results, and section 6 concludes.

2. Conceptual framework

The sectoral composition of growth is relevant for poverty reduction when there are asymmetries between sectors in terms of technology, which lead to some sectors being more labor-intensive than others. Loayza & Raddatz (2010) model poverty reduction as a linear function of real wage growth, assuming that the income of the poor is essentially labor income and that the main channel for poverty reduction is employment. With perfect competition among firms and holding labor supply constant, real wage growth depends on both a growth component and a labor reallocation component. The growth component implies that higher output per worker leads to higher wages which in turn lead to higher per capita income. How much a sector contributes to this growth (direct effect) only depends on its size, captured as its share of final-goods output. The reallocation effect (or indirect, cross-sector effect) depends on the elasticity of substitution across sectors in the production of the final good, and on a sector's labor intensity. If the elasticity of substitution is sufficiently high, growth in a labor intensive sector will have an additional effect on wages beyond its effect through aggregate value-added growth, because labor will move into this sector, pushing the wage rate up. The reallocation component is important because it implies that even a sector with a relatively small contribution to total output can have a significant localized poverty reduction effect if it is labor intensive and if labor can move into the growing sector.

We share Loayza and Raddatz's (2010) assumption that the main income of the poor is labor income and that the main channel for poverty reduction is employment. The ability of food manufacturing to reduce poverty thus depends, among other factors, on its size, technology, labor intensity, ability to generate backward and forward linkages, employment multiplier and spatial distribution relative to the spatial distribution of the poor. With respect to the latter, strong theoretical reasons, as well as empirical evidence, suggest that firm location decisions and spatial distribution are influenced by differences among territories in the initial distribution of agro-ecological, geographic and socio-economic characteristics, and in particular by the unequal distribution of physical assets and human capital, as well as by disparities in terms of infrastructure, market access and institutional factors (among others, Carlton, 1983; Schmenner et al., 1987; Goetz, 1997; Carod, 2005; Cohen and Paul, 2005; Davis and Schluter, 2005; Almeida and Fernandes, 2013). The spatial distribution of firms, in turn, influences the spatial distribution and sectoral composition of growth, and thereby poverty reduction.

The location of food manufacturers is the result of self-selection on the basis of maximization of the expected benefits of a particular location versus the available alternatives, which depends on the trade-offs between transportation costs and economies of scale, between input and output transportation costs, and between the benefits and costs of agglomeration (as highlighted by the rich theoretical and empirical work on firm location which started with the seminal paper by Carlton in 1983, including Henderson, 1994; Goetz, 1997; Guimaraes et al., 2004; Arauzo et al., 2010). The self-selection nature of the location decision and the role of local characteristics in determining firm placement complicate the estimation of the effect of food manufacturing growth on local poverty, because those very same characteristics that influence the location decision may also affect the poverty outcome (Barrett et al., 2012). If not controlled for, this would lead to a biased and inconsistent impact estimate. We control for those local characteristics that simultaneously influence food manufacturing placement and poverty outcomes, and we adopt a multi-theory approach to the modeling of food manufacturing placement, following Lambert and McNamara (2009) and considering factors related to natural endowments (Felkner and Townsend, 2011; Behrens et al., 2006; Rappaport and Sachs, 2003), stock of infrastructure and services (Deller et al., 2001; Deichman et al., 2008), institutional characteristics (Lambert and McNamara, 2009), and agglomeration economies, in particular urbanization and localization economies and market access (Glaeser, 1992 and 2009; Henderson, 1995, Fingleton and Fisher, 2010).

3. Evaluation methodology

We study the effect of food manufacturing growth on poverty as an evaluation problem where the "treated" group is composed by municipalities where the number of formal agriprocessing establishments grew over the period of analysis (in short, "agriprocessing municipalities"). These are 77 in Chile and 416 in Mexico. The comparison group is made of municipalities with similar characteristics but where the sector remained absent over the period (in short, "non-agriprocessing municipalities"). These are 159 in Chile and 1649 in Mexico. We exclude from the analysis those municipalities where agriprocessing existed at the beginning of the period, but where the number of establishments declined or remained stable over time. These are 107 in Chile, and 391 in Mexico. The outcomes of interest are the magnitude and speed of the reduction in the incidence of local poverty. The magnitude of local poverty reduction is captured by the difference in levels of the poverty headcount ratio between periods using a panel of municipalities, while its speed is measured as the percentage change in the headcount ratio between periods.

Our evaluation methodology takes into account the possibility that local initial conditions determine food manufacturing location as well as influence the subsequent path of local growth and poverty reduction (Jalan and Ravallion, 1998). We address this potential source of bias by combining difference-in-difference (DiD) with propensity score matching methods (PS), as in van de Walle and Mu (2009). To allow for the possibility of time variant selection bias due to initial observables, we use the predicted probability of growth in the number of establishments in a municipality (the propensity score) to match treatment and comparison municipalities. Our impact estimates are then constructed by comparing the before and after outcome measure for the treated municipalities with those of the matched comparison municipalities, considering both the full sample and restricting the analysis to municipalities within the common support.

PS-weighted DiD is based on two key assumptions (Abadie, 2005). First, that selection bias is conditional on the observed location covariates in the baseline. The estimates will be biased if there are unobservables that affect both agriprocessing location and poverty reduction. We are able to at least partly control for this by including in the PS-model (the location equation) an array of initial conditions that not only affect firm location, but may also subsequently affect poverty changes in the municipality. Second, the key identifying assumption of any DiD estimator is the so-called “equal trends” assumption, namely that the average change in outcome for the treated in the absence of treatment equals the average change in outcome for the non-treated. The DiD estimator attributes to the treatment itself any differences in trends between the two groups that occur at the same time as the treatment. However, the estimation will be biased if such difference has other causes. The parallel trends assumption is an identifying, and therefore untestable, assumption, but we examined trends in the outcome variable in a previous period and found that the two groups appear to follow the same trend before treatment. We further address this issue by controlling in the DiD equation for a range of other simultaneous changes that may affect poverty reduction trends in the two groups. We follow Ravallion and Datt (2002) and include growth in the other sectors and female education, as well as labor force participation, remoteness, average age in the municipality and presence of food manufactures in neighboring municipalities.

Because of data availability, we are able to implement the PS-weighted DiD methodology to the estimation of the magnitude of poverty change only, while the speed of poverty reduction is estimated by least squares, both for the full sample and restricted to the common support. For both magnitude and speed, in order to test the robustness of our results, we also implement a double-robust estimation following Lunceford and Davidian (2004) and Emsley et al. (2008), in which both models (the propensity score and the outcome) are estimated simultaneously, providing an unbiased and consistent estimate of the treatment effect if either one (not necessarily both) of the two models is correctly specified.[4]

We model food manufacturing growth as a binary treatment variable. Since our period of analysis covers seven years in Chile and ten years in Mexico, our treatment variable can be interpreted as the overall long-run effect of an increase in the number of formal agriprocessing establishments on local poverty. We also tested for the existence of non-linearities and tipping points in impacts depending on the magnitude of the local increase in agriprocessing activity, that is, on the "intensity of treatment" (Imbens, 2000), which we proxied with a multi-valued treatment variable equal to the positive cumulative change in the number of agriprocessing establishments over the period in a given municipality. This, however, did not provide significant additional insights, and in the rest of this paper we focus on the evaluation of the impacts of growth versus absence of food manufacturing.[5]

The average impact of agriprocessing on the magnitude of poverty reduction in treated municipalities is

$$DD = \sum_{N_T} DD_i / N_T \qquad 1$$

where

$$DD_i = (Y_{i1}^T - Y_{i0}^T) - \sum_j W_{ij}(Y_{j1}^{NT} - Y_{j0}^{NT}) \qquad 2$$

is the impact estimate for municipality i, T and NT denote agriprocessing (treated) and non-agriprocessing (comparison) municipalities respectively, $(Y_{i1}^T - Y_{i0}^T)$ is the change in the outcome measure for agriprocessing municipality i, $Y_{j1}^{NT} - Y_{j0}^{NT}$ is the change in the outcome measure for comparison municipality j, and W_{ij} is the weight given to the j^{th} municipality in

[4] See Bang and Robins (2005), Robins, Rotnitzky and Zhao (1995), Robins (2000) for the concept of double-robust estimators applied mainly to missing data and Tsiatis (2007), Neugebauer and van der Laan (2005) for the statistical literature on these estimators.
[5] Results for the intensity of treatment analysis are available from the authors.

making a comparison with the i^{th} treated municipality, which is the inverse of the estimated propensity score.[6] N_T is the total number of treated municipalities.

The average impact of food manufacturing growth on the speed of poverty reduction is estimated with a dynamic equation where the percentage change in the local poverty headcount ratio is the dependent variable, and we control for the initial level of poverty. The estimated equation is:

$$W_i\dot{Y}_i = W_i(\alpha + \beta Y_{0i} + \gamma T + \boldsymbol{X_i}\delta + u_i) \qquad 1$$

Where:

$\dot{Y}_i = Percentage\ change\ of\ FGT0\ \ in\ municipality\ i\ between\ period\ 0\ and\ period\ 1$

$Y_{0i} = FGT0\ of\ municipality\ i\ in\ period\ 0$

$T = Treatment\ status\ and\ impact\ of\ interest$

$\boldsymbol{X_i} = Vector\ of\ covariates$

$\boldsymbol{W_i} = Weights\ obtained\ as\ the\ inverse\ of\ the\ propensity\ score, the\ same\ used\ in\ eq. 2.$

For estimations restricted to the common support, we define the restricted sample by applying nonparametric kernel matching imposing the constraint that matches can only be taken from observations within the common support. With kernel matching, *all* the non-agriprocessing municipalities within the common support are used as matches for each agriprocessing municipality, each weighted according to a kernel function of the predicted propensity score which assigns more weight to more similar observations, following Heckman, Ichimura, and Todd (1998). This technique ensures valid bootstrapped standard errors (Abadie and Imbens, 2006).

[6] In the case of the treated municipalities, the weight is given by the inverse of the propensity score, while for control municipalities it takes the value of the inverse of one minus the propensity score.

The propensity score used to construct W_{ij} is obtained from a probit model where the dependent variable is equal to one if the municipality experienced an increase in the number of agriprocessing establishments, and zero if the sector remained absent over the period of analysis. This can be interpreted as a firm location model estimating the role of local characteristics in attracting new agriprocessing establishments. Firm location decision, resulting in the spatial distribution of agriprocessing establishments, is a relevant intellectual question given the rise of economic theories of agglomeration. Focusing on the agriprocessing sector is particularly interesting because the spatial distribution of suppliers and raw materials suggests for this sector a different location pattern from agglomeration around large cities. This issue will be investigated in depth in a different paper exploring the relevance of New Economic Geography theories for food manufacturing in middle income countries, given its different agglomeration incentives and firm heterogeneity. In this paper, on the other hand, we deal with firm location in an instrumental way, as it is necessary to control for food manufacturers placement in order to retrieve an unbiased estimator of the average impact on the "treated". While in the conceptual framework we refer to the individual decision of firms, in the empirical analysis the variable of interest is the realization of that decision at the aggregate level of municipalities. We follow the literature in assuming that the essential aspects of the individual decision are maintained also at the aggregate level (among others, Guimaraes et al., 2004; Schmidtner et al., 2011).

The use of municipalities as unit of analysis requires taking into account that economic interactions do not necessarily follow administrative boundaries. One can expect the decisions of agriprocessors to be influenced not only by the characteristics of the chosen municipality, but also by the characteristics of its neighbors, which can provide raw materials, labor and access to markets. Moreover, at least in theory, the expected benefits of firms in municipality i are not independent of whether or not food manufacturing is present in neighboring municipality j. In fact, the decision of a firm to locate in a municipality can generate spatial externalities that spread across administrative boundaries and modify relative factor prices and other production costs in other municipalities. Locating in relative proximity or distance from other agriprocessors is the result of the trade-off between the benefits of agglomeration (such as availability of a large and/or specialized labor pool, knowledge spillovers, or access to specialized services and infrastructure), which encourage spatial concentration; and the cost of competing for raw materials and labor, which bids factor prices up and encourages spatial dispersion of food manufactures, a tension recognized in the New Economic Geography literature (Fujita and Thisse, 1996). Therefore, the location decisions of food manufactures in neighboring municipalities may change the marginal utility of food manufacturers' decisions in municipality *i*, and may be simultaneously modified by what is happening in municipality *i*, generating a pattern of spatial interdependence of location decisions across municipalities.

In order to take such interdependence into account, we construct spatial weights matrices and estimate the location model first as a non-spatial probit model, and then add, progressively, an endogenous spatial lag of the dependent variable; semi-parametric spatial filtering; and spatial lags of explanatory variables (spatial Durbin model). The spatial filtering method aims at filtering out spurious spatial dependence in agriprocessing growth among municipalities (Griffith, 2002). The spatial Durbin model includes spatially lagged explanatory variables to control for the importance of neighbors' characteristics for firm location in a municipality (See Appendix A for a brief description of the spatial weighting and spatial methods used). In the poverty outcome equations, we control for the possible externalities arising from presence of food manufacturers in neighboring municipalities (for instance as a source of demand for labor and raw materials) by including the spatial lag of the treatment variable as an additional explanatory variable.

4. Data, definitions and descriptive statistics

4.1. Definitions and data

We define agriprocessing as the manufacturing of food, beverages and tobacco, according to codes 311 and 312 from the North American Industry Classification (NAICS). We exclude bakeries from the analysis due to the different rationale of their spatial distribution. Furthermore, we also exclude micro-enterprises from the analysis, even though they concentrate an important share of agriprocessing employment, for reliability reasons, since in some cases the structure of micro-enterprises is closer to the informal sector, and data on micro-enterprises tends to be more sensitive to measurement errors. The choice of period of analysis was driven by an interest in the post-liberalization period (from the 1990s onwards) and the resulting dynamics of firm location. Moreover, we were constrained by the availability of locally representative poverty data. Therefore, we study the period 1992-2002 in Chile and 2000-2010 in Mexico. Data on the number of food manufacturing establishments per municipality are taken from the 1995 and 2002 National Annual Industrial Surveys (ENIA) for Chile and from the 1999 and 2009 Economic Censuses for Mexico.

Our poverty measure is the FGT0, or poverty headcount ratio, that is, the number of people below the poverty line as a percentage of the total population (Foster et al. 1984, 2010).[7] For Chile we use monetary poverty (the only officially adopted poverty measure at the time of writing) and the official poverty line definition, which considers basic needs corrected by food price variation over time. For Mexico, we use assets poverty, which indicates the insufficiency of income in order to afford food, clothing, health expenses, transportation, housing and education. This provides a measure comparable with monetary poverty in Chile. Nevertheless, in order to analyze the sensitivity of our results to the choice of poverty measure, food poverty is used as a robustness check for Mexico.

Because of our geographical focus on local poverty at the municipal level, and given the difficulty of obtaining locally representative values from surveys, we measure FGT0 using Small Area Estimates (SAE), a methodology developed by Elbers, Lanjouw, and Lanjouw (2002, 2003) that improves the accuracy of survey estimates, by combining them with other sources such as population censuses through econometric non-linear models. Municipal SAE are obtained, for Chile, from Modrego et al., (2009) for 1992 and 2002, and from World Bank data for Mexico.[8] In both cases, the estimates include standard errors that allow us to assess whether the differences in the headcount ratio at the municipality level between the initial and final point in

---

[7] FGT is a family of poverty measures that allows varying the weight of the income level of the poorest individual. It weights the normalized poverty gap, by the level of poverty aversion (Foster et al., 2010).

[8] The World Bank SAE estimates include 1989 out of the 2,065 observations included in the analysis. Only four of them are treatment municipalities. In order to assess the bias that could arise from excluding these municipalities from the analysis, we also estimated the DiD and OLS equations using assets poverty data from CONEVAL, which do not include standard errors, and results remain basically unchanged. Thus, excluding these observations does not bias our results.

time are statistically significant. For Mexico, municipal SAE are obtained from, which also allow us to assess whether the differences between 2000 and 2010 are statistically significant. In both Chile and Mexico we assume independence between the two samples (initial and final). When the difference in poverty rates between the initial and final period is not statistically significant, we assume that poverty levels have remained unchanged.[9]

Among the location determinants we include variables capturing agglomeration economies, input and output markets, human capital, infrastructure, agrarian structure, and, for Mexico, agro-climatic conditions (temperature and rainfall). Inclusion of the latter was not possible in Chile due to data limitations, and we control for agro-climatic conditions by including region fixed effects, which are a useful proxy given that Chile's administrative division into regions goes from north to south. In the spatial Durbin model we include availability of raw materials and human capital, and access to the sea, of neighboring municipalities. Among the controls for the outcome equation we include the initial poverty rate, female initial education and labor force participation, change in the rest of employment, remoteness and share of rural population, and presence of food manufactures in neighboring municipalities. Data sources and definitions are detailed in Appendix B.

When the analysis is restricted to the common support, we lose 31 municipalities in Chile and 40 in Mexico (all agriprocessing in both cases). In Chile, agriprocessing municipalities off the common support are significantly better off than the rest of agriprocessing municipalities, and about half of them are located in or around the two main metropolitan areas surrounding the capital city and the second largest metropolis, Concepción. Municipalities off the common support tend to be more specialized in agriprocessing, to have a larger and higher educated labor force and a larger share of employed in the manufacturing industry. They are closer to regional and national capitals and better connected via motorway, and tend to be better endowed also in terms of availability of raw materials and services (water, telecommunications and financial services). In Mexico, half of the municipalities are located in the North and Central-North

[9] Standard error for the difference in means of the two samples are calculated assuming that the two samples are independent. That is, as the square root of the sum of the square of each standard error divided by its sample size n_i.

regions of the country, and six of them are in the capital area and they have similar characteristics to the off-support municipalities of Chile.

4.2. Local poverty and food manufacturing growth since the 1990s

Poverty in Chile fell markedly from about 32% in 1992 to 20% in 2002. In Mexico, the national assets poverty headcount ratio dropped from 54% in 2000 to 51% in 2010. It had reached its minimum in 2006, at 43%, but then rose again as a result of the global crisis of 2008.[10] In both countries, however, national averages hide substantial differences across regions, in both poverty rates and speed of poverty reduction. Poverty in Chile declined across all regions, but very little in the southern region of Araucanía, which has historically presented the lowest standards of living in Chile. On the other hand, the central regions of Valparaíso, Bío Bío and Los Lagos, where much of agriprocessing activity is concentrated, were among the ones that achieved faster poverty reduction. In Mexico, asset poverty rates increased over time in the North and Capital regions, while the largest decrease occurred in the Pacific, which is also the region that concentrates most of agriprocessing activities.

With respect to the spatial distribution of the agriprocessing sector and its changes over time, Chile and Mexico share a number of similarities. First, in both countries the total number of establishments remains stable over the period under study, while its employment and sales income increase, respectively, by 18% and 29% in Chile and by 15% and 50% in Mexico. Second, the sector tends to concentrate in the regions with the most suitable agro-ecological conditions for agriculture, but is less spatially concentrated than the rest of manufacturing, as also found by Saito and Gopinath (2009) for Chile. Spatial dispersion is particularly marked in Chile, where only 26% of total agriprocessing employment is concentrated in the capital, versus 59% for the rest of manufacturing, while in Mexico about 60% of manufacturing is concentrated between the North and the capital, versus only 40% of agriprocessing. In both countries the concentration of agriprocessing around metropolitan areas declines over time.

[10] Considering the food poverty headcount ratio instead of assets poverty, however, we observe an important decline, as the whole density curve shifts to the left.

Comparing initial characteristics between municipalities where the sector grows versus those where it remains absent, it appears that, in both countries, agriprocessors avoid locating in the poorest municipalities: the sector tends to remain absent from areas that are more remote, with smaller labor force and lower availability of raw materials, lower access to infrastructure and services (water, power and communication) and lower levels of human capital. However, in both countries we observe a movement of agriprocessors over time towards lower income areas characterized by lower levels of human capital and worse access to infrastructure, both characteristics associated with rural areas. A Local Indicator of Spatial Association (LISA) cluster map[11] describing the pattern of spatial associations between initial poverty rates and growth in the number of agriprocessing establishments shows a general trend of low or nonexistent growth of the sector in poor areas, but also some heterogeneity, as some of the lower income municipalities do experience growth in food manufacturing, in terms of both number of establishments and employment (See Figures 1 and 2 in Appendix C). For the case of Mexico, this is consistent with results in Pereira and Soloaga (2013) on the location behavior of low-tech industries, while clusters of high poverty and low activity in both countries coincide with localized poverty traps identified in other studies (including Yúnez-Naude et al., 2013; Soloaga and Yúnez-Naude, 2013).

How much of the change in poverty rates experienced over the period, if any, can be attributed to agriprocessing? *Prima facie*, the magnitude and speed of poverty reduction appear to be larger in Chile among agriprocessing municipalities (t-stat = 3.01 and 2.37 respectively), while in Mexico there appears to be no difference. The econometric analysis in the next section investigates the causal impact of agriprocessing on local poverty.

[11] See Anselin (1995) for further information regarding LISAs.

5. Results

5.1. Probability of food manufacturing growth in the municipality

Results for the probit model of food manufacturing growth are robust to different specifications and very similar between countries. Table 1 presents results from the baseline non-spatial probit and from the spatial Durbin probit with filtering (our preferred specification). Appendix D presents additional results from the probit model with endogenous spatial lag and with spatial filtering.

Agriprocessing growth in Chile and Mexico is favored by the availability of labor and of raw materials. Food manufacturing in Chile also appears to consider the availability of these key inputs in neighboring municipalities. Infrastructure and services prove to be critical for agriprocessing growth, especially piped water in Chile, and telephone services, electricity and kilometers of interstate roads in Mexico. Distance from regional capitals slows down agriprocessing growth in Chile, while distance from the national capital does not appear to be relevant, suggesting that the presence of intermediate cities is important for agriprocessing growth, as it simultaneously provides closeness to raw materials as well as labor, infrastructure and services.

Location externalities behave in an interesting way in both countries. The specialization of a municipality in food manufacturing seems to encourage firm location, as indicated by the positive coefficient of the location quotient. In Mexico, agriprocessors are also attracted by the possibility of labor pooling, that is, by a large share of manufacturing workers, which is another source of agglomeration benefits. However, location in a particular municipality is hindered by the presence of food manufactures in *neighboring* municipalities, as indicated by the negative coefficient of the spatial lag. This suggests a tension, recognized in the literature on New Economic Geography, between the benefits of agglomeration and the costs of competition with other firms (Fujita and Thisse, 1996). In particular, the benefits of agglomeration appear to be strongly local and to decay rapidly across space; beyond the boundary of the municipality, the costs of having to compete with other agriprocessors for labor and raw materials appear to outweigh the benefits of proximity. This result is consistent with what we know about spatially bounded knowledge externalities (Audretsch and Feldmann, 2004) and demand linkages (Hanson, 2005).

With respect to the relationship between food manufacturing growth and local human capital, in Chile we find a negative relationship between agriprocessing growth and the share of the adult population with higher education. Lower levels of education in Chile are prevalent in non-metropolitan areas (correlation coefficient of -0.47, significant at 1% level) and are negatively correlated with cultivated land area (correlation coefficient of -0.18, significant at 1% level). Thus, agriprocessors seem to be trading off availability of higher-level human capital for the closeness to raw materials that rural areas provide. Nonetheless, and although agriprocessing is a low-technology sector, acknowledgment of the need for more qualified labor was a recurrent finding of our interviews with Chilean agriprocessors. In Mexico, the existing level of human capital does not seem to influence firm placement[12], but the presence of technical schools or junior colleges significantly contributes to local food manufacturing growth. This suggests that these firms favor the possibility of acquiring specific technical abilities over the existing stock of education. This is consistent with the evidence obtained from interviews with Mexican agriprocessors, who indicated that higher human capital is relevant for higher managerial positions, but is not an important location determinant for the establishment of new plants.

Overall, it appears that location incentives of food manufacturers are strongly linked to proximity to raw materials and thus to non-metropolitan areas, which contributes to a spatially dispersed location pattern possibly strengthening the poverty-reduction potential of the sector.

Estimated propensity scores are similar across specifications. The impact effect estimation discussed in the next section is weighted using the propensity score obtained from the specification that provides the best comparability between agriprocessing and non-agriprocessing municipalities, that is, the non-spatial probit for both countries. Results (available from the authors) remain basically unchanged regardless of the weights used.

[12] Considering that the average years of schooling for people working in the manufacturing sector is 9.4 years, the threshold of nine years (high-school or more) appears more suitable in the case of Mexico than the percentage of people with some college education or more. We also tested alternative specifications with other thresholds and results do not change in magnitude or statistical significance.

5.2. The impact of agriprocessing on poverty

Table 2 summarizes the results of the impact estimation of the magnitude and speed of the reduction in local poverty rates, both for the full sample and restricted to the common support, controlling for covariates. Appendix E presents the full results and also includes estimations with and without covariates. For Chile, the models explain between 60% and 77% of the observed variance over time in municipal poverty rates, and between 47% and 58% of the variance in the speed of poverty reduction. For Mexico, they explain between 79% y 88% for magnitude, and between 25% and 33% for speed.

In general, controlling for other factors, local presence of agriprocessing has a significant poverty-reducing effect. The impact of agriprocessing on the magnitude and speed of local poverty reduction is always statistically significant in both countries, regardless of model specification and for both the full and restricted (to the common support) sample. With respect to the PS-weighted Diff-in-Diff estimation of the magnitude of poverty reduction, controlling for other factors, the presence of agriprocessing in a municipality reduces the local headcount ratio, over a ten-year period, between 3.1 and 3.6 percentage points in Chile and by approximately 5 percentage points in Mexico, as indicated by the Diff-in-Diff coefficient. The magnitude of the effect for the restricted sample is slightly larger in Mexico, and slightly smaller in Chile. Given that the restricted sample in Chile excludes better-off agriprocessing municipalities, this result suggests that the pro-poor effect of agriprocessing, in terms of the magnitude of the local poverty rate, is stronger when local conditions are more favorable with respect to quality of human capital, infrastructure and services.

With respect to the PS-weighted least squares estimation of the speed of poverty reduction, controlling for other factors, results show that the speed of poverty reduction in agriprocessing municipalities is 6% to 7% faster than in non-agriprocessing municipalities in Chile, and 4% faster in Mexico. Controlling for covariates, the magnitude of the coefficient is very similar in Mexico for both the full and restricted sample. In Chile, on the other hand, it appears that poverty reduction is faster among worse-off agriprocessing municipalities, as indicated by the larger coefficient when restricting to the common support. This suggests an important role of agriprocessing for promoting convergence towards lower poverty rates in non-metropolitan, relatively marginalized areas. Moreover, poverty reduction in Chile is faster not only with local presence of food manufactures, but also with presence of agriprocessing activities in *neighboring* municipalities, suggesting the existence of significant spatial spillovers, probably through employment and procurement of raw materials across administrative units.

With respect to the other significant covariates, results for Chile and Mexico are similar. In both countries, and especially in Mexico, local poverty reduction is larger and faster where initial female labor force participation and education are higher. The latter result is consistent with Ravallion and Datt (2002). The magnitude of poverty reduction, and in Chile also its speed, is larger in rural municipalities, where initial poverty was higher. Poverty reduction in Mexico is significantly lower and slower for more remote municipalities, as indicated by the positive coefficient of the distance from the regional capital. In Chile, poverty appears to decline more and faster also when growth in the rest of the employment is larger (but only when better-off agriprocessing municipalities are included); and in municipalities where initial average age of the population is older, while this variable is not significant for Mexico. Considering that average age per municipality in Chile is 29, ranging from 21 to 38, this result seems to be due to a larger share of working-age population.

Double-robust estimates for both magnitude and speed of poverty, reported in Table 2, show that even though the magnitude of the coefficients change slightly, the finding of a significant poverty-reducing role of agriprocessing is confirmed.

In order to further assess the robustness of these results, considering that the other mechanism to reduce poverty besides pro-poor growth are transfers, we also included as a control a variable that accounts for poverty related direct interventions, using for Mexico the average transfers from the PROGRESA/OPORTUNIDADES program between 2000 and 2010 and for Chile the share of the population receiving transfers in 2001. In both cases, the variable was significant but the results remained substantially unchanged. Controlling for population change, which is not included in the equation as it is highly correlated with change in the rest of employment, the magnitude of the impact estimates reduce slightly but conclusions do not change. Finally, for Mexico we also replaced asset poverty with food poverty as outcome variable, with food representing a narrower definition of poverty compared to assets. In this case the significance of the impact parameter was sensitive to the specification used, even though in some specifications we obtained results in line with those discussed above. This could indicate that the effects of agriprocessing on poverty reduction happen mainly for communities closer to the poverty line and not for the extremely poor. This is consistent with what we observed regarding the location of some agriprocessing firms in relatively poor locations but not the poorest.[13]

6. Discussion and conclusions

The spatial distribution and sectoral composition of growth are important factors for poverty reduction particularly where important territorial inequalities are found and when economic growth is led by labor-intensive industries. Food manufacturing has potential for reducing poverty, especially in rural areas still heavily dependent on agriculture, because it is less spatially concentrated than other sectors, tends to locate in relatively lower income regions, and it is able to generate backward and forward linkages with other industries.

This paper analyzed the contribution of food manufacturing to local poverty reduction in Chile and Mexico, using a combination of difference-in-differences and propensity score matching methods, and controlling for the non-random spatial distribution of agriprocessors. Controlling for other characteristics, we find that agriprocessing activity does have a poverty reducing effect in both countries, in terms of the magnitude and the speed of the fall in local poverty rates. This effect is robust to different specifications and estimation methods. Moreover, finding similar results in Chile and Mexico suggests that food manufacturing is an important source of poverty reduction in times of both fast and stagnant overall economic growth, as was the case of Chile and Mexico respectively over the period under study.

[13] Results of all robustness checks are not reported but available upon request.

However, the descriptive and econometric analysis shows that, geographically, this industry locates in municipalities with suitable agro-ecological conditions, which happen to be relatively poor, but not the poorest municipalities. Thus, attraction of food manufactures appears to benefit relatively poor communities, but will not represent a solution for the poorest ones, who may still need to rely on targeted social policies.

The analysis of the determinants of food manufacturing growth indicates that besides the availability of raw materials, which is closely related to the agro-ecological conditions of the municipality, most of the factors that affect location are related to services and infrastructure, such as piped water, electricity, fixed telephone services and kilometers of interstate roads. These variables can clearly be improved in the short- and medium-term by policies that do not need to be specifically targeted to agriprocessing activities, nor would go to the exclusive benefit of this sector, but can benefit other sectors as well. Therefore, there is no necessary trade-off with the rest of the economy and no need to design specific policies to promote food manufacturing growth: rather than "picking the winner" strategies, general place-based interventions should be sufficient for food manufacturing growth and can attract other economic activity as well. Moreover, our results suggest that a better local environment with respect to infrastructure, services and human capital also increases the ability of food manufacturing to reduce local poverty.

Future extensions to this research include investigating plant heterogeneity within the sector, in terms of both size and sub-sectors. Considering that we excluded micro and informal agriprocessing firms from this analysis and that a deeper analysis of the determinants of industry location finds that there is heterogeneity according to firm size (Cazzuffi et al, 2014), it is important to further characterize the relation of poverty reduction with agriprocessing firms of different sizes. Furthermore, while in this paper we focus on the overall relationship of the food manufacturing sector with poverty, it is also important to investigate the particularities of its different subsectors. Does export-oriented agriprocessing have a different effect on poverty reduction *vis-à-vis* food manufacturing oriented to national markets? What about crop-based versus livestock-based food manufacturing? These are all questions that deserve further study.

7. References

Abadie, A., 2005. Semiparametric difference-in-differences estimators. *Review of Economic Studies.* **72**(1), 1-19.

Abadie, A., Imbens, G., 2006. Large sample properties of matching estimators for average treatment effects. *Econometrica.* **74**(1), 235-267.

Almeida, R., Fernandes, A., 2013. Explaining local manufacturing growth in Chile: the advantages of sectoral diversity. *Applied Economics.* **45**, 2201-2213.

Anríquez, G., López, R., 2007. Agricultural growth and poverty in an archetypical middle income country: Chile 1987-2003. *Agricultural Economics.* **36**(2), 191-202.

Anselin, L., 1995. Local indicators of spatial association. *Geographical Analysis.* **27**(2), 93–115

Arauzo, J., Liviano-Solis, D., Manjón-Antolín, M., 2010. Empirical studies in industrial location: an assessment of their methods and results. *Journal of Regional Science.* **50**(3), 685-711.

Atienza, M., Aroca, P., 2013. ¿Es la concentración espacial un problema para el crecimiento en América Latina?. Documentos de Trabajo en Economia y Ciencia Regional 41, Universidad Católica del Norte, Chile, Department of Economics.

Audretsch, D., Feldman, M., 2004. Knowledge spillovers and the geography of innovation, in V. Henderson and J. F. Thisse, eds., *Handbook of Regional and Urban Economics*. Elsevier, edition 1, volume 4, number 4.

Bang, H., Robins, J. M. 2005. Doubly robust estimation in missing data and causal inference models. *Biometrics*. **61**(4), 962-973.

Barrett, C. B., Bachke, M., Bellemare, M., Michelson, H., Naraynan, S., 2012. Smallholder Participation in Contract Farming: Comparative Evidence from Five Countries. *World Development.* **40**(4), 715-730.

Barron, M., Rello, F., 2000. The impact of the tomato agroindustry on the rural poor in Mexico. *World Development* **23**, 289-297.

Behrens, K., Gaigné, C., Ottaviano, G., Thisse, J., 2006. Is remoteness a locational disadvantage?. *Journal of Economic Geography.* **6**(2006), 347-368.

Berdegue, J., Modrego Benito, F., 2012. *De Yucatán a Chiloé. Dinámicas Territoriales en América Latina*. Buenos Aires, Teseo.

Brülhart M., Sbergami F., 2009. Agglomeration and growth: Cross-country evidence. *Journal of Urban Economics*. **65**, 48-63.

Byerlee, D., Diao, X., Jackson, C., 2005. Agriculture, rural development and pro-poor growth. Country experiences in the post-reform era. *Agriculture and Rural Development Discussion Paper 21*. The World Bank.

Carlton, D. W., 1983. The Location and Employment Choices of New Firms: An Econometric Model with Discrete and Continuous Endogenous Variables. *The Review of Economics and Statistics*. **65**(3), 440-449.

Carod, J.M.A., 2005. Determinants of industrial location: An application for Catalan municipalities. *Papers in Regional Science*. **82**(1), 105–120.

Cazzuffi, C., Pereira, M., Soloaga, I., Barrantes, R., 2014 (*forthcoming*). Firm size and location determinants of food manufacturing in Chile, Mexico and Peru. *Mimeo.*

Christiaensen, L., Todo, Y., 2014. Poverty Reduction during the Rural–Urban Transformation – The Role of the Missing Middle. *World Development*, forthcoming.

Christiaensen, L., Demery, L., Kuhl, J., 2011. The (evolving) role of agriculture in poverty reduction - An empirical perspective. *Journal of Development Economics*. **96**(2), 239-254.

Cohen, J.P., Paul, C.M., 2005. Agglomeration economies and industry location decisions: The impacts of spatial and industrial spillovers. *Regional Science and Urban Economics*. **35**, 215–237.

Da Silva, C., Baker, D., Shepherd, A., Jenane, C., Miranda da Cruz, S., 2013. *Agroindustrias para el desarrollo*. FAO. Roma.

Davis, D.E., Schluter, G.E., 2005. Labor-force heterogeneity as a source of agglomeration economies in an empirical analysis of county-level determinants of food plant entry. *Journal of Agricultural and Resource Economics* **30**(3), 480–501

De Janvry, A., Sadoulet, E. 2010. Agricultural growth and poverty reduction: Additional evidence. *The World Bank Research Observer*. **25**(1),1-20.

De Ferranti, D., Perry, G., Foster, W., Lederman, D., Valdés, A., 2005. *Beyond the City. The rural contribution to development*. World Bank Latin American and Caribbean Studies.

Deichman, U., Lall, S., Redding, S., Venables, T., 2008. Industrial location in developing countries. *The World Bank Research Observer*. **23**(2), 220-246.

Deller, S., Tsai, T., Marcoullier, D., English, D., 2001. The role of amenities and quality of life in rural economic growth. *American Journal of Agricultural Economics.* **83**(2), 352-365.

Dercon, S., 2009. Rural Poverty: Old Challenges in New Contexts. *The World Bank Research Observer.* **24**(1), 1-28.

Elbers, C., Lanjouw, J. O., & Lanjouw, P.,2002. *Micro-level estimation of welfare*. World Bank Publications, Vol. 2911.

Elbers, C., Lanjouw, J. O., Lanjouw, P., 2003. Micro–Level Estimation of Poverty and Inequality. *Econometrica.* **71**(1), 355-364.

Emsley, R., Lunt, M., Pickles, A., Dunn, G. (2008). Implementing double-robust estimators of causal effects. *Stata Journal*. **8**(3), 334-353.

Escobal J., Ponce, C., 2011. Spatial Patterns of Growth and Poverty Changes in Peru (1993 – 2005). *Documento de Trabajo N° 78*. Programa Dinámicas Territoriales Rurales. Rimisp: Santiago, Chile.

FAO (2004). *Socio-Economic Analysis and Policy Implications of the Roles of Agriculture in Developing Countries: Research Programme Summary Report 2004*. Rome.

Felkner, J., Townsend, R., 2011. The Geographic Concentration of Enterprise in Developing Countries. *Quarterly Journal of Economics.* **126**(4), 2005-2061.

Fingleton, B., Fisher, M., 2010. Neoclassical theory versus new economic geography: competing explanations of cross-regional variation in economic development. *Annals of Regional Science* **44**, 467-491.

Foster, J., Greer, J., Thorbecke, E., 1984. A class of decomposable poverty measures. *Econometrica.* **52**, 761–776 (1984)

Foster, J., Greer, J., & Thorbecke, E., 2010. The Foster–Greer–Thorbecke (FGT) poverty measures: 25 years later. *The Journal of Economic Inequality.* **8**(4), 491-524.

Fujita, M., Thisse, J.F., 1996. Economics of Agglomeration. *Journal of the Japanese and International Economies.* **10**, 339–378.

Glaeser, E. L., Gottlieb, J. D., 2009. The Wealth of Cities: Agglomeration Economies and Spatial Equilibrium in the United States. *Journal of Economic Literature.* **47**(4), 983-1028.

Glaeser, E. L., Kallal, H., Scheinkman, J.A., Shleifer, A., 1992. Growth in Cities. *Journal of Political Economy.* **100**(6), 1126-1152.

Goetz, S., 1997. State- and county-level determinants of food manufacturing establishment growth: 1987–1993. *American Journal of Agricultural Economics.* **79**(3), 838–850

Griffith, D., 2002. A spatial filtering specification for the auto-Poisson model. *Statistics and Probability Letters.* **58**(2002), 245-251.

Guimaraes, P., Figueiredo O., Woodward, D., 2004. Industrial location modelling: extending the random utility framework. *Journal of Regional Science.* **44**(1), 1-20.

Hanson, G., 2005. Market potential, increasing returns and geographic concentration. *Journal of International Economics* **67**(1), 1-24.

Heckman, J., Ichimura, H., Todd, P., 1998. Matching as an econometric evaluation estimator. *Review of Economic Studies.* **65**, 261-294.

Henderson, V., 1994. Where does an industry locate? *Journal of Urban Economics.* **35**, 83-104.

Henderson, I. V., A. Kuncoro, Turner, M., 1995. Industrial Development in Cities. *Journal of Political Economy.* **103**(5), 1067-1090.

Imbens, G., 2000. The role of the propensity score in estimating dose-response functions. *Biometrika.* **87**(3), 706-710.

Jalan, J., Ravallion, M., 1998. Are There Dynamic Gains from a Poor-Area Development Program? *Journal of Public Economics.* **67**(1), 65–85.

Khandker, S., Bakht, Z., Koolwal, G., 2009. The Poverty Impacts of Rural Roads: Evidence from Bangladesh. *Economic Development and Cultural Change.* **57**(4), 685–722.

Lambert, D. M., McNamara K. T., 2009. Location determinants of food manufacturers in the United States, 2000–2004: are nonmetropolitan counties competitive? *Agricultural Economics.* **40**(6), 617-630.

Loayza, N., Raddatz, C., 2010. The composition of growth matters for poverty alleviation. *Journal of Development Economics.* **93**(1), 137-151.

Maertens, M., and Swinnen, J., 2012. Gender and modern supply chains in developing countries. *Journal of Development Studies* **48**(10), 1412-1430.

Maertens, M., Minten, B., Swinnen, J., 2012. Modern food supply chains and development: evidence from horticulture export sectors in Sub-Saharan Africa. *Development Policy Review.* **30**(4), 473-497.

Modrego, F., Ramírez, E., Tartakowsky, A., 2009. La heterogeneidad espacial del desarrollo económico en Chile: Radiografía a los cambios en bienestar durante la década de los 90 por estimaciones en áreas pequeñas. *Documento de Trabajo N° 9*. Programa Dinámicas Territoriales Rurales. Rimisp, Santiago, Chile.

Mureddu, F., Cerina, F., 2009. Is Agglomeration really good for Growth? Global Efficiency, Interregional Equity and Uneven Growth. *Working Paper CRENoS 200913*, Centre for North South Economic Research, University of Cagliari and Sassari, Sardinia.

Neugebauer, R., van der Laan, M. 2005. Why prefer double robust estimators in causal inference?. *Journal of Statistical Planning and Inference*. **129**(1), 405-426.

Pereira, M., Soloaga, I., 2013. Determinants of Regional Growth by Manufacturing Sector in Mexico, 1988-2008. *Working Paper No. 7*. Department of Economics. Universidad Iberoamericana, Mexico.

Rappaport, J., Sachs, J., 2003. The United States as a coastal nation. *Journal of Economic Geography*. **8**, 5-46.

Ravallion, M Datt, G., 1996. How Important to India's Poor Is the Sectoral Composition of Economic Growth?. *World Bank Economic Review*. **10**(1), 1-25.

Ravallion, M., Datt, G., 2002. Why has economic growth been more pro-poor in some states of India than others?. *Journal of Development Economics*. **68**(2), 381-400.

Robins, J. M., Rotnitzky, A., Zhao, L. P. 1995. Analysis of semiparametric regression models for repeated outcomes in the presence of missing data. *Journal of the American Statistical Association*. 90(429), 106-121.

Saito, H., Gopinath, M., 2009. Plants´self-selection, agglomeration economies and regional productivity in Chile. *Journal of Economic Geography*. 9(2009), 539-558.

Saito, H., Gopinath, M., 2011. Knowledge spillovers, absorptive capacity, and skill intensity of Chilean manufacturing growth. *Journal of Regional Science*. **51**(1), 83-101.

Schmenner, R.W., Huber, J.C., Cook, R.L., 1987. Geographic differences and the location of new manufacturing facilities. *Journal of Urban Economics*. **21**(1), 83–104.

Schmidtner, E., Lippert, C., Engler, B., Haring, A., Aurbacher, J., Dabbert, S., 2011. Spatial distribution of organic farming in Germany: does neighborhood matter? *European Review of Agricultural Economics*. September 24, 2011, 1-23.

Soloaga, I., Yúnez-Naude A. 2013. Dinámicas del bienestar territorial en México basadas en los territorios funcionales: 2005-2010. *Documento de Trabajo No. 25*. Rimisp.

Suryahadi, A., Suryadarma, D., Sumarto, S., 2009. The effects of location and sectoral components of economic growth on poverty: Evidence from Indonesia. *Journal of Development Economics.* **89**(1), 109-117.

Thorbecke, E., Jung, H., 1996. A Multiplier Decomposition Method to Analyze Poverty Alleviation". *Journal of Development Economics.* **48**, 225-252.

Tsiatis, A. 2007. *Semiparametric theory and missing data*. Springer.

Valdes, A. and W. Foster, 2003. The Positive Externalities of Chilean Agriculture: the Significance of its Growth and Export Orientation: A Synthesis of the ROA Chile Case Study. Santiago, Chile: Pontificia Universidad Católica de Chile.

van de Walle, D., Mu, R., 2008. Rural Roads and Poor Area Development in Vietnam. *Policy Research Working Paper* 4340, World Bank, Washington, DC.

World Bank, 2008. *World Development Report 2008: Agriculture for Development*. Washington, DC: World Bank.

World Bank, 2009. *World Development Report 2009: Reshaping Economic Geography*. Washington, DC: World Bank.

Yúnez-Naude, A., Arellano, J., Méndez, J. 2013. Dinámicas del bienestar territorial en México basadas en municipios: 1990-2005¬-2010. *Documento de Trabajo No. 24*. Rimisp.

Tables

Table 1: Probit model regression results for the probability of manufacturing growth in municipalities, Chile (1995-2003) and Mexico (1998-2008): non-spatial probit and spatial Durbin probit

	Chile		Mexico	
	(1) Non-spatial probit	(2) Spatial Durbin probit	(3) Non-spatial probit	(4) Spatial Durbin probit
Location quotient	1.250***	2.119***	0.034***	0.032***
	(0.336)	(0.413)	(0.005)	(0.005)
% of employed in manufacturing	-0.005	0.036	0.003***	0.003***
	(0.026)	(0.035)	(0.001)	(0.001)
Labor force	0.902***	1.329***	0.078***	0.077***
	(0.259)	(0.368)	(0.010)	(0.010)
% of population with higher education	-0.108	-0.240***	-0.000	-0.000
	(0.088)	(0.089)	(0.001)	(0.001)
Distance from national capital (km)	0.001	-0.006	0.000	0.000
	(0.002)	(0.007)	(0.000)	(0.000)
Distance from regional capital (km)	-0.005	-0.015**	-0.000	-0.000
	(0.003)	(0.006)	(0.000)	(0.000)
Cultivated land area (ha)	0.000***	0.000***	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
% irrigated land	0.012	0.020	0.000	0.000
	(0.009)	(0.014)	(0.000)	(0.000)
% of small farmers	0.011	0.019	-0.000	-0.000
	(0.009)	(0.012)	(0.000)	(0.000)
Municipality has access to sea (d)	0.913**	1.010*	0.024	0.026
	(0.442)	(0.592)	(0.035)	(0.035)
% of households with access to pipe water	0.037**	0.055***	-0.000	-0.000
	(0.015)	(0.021)	(0.000)	(0.000)

	Chile		Mexico	
	(1) Non-spatial probit	(2) Spatial Durbin probit	(3) Non-spatial probit	(4) Spatial Durbin probit
% of households with fixed phone	-1.265	0.071	0.005***	0.004***
	(3.170)	(4.536)	(0.001)	(0.001)
Technical school, junior college (d)			0.080***	0.075***
			(0.024)	(0.023)
% of households with access to electricity[1]			0.004***	0.004***
			(0.001)	(0.001)
Financial services in municipality	-0.003	0.004	0.008	0.007
	(0.008)	(0.008)	(0.011)	(0.010)
Main road[2]	-0.552*	-0.273	0.001***	0.001***
	(0.312)	(0.423)	(0.000)	(0.000)
Average precipitations 1971-2000 (millimeters)[3]			0.000	0.000
			(0.000)	(0.000)
Average temperature (Celsius degrees)[3]			-0.002	-0.001
			(0.021)	(0.019)
Spatial lag		-79.337***		-0.092**
		(14.688)		(0.039)
Cultivated land area of neighbors		0.001*		0.000
		(0.000)		(0.000)
% of irrigated land of neighbors		0.082		-0.000
		(0.226)		(0.001)
Labor force of neighbors		20.005***		0.010
		(5.314)		(0.011)
Access to sea of neighbors		5.483		0.039
		(10.559)		(0.057)
Observations	213	213	2045	2045
Pseudo R^2	0.55	0.75	0.51	0.52

Robust standard errors in parentheses; NS: Non-spatial Probit; ESP: Probit with endogenous spatial lag; Filtering: Probit with spatial filtering; DSP: Spatial Durbin Probit; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[1] Access to electricity is not included in Chile due to its very high correlation with access to pipe water (0.88) and because its correlation with other covariates is larger than for access to pipe water.

[2] This variable is measured in Mexico as Kilometers of interstate road in the municipality; this information is not available in Chile at this level of spatial disaggregation, and the variable is proxied with a dummy equal to 1 if a motorway passes through the municipality and zero otherwise.

[3] Agro-climatic variables are not available for Chile and are proxied with the inclusion of region fixed effects.

[4] In the case of Mexico, due to data availability for some municipalities, the sample is reduced from 2065 to 2045 observations. In order to assess the sensibility of our propensity score to the exclusion of these 20 municipalities (six of which are agriprocessing), the model was also estimated using confidential information from the 2000 Population and Housing Census, INEGI, which leads to a sample of 2062 observations. The correlation between the probabilities obtained from these two different regressions is 0.998 and results remain unchanged.

Table 2: Impact estimates of the effect of agriprocessing on the magnitude and speed of poverty reduction, controlling for other covariates, Chile 1992-2002, Mexico 2000-2010

	Magnitude		Speed	
	Chile	Mexico	Chile	Mexico
Full sample	-0.036**	-0.050*	-0.059**	-0.036**
	(0.014)	(0.026)	(0.030)	(0.015)
Common support	-0.031*	-0.051*	-0.069**	-0.035**
	(0.016)	(0.027)	(0.030)	(0.016)
Double-Robust	-0.067***	-0.036***	-0.070***	-0.075**
	(0.006)	(0.009)	(0.020)	(0.036)
N obs. full sample	418	3978	209	1989
N obs. common support	356	3898	178	1949

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix A. Note on spatial weighting and spatial methods

The structure of spatial interdependencies across municipalities, used to construct the lag of independent and dependent variables, is represented by a contiguity spatial weights matrix (W_c) and an inverse distance weights matrix (W_d). W_c is constructed attributing the value of 1 to all municipalities sharing a border with municipality *i*, and 0 to the rest, which implies the assumption that the location decisions of agriprocessors in municipality *i* depend on the decisions of agriprocessors located in neighboring municipalities only. W_d is constructed using the inverse of the Euclidean distance between the centroid of the municipality *i* and the centroids of all the other municipalities, which implies that the location decisions of agriprocessors in municipality *i* take into account the behavior of agriprocessors in all municipalities, but give more weight to what is happening closer to home. We report results obtained using the inverse distance matrix. The results using the contiguity matrix are substantially unchanged and available upon request.

The semi-parametric spatial filtering technique used in our estimates is based on the decomposition of spatial weights matrices and does not assume a linear relationship between dependent and independent variables like many other spatial autoregressive models. This technique uses eigenvector decomposition to extract orthogonal and uncorrelated new "variables" (as in principal component analysis) from an *N x N* spatial weights matrix. The eigenvectors extracted are those that represent map patterns with moderate to strong spatial correlation (based on Moran´s I values), and are then included in a regression framework as a proxy for missing explanatory variables. There is no guideline in the literature about the optimum number of eigenvectors to include and we choose to include a conservative set of eight (most of Griffith's estimations (2002) include between 5 and 8 eigenvectors).

Appendix B. Data sources and definitions

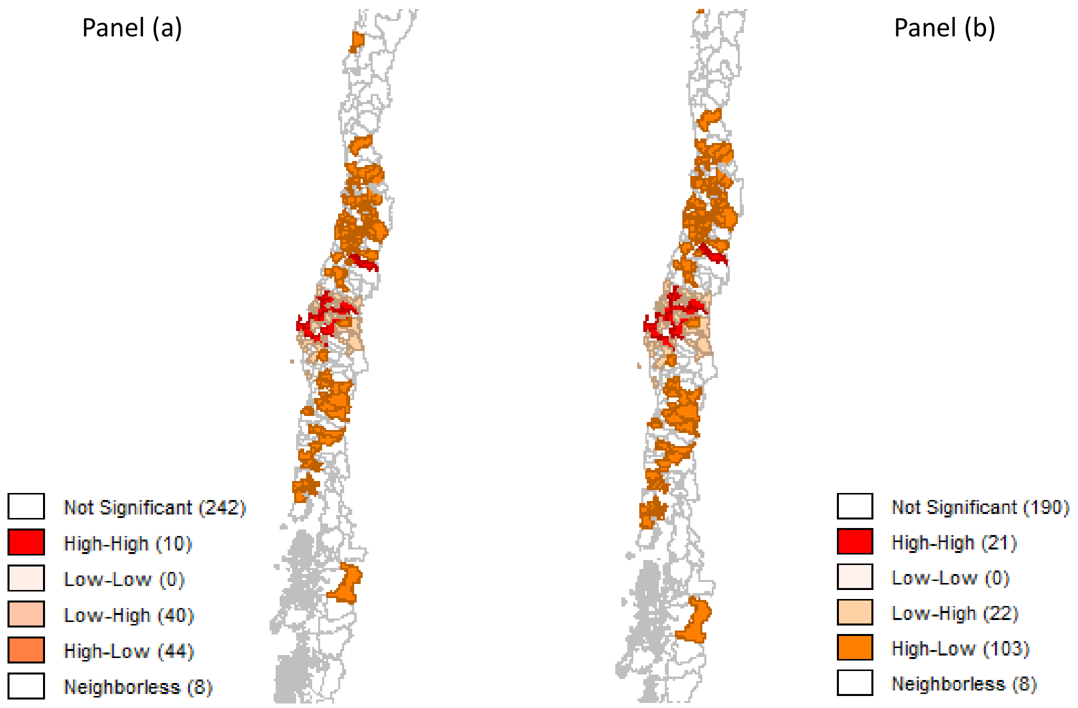
Table 3: Data sources and definitions

Variable	Definition	Source	
		Chile	Mexico
Firm location covariates			
Location quotient	Relative share of sector i in location j versus the same sector's share in the national industry: $\rho_{ij,t-\tau} = \frac{\frac{l_{ij,t-\tau}}{\Sigma_i l_{ij,t-\tau}}}{\frac{\Sigma_j l_{ij,t-\tau}}{\Sigma_i \Sigma_j l_{ij,t-\tau}}}$	Authors' calculations with data from the Population and Housing Census 1992	Authors' calculations with data from the Economic Census, INEGI (1999)
% employed in manufacturing	% of employed people who works in the manufacturing sector.	Population and Housing Census 1992	Population and Housing Census, INEGI (2000)
Labor force	% of people with 12 years old or more who is either working or searching for a job.	Population and Housing Census 1992	Population and Housing Census, INEGI (2000)
% of population with higher education (12 years)	Percentage of people between 25 and 65 years that have 12 or more years of schooling	Population and Housing Census 1992	Population and Housing Census, INEGI (2000)
Distance from national capital (km)	Distance in kilometers from the centroid of the municipality to the centroid of the municipality that is in the center of the capital state. (Coyoacan, Distrito Federal)	Authors' calculations using GIS	Authors' calculations using GIS with geographical data from INEGI
Distance from regional capital (km)	Distance from the municipality seat to the closest urban center of 50 thousand inhabitants or more	Authors' calculations using GIS	Territorial Integration System (ITER), INEGI (2005 y 2010)
Cultivated land area	Ha of cultivated land in the municipality.	Ministry of Agriculture, 1993-1995	Agricultural and Fisheries Information Service (SIAP) 2003
% of irrigated land	Share of cultivated land which is irrigated	Ministry of Agriculture, 1993	SIMBAD, INEGI (1998)*
% of small farmers	Percentage of total agricultural establishments	Ministry of Agriculture, 1993	Economic Census (2004)
Municipality has access to sea	=1 if the municipality has access to the sea.	Authors' calculations using GIS	Authors' calculations using GIS with geographical data from INEGI
% of households with access to water	Percentage of all households in the 2000 Census that have water.	Population and Housing Census 1992	Population and Housing Census, INEGI (2000)
% of households with fixed phone	Percentage of all households in the 2000 Census that have fixed phone	Population and Housing Census 1992	Population and Housing Census, INEGI (2000)
Technical school, junior college	=1 if there is a technical school or junior college in the municipality	-	Secretariat of Public Education (SEP)
% of households with access to electricity	Percentage of all households in the 2000 Census that have electricity	Population and Housing Census 1992	Population and Housing Census,

			INEGI (2000)
Financial services in municipality	Number of commercial and development bank branches in the municipality	Superintendencia de Bancos y Valores, 1992	SIMBAD, INEGI (1998)*
Transport infrastructure	Chile: Dummy = 1 if a motorway passes through the municipality; Mexico: Kilometers of interstate road in each municipality	Author´s calculation using GIS	SIMBAD, INEGI (1998)*
DiD and OLS covariates			
Gini	Gini coefficient	SAE (Rimisp 2011)	World Bank (2000 and 2010)
Rural	Share of rural population in the municipality. This variable is defined using information at the locality level. A locality is defined as rural if it has less than 12 thousand inhabitants	Population and Housing Census 1992	ITER, Population and Housing Census, INEGI (2000 and 2010)
Average age	Average age of the municipality's inhabitants	Population and Housing Census 1992	Population and Housing Census, INEGI (2000 and 2010)
Female education	Years of schooling of women aged 25-65.	Population and Housing Census 1992	Population and Housing Census, INEGI (2000 and 2010)
Female labor force participation	Share of women in the labor force	Population and Housing Census 1992	Population and Housing Census, INEGI (2000 and 2010)
Change in the rest of employment	Change in employment of all sectors different from agriprocessing	Population and Housing Census 1992	Population and Housing Census, INEGI (2000 and 2010)
Distance from regional capital (km)	Distance from the municipality seat to the closest urban center of 50 thousand inhabitants or more	Authors' calculations using GIS	Territorial Integration System (ITER) 2005 y 2010.

Appendix C. LISA cluster maps of initial poverty rates and growth in agriprocessing.

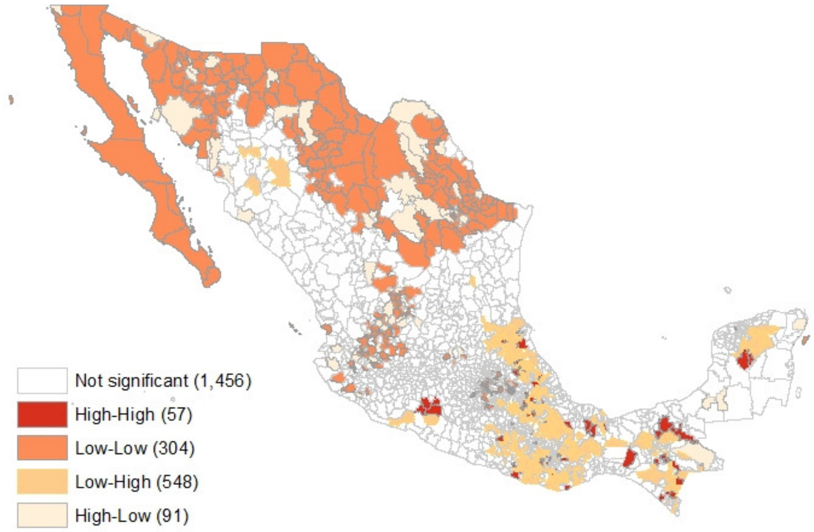
Figure 1: Bivariate LISA cluster map, central regions of Chile: Panel (a): Growth in number of agriprocessing plants 1995-2002 and FGT0 in 1992; Panel (b): Growth in number of people employed in agriprocessing 1995-2002 and FGT0 in 1992



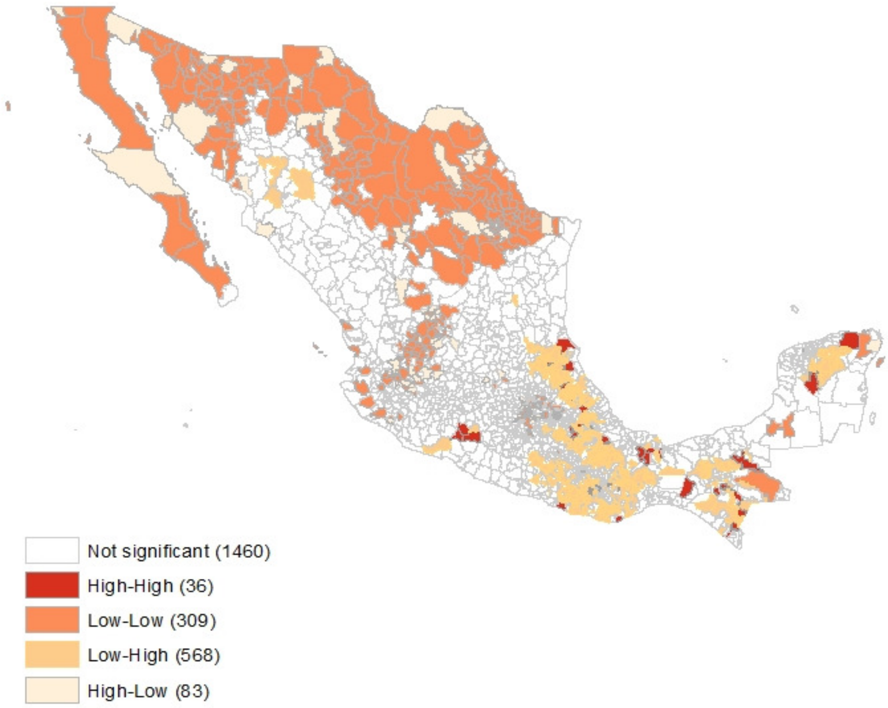
Source: Authors' calculations using data from the 1995 and 2002 National Annual Industrial Survey (INE) and poverty SAE measures from Modrego et al (2009).
The four categories are as follows: High-High = High growth in agriprocessing and high initial poverty rates; Low-Low = Low growth in agriprocessing and low initial poverty rates; Low-High = Low growth in agriprocessing and high initial poverty rates; High-Low = High growth in agriprocessing and low initial poverty rates.

Figure 2: Bivariate LISA correlation between agriprocessing growth and initial assets poverty, Mexico

Panel (a) Growth in the number of agriprocessing plants 1998-2008 vs. Assets FGT0 in 2000



Panel (b) Growth in agriprocessing employment 1998-2008 vs. Assets FGT0 in 2000



Source: Authors' calculations using data from the 1999 and 2009 Economic Censuses and poverty SAE measures from World Bank.

The four categories are as follows: High-High = High growth in agriprocessing and high initial poverty rates; Low-Low = Low growth in agriprocessing and low initial poverty rates; Low-High = Low growth in agriprocessing and high initial poverty rates; High-Low = High growth in agriprocessing and low initial poverty rates.

Appendix D. Probability of food manufacturing growth: additional results

Table 4: Probit model regression results for the probability of manufacturing growth in municipalities, Chile (1995-2003) and Mexico (1998-2008): results of models with endogenous spatial lag (ES) and spatial filtering.

	Chile		Mexico	
	(1) ES	(2) Filtering	(3) ES	(4) Filtering
Location quotient	1.594*** (0.373)	2.202*** (0.386)	0.034*** (0.005)	0.032*** (0.005)
% of employed in manufacturing	-0.005 (0.027)	-0.005 (0.024)	0.003*** (0.001)	0.003*** (0.001)
Labor force	1.064*** (0.260)	1.144*** (0.312)	0.079*** (0.010)	0.077*** (0.010)
% of population with higher education	-0.108 (0.076)	-0.104 (0.072)	-0.000 (0.001)	-0.000 (0.001)
Distance from national capital (km)	-0.002 (0.002)	-0.006 (0.004)	0.000 (0.000)	0.000 (0.000)
Distance from regional capital (km)	-0.008* (0.004)	-0.016*** (0.005)	-0.000 (0.000)	0.000 (0.000)
Cultivated land area (ha)	0.000** (0.000)	0.000** (0.000)	0.000** (0.000)	0.000** (0.000)
% irrigated land	0.016* (0.009)	0.025** (0.011)	0.000 (0.000)	0.000 (0.000)
% of small farmers	0.005 (0.009)	0.015 (0.011)	-0.000 (0.000)	-0.000 (0.000)

	Chile		Mexico	
	(1) ES	(2) Filtering	(3) ES	(4) Filtering
Municipality has access to sea (d)	0.926**	1.104*	0.018	0.022
	(0.434)	(0.565)	(0.034)	(0.035)
% of households with access to pipe water	0.032**	0.030*	-0.000	-0.000
	(0.014)	(0.016)	(0.000)	(0.000)
% of households with fixed phone	-1.253	-1.884	0.005***	0.004***
	(3.447)	(4.174)	(0.001)	(0.001)
Technical school, junior college (d)			0.078***	0.075***
			(0.023)	(0.023)
% of households with access to electricity[1]			0.004***	0.004***
			(0.001)	(0.001)
Financial services in municipality	-0.006	-0.029	0.008	0.007
	(0.008)	(0.031)	(0.011)	(0.010)
Main road[2]	-0.602*	-0.464	0.001***	0.001***
	(0.326)	(0.385)	(0.000)	(0.000)
Average precipitations 1971-2000 (millimeters)[3]			0.000	0.000
			(0.000)	(0.000)
Average temperature (Celsius degrees)[3]			-0.002	-0.001
			(0.021)	(0.020)
Spatial lag	-14.199***	-40.348***	-0.068*	-0.072**
	(4.069)	(6.818)	(0.035)	(0.034)
Observations	213	213	2045	2045
Pseudo R^2	0.59	0.69	0.52	0.52

Robust standard errors in parentheses; NS: Non-spatial Probit; ESP: Probit with endogenous spatial lag; Filtering: Probit with spatial filtering; DSP: Spatial Durbin Probit; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[1] Access to electricity is not included in Chile due to its very high correlation with access to pipe water (0.88) and because its correlation with other covariates is larger than for access to pipe water.

[2] This variable is measured in Mexico as Kilometers of interstate road in the municipality; this information is not available in Chile at this level of spatial disaggregation, and the variable is proxied with a dummy equal to 1 if a motorway passes through the municipality and zero otherwise.

[3] Agro-climatic variables are not available for Chile and are proxied with the inclusion of region fixed effects.

[4] In the case of Mexico, due to data availability for some municipalities, the sample is reduced from 2065 to 2045 observations. In order to assess the sensibility of our propensity score to the exclusion of these 20 municipalities (six of which are agriprocessing), the model was also estimated using confidential information from the 2000 Population and Housing Census, INEGI, which leads to a sample of 2062 observations. The correlation between the probabilities obtained from these two different regressions is 0.998 and results remain unchanged.

Appendix E. The impact of agriprocessing on poverty

Table 5: PS-weighted DiD estimation of the effect of agriprocessing on the magnitude of poverty reduction, Chile 1992-2002, Mexico 2000-2010

	Chile				Mexico			
	(1) Baseline	(2) Baseline common support	(3) With covariates	(4) Covariates and common support	(5) Baseline	(6) Baseline common support	(7) With covariates	(8) Covariates and common support
Growth in agriprocessing	0.020*	0.012	0.010	0.004	0.025	0.028*	0.023*	0.022*
	(0.012)	(0.013)	(0.010)	(0.011)	(0.017)	(0.017)	(0.013)	(0.013)
Time	-0.077***	-0.077***	-0.077***	-0.077***	-0.004	-0.004	-0.004	-0.004
	(0.010)	(0.010)	(0.008)	(0.008)	(0.020)	(0.020)	(0.006)	(0.006)
Diff-in-Diff	-0.036**	-0.031	-0.036**	-0.031*	-0.050*	-0.051*	-0.050*	-0.051*
	(0.017)	(0.019)	(0.014)	(0.016)	(0.027)	(0.027)	(0.026)	(0.027)
Gini			-0.008	0.010			0.069	0.072
			(0.085)	(0.099)			(0.113)	(0.112)
% Rural			-0.184***	-0.180***			-0.040**	-0.039**
			(0.020)	(0.023)			(0.018)	(0.018)
Average age			-0.006**	-0.005*			-0.003	-0.003
			(0.003)	(0.003)			(0.002)	(0.002)
Female education			-0.037***	-0.036***			-0.053***	-0.053***
			(0.010)	(0.011)			(0.005)	(0.005)
Female labor force participation (%)			-0.005***	-0.005***			-0.003***	-0.003***
			(0.001)	(0.001)			(0.001)	(0.001)
Change in the rest of employment			-0.000**	-0.000			-0.002	-0.003
			(0.000)	(0.000)			(0.007)	(0.007)

Distance from regional capital (Km)			0.000	0.000			0.001***	0.001***
			(0.000)	(0.000)			(0.000)	(0.000)
Spatial lag of treatment			-0.031	-0.095			-0.034	-0.034
			(0.086)	(0.104)			(0.027)	(0.028)
Constant	0.349***	0.351***	1.039***	1.009***	0.543***	0.550***	1.026***	1.023***
	(0.017)	(0.018)	(0.086)	(0.092)	(0.025)	(0.026)	(0.141)	(0.141)
Observations	418	356	418	356	3978	3898	3978	3898
R^2	0.60	0.61	0.76	0.77	0.79	0.79	0.88	0.88

Robust standard errors in parentheses; Estimations for Chile include region effects; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: PS-weighted OLS estimation of the effect of agriprocessing on the speed of poverty reduction, Chile 1992-2002, Mexico 2000-2010

	Chile				Mexico			
	(1) Baseline	(2) Baseline common support	(3) With covariates	(4) Covariates and common support	(5) Baseline	(6) Baseline common support	(7) With covariates	(8) Covariates and common support
Growth in agriprocessing	-0.057**	-0.064**	-0.059**	-0.069**	-0.036**	-0.035**	-0.034**	-0.037**
	(0.026)	(0.029)	(0.030)	(0.030)	(0.015)	(0.016)	(0.016)	(0.016)
Initial poverty rate	-1.003***	-1.059***	-1.716***	-1.745***	-0.489***	-0.486***	-1.008***	-1.002***
	(0.173)	(0.196)	(0.219)	(0.250)	(0.064)	(0.065)	(0.173)	(0.173)
Gini			-0.174	-0.191			-0.128	-0.107
			(0.290)	(0.318)			(0.263)	(0.263)
% Rural			-0.361***	-0.344***			-0.061	-0.059
			(0.083)	(0.093)			(0.041)	(0.041)
Average age			-0.007	-0.005			0.000	0.000
			(0.011)	(0.011)			(0.004)	(0.004)
Female education			-0.061*	-0.053			-0.048***	-0.047***
			(0.037)	(0.039)			(0.018)	(0.018)
Female labor force participation (%)			-0.005	-0.004			-0.003**	-0.003**
			(0.005)	(0.006)			(0.001)	(0.001)
Change in the rest of employment			-0.000***	-0.000			-0.006	-0.008
			(0.000)	(0.000)			(0.012)	(0.013)
Distance from regional capital (Km)			0.000	0.000			0.001***	0.001***
			(0.000)	(0.000)			(0.000)	(0.000)
Spatial lag of treatment			-0.370	-0.943**			0.009	0.009

			(0.357)	(0.431)			(0.050)	(0.051)
Constant	0.225***	0.246***	1.644***	1.684***	0.414***	0.436***	1.160***	1.176***
	(0.081)	(0.083)	(0.445)	(0.469)	(0.075)	(0.076)	(0.424)	(0.424)
Observations	209	178	209	178	1989	1949	1989	1949
R^2	0.51	0.47	0.59	0.58	0.25	0.25	0.33	0.33

Robust standard errors in parentheses; Estimations for Chile include region effects; $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$