Inequality at Low Levels of Aggregation in Chile*

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Abstract

Despite success in reducing poverty over the last twenty years, inequality in Chile has remained virtually unchanged, making Chile one of the least equal countries in the world. High levels of inequality have been shown to hamper further reductions in poverty as well as economic growth, and local inequality has been shown to affect such outcomes as violence and health. The study of inequality at the local level is thus crucial for understanding the economic well-being of a country. Local measures of inequality have been difficult to obtain, but recent theoretical advances have enabled the combination of survey and census data to generate estimates of inequality that are robust at disaggregated geographic levels. In this paper, we employ this methodology to produce consistent and precise estimates of inequality for every county in Chile. We find considerable heterogeneity in county-level estimates of inequality, with Gini coefficients ranging from 0.41 to 0.63. An appendix includes estimated inequality for each county so the broader research community may assess the effect of local inequality on a broad range out outcomes, as well as analyze the determinants of inequality itself.

Keywords: inequality, poverty mapping, government subsidies, cash transfers, Chile

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1. Introduction

Between 1986 and 2005 per capita GDP in Chile grew by 203%. The engine underlying this dramatic economic performance was a series of economic reforms begun in the mid-1970s, many of which were deepened during the 1990s (see, for example, Clapp 1995). Although privatization and deregulation were the hallmarks of these reforms, poverty reduction was also an important policy objective beginning in the early 1980s, and gains against poverty have been as impressive as Chile's growth statistics. Using a standardized form[1] that evaluates housing characteristics to identify poor households, the government coupled housing subsidies with cash and in-kind transfers to the poor.[2] Housing criteria were also used to identify locations for new schools and health care facilities. Chile thus took a multi-pronged approach to poverty reduction (Beyer 1997, Valdés 1999), and poverty rates fell from approximately 39.4 % in 1987 to 18.7% in 2003; indigence rates also fell dramatically during this period, from approximately 14.2% to 4.7%.

However, inequality has remained relatively constant during this period, and the Gini continues to be among the highest in the world (Contreras and Larrañaga, 1999; Ferreira and Litchfield, 1999; Contreras, Larrañaga, and Valdés, 2001; Contreras, 2003) despite the global trend towards convergence evident since the 1980s. For example, the Gini coefficient was 0.547 in 1987 and 0.546 in 2003 (Figure 1). Income inequality has been buoyed by low levels of migration (Soto and Torche 2004), uneven returns to education (Gindling and Robbins, 2001),

[1]The "CAS Card," renamed the "CAS-2 Card" after revisions in 1987.
[2] Such subsidies fall into five main categories: 1. Family Subsidy (SUF): A subsidy provided to pregnant women, parents with children not covered by social security, and parents or guardians of persons with physical disabilities. To be eligible, beneficiaries must agree to take children under age 6 for regular medical checkups and to send children aged 6 to 18 years to school; 2. Unemployment: A monthly payment for up to one year for unemployed workers who lost work through no fault of their own; 3. Assistance Pensions (PASIS): Pensions are provided for adults aged 65 and over, physically-disabled adults, and mentally-disabled individuals regardless of age who have a total income below half of the minimum pension allowance; 4. Solidarity Subsidy (Chile Solidario): A subsidy that targets indigent families and households with female heads. 5. Water and Sewage Subsidy (SAP): A three-year, renewable subsidy to offset the cost of water among poor households.

foreign competition in labor-intensive goods (Beyer, Rojas, and Vergara, 1999), increased labor market participation among women (Contreras, Puentes, and Bravo, 2005), and an increasing reliance on seasonal and fixed-contract labor (Amuedo-Dorantes, 2005).

Inequality has been shown to have important effects on poverty, on social outcomes, and on public finance, and has thus become a growing concern for the public and policymakers alike. For example, for any given level of average income, greater inequality generally implies higher levels of poverty. Moreover, Ravallion (1997, 2004) shows that greater inequality causes poverty levels to fall at a lower rate. In terms of social outcomes, inequality at the local level impacts health, education, and the incidence of crime and violence (Deaton 1999). The levels and heterogeneity of local inequality may also impact tax collections and may influence the optimal degree of decentralization and provision of public goods (Bardhan and Mookherjee 1999).

National policies that target poverty reduction may have an impact on inequality. For example, progressive taxation and appropriately-targeted cash subsidies may reduce both poverty and income inequality. However, poverty-reduction programs may also raise inequality; as a case in point, improving the quality of education has been more effective in reducing poverty than expanding access to education (Chumacero and Paredes 2005), yet the resulting disparities in access raise income inequality. Similarly, Chile's generous housing subsidies have been effective at reducing poverty, yet they have also had the undesirable effect of tying individuals to their places of origin, thereby preventing migration to more productive areas with higher wages (Soto and Torche 2004).

Policy implementation may similarly affect inequality. On the one hand, local authorities have better information about local needs; on the other, they may be more susceptible to influence from vested interests and local elites (Bardhan and Mookherjee 2006). Elite capture of funding for poverty alleviation is difficult to test because detailed income data that are representative at low levels of aggregation are not available for most countries.

As with most countries, income data in Chile are derived from household surveys; although surveys such as the National Survey of Socioeconomic Characterization (*Casen*) contain detailed information on income and a wealth of other information for a large number of households, they are not representative at the sub-regional level. As a result, poverty and inequality in Chile have primarily been studied at the national and regional level (e.g., Contreras 1996; Contreras and Ruiz-Tagle 1997; Feres 2000; Contreras 2001; Pizzolito 2005a, 2005b) rather than at the sub-regional level of provinces or counties. Census data, by contrast, is representative at every level of aggregation (by definition), although they typically do not collect any information whatsoever about income. Censuses thus cannot not been used in the study of income inequality.

This problem has motivated research into methods for combining survey and census data in order to obtain geographically-disaggregated estimates of inequality. The sophistication of these methods has advanced a great deal in recent years, and it is now possible to obtain estimates that are statistically precise and reliable (e.g., Hentschel, et al.1999).[3] In this paper, we adapt the methodology formalized by Elbers, Lanjouw, and Lanjouw (2003) to obtain estimates of inequality at the county-level in Chile. We find considerable heterogeneity in inequality among Chile's 341 counties and suggest that geographic considerations may be appropriate for policymakers who wish to address inequality. An appendix provides the estimated Gini coefficients and standard errors so that the broader research community may explore the impact

[3] This methodology has since been use to estimate wellbeing at the local level in Ecuador and Madagascar (Demombynes, et al. 2002), South Africa (Demombynes and Özler 2005), Mozambique (Elbers, et al. 2003), India (Kijima and Lanjouw 2003), and Cambodia (Elbers, et al. 2007).

of precisely-estimated measures of inequality on a spectrum of socioeconomic outcomes, as well as the determinants of inequality itself.

The remainder of the paper is organized as follows: section 2 explains the methodology being used, both conceptually and in detail; section 3 provides a detailed description of the data; section 4 presents the results with detailed maps describing inequality at the county level; and section 5 offers a brief conclusion and suggestions for further research.

2. Methodology

The intuition behind the methodology proposed by Hentschel, et al.(1999) and developed by Elbers, Lanjouw, and Lanjouw (2003) is conceptually straightforward: a model of income or consumption is first estimated using survey data, restricting the explanatory variables to those also available in both the survey and a census undertaken at a similar point in time. These parameters are then used to estimate income or consumption for the entire population based on the census data. Finally, poverty and inequality indicators are estimated for geographic areas for which the census is representative but for which the survey is not.

Statistically, the methodology consists of estimating the joint distribution of the income or consumption and a vector of explanatory variables. Restricting the set of explanatory variables to those available in the census, the estimated joint distribution can be used to generate the distribution of the variable of interest for any subgroup of the population in the census, conditional to the observed characteristics of that subgroup. This also allows for the generation of a conditional distribution, point estimates, and prediction errors of the associated indicators such as poverty and inequality.

In a first stage, a model is created that relates the income per capita of household ***h*** (Y_h) in cluster ***c*** with a group of observable characteristics (X_h):

$$\ln Y_{hc} = E[\ln Y_{hc} \mid X_{hc}] + u_{hc} = X_{hc} + u_{hc}$$

where the error vector ***u*** is distributed $\Gamma(0,\sum)$. To allow correlation within each cluster, the error term is further assumed to consist of a cluster component (η) and an idiosyncratic error (ε):

$$u_{hc} = \eta_c + \varepsilon_{hc}$$

The two components are assumed to be independent of each other and uncorrelated with the observable variables X_{hc}.

It is not necessary to specify a restrictive functional form for the idiosyncratic component of the error, σ_{ε}^2. Indeed, with consistent estimators of β, the residuals of the decomposition of the estimated error,

$$\hat{u}_{hc} = \hat{u}_{.c} + (\hat{u}_{hc} - \hat{u}_{.c}) = \hat{\eta}_c + \hat{\varepsilon}_{hc}$$

can be used to estimate the variance of ε.[4] The functional form commonly used for estimating the variance of the idiosyncratic error is:

[4] The subindex "." in the equation represents the average over the index.

$$\sigma_{\varepsilon}^{2} = \left[\frac{A\hat{\varepsilon}^{z_{hc}^{T}\alpha} + B}{1 + \hat{\varepsilon}^{z_{hc}^{T}\alpha}} \right]$$

The upper and lower limits, *A* and *B*, can be estimated together with the parameter α using the standard pseudo-maximum likelihood; the advantage of this approach is that it eliminates negative and excessively high values for the predicted variances.

The simplest means of estimating the model is to use a linear approximation of the conditional expectation, allowing geographic effects and heteroskedasticity into the distribution of the error term. It is important to note that the cluster component of the residual can significantly reduce the power of the estimates in the second stage, and that it is thus important to explain the variation in income or consumption due to location via observable variables to the greatest extent possible.

The result of this first-stage estimation is a vector of coefficients, β, a variance-covariance matrix associated with this vector, and a set of parameters that describe the distribution of the errors. The second stage utilizes this set of parameters along with the characteristics of the individuals or households in the census in order to generate predicted values of the log of income and the relevant errors. For these effects, a bootstrap method is used to simulate values of income of each household or each individual. These simulated values are based on the prediction of the income and the error terms, η and ε:

$$\hat{Y}_{hc} = \exp(X_{hc}\hat{\beta} + \hat{\eta}_{c} + \hat{\varepsilon}_{hc})$$

For each household, the two components of the error term are taken from the empirical distribution described by the parameters estimated in the first stage. The coefficients $\hat{\beta}$, are taken from the normal multivariate distribution described by the estimators of β in the first stage and the associated variance-covariance matrix. The complete set of simulated values of $\hat{Y}_{hc}$ is then used to calculate the expected value of poverty or inequality measures by area. This procedure is repeated ***n*** times, taking a new set of coefficients β and errors for each simulation; the mean and the standard deviations of the βs constitute the point estimates and the standard deviations for the wellbeing indicator, respectively.

We will call the inequality indicator $G(n_c, X_c, \beta, u_c)$, where n_c is a N_c vector of the number of household members in county c, X_c is a $N_c x k$ vector of their observable characteristics, and u_c is a N_c error vector. Thus, the expected value of the inequality indicator is estimated given the characteristics of the individuals and the households and the model estimated in the first stage, i.e.:

$$G_c^E = E[G \mid n, X; \xi]$$

where ξ is the vector of parameters of the model, including the parameters that describe the distribution of the error term. Replacing the unknown vector ξ, with a consistent estimator $\hat{\xi}$, we get:

$$G_c^E = E[G \mid n, X, \hat{\xi}]$$

This conditional expected value is generally impossible to resolve analytically, making it necessary to use Monte Carlo simulations to obtain an estimator $\tilde{G}_c^E$.

One complication associated with this methodology is calculating the correct standard errors, which is not trivial. Because it is not possible to calculate them analytically, we again resort to bootstrapping techniques and Monte Carlo simulations. Suppressing the subscripts, the difference between the estimator of the expected value of *G*, $\tilde{G}_c^E$, and the actual level of the inequality indicator for the geographic area can be decomposed into:

$$G - \tilde{G}^E = (G - G^E) + (G^E - \hat{G}^E) + (\hat{G}^E - \tilde{G}^E)$$

The prediction error thus has three components: the first is due to the presence of a stochastic error in the first stage model, implying that the actual household incomes deviate from their expected values (idiosyncratic error); the second is due to the variance in the estimators of the parameters of the model from the first stage (model error); and the third is due to the use of an inexact method to calculate $\hat{G}_c$ (calculation error).

The variance of the estimator due to the idiosyncratic error shrinks proportionally with the population in each geographic area. Thus, smaller populations within each geographic area are associated with larger idiosyncratic errors, introducing a limit to the extent of disaggregation that may be achieved. The variance of the estimator due to the model error can be calculated using the delta method:

$$V_{Model} = \nabla^T V(\hat{\xi}) \nabla$$

where $\nabla = [\partial G^E / \partial \xi]$, $V(\xi)$ is the variance-covariance matrix of the first stage estimators, and $\hat{\xi}$ is a consistent estimator of ξ, also obtained from the first stage. This component of the predicted errors is determined by the properties of the first-stage estimators and therefore doesn't systematically change with the population in each geographic area; its magnitude depends only on the precision of the first-stage estimates. The variance of the estimator due to computational error depends on the computational methodology used. Since Monte Carlo simulations are employed here, it is possible to reduce this error component by increasing the number of simulations; we use 250 simulations to minimize the error component to the greatest extent possible.

The expected value of the inequality indicator coefficient is thus conditional on the first stage regression, the variance due to the idiosyncratic component of income per capita of the households, and the gradient vector. The Monte Carlo simulation generates 250 vectors of error terms from the distribution estimated in the first stage. With each set of vectors, the inequality indicator is calculated. Then, the expected value simulated for the inequality indicator is the average of the 250 responses:

$$\tilde{G}^E = \frac{1}{250} \sum_{d=1}^{250} \left(\hat{G}_d^E \right)$$

The variance of G is estimated using the same simulated values, such that:

$$V_{Model} = \frac{1}{250} \sum_{d=1}^{250} \left(G_d - \tilde{G}^E \right)^2$$

Finally, it is important to underscore the crucial assumption that the models estimated using survey data are applicable to the observations of the census. This assumption is reasonable enough if the year of the census and the survey coincide or are close. In the case of this particular study, the 2002 census is matched with the 2003 *Casen* survey, making the assumption implicit in the methodology reasonable.

3. Data

The survey employed in the first stage of the methodology described above is the November 2003 National Survey of Socioeconomic Characterization (*Casen*). The data collected include demographic characteristics for the household members, distinct sources of income including state transfers, living conditions, ownership of certain durable goods, access to sanitation, and health and education characteristics. The *Casen* survey is undertaken by the Ministry of Planning (*Mideplan*), but the data are adjusted by the Economic Commission for Latin America and the Caribbean (ECLAC) using a system of national accounts as a reference. These adjustments consider the problems generated by the lack of income data for some households and the under or over representation of some income categories in the sample.[5]

The survey utilizes a multistage method of random sampling with stratification. In the first stage, the country was divided between rural and urban areas for each of the 13 regions, and the primary sampling units are selected with probabilities proportional to the population. In the second stage, households are selected into the sample with equal probability. The final sample includes 68,153 households comprising 257,077 people. These households represent 315 of the

[5] Although the ECLAC adjustments could generate some bias, Contreras and Larrañaga 1999 present evidence to the contrary. Regardless, the unadjusted data are not available.

342 counties in Chile, with as few as 49 and as many as 315 households surveyed in each county. While coverage of counties in northern and central Chile is nearly complete, the survey poorly represents counties in southern Chile. Although *Mideplan* considers the *Casen* to be representative at the regional level and for 301 self-reporting counties, there is no consensus with respect to the validity of the county representativeness, and various researchers consider the representativeness to be only national and regional (e.g., Valdés 1999; Contreras, et al. 2001; Pizzolito 2005a, 2005b).

Using the *Casen* alone to calculate inequality yields results that allow for very few conclusions given the magnitude of the errors, a problem that persists at the regional level as well as the county level. For example, the Gini coefficient estimated by the *Casen* for the Region I is 0.495**,** but with a standard error of 0.053, the 95% confidence interval ranges from 0.392 to 0.599. The evidence presented in the results section below as well as those obtained from similar studies in other countries show that the standard errors obtained by imputing income to census data are much lower than those obtained using survey data (Elbers et al., 2003).

The National Institute of Statistics conducts a population and housing census every ten years, the most recent (and that used in this analysis) being undertaken in April 2002. The census covered 4,112,838 households composed of 15,545,921 individuals. The data include demographic characteristics, labor status, educational level, ownership of certain assets, access to basic sanitation, and migration activities during the previous ten years, but neither income nor consumption.

To impute income data into the census, a set of explanatory variables common to both the *Casen* and the census must be identified. Although some explanatory variables are defined identically in both data sets, others were constructed, the means and variances of both types of variables were evaluated to ensure that the explanatory variables from the census are indeed the same as those in the *Casen*. Using step-wise regression to detect the best fit for each region, we determined that household demographics, characteristics of the household head, characteristics of the house itself, and assets were the strongest predictors of household income. The model estimated in the first stage may thus be written:

$$\ln Y_{hc} = \beta_0 + \beta_1 D + \beta_2 H + \beta_3 V + \beta_4 A + u_{hc}$$

where the dependent variable Y_{hc} is total per capita income of the household. D is a vector of the demographic characteristics, including the number of household members and the fraction household membership that is below school-age. H is a vector of characteristics of the head of household that includes gender, education level, and ethnicity. V is a vector of characteristics of the house itself, including the number of rooms, the principal construction material of the house, the type of flooring, the primary water source, and the distribution system of water. A is a vector of dummy variables that describes the ownership of various assets, including a washing machine, hot water heater, land line telephone, cellular phone, satellite or cable television, microwave, computer, and Internet access. Additionally, location dummy variables are included to control for unobserved heterogeneity.

It is important to note that the objective of this first-stage regression is not to determine causality, but rather to make the best possible prediction of per capita income based on observable characteristics of each household. Given that the observable predictors vary across Chile's 13 regions, separate regressions are estimated for each. In each, county dummies variables were also included to capture the local geographic effects.

4. Results

From the coefficients and the variance-covariance matrix estimated in the first stage, the methodology described above is used to estimate the Gini coefficient of each county within each region together with its respective standard error.[6] Gini coefficients range from 0.409 in Pumanque county (Region VI) to 0.627 in San Fabián county (Region VIII).

Figure 2 shows the distribution of inequality, measured by the Gini coefficient, in northern Chile, Regions I (Tarapacá), II (Antofogasta), III (Atacama), and IV (Coquimbo). The counties with the highest estimated inequality in northern Chile are La Serena in Region IV and Iquique in Region I, with estimated Gini coefficients of 0.502 (standard error of 0.008) and 0.487 (standard error of 0.007), respectively. Conversely, the counties with the lowest inequality are La Higuera and Andacollo, both in Region IV, with Gini coefficients of 0.424 (standard error of 0.010) and 0.442 (standard error of 0.007).

Figure 3 depicts estimated inequality in Regions VI (O'Higgins), VII (Maule), VII (Bío-Bío), and IX (Araucanía). As noted above, the extremes values for estimated inequality are found in central Chile. The counties with the highest levels of inequality are San Fabián and San Pedro de la Paz, both in Region VIII, with Gini coefficients of 0.607 (standard error of 0.040) and 0.541 (standard error of 0.005), respectively. The counties with the lowest estimated Gini coefficients are Pumanque and Paredones, both in Region VI, with Gini coefficients of 0.410 (standard error of 0.010) and 0.413 (standard error of 0.008).

[6] Although the methodology is identical for any common indicator of inequality, we choose to focus on the Gini coefficient is used for two reasons. First, the Gini coefficient is widely used measure and generally well understood. Second, experiments and surveys that measure aversion to inequality empirically have shown that a function of wellbeing based on the Gini coefficient presents a much better description of the data than measures based on the absolute or relative aversion to inequality (Amiel, Creedy, and Hurn 1999).

Figure 4 depicts inequality in southern Chile, including Regions X (Los Lagos), XI (Aisén), and XII (Magallanes). Here, Río Verde and Primavera in Region XII display the highest levels of income inequality, with estimated Gini coefficients of 0.541 (standard error of 0.040) and 0.534 (standard error of 0.020), respectively. The counties with the lowest inequality are San Juan de la Costa and Puqueldón, both in Region X, with Gini coefficients of 0.433 (standard error of 0.007) and 0.446 (standard error of 0.010).

Finally, Figure 5 shows the distribution of inequality for Regions V (Valparaíso) and XIII (the Santiago Metropolitan Region). Here, the districts with the greatest inequality are Calera de Tango and Colina with Gini coefficients of 0.54 and 0.53, respectively, both in Region XIII. The districts with the least inequality are Juan Fernández in Region V and Vitacura in Region XIII, both of which have estimated Gini coefficients of 0.43. The relative homogeneity of income within these two wealthy counties is noteworthy, as is the equality of incomes across Region V, wherein estimated Gini coefficients range from 0.43 to 0.47.

These inequality maps show that heterogeneity in county-level inequality is high. Figure 6 underscores this observation by showing the distribution of Gini coefficients for each county in Chile with its respective confidence intervals. Also included in the graph is a line representing the national Gini coefficient according to the *Casen* survey. Comparing the distribution of the county Gini coefficients to the national Gini coefficient shows that all but two counties have levels of inequality below the national level. This shows that although the inequality between counties is very important, there also exists a considerable amount of variation between the households within each county. This result is not at all surprising – the evidence from Ecuador, Madagascar and Mozambique is similar (Demombynes, et al. 2002) – and simply reflects that local communities are more homogeneous than Chile as a whole.

Perhaps the best way to represent the variability of inequality is to estimate its distribution. Figure 7 thus shows a histogram of the Gini coefficients together with a Kernel estimation for the distribution. As the figure shows, the estimated empirical distribution is not symmetrical and there is a greater proportion of counties with relatively more inequality, with respect to the average, than counties with less inequality.[7] In the future, it would be interesting to repeat the exercise using the 1992 census and the 1992 *Casen* survey. This would allow a comparison of two inequality distributions with ten years of difference to better understand the evolution of inequality at the local level.

5. Conclusion and Discussion

The principal objective of this work was to produce disaggregated estimates of inequality for Chile. This was achieved by applying the methodology developed by Hentschel, et al.(1999) and Elbers, et al. (2003) to the Chilean context using the 2002 population census and the 2003 *Casen* survey. We find that income inequality at the county level is much lower than national estimates of income inequality, although there is considerable heterogeneity in inequality among counties. This suggests that between-county inequality is driving Chile's high and persistent income inequality.

The estimates developed in this paper make it possible to extend the analysis of income distribution at the regional level exemplified by Contreras (1996) and Contreras and Ruiz-Tagle (1997) to sub-regional units. Another application for which the estimates have obvious use is to develop better targeting for policies aimed at reducing poverty and inequality; such interventions may prove more effective than existing efforts in reducing Chile's high income inequality. In addition, the estimates may be used to analyze the effect of poverty on a wide spectrum of social

[7] For this reason, nonparametric estimation was used when implementing the estimation methodology.

outcomes for which local measures of inequality are more likely to have an impact than national measures of inequality, e.g., health and crime (Deaton 1999). Finally, the estimates enable further research into the effects of local income inequality on public finance, including the diversion of funds for poverty reduction to local elites (Bardhan and Mookherjee, 2005).

References

Amuedo-Dorantes, C. (2005), "Wage Contracts and Earnings Inequality: The Case of Chile." *Journal of Development Studies* 41(4): 589-616.

Bardhan, P. and D. Mookherjee (2006). "Relative Capture of Local and Central Governments: An Essay in the Political Economy of Decentralization," Working Paper 1013, *Center for International and Development Economics Research, Institute for Business and Economic Research*, UC Berkeley.

Beyer, H. (1997), "Distribución del Ingreso: Antecedentes para la Discusión". *Estudios Públicos* 65: 5-58.

Beyer, H., P. Rojas, and R. Vergara, (1999), "Trade Liberalization and Wage Inequality." *Journal of Development Economics* 59(1): 103-123.

Chumacero, R. A. and R. D. Paredes (2004), "Characterizing Income Distribution for Poverty and Inequality Analysis." *Estudios de Economía* 32(1): 97-117.

Clapp, R. A. (1995), "Creating Competitive Advantage: Forest Policy as Industrial Policy in Chile." *Economic Geography* 71(3): 273-296.

Contreras, D. (2001), "Economic Growth and Poverty Reduction by Region: Chile 1990-96", *Development Policy Review* 19(3).

Contreras, D. (2003), "Poverty and Inequality in a Rapid Growth Economy: Chile 1990-96", *Journal of Development Studies* 39(3).

Contreras, D. (1996), "Pobreza and Desigualdad en Chile: 1987-1992. Discurso, Metodología y Evidencia Empírica", *Estudios Públicos* 64, Spring.

Contreras, D. and O. Larrañaga (1999), "Activos y Recursos de la Población Pobre en Chile", El *Trimestre Económico* 66(263).

Contreras, D., O. Larrañaga, J. Litchfield and A. Valdés (2001), "Poverty and Income Distribution in Chile 1987-1998: New Evidence",*Cuadernos de Economía* 114.

Contreras, D. and J. Ruiz-Tagle (1997), "Como Medir la Distribución del Ingreso en Chile", *Estudios Públicos* 65.

Contreras, D., E. Puentes, and D. Bravo (2005), "Female Labor Force Participation in Greater Santiago, Chile: 1957-1997. A Synthetic Cohort Analysis." *Journal of International Development* 17(2): 169-186.

Deaton, A. (2001), "Inequalities in Income and Inequalities in Health", en F. Welch (ed.) *The Causes and Consequences of Increasing Inequality*, The University of Chicago Press.

Demombynes, G., C. Elbers, J. Lanjouw, P. Lanjouw, J. Mistiaen and B. Özler (2002), "Producing an Improved Geographic Profile of Poverty", *World Institute for Development Economics Research Discussion Paper* No.2002-39.

Demombynes, G. and B. Özler (2005), "Crime and Local Inequality in South Africa", Journal of Development Economics 76(2).

Elbers, Chris, J.O. Lanjouw and Peter Lanjouw. (2003) "Micro-Level Estimation of Poverty and Inequality", *Econometrica*, Vol. 71, No.1.

Elbers, C., P Lanjouw, J. Mistiaen, B. Özler and K. Simler (2003), "Are Neighbours Equal?", *World Institute for Development Economics Research Discussion Paper* No. 2003-52

Elbers, C., P Lanjouw, J. Mistiaen, B. Özler and K. Simler (2004), "On the Unequal Inequality of Poor Communities", World Bank Economic Review 18(3).

Elbers, C., T. Fujii, P. Lanjouw, B. Özler, and W. Yin (2007), "Poverty Alleviation Through Geographic Targeting: How Much Does Disaggregation Help?", *Journal of Development Economics,* 83.

Feres, J.C. (2000), "La Pobreza en Chile en el año 2000", Serie Estudios Estadísticos y Prospectivos No. 14, CEPAL.

Ferreira, F. and J. A. Litchfield (1999), "Calm after the Storms: Income Distribution and Welfare in Chile 1987-1994", *World Bank Economic Review* 13(3).

Gindling, T.H. and D. Robbins, (2001). "Changes and Patterns of Changing Wage Inequality in Chile and Costa Rica During Structural Adjustment." World Development 29(4): 725-745.

Hentschel, J., J. Lanjouw, P. Lanjouw and J. Poggi (1999), Combining Survey Data with Census Data to Construct Spatially Disaggregated Poverty Maps: A Case Study of Ecuador, *World Economic Bank Review*, Vol. 14, No.1.

Kijima, Y. and P. Lanjouw (2003), "Poverty in India During the 1990s: A Regional Perspective" The World Bank, *DECRG Working Paper*.

Pizzolito, G. (2005a), "Monitoring Socio-Economic Conditions in Argentina, Chile, Paraguay, and Uruguay: Chile", *CEDLAS-World Bank Report*, December.

Pizzolito, G. (2005b), "Poverty and Inequality in Chile: Methodological Issues and a Literature Review", *Documento de Trabajo* No. 20, CEDLAS.

Ravallion, M. (1997), "Can High Inequality Development Countries Escape Absolute Poverty?", *Economics Letters* 56.

Ravallion, M. (2004), "Pro-Poor Growth: A Primer", *The World Bank, Policy Research Working Paper* No. 3242.

Soto, R. and A. Torche (2004), "Spatial Inequality, Growth, and Migration in Chile." *Cuadernos de Economía* 41: 401-424.

Valdés, A. (1999), "Pobreza y Distribución del Ingreso en una Economía de Alto Crecimiento: Chile, 1987-1995", *Estudios Públicos* 75.

Appendix

This appendix prsents the estimated Gini coefficients and standard errors for each of Chile's 341 counties. All estimates are based on the methodology proposed by Elbers, et al. (2003).

Reg.	County	Census Code	Gini Coef.	Std. Error	Reg.	County	Census Code	Gini Coef.	Std. Error
I	Iquique	1101	0.4809	0.00580	VIII	San Rosendo	8310	0.4673	0.01260
I	Camiña	1102	0.4796	0.01813	VIII	Santa Bárbara	8311	0.4849	0.00656
I	Colchane	1103	0.4947	0.02219	VIII	Tucapel	8312	0.4832	0.01053
I	Huara	1104	0.4874	0.01354	VIII	Yumbel	8313	0.4701	0.00586
I	Pica	1105	0.4880	0.01209	VIII	Chillán	8401	0.5130	0.00392
I	Pozo Almonte	1106	0.4806	0.00938	VIII	Bulnes	8402	0.4897	0.00961
I	Arica	1201	0.4829	0.00604	VIII	Cobquecura	8403	0.4681	0.01006
I	Camarones	1202	0.4857	0.01824	VIII	Coelemu	8404	0.4749	0.00714
I	Putre	1301	0.4735	0.01587	VIII	Coihueco	8405	0.4659	0.00559
I	General Lagos	1302	0.4828	0.02196	VIII	Chillán Viejo	8406	0.4888	0.00701
II	Antofagasta	2101	0.4689	0.00712	VIII	El Carmen	8407	0.4543	0.00617
II	Mejillones	2102	0.4503	0.00928	VIII	Ninhue	8408	0.4596	0.01349
II	Sierra Gorda	2103	0.4720	0.02039	VIII	Ñiquén	8409	0.4519	0.00688
II	Taltal	2104	0.4584	0.00873	VIII	Pemuco	8410	0.4526	0.00805
II	Calama	2201	0.4683	0.00732	VIII	Pinto	8411	0.4692	0.00771
II	Ollague	2202	0.4659	0.04078	VIII	Portezuelo	8412	0.4775	0.01365
II	San Pedro de Atacama	2203	0.4759	0.01081	VIII	Quillón	8413	0.4673	0.00651
II	Tocopilla	2301	0.4737	0.01037	VIII	Quirihue	8414	0.4780	0.00727
II	María Elena	2302	0.4572	0.01586	VIII	Ránquil	8415	0.4614	0.01068
III	Copiapo	3101	0.4791	0.00696	VIII	San Carlos	8416	0.5044	0.00969
III	Caldera	3102	0.4670	0.00904	VIII	San Fabián	8417	0.6360	0.08344
III	Tierra Amarilla	3103	0.4695	0.01634	VIII	San Ignacio	8418	0.4542	0.00688
III	Chañaral	3201	0.4709	0.00983	VIII	San Nicolás	8419	0.4567	0.00797
III	Diego de Almagro	3202	0.4846	0.00849	VIII	Treguaco	8420	0.4409	0.00978
III	Vallenar	3301	0.4833	0.00698	VIII	Yungay	8421	0.4903	0.00659
III	Alto del Carmen	3302	0.4647	0.01079	IX	Temuco	9101	0.5321	0.00651
III	Freirina	3303	0.4607	0.01044	IX	Carahue	9102	0.4773	0.00649
III	Huasco	3304	0.4712	0.00956	IX	Cunco	9103	0.4633	0.00558
IV	La Serena	4101	0.5024	0.00778	IX	Curarrehue	9104	0.4634	0.00934
IV	Coquimbo	4102	0.4852	0.00666	IX	Freire	9105	0.4646	0.00690
IV	Andacollo	4103	0.4432	0.00748	IX	Galvarino	9106	0.4679	0.00708
IV	La Higuera	4104	0.4245	0.01021	IX	Gorbea	9107	0.4724	0.00643
IV	Paiguano	4105	0.4570	0.01037	IX	Lautaro	9108	0.5088	0.00636
IV	Vicuña	4106	0.4658	0.00727	IX	Loncoche	9109	0.4745	0.00557
IV	Illapel	4201	0.4745	0.00711	IX	Melipeuco	9110	0.4671	0.01029
IV	Canela	4202	0.4469	0.00753	IX	Nueva Imperial	9111	0.4835	0.00532
IV	Los Vilos	4203	0.4745	0.00766	IX	Padre las Casas	9112	0.4794	0.00474
IV	Salamanca	4204	0.4736	0.00856	IX	Perquenco	9113	0.4783	0.01302
IV	Ovalle	4301	0.4736	0.00535	IX	Pitrufquén	9114	0.4871	0.00751
IV	Combarbalá	4302	0.4584	0.00698	IX	Pucón	9115	0.5019	0.00649
IV	Monte Patria	4303	0.4470	0.00670	IX	Saavedra	9116	0.4539	0.00685
IV	Punitaqui	4304	0.4487	0.00743	IX	Teodoro Schmidt	9117	0.4617	0.01558
IV	Río Hurtado	4305	0.4552	0.01086	IX	Toltén	9118	0.4712	0.00812
V	Valparaíso	5101	0.4441	0.00298	IX	Vilcún	9119	0.4743	0.00596
V	Casablanca	5102	0.4376	0.00512	IX	Villarrica	9120	0.4967	0.00594
V	Concón	5103	0.4620	0.00481	IX	Angol	9201	0.5222	0.00639
V	Juan Fernández	5104	0.4255	0.02248	IX	Collipulli	9202	0.4846	0.00617

Reg.	County	Census Code	Gini Coef.	Std. Error
V	Puchuncaví	5105	0.4350	0.00590
V	Quilpué	5106	0.4406	0.00352
V	Quintero	5107	0.4468	0.00549
V	Villa Alemana	5108	0.4376	0.00349
V	Viña del Mar	5109	0.4594	0.00374
V	Isla de Pascua	5201	0.4421	0.01035
V	Los Andes	5301	0.4481	0.00387
V	Calle Larga	5302	0.4397	0.00778
V	Rinconada	5303	0.4337	0.00795
V	San Esteban	5304	0.4354	0.00594
V	La Ligua	5401	0.4404	0.00476
V	Cabildo	5402	0.4342	0.00503
V	Papudo	5403	0.4333	0.00922
V	Petorca	5404	0.4269	0.00684
V	Zapallar	5405	0.4297	0.00788
V	Quillota	5501	0.4463	0.00365
V	Calera	5502	0.4409	0.00379
V	Hijuelas	5503	0.4269	0.00501
V	La Cruz	5504	0.4484	0.00686
V	Limache	5505	0.4440	0.00430
V	Nogales	5506	0.4336	0.00505
V	Olmué	5507	0.4461	0.00553
V	San Antonio	5601	0.4387	0.00344
V	Algarrobo	5602	0.4528	0.00720
V	Cartagena	5603	0.4386	0.00546
V	El Quisco	5604	0.4403	0.00648
V	El Tabo	5605	0.4359	0.00693
V	Santo Domingo	5606	0.4700	0.00853
V	San Felipe	5701	0.4445	0.00352
V	Catemu	5702	0.4332	0.00656
V	Llaillay	5703	0.4332	0.00530
V	Panquehue	5704	0.4355	0.00901
V	Putaendo	5705	0.4319	0.00583
V	Santa María	5706	0.4304	0.00668
VI	Rancagua	6101	0.4504	0.00562
VI	Codegua	6102	0.4247	0.00753
VI	Coinco	6103	0.4358	0.00893
VI	Coltauco	6104	0.4237	0.00646
VI	Doñihue	6105	0.4304	0.00620
VI	Graneros	6106	0.4386	0.00657
VI	Las Cabras	6107	0.4208	0.00605
VI	Machalí	6108	0.4589	0.00668
VI	Malloa	6109	0.4273	0.00708
VI	Mostazal	6110	0.4330	0.00615
VI	Olivar	6111	0.4344	0.00808
VI	Peumo	6112	0.4351	0.00735
VI	Pichidegua	6113	0.4168	0.00576
VI	Quinta de Tilcoco	6114	0.4222	0.00749
VI	Rengo	6115	0.4407	0.00513
VI	Requínoa	6116	0.4395	0.00648
VI	San Vicente	6117	0.4423	0.00559
VI	Pichilemu	6201	0.4347	0.00659
VI	La Estrella	6202	0.4193	0.01168
VI	Litueche	6203	0.4254	0.00910
IX	Curacautín	9203	0.5007	0.00700
IX	Ercilla	9204	0.4637	0.00833
IX	Lonquimay	9205	0.4748	0.00794
IX	Los Sauces	9206	0.5013	0.02288
IX	Lumaco	9207	0.4767	0.00829
IX	Purén	9208	0.4887	0.00724
IX	Renaico	9209	0.4685	0.00875
IX	Traiguén	9210	0.5219	0.00768
IX	Victoria	9211	0.5168	0.00646
X	Puerto Montt	10101	0.5029	0.00582
X	Calbuco	10102	0.4650	0.00519
X	Cochamó	10103	0.4496	0.01001
X	Fresia	10104	0.4615	0.00637
X	Frutillar	10105	0.4895	0.00722
X	Los Muermos	10106	0.4761	0.01689
X	Llanquihue	10107	0.4924	0.00638
X	Maullín	10108	0.4490	0.00544
X	Puerto Varas	10109	0.5262	0.00879
X	Castro	10201	0.4973	0.00569
X	Ancud	10202	0.4824	0.00447
X	Chonchi	10203	0.4761	0.00742
X	Curaco de Vélez	10204	0.4524	0.01297
X	Dalcahue	10205	0.4542	0.00696
X	Puqueldón	10206	0.4460	0.01157
X	Queilén	10207	0.4586	0.00965
X	Quellón	10208	0.4802	0.00874
X	Quemchi	10209	0.4643	0.00812
X	Quinchao	10210	0.4967	0.00888
X	Osorno	10301	0.4968	0.00390
X	Puerto Octay	10302	0.4775	0.00787
X	Purranque	10303	0.4697	0.00571
X	Puyehue	10304	0.4548	0.00715
X	Río Negro	10305	0.4634	0.00650
X	San Juan de La Costa	10306	0.4325	0.00737
X	San Pablo	10307	0.4623	0.00875
X	Chaitén	10401	0.4919	0.00964
X	Futaleufú	10402	0.4676	0.01500
X	Hualaihué	10403	0.4512	0.00793
X	Palena	10404	0.4690	0.01447
X	Valdivia	10501	0.5001	0.00448
X	Corral	10502	0.4592	0.00965
X	Futrono	10503	0.4733	0.00670
X	La Unión	10504	0.4862	0.00512
X	Lago Ranco	10505	0.4601	0.00769
X	Lanco	10506	0.4648	0.00663
X	Los Lagos	10507	0.4598	0.00503
X	Máfil	10508	0.4713	0.00923
X	Mariquina	10509	0.4670	0.00629
X	Paillaco	10510	0.4652	0.00564
X	Panguipulli	10511	0.4732	0.00494
X	Río Bueno	10512	0.4859	0.01423
XI	Coihaique	11101	0.5139	0.01166
XI	Lago Verde	11102	0.4831	0.02205
XI	Aisén	11201	0.5068	0.01366

Reg.	County	Census Code	Gini Coef.	Std. Error	Reg.	County	Census Code	Gini Coef.	Std. Error
VI	Marchihue	6204	0.4153	0.00808	XI	Cisnes	11202	0.4994	0.01520
VI	Navidad	6205	0.4192	0.00949	XI	Guaitecas	11203	0.4878	0.02055
VI	Paredones	6206	0.4129	0.00807	XI	Cochrane	11301	0.5096	0.01702
VI	San Fernando	6301	0.4501	0.00534	XI	O'Higgins	11302	0.4732	0.03027
VI	Chépica	6302	0.4347	0.01375	XI	Tortel	11303	0.4879	0.03486
VI	Chimbarongo	6303	0.4231	0.00519	XI	Chile Chico	11401	0.5065	0.01373
VI	Lolol	6304	0.4252	0.00952	XI	Río Ibáñez	11402	0.4826	0.01441
VI	Nancagua	6305	0.4243	0.00620	XII	Punta Arenas	12101	0.5217	0.00944
VI	Palmilla	6306	0.4302	0.01873	XII	Laguna Blanca	12102	0.5317	0.03654
VI	Peralillo	6307	0.4223	0.00729	XII	Río Verde	12103	0.5412	0.04603
VI	Placilla	6308	0.4253	0.00859	XII	San Gregorio	12104	0.5028	0.02767
VI	Pumanque	6309	0.4098	0.01144	XII	Cabo de Hornos	12201	0.4995	0.01777
VI	Santa Cruz	6310	0.4440	0.00582	XII	Antártica	12202	0.4145	0.08954
VII	Talca	7101	0.4967	0.00779	XII	Porvenir	12301	0.5238	0.01362
VII	Constitución	7102	0.4865	0.00664	XII	Primavera	12302	0.5341	0.02869
VII	Curepto	7103	0.4463	0.00718	XII	Timaukel	12303	0.5088	0.04143
VII	Empedrado	7104	0.4315	0.01075	XII	Natales	12401	0.5207	0.00969
VII	Maule	7105	0.4582	0.00745	XII	Torres del Paine	12402	0.5041	0.03358
VII	Pelarco	7106	0.4349	0.00813	XIII	Santiago	13101	0.4696	0.00344
VII	Pencahue	7107	0.4454	0.00783	XIII	Cerrillos	13102	0.4732	0.00327
VII	Río Claro	7108	0.4315	0.00667	XIII	Cerro Navia	13103	0.4527	0.00280
VII	San Clemente	7109	0.4412	0.00445	XIII	Conchalí	13104	0.4656	0.00333
VII	San Rafael	7110	0.4416	0.00783	XIII	El Bosque	13105	0.4738	0.00574
VII	Cauquenes	7201	0.4793	0.00543	XIII	Estación Central	13106	0.4717	0.00273
VII	Chanco	7202	0.4533	0.00805	XIII	Huechuraba	13107	0.5114	0.00447
VII	Pelluhue	7203	0.4505	0.00863	XIII	Independencia	13108	0.4684	0.00337
VII	Curicó	7301	0.4937	0.00626	XIII	La Cisterna	13109	0.4729	0.00305
VII	Hualañé	7302	0.4466	0.00722	XIII	La Florida	13110	0.4733	0.00226
VII	Licantén	7303	0.4653	0.00932	XIII	La Granja	13111	0.4551	0.00247
VII	Molina	7304	0.4673	0.00580	XIII	La Pintana	13112	0.4480	0.00226
VII	Rauco	7305	0.4526	0.00849	XIII	La Reina	13113	0.4760	0.00292
VII	Romeral	7306	0.4653	0.00800	XIII	Las Condes	13114	0.4462	0.00206
VII	Sagrada Familia	7307	0.4465	0.00663	XIII	Lo Barnechea	13115	0.5057	0.00378
VII	Teno	7308	0.4461	0.00586	XIII	Lo Espejo	13116	0.4535	0.00299
VII	Vichuquén	7309	0.4465	0.01152	XIII	Lo Prado	13117	0.4637	0.00272
VII	Linares	7401	0.4922	0.00648	XIII	Macul	13118	0.4778	0.00299
VII	Colbún	7402	0.4440	0.00635	XIII	Maipú	13119	0.4605	0.00220
VII	Longaví	7403	0.4339	0.00553	XIII	Ñuñoa	13120	0.4603	0.00233
VII	Parral	7404	0.4792	0.00570	XIII	Pedro Aguirre Cerda	13121	0.4967	0.02831
VII	Retiro	7405	0.4329	0.00572	XIII	Peñalolén	13122	0.5121	0.01056
VII	San Javier	7406	0.4712	0.00545	XIII	Providencia	13123	0.4396	0.00231
VII	Villa Alegre	7407	0.4639	0.00718	XIII	Pudahuel	13124	0.4595	0.00228
VII	Yerbas Buenas	7408	0.4398	0.00648	XIII	Quilicura	13125	0.4645	0.00265
VIII	Concepción	8101	0.5188	0.00470	XIII	Quinta Normal	13126	0.4698	0.00356
VIII	Coronel	8102	0.4731	0.00346	XIII	Recoleta	13127	0.4738	0.00271
VIII	Chiguayante	8103	0.5152	0.00500	XIII	Renca	13128	0.4572	0.00291
VIII	Florida	8104	0.4594	0.00719	XIII	San Joaquín	13129	0.4676	0.00292
VIII	Hualqui	8105	0.4683	0.00617	XIII	San Miguel	13130	0.4798	0.00336
VIII	Lota	8106	0.4708	0.00470	XIII	San Ramón	13131	0.4576	0.00284
VIII	Penco	8107	0.4857	0.00570	XIII	Vitacura	13132	0.4297	0.00266
VIII	San Pedro de la Paz	8108	0.5403	0.00500	XIII	Puente Alto	13201	0.4722	0.00836
VIII	Santa Juana	8109	0.4532	0.00627	XIII	Pirque	13202	0.5281	0.00775
VIII	Talcahuano	8110	0.4933	0.00355	XIII	San José de Maipo	13203	0.5024	0.00611
VIII	Tomé	8111	0.5106	0.01724	XIII	Colina	13301	0.5329	0.01910

Reg.	County	Census Code	Gini Coef.	Std. Error	Reg.	County	Census Code	Gini Coef.	Std. Error
VIII	Lebu	8201	0.4936	0.00578	XIII	Lampa	13302	0.4933	0.00546
VIII	Arauco	8202	0.5052	0.00570	XIII	Tiltil	13303	0.4638	0.00592
VIII	Cañete	8203	0.5092	0.00686	XIII	San Bernardo	13401	0.4821	0.00281
VIII	Contulmo	8204	0.4825	0.01000	XIII	Buin	13402	0.4904	0.00390
VIII	Curanilahue	8205	0.4806	0.00473	XIII	Calera de Tango	13403	0.5424	0.00709
VIII	Los Alamos	8206	0.4663	0.00562	XIII	Paine	13404	0.4808	0.00412
VIII	Tirúa	8207	0.5470	0.05998	XIII	Melipilla	13501	0.4830	0.00404
VIII	Los Angeles	8301	0.5216	0.00463	XIII	Alhué	13502	0.4521	0.00918
VIII	Antuco	8302	0.4731	0.01151	XIII	Curacaví	13503	0.4885	0.00525
VIII	Cabrero	8303	0.4744	0.00699	XIII	María Pinto	13504	0.4573	0.00919
VIII	Laja	8304	0.5033	0.00597	XIII	San Pedro	13505	0.4406	0.00786
VIII	Mulchén	8305	0.4903	0.00573	XIII	Talagante	13601	0.4964	0.00429
VIII	Nacimiento	8306	0.4841	0.00552	XIII	El Monte	13602	0.4930	0.01591
VIII	Negrete	8307	0.4624	0.00834	XIII	Isla de Maipo	13603	0.4852	0.00551
VIII	Quilaco	8308	0.4583	0.01042	XIII	Padre Hurtado	13604	0.4720	0.00453
VIII	Quilleco	8309	0.4525	0.00768	XIII	Peñaflor	13605	0.5120	0.02866

Figure 1. Poverty and Inequality in Chile, 1987-2003

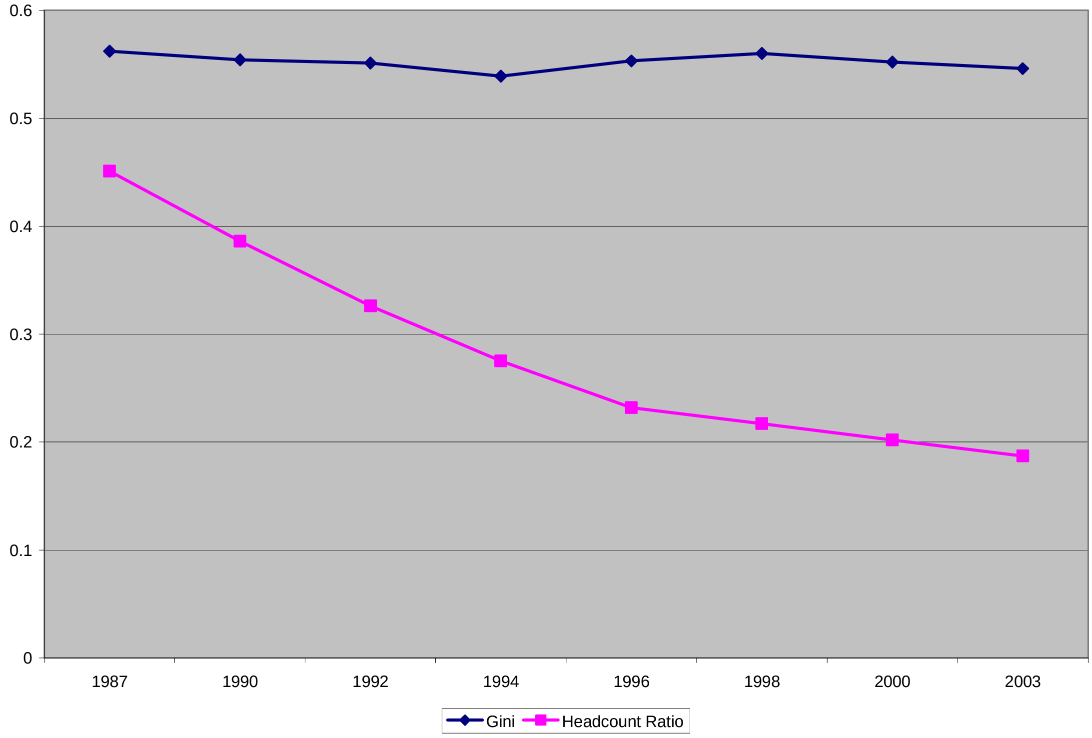

Figure 2. Estimated Ginis in Regions I, II, III, and IV

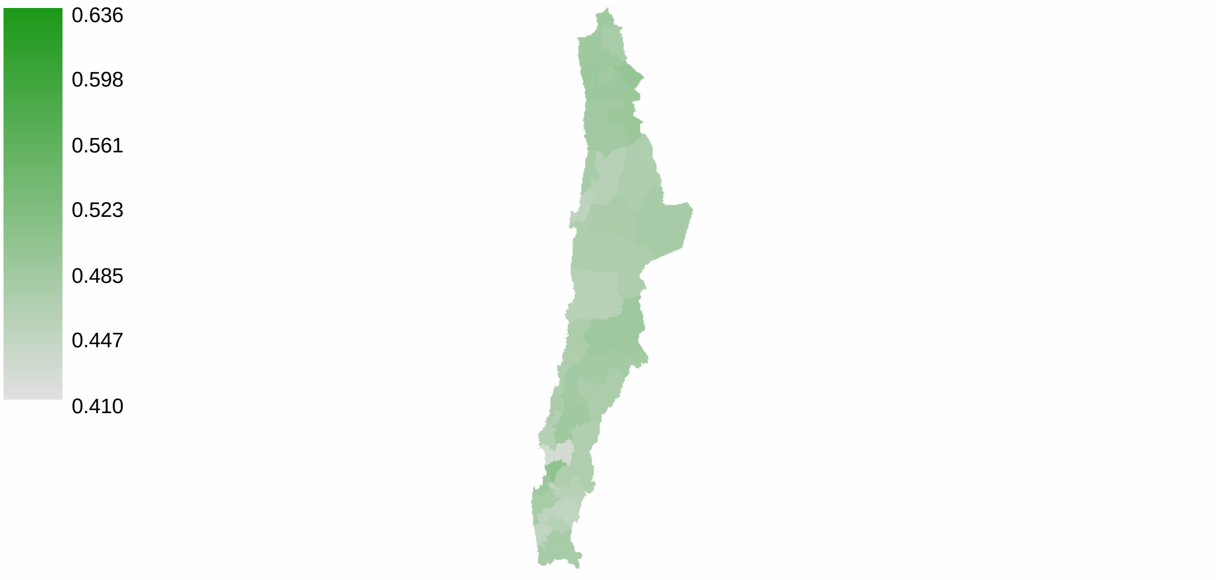

Figure 3. Estimated Ginis in Regions VI, VII, VIII, and IX

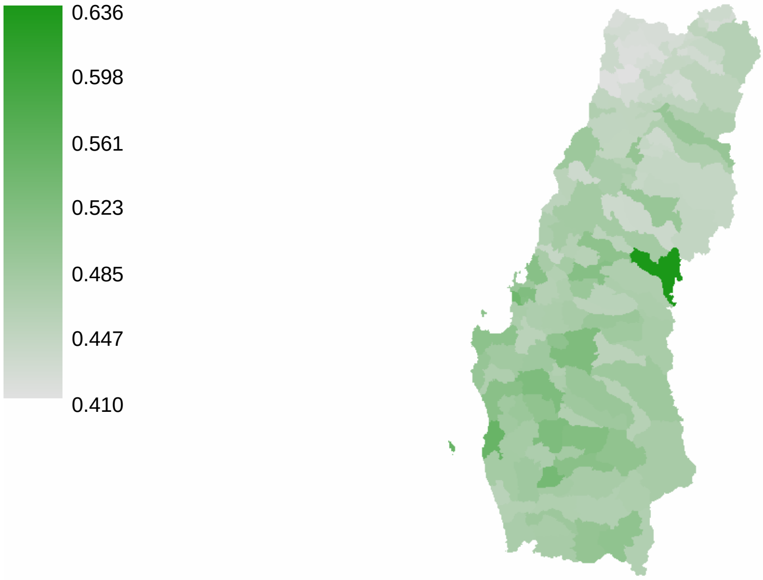

Figure 4. Estimated Ginis in Regions X, XI, and XII

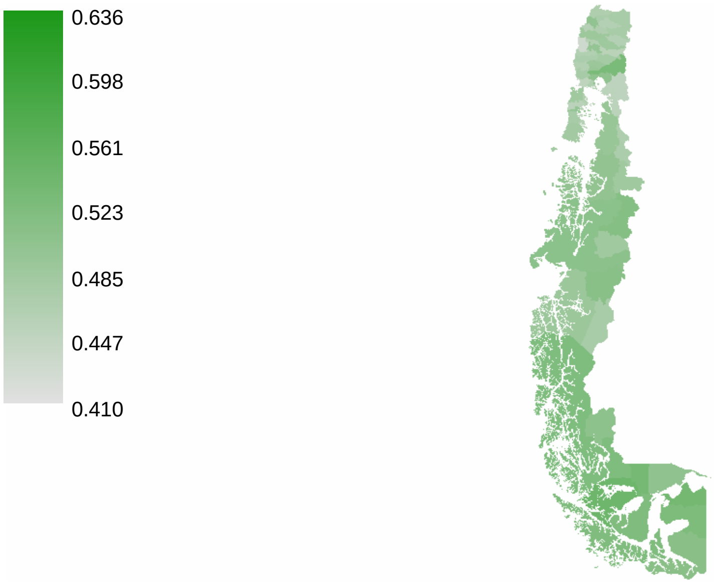

Figure 5. Estimated Ginis in Regions V and XIII

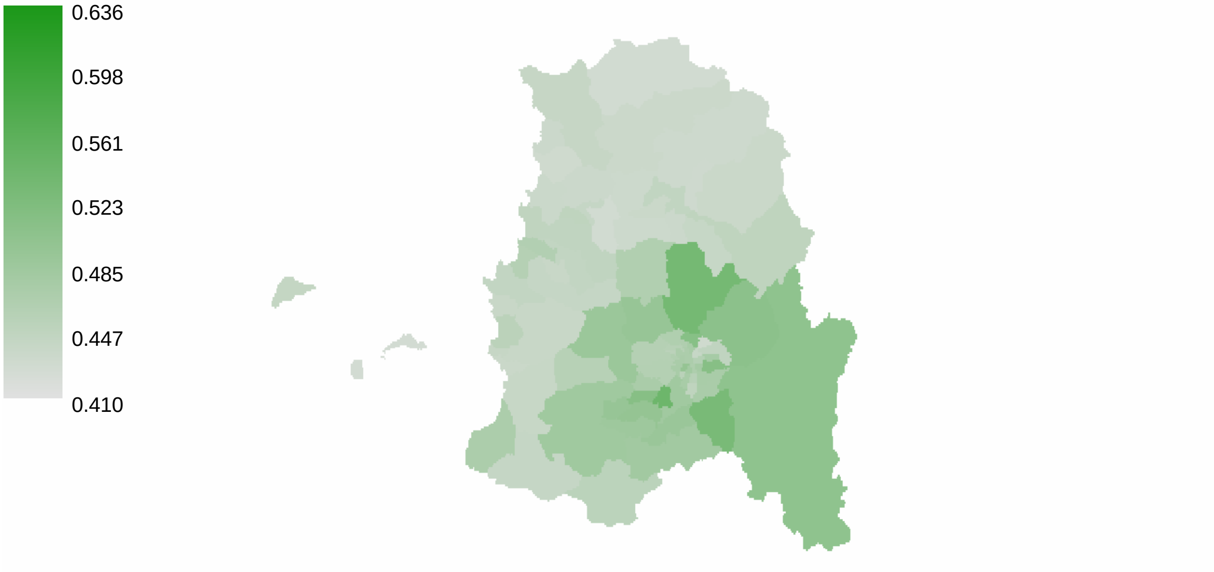

Figure 6. Estimated Ginis with Confidence Intervals

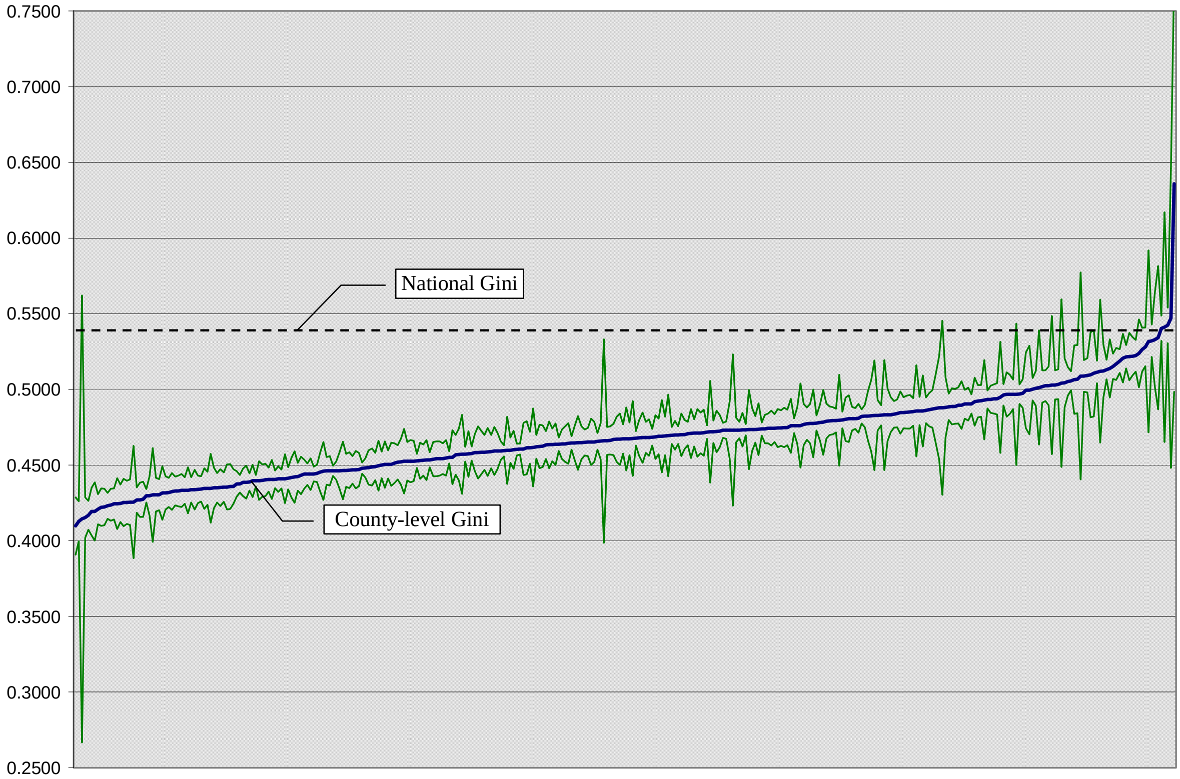

Figure 7: Kernel distribution of Gini coefficients