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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 obtain estimators of inequality that are robust at disaggregated geographic levels. In this paper, we employ this methodology to produce consistent estimators of inequality for every county in Chile. We find a great deal of variation in inequality, with county-level Gini coefficients ranging from 0.41 to 0.63.

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1. Introduction

Chile has been particularly successful in the reduction of poverty during the past 20 years, reducing the poverty rate from 45.1% in 1987 to 18.8% in 2003. However, inequality has remained relatively constant during this period, and it continues to be among the highest in the world (Contreras and Larrañaga 1999; Ferreira and Litchfield 1999; Contreras, Larrañaga, and Valdés 2001; Contreras 2003. For example, the Gini coefficient was 0.547 in 1987 and 0.546 in 2003. This persistence of inequality has become a growing concern of the public and policymakers alike in recent years.

Inequality has been shown to have important effects on poverty, on social outcomes, and on local public finance. 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 impact may also impact tax collections and may have influence the optimal degree of decentralization and provision of public goods (Bardhan and Mookherjee 1999). As a result, new theoretical advances in development economics have returned to emphasizing income distribution as an important outcome (Alesina and Rodrik 1994; Persson and Tabellini 1994; Aghion and Bolton 1997).

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 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 poverty and inequality. The design of these methods has advanced a great deal in recent years, and it is now possible to obtain disaggregated estimates that are statistically precise and reliable. This methodology originates with Hentschel, et al (1999), who modeled consumption behavior in Ecuador using a group of explanatory variables that were available in both a nationally-representative survey and the census. Using first-stage estimates based on the survey data, they estimated incomes for every individual in the census, thereby allowing the estimation of geographically-disaggregated poverty rates. The statistical reliability of this method was improved considerably by Elbers, Lanjouw and Lanjouw (2003), who thoughtfully incorporated errors from the first stage to obtain more precise estimates of income, and thus better estimates of poverty at the local level. 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), and India (Kijima and Lanjouw 2003), and Cambodia (Elbers, et al. 2007).[1] In this paper, we adapt this methodology to the Chilean context to obtain precise estimations of inequality for every county in Chile.

The remainder of the paper is organized as follows: section 2 explains the methodology being used, both conceptually and in detail; section 3 provides detailed information about the data; section 3 describes the application of the methodology to Chile; section 5 presents the results with detailed maps describing inequality at the county level; and section 6 concludes.

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

[1] See also Elbers, et al (2003) and Elbers, et al (2004).

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.[2] The functional form commonly used for estimating the variance of the idiosyncratic error is:

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

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 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:

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

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

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 $N_c xk$ 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.:

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

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:

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

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

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 $\nabla = \left[\partial G^E / \partial \xi\right]$, $V(\xi)$ 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.[3]

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.[4] The final sample includes 68,153 households comprising 257,077 people. These households represent 315 of the 342 counties in Chile, with as few as 49 and as many as 315 households surveyed in each county. Figure 1 shows the counties covered by the 2003 *Casen* survey in black. As is evident from the figure, the survey poorly represents counties in southern Chile. It is important to mention that although *Mideplan* considers the *Casen* to be representative at the regional level and also for 301 self-reporting counties[5], 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

[3] Although the ECLAC adjustments could generate some bias, Contreras and Larrañaga 1999 present evidence to the contrary. Regardless, the unadjusted data are not available.
[4] For further methodological details, see Pizzolito (2005b) and http://www.mideplan.cl/casen/pdf/Metodologia_%202003.pdf
[5] However, this representation would be for the whole county without representation for urban and rural zones within the counties

imputing income (or consumption) to census data are much lower than the ones obtained using survey data (Elbers et al., 2003).

Figure 1: Counties included in the *Casen* survey

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.

4. Methodology applied to Chile

To impute income or consumption 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; regardless, the means and variances of the variables we employ were evaluated to ensure that the explanatory variables are indeed the same. Table 1 lists the set of variables available in both the census and the *Casen*.

Table 1: Explanatory variables

Variable	Casen Survey Question			Census Survey Question	
	Section	Number	Variable	Number	Variable
Sex	Residents	2	SEXO	18	P18
Age	Residents	3	EDAD	19	P19
Marital Status	Residents	6	ECIVIL	27	P27
Head of Household	Residents	13	PCO1	17	P17
Disability	Residents	8	R8A,R8B,R8C	20	P20
Ethnicity	Residents	25	R25	21	P21
Zone	Residents	4	Z		AREA
Literacy	Education	1	E1	25	P25
Education	Education	7	E7C,E7T	26	P26A
Occupation	Employment	9	O9	30	P30
Economic Sector	Employment	8	O8	32	P32
Type of Employment	Employment	7	O7	31	P31
Material of Roof	Housing	226	V10A	4B	V4B
Material of Floor	Housing	224	V9A	4C	V4C
Material of External Walls	Housing	222	V8A	4A	V4A
Source of Electricity	Housing	221	V7	5	V5
Source of Water	Housing	218	V4	6	V6
Water Distribution System	Housing	219	V5	7	V7
Sanitation System	Housing	220	V6	8	V8
Washing Machine	Housing	23	R10A	15	H15_6
Refrigerator	Housing	24	R10B	15	H15_8
Telephone	Residents	24	R10C	15	H15_14
Video	Residents	26	R10D	15	H15_3
Microwave	Residents	27	R10E	15	H15_10
Computer	Residents	28	R10F	15	H15_15
Internet Access	Residents	29,30	R10G, R10H	15	H15_16
Hot Water Heater	Residents	31	R10I	15	H15_12
TV Cable/Satellite	Residents	32,33	R10J, R10K	15	H15_4
Number of Rooms	Housing	210	V3A	10A	V10A
Housing Situation	Housing	229	V12	3	V3
Type of House	Housing	228	V11	1	V1

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.

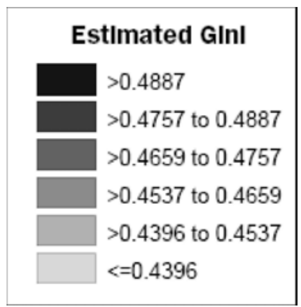
It is important to note that the objective of this first-stage regression is not to determine causality, but rather to make the best possible prediction of per capita income based on observable characteristics of each household. Given that the observable predictors vary across Chile's 13 regions, separate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

5. Results

The five tables in the Appendix show the results of the first-stage regression for the thirteen regions in Chile. Although the coefficients of each explanatory variable vary between distinct regions, the predictive ability of the model is very high enough for cross-sectional data, with R^2 values ranging between 0.36 and 0.52. Additionally, certain empirical regularities emerge for all of the regions. For example, households headed by female have lower per capita incomes than households headed by males.

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).[7] The next section maps the estimated Gini coefficient for each county according to the legend shown in Figure 2.

Figure 2: Estimated Gini coefficient levels



5.1 Inequality maps

Figure 3 shows the distribution of inequality, measured by the Gini coefficient, in the north of Chile, Region I through Region IV. 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, Gini coefficients of 0.424 (standard error of 0.010) and 0.442 (standard error of 0.007).

[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).
[7] The estimated Gini coefficient and standard errors for each county are available at: http://www.economiaynegocios.uahurtado.cl/html/claudio_agostini.html

Figure 3: County-level inequality in northern Chile

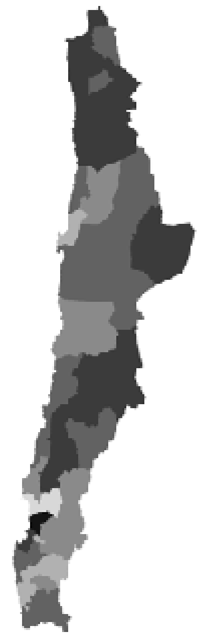


Figure 4 shows the distribution of Gini coefficients in central Chile, including Region VI, Region VII, and Region VIII. To allow greater detail, the Santiago Metropolitan Region is shown separately below. Central Chile includes the extremes of inequality in Chile. The counties with the highest levels 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).

Figure 5 covers southern Chile, including Region IX and Region X. Here, Temuco in Region IX and Puerto Varas Region X display the highest levels of inequality, with Gini coefficents of 0.532 (standard error of 0.006) and 0.526 (standard error of 0.008), 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).

Figure 6 presents the inequality map for the far south of Chile that is often referred to as Patagonia, including the Region XI and Region XIII. In Chilean Patagonia, Río Verde

Figure 4: County-level inequality in central Chile

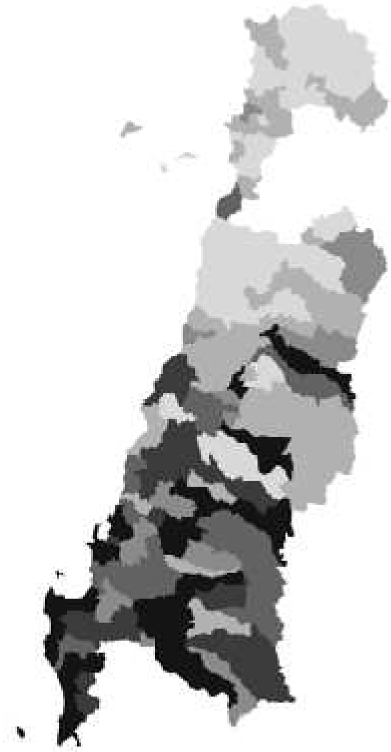
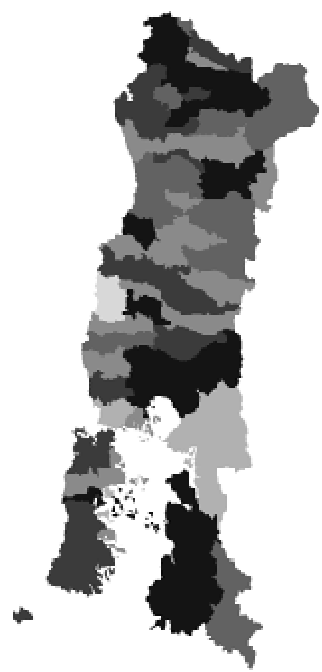
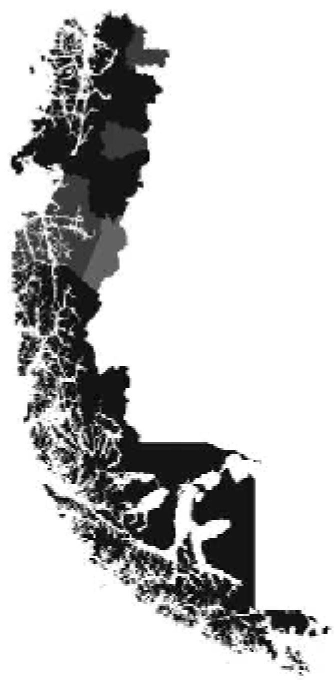


Figure 5: County-level inequality in southern Chile



and Primavera in Region XII display the highest levels of income inqualiity, with estimated Gini coefficients of 0.541 (standard error of 0.040) and 0.534 (standard error of 0.020), respectively. Conversely, O'Higgins and Río Ibañez, both in Region XI, have Gini coefficients of 0.473 (standard error of 0.030) and 0.483 (standard error of 0.010). Thus, although high-inequality counties in Chile's far south do not experience as much inequality as some counties in central Chile, low-inequality counties here are less equal than most counties elsewhere in Chile.

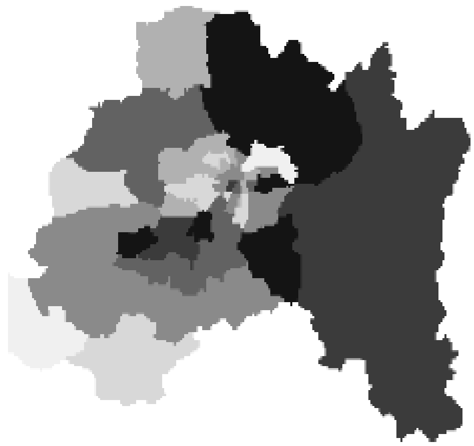
Figure 6: County-level inequality in Chilean Patagonia



Finally, Figure 7 shows the distribution of inequality for the Santiago Metropolitan Region (Region XIII). Here, the districts with the greatest inequality are Calera de Tango and Colina with Gini coefficients of 0.54 and 0.53, respectively. The districts with the least inequality are Vitacura and Providencia, with Gini coefficients of 0.43 and 0.44. The relative homogeneity of income within these two wealthy counties is noteworthy.

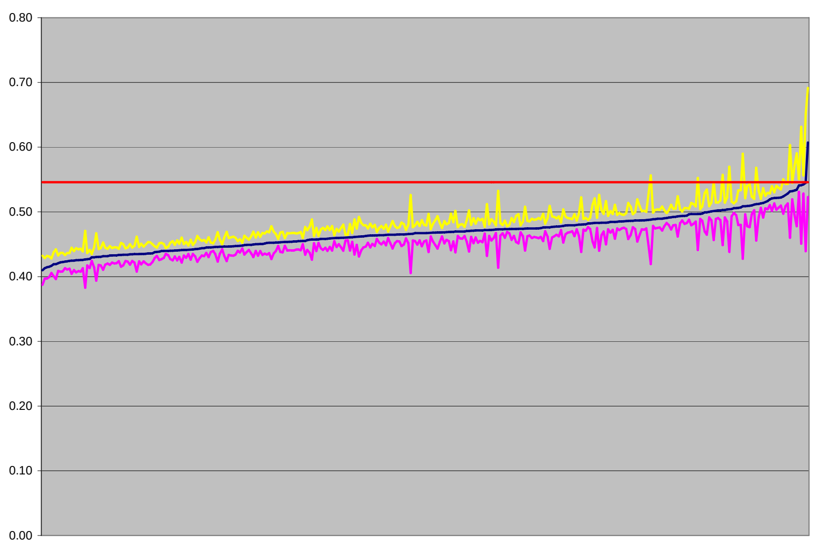
These inequality maps show that variability in county-level inequality is quite high. Figure 8 underscores this observation by showing the distribution of Gini coefficients for

Figure 7: County-level inequality in the Santiago Metropolitan Region



every county in Chile with their respective confidence intervals. Also included in the graph is a line representing the national Gini coefficient according to the *Casen* survey.

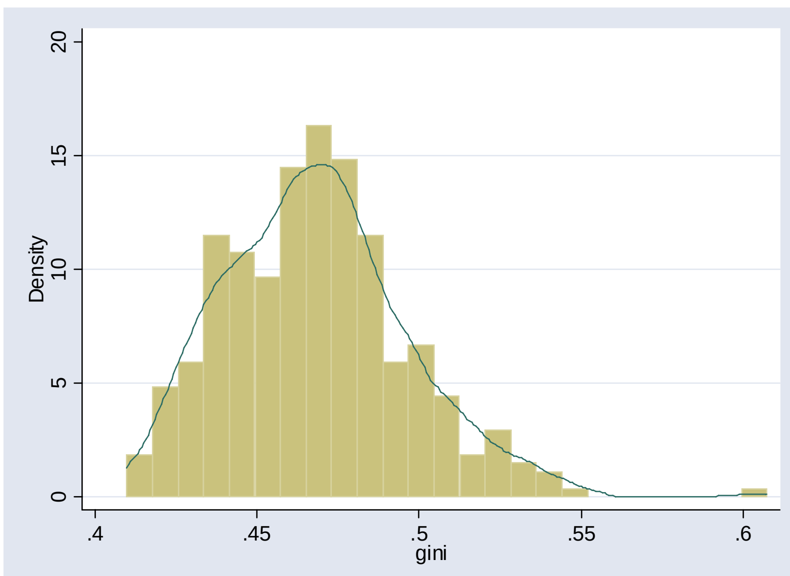
Figure 8: Gini coefficients for all counties and for the whole country



Comparing the distribution of the county Gini coefficients to the national Gini coefficient shows that the great majority of 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 9 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.[8]

Figure 9: Kernel distribution of Gini coefficients



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.

6. Conclusions

The principal objective of this work was to produce disaggregated estimates of inequality for Chile. This was achieved by applying the methodology developed by

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

Hentschel, et al (1999) and perfected by Elbers, et al. (2003) to the Chilean context using the 2002 population census and the 2003 *Casen* survey. The resulting estimates 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.

One application for which our estimates have obvious use is develop better targeting for public policies aimed at reducing inequality. Moreover, these measures of local inequality enable the new investigations into the effects of inequality on a wide spectrum of social outcomes.

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Appendix: First-stage estimates

Table 2: Northern Chile

	Region I	Region II	Region III	Region IV
N Household	-0.42**	-0.401**	-0.465**	-0.372**
N Household^2	0.022**	0.024**	0.031**	0.022**
Educ. Head of Household	0.042**	0.017**	0.017**	0.020**
Female Head of Household	-0.209**	-0.316**	-0.266**	-0.186**
% Children	-1.362**	-0.618**	-0.499**	-0.432**
Washing Machine	0.177**	0.074*	0.142**	0.128**
Heater	0.217**	0.322**	0.191**	0.221**
Cell Phone	0.181**	0.118**	0.137**	0.133**
Fixed Line Phone	0.15**	0.172**	0.160**	
TV Cable/Satellite	0.148**	0.124**	0.194**	0.257**
Microwave	0.131**			
Computer		0.161**	0.190**	0.166**
Internet Access	0.216**	0.190**	0.341**	0.269**
Number of Bedrooms	0.072**	0.072**	0.068**	0.071**
Adobe Walls	-0.12**			
Tiled Roof				0.556**
Zinc Roof				0.338**
Electricity Web	-0.18**	-0.402**		
Individual Generator	-0.145**			
Without Electricity		-0.253**		
Sewer System		-0.244**		
Septic Tank	0.131**			
Constant	11.731**	12.53**	11.772**	11.030**
R^2	0.4496	0.3636	0.4199	0.4045
F	97.71	64.27	102.27	131.86
N	2172	1817	1851	3123

* significant at 5%; ** significant at 1%

Table 3: Central Chile

	Region I	Region II	Region III	Region IV
N Household	-0.339**	-0.392**	-0.363**	-0.420**
N Household^2	0.019**	0.027**	0.023**	0.027**
Educ. Head of Household	0.021**	0.012**	0.015**	0.020**
Female Head of Household	-0.139**	-0.130**	-0.103**	-0.137**
Ethnicity Head of Household				-0.091**
% Children	-0.681**	-0.730**	-0.712**	-0.517**
% Disabled		-0.197**		-0.281**
Washing Machine	0.142**	0.103**	0.100**	0.111**
Heater	0.136**	0.180**	0.185**	0.240**
Cell Phone	0.118**	0.158**	0.100**	0.128**
Fixed Line Phone	0.111**	0.231**	0.212**	0.213**
TV Cable/Satellite	0.143**	0.169**	0.199**	0.216**
Microwave	0.157**	0.185**	0.242**	0.201**
Computer	0.202**	0.259**	0.248**	0.264**
Internet Access	0.252**	0.305**	0.224**	
Number of Bedrooms	0.091**	0.078**	0.110**	0.102**
Dirt Floor				-0.076**
Well Water	0.078**			
Adobe Walls		0.749**		
Cement Walls		0.844**		
Brick Walls		0.723**		
Dividing Walls NF		0.747**		
Dividing Walls F		0.750**		
Electricity Web	-0.224**			
Sewer System	-0.078**	-0.061**	-0.097**	
Septic Tank	-0.068**			0.097**
Constant	11.528**	10.760**	11.223**	
R^2	0.3889	0.3996	0.3601	0.4116
F	256.36	101.64	220.2	386.69
N	7271	3229	6278	11077

* significant at 5%; ** significant at 1%

Table 4: Southern and Far Southern Zones

	Region I	Region II	Region III	Region IV
N Household	-0.378**	-0.388**	-0.511**	-0.513**
N Household^2	0.022**	0.024**	0.036**	0.030**
Educ. Head of Household	0.021**	0.028**	0.036**	0.046**
Female Head of Household	-0.136**	-0.113**	-0.239**	-0.194**
% Children	-0.641**	-0.469**		
% Disabled		-0.125**	-0.313**	-0.640**
Washing Machine	0.137**	0.142**	0.246**	0.157**
Heater	0.200**	0.261**		
Cell Phone	0.134**	0.132**	0.143**	
Fixed Line Phone	0.186**	0.206**	0.264**	0.135**
TV Cable/Satellite	0.286**	0.125**	0.272**	0.256**
Microwave	0.172**	0.218**		0.184**
Computer	0.298**	0.228**	0.287**	0.198**
Internet Access	0.251**	0.176**		
Number of Bedrooms	0.102**	0.096**	0.099**	0.130**
Well Water	0.198**	0.116**		
Canal or River Water	0.216**	0.141**		
Adobe Walls	0.729**	0.427**		
Cement Walls	0.978**			
Brick Walls	0.861**			
Dividing Walls NF	0.696**			
Dividing Walls F	0.779**			
Tiled Roof			-0.292**	
Electricity Web				-0.704**
Individual Generator		0.400**		
Without Electricity			0.330**	
Septic Tank	0.116**	0.088**		
Constant	10.313**	11.167**	11.661**	12.265**
R^2	0.433	0.413	0.375	0.405
F	217.550	286.120	40.620	44.770
N	6283.000	8172.000	895.000	802.000

* significant at 5%; ** significant at 1%

Table 5: Santiago Metropolitan Region

	Metropolitan Region
N Household	-0.401**
N Household^2	0.024**
Educ. Head of Household	0.037**
% Children	-0.079**
% Disabled	-0.033**
Washing Machine	0.107**
Heater	0.136**
Cell Phone	0.190**
Fixed Line Phone	0.149**
TV Cable/Satellite	0.310**
Microwave	0.136**
Computer	0.155**
Internet Access	0.376**
Number of Bedrooms	0.133**
Dirt Floor	0.184**
Well Water	0.111**
Sewer System	-0.128**
Constant	11.14**
R^2	0.5248
F	877.83
N	13530

* significant at 5%; ** significant at 1%