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LOCAL DISTRIBUTIONAL EFFECTS OF GOVERNMENT CASH TRANSFERS IN CHILE

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Despite rapid economic growth and poverty reduction, inequality in Chile has remained high and remarkably constant over the last 20 years, prompting academic and public interest in the subject. Due to data limitations, however, research on inequality in Chile has concentrated on the national and regional levels. The impact of cash subsidies to poor households on local inequality is thus not well understood. Using poverty-mapping methods to asses this impact, we find heterogeneity in the effectiveness of regional and municipal governments in reducing inequality via poverty-reduction transfers, suggesting that alternative targeting regimes may complement current practice in aiding the poor.

1. INTRODUCTION

If targeting is effective, then government programs which aim to reduce poverty may also reduce inequality. These reductions in inequality can serve as a catalyst for further reductions in poverty (Ravallion, 1997), sparking a virtuous cycle. Even in the absence of such benefits, however, reductions in inequality—particularly at the local level—are likely to enhance social cohesion while also improving individual wellbeing.

For example, Ehrlich (1973) and Chiu and Madden (1998) argue that the incentive to commit crimes rises in communities with greater inequality, and Demombynes and Özler (2005) provide empirical evidence of a causal relationship between local inequality and residential burglaries. Deaton (2001) further shows that income inequality within the local community represents a greater hazard to health than inequality at the national level. Moreover, Frank (1997) notes that U.S. counties with high income inequality exhibit higher median housing prices, higher personal bankruptcy rates, and higher divorce rates. In addition, Easterlin (1995) reports a positive correlation between individual income and self-reported happiness, but finds that happiness is not highly correlated with either national

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income or with increases in income over time (see also Frank, 1985; Oswald, 1997). Indeed, local income inequality may exacerbate ethnic and class conflict and contribute to social strife (Blau and Blau, 1982). These findings suggest that identifying instruments for resolving inequality at the local level is of critical policy importance.

The Chilean government has implemented an aggressive campaign to reduce poverty via a series of targeted cash transfers. However, the implications of such transfers for income inequality are unclear. On the one hand, Engel *et al.* (1999) demonstrate that targeted transfers would be far more effective than radical tax reforms in reducing inequality at the national level in Chile. On the other hand, transfers may also raise national inequality; as a case in point, Chile's generous housing subsidies have had the undesirable effect of tying individuals to specific locations, thereby preventing migration to more productive areas with higher wages (Soto and Torche, 2004). The effects of cash transfers on local inequality are even less well understood because surveys with detailed income and transfer information are not representative at low levels of aggregation.

In this paper, we adapt the poverty mapping methodology pioneered by Hentschel *et al.* (2000) and refined by Elbers *et al.* (2003) to the Chilean context with the goal of assessing how government transfers to poor households affect inequality at the county level.

Specifically, poverty mapping techniques are used to generate estimates of inequality twice—once before households receive any transfers from the government and once afterward. Comparing the two estimates of inequality for each locality, we find that the effect of transfers on inequality varies considerably by region.[1] In Regions IV, VII, VIII, IX, and X, for example, transfers that exceed the national average produce statistically significant reductions (at the 0.01 level) in inequality in all but two of 179 counties. Estimated inequality falls in 84 percent of the counties in Regions III, V, and VI despite below-average to average transfers in these areas. In Regions I, II, and XII, very modest gains against inequality are perhaps not surprising given the low expected values of subsidies. Finally, Region XI sees very little reduction in inequality despite very high transfers, while inequality falls in 73 percent of counties in Region XIII despite having the lowest expected value of transfers. Such heterogeneity in outcomes implies either that the eligibility criteria for cash transfers does not always identify households at the bottom of the income distribution or that poverty-alleviation transfers are sometimes diverted to alternative purposes.

The remainder of this paper is organized as follows: Section 2 summarizes the methodology; Section 3 describes government programs for poverty reduction in Chile, including the various subsidies, as well as special features of the Chilean case; Section 4 discusses the data used in the analysis; Section 5 presents the empirical results; and Section 6 concludes.

[1]Chile is comprised of 13 administrative regions. Each has a formal name and a Roman numeral, the latter more commonly used. The numbers are assigned sequentially from north to south, with the exception of Region XIII (the Santiago Metropolitan Region), which is located between Regions V and VI. Each region consists of multiple provinces, which are further divided into 342 counties. Each county has its own government except Antártica, which is governed by Cabo de Hornos County. We focus on the 341 independent counties.

2. Methodology

The methodology proposed by Hentschel *et al.* (2000) and refined by Elbers *et al.* (2003) takes advantage of the detailed data in household surveys and the universal coverage of censuses. The intuition is conceptually straightforward: household income is estimated using survey data, restricting the explanatory variables to those available in both the survey and a census from a similar point in time. These parameters are then used to estimate income 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.[2] For the purposes of this paper, we produce *two* sets of local inequality indicators—one for per capita autonomous income (i.e., pre-transfer income) for each household and one for per capita total income (which consists of autonomous income plus all government cash transfers)—for each household. These estimates are then formally compared to determine the effect of government transfers on inequality.

The execution of the method is somewhat more complicated. We provide a brief overview here and a detailed accounting in Appendix 1; readers who are interested in the complete statistical properties of the estimators are referred to Elbers *et al.* (2003). First, a detailed household survey is used to estimate the joint distribution of household income and a vector of explanatory variables. Restricting the set of explanatory variables to those available in the census, these "first stage" estimates are then used to generate the distribution of income for any subgroup of the population, conditioning on the observed characteristics of that subgroup. The simplest means of estimating the model is via a linear approximation of the conditional expectation, allowing geographic effects and heteroskedasticity in 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, so it is important to explain the variation in income due to location via observable variables to the greatest extent possible; stepwise regression is therefore used to derive the best-fitting specification for each of Chile's 13 regions.

The result of this first-stage estimation is a vector of coefficients, 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 income and the relevant errors. For these effects, bootstrapping is used to simulate values of household income. The complete set of simulated values is then used to calculate the expected value of inequality for each subgroup. This procedure is repeated 250 times, taking a new set of coefficients and errors for each simulation; the mean and the standard deviations of the coefficients constitute the point estimates and the standard deviations for the inequality indicator, respectively.

[2]Poverty mapping has been used to estimate wellbeing at the local level in Cambodia, Ecuador, Madagascar, Mozambique, South Africa, Tanzania, and elsewhere (see, for example, Demombynes *et al.*, 2002; Elbers *et al.*, 2003; Elbers *et al.*, 2004; Demombynes and Özler, 2005; Simler and Nhate, 2005; Simler, 2006; Elbers *et al.*, 2007).

Finally, the standard error of the inequality indicator must be estimated as accurately as possible in order to infer precise conclusions from the estimates. As shown in Appendix 1, the prediction error has three components: the first is given by the presence of a stochastic error in the first stage model, which implies that the actual income of the household deviates from its expected value (idiosyncratic error); the second is determined by the variance of the first stage parameter estimators (model error); and the third is given by the use of an inaccurate method to calculate the estimator of the inequality indicator (computation error). The idiosyncratic error falls proportionately with the size of the population in each area. This component of the error rises with lower levels of geographic disaggregation, limiting the extent of disaggregation possible. The model error is determined by the properties of the first stage estimators; its magnitude thus depends only on the precision of the first stage parameter estimates. For this reason, we made every effort to obtain the best fir in the first-stage regression. The computation error falls by increasing the number of simulations. Several papers that use this methodology specify 100 simulations. Despite the computationally-intensive simulation process, we specify 250 simulations to reduce this component of the error as much as possible.[3]

The precision of the estimates obtained using this methodology has received considerable attention in the recent literature. In particular, Tarozzi and Deaton (2008) provide evidence based on Monte Carlo simulations that welfare estimates obtained via poverty mapping may be less precise than initially believed. Their main observations are two-fold: first, that estimating a model at an aggregated geographic level to predict welfare at a lower level implicitly assumes homogeneity within regions; second, that the assumptions of homoskedasticity and iid errors in the cluster effect may not hold in the presence of spatial correlation among small areas within the same region. To address these concerns, we estimate a different model for each of the 13 regions in Chile, reducing the size of the aggregate level at which homogeneity is assumed. Second, although inequality estimates are obtained at the county level, we include cluster effects at a lower level of aggregation than counties to control for latent location effects. Third, we control for a wide variety of observable household characteristics (including demographics, housing characteristics, and asset ownership) which, as shown by Elbers *et al.* (2008), partially captures the potential spatial correlation. Fourth, we address the concern related to the homoskedasticity assumption of the error term by explicitly modeling a heteroskedastic household error. Elbers *et al.* (2008) show that the poverty mapping procedure performs very well under such circumstances.

3. Public Policy in Chile

Beginning in the early 1980s, the government adopted a wide-ranging set of policies to reduce poverty. Central to the government's anti-poverty policy was the development of a standardized form (the "CAS Card," renamed the "CAS-2 Card" after revisions in 1987) to identify poor households on the basis of housing criteria, especially construction materials, housing density, access to potable water,

[3]There are no significant gains in efficiency by further increasing the number of repetitions.

and assets.[4] Indeed, this form became the primary data point for setting government priorities in the provision of public housing, with the concentration of poor households in any given region in 1982 and 1992 directly influencing the allocation of housing subsidies over the subsequent decade (Soto and Torche, 2004). Between 1990 and 2000, housing subsidies increased at an average rate of 10 percent per year in real terms, and poor neighborhoods received additional subsidies to develop public sewerage and electric systems on the basis of these criteria. Although the efficacy of using housing criteria to identify beneficiaries of other social programs deserves scrutiny, these criteria were also used to identify locations for new schools and healthcare facilities as well as to identify indigent households to receive direct cash transfers.

There are five programs through which the government makes cash transfers to poor households in Chile, as follows:

(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. Eligibility is determined by the CAS-2 Card. This program is administered by individual counties, but the budget is assigned by the regional governments according to the distribution of CAS-2 Card scores in each county. The benefit was CH$4,126 per month[5] per recipient in 2003, and it is indexed to inflation.

(2) Assistance Pensions (PASIS): Pensions 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.[6] These transfers are only available to individuals who have at least three continuous years of residency in Chile and who do not receive any other pensions. The regional government evaluates households for eligibility based on the CAS-2 Card score; however, because the number of subsidies available to each region is fixed by the Social Security Commission, the cut-off score varies by region (and, potentially, by county). In 2003, the benefit totaled CH$45,091 per month for the physically disabled and twice that amount for the mentally disabled; it, too, is indexed to inflation.

(3) Chile Solidario: A cash transfer program for immediate poverty alleviation that also explicitly seeks to provide the poor with the tools to allow them to permanently escape poverty by their own means. For this reason, the program includes both cash and counseling services for indigent and high-risk households, particularly those with female heads. Eligibility is determined by the CAS-2 Card. During the first phase of the program, beneficiaries receive a monthly payment that decreases from CH$10,500 to CH$4,126 over 24 months (2003 rates), conditional on frequent meetings with counselors to learn budgeting, goal-setting, and employment skills; counselors also offer guidance on other support programs for which the household may be eligible. After two years, beneficiaries who

[4]Soto and Torche (2004) provide additional details on the CAS form and the criteria for poverty it formalizes. Officially designated poor households are re-evaluated every three years for eligibility.

[5]In 2003, US$1 = CH$691.4 on average.

[6]The minimum monthly pension allowance was CH$89,715 in 2006.

have successfully completed the counseling program are automatically enrolled in the SUF program for up to 36 months. Even though this program also considers in-kind transfers such as counseling, only the cash component is used in the empirical part of this study for two reasons: first, it is difficult to asses the value of in-kind components; second, the cross-sectional data employed in this city do not allow us to evaluate impacts (such as counseling) that accrue over time.

(4) Water and Sewage Subsidy (SAP): A three-year, renewable subsidy to offset the cost of water among poor households. Eligibility is determined by the CAS-2 Card. Although the program is administered by the county government, the Ministry of Finance sets the budget available to each region and regional governments set the number of subsidies available to each county; as such, the cut-off score may vary by county. This subsidy covers between 20 and 85 percent of the cost of water for up to 15 cubic meters per month; it is paid directly to water providers and discounted from the water bills of beneficiaries.

(5) Unemployment: A decreasing monthly payment for up to 12 months for individuals who lost work through no fault of their own. Eligibility is based on formal employment for at least 52 weeks during the previous two years[7] and not having rejected job opportunities offered by the National Training and Employment Service or the county government. Although the CAS-2 Card is not used to assign this subsidy, it is designed with the intention of preventing households from falling into poverty as a result of employment shocks. In 2003, the benefit was CH$17,338 the first 3 months, decreasing to CH$11,560 for the next three months, and to CH$8669 the last 6 months of eligibility.

The cash components of all five of these transfers are included in our analysis.[8]

The institutional design of government cash transfers in Chile is as follows: the central government determines the aggregate budget for cash transfer programs in a discussion with the National Congress, and then it fixes the budget for of each region. Within each region, the regional government (appointed by the central government) fixes the budget for each county and delegates the task of choosing beneficiaries to democratically elected county governments, which use the CAS-2 Card to do so. The CAS-2 Card assigns a score that allows county governments to rank poor households from the worse-off to the better-off, and transfers are assigned based on this ranking. Because the poorest people in any given area have the highest priority, transfers should reduce inequality if there is good targeting.[9] Additionally, the Chile Solidario program targets the worse-off poor that had been hard to reach through other programs, and a significant objective of this program is to make beneficiaries aware of other social programs

[7]For self-employed workers, eligibility is based on 12 consecutive months of contributions to social security in the previous two years.

[8]For example, Chile Solidario includes both cash and in-kind transfers, yet only the cash component is considered in the analysis.

[9]With a different mechanism, the expected impact would be uncertain. For example if the better-off poor households were ranked first in order to reduce the poverty rate, inequality could increase.

to which they are entitled, again reinforcing the idea that good targeting in this context should reduce inequality.

The Chilean Constitution forbids earmarking taxes to individual expenditures, so there is no specific financing for poverty-reduction transfers. Therefore, such transfers are financed out of total tax revenues. In 2003, 51.6 percent of total tax revenues came from the Value Added Tax, 27.4 percent from income taxes, 12.1 percent from excise taxes, 4.5 percent from tariffs, and 4.4 percent from transaction taxes. There are no local taxes in Chile, so neither regional nor county governments can supplement their budgets for the cash transfers budget they receive. Rather, their main role is basically to allocate the budget among poor people. Still, given that the Value Added Tax is likely to be regressive and that the progressive income tax is applied to only 18 percent of the labor force, it may be the case that taxes exacerbate inequality. Our estimates of the impact of cash transfers would thus be biased upward.[10] Similarly, because our estimates of the impact of cash transfers on inequality do not deal with the potential offsetting behavioral effects, they could be interpreted as an upper bound: specifically, in the absence of transfers, people would have to work more or exercise more effort in order to increase their incomes. On the other hand, cash transfers may facilitate greater labor force participation, and thus the effect of transfers on inequality may be understated. For example, the Chile Solidario transfer that targets female-headed households may enable single parents to pay for day care that they may otherwise not be able to afford. Similarly, pensions may enable less-productive elderly people to substitute child care duties for more productive young women.

Table 1 provides summary statistics for the number of recipients in each of Chile's 13 regions. Nearly 954,000 individuals (6.3 percent of the population) receive the Family Subsidy each month. Almost 13 percent of the people living in Region IX benefit, while fewer than 2.3 percent of households in Region XII do. By contrast, only 3,682 individuals received Unemployment transfers each month on average, although this is at least partially due to the fact that the government replaced the transfer with mandatory unemployment insurance for those starting new jobs since 2002; this transfer therefore ceases to be a policy tool for addressing either poverty or inequality. The average monthly value of Unemployment payments is CH$11,491. Assistance Pensions dwarf the other subsidies, with an average benefit of CH$45,059. However, only 2.8 percent of Chile's population receives these transfers. The distribution of this subsidy is similar to that of the Family Subsidy.

The Solidarity Subsidy and Water and Sewage Subsidy are provided to households rather than individuals. Approximately 1.1 percent of households receive the former, with the greatest share in Regions III and VII. The average monthly value of the Solidarity Subsidy is CH$9,842. Finally, the Water and Sewage Subsidy is allocated to almost 16 percent of households. The subsidy is particularly prevalent in the arid north of Chile (Regions I, II, III, and IV) and in Region XI. Fewer than 7 percent of the households in Region XIII receive this subsidy. Moreover, unlike

[10]For this reason, our estimates must be considered as measuring the impact of cash transfers on after-tax income and not as the net impact of cash transfers on poverty.

TABLE 1

Poverty-Reduction Transfers by Region

Region	Family Subsidy[A]				Unemployment[A]				Assistance Pensions[A]			
	Recipients†	Share‡	Amount*	Average**	Recipients†	Share‡	Amount*	Average**	Recipients†	Share‡	Amount*	Average**
I	19,122	4.50%	$76,603	$4,006	135	0.03%	$1,524	$11,291	6,249	1.47%	$282,220	$45,163
II	15,454	3.21%	$61,169	$3,958	47	0.01%	$540	$11,498	5,862	1.22%	$263,641	$44,975
III	18,328	7.24%	$74,011	$4,038	70	0.03%	$797	$11,388	5,980	2.36%	$270,571	$45,246
IV	50,402	8.36%	$200,837	$3,985	149	0.02%	$1,716	$11,514	20,273	3.36%	$920,557	$45,408
V	81,648	5.33%	$326,416	$3,998	519	0.03%	$6,053	$11,663	32,502	2.12%	$1,461,835	$44,977
VI	52,494	6.77%	$208,443	$3,971	114	0.01%	$1,297	$11,374	23,730	3.06%	$1,065,764	$44,912
VII	100,010	11.05%	$396,176	$3,961	144	0.02%	$1,651	$11,468	30,825	3.40%	$1,388,065	$45,030
VIII	180,915	9.73%	$717,320	$3,965	544	0.03%	$6,266	$11,517	77,195	4.15%	$3,450,309	$44,696
IX	109,755	12.65%	$447,964	$4,081	190	0.02%	$2,270	$11,949	54,944	6.33%	$2,490,582	$45,329
X	117,391	11.01%	$471,432	$4,016	203	0.02%	$2,358	$11,617	56,699	5.32%	$2,570,569	$45,337
XI	8,732	9.70%	$35,546	$4,071	9	0.01%	$109	$12,056	4,144	4.61%	$187,565	$45,262
XII	3,296	2.23%	$13,059	$3,962	29	0.02%	$342	$11,776	2,107	1.43%	$96,191	$45,653
XIII	196,350	3.25%	$799,425	$4,071	1,475	0.02%	$16,768	$11,368	103,829	1.72%	$4,672,439	$45,001
Total	953,897	6.34%	$3,828,403	$4,013	3,628	0.02%	$41,691	$11,491	424,339	2.82%	$19,120,309	$45,059

Region	Solidarity Subsidy[B]				Water Subsidy[B]				Expected Value of Subsidy
	Recipients†	Share‡	Amount*	Average**	Recipients†	Share‡	Amount*	Average**	
I	1,690	1.51%	$16,739	$9,905	32,595	29.14%	$181,758	$5,576	$1,317
II	910	0.73%	$8,749	$9,615	37,787	30.45%	$276,450	$7,316	$1,267
III	1,683	2.45%	$16,425	$9,760	25,355	36.91%	$87,661	$3,457	$1,775
IV	1,809	1.08%	$17,837	$9,860	43,160	25.86%	$169,403	$3,925	$2,173
V	4,559	1.03%	$45,113	$9,895	81,311	18.45%	$315,421	$3,879	$1,408
VI	2,562	1.20%	$24,642	$9,618	33,872	15.81%	$90,136	$2,661	$1,792
VII	4,900	1.94%	$47,824	$9,760	63,292	25.10%	$133,662	$2,112	$2,173
VIII	6,612	1.31%	$65,342	$9,882	103,670	20.61%	$368,358	$3,553	$2,478
IX	3,815	1.60%	$38,189	$10,010	52,692	22.11%	$139,084	$2,640	$3,595
X	4,881	1.65%	$48,541	$9,945	50,919	17.21%	$194,525	$3,820	$3,083
XI	371	1.44%	$3,710	$10,000	9,253	36.01%	$47,448	$5,128	$3,049
XII	528	1.22%	$5,134	$9,723	8,612	19.93%	$28,475	$3,307	$971
XIII	9,898	0.60%	$96,938	$9,794	109,236	6.59%	$251,741	$2,305	$966
Total	44,218	1.07%	$435,184	$9,842	651,752	15.74%	$2,284,122	$3,505	$1,708

Notes:
[A]Source: Superintendent of Social Security. The Family Subsidy, Unemployment, and Assistance Pensions are given to individuals.
[B]Source: Executive Committee, Chile Solidario, Ministry of Planning. The Solidarity Subsidy and Water Subsidy are given to households.
†Represents the average number of beneficiaries each month.
‡Indicates the percentage of individuals or households in the region that receive the subsidy.
*Represents the total monthly value of the transfer, by region, in thousands of Chilean Pesos.
**Indicates the average monthly value of the transfer for all recipients in the region.

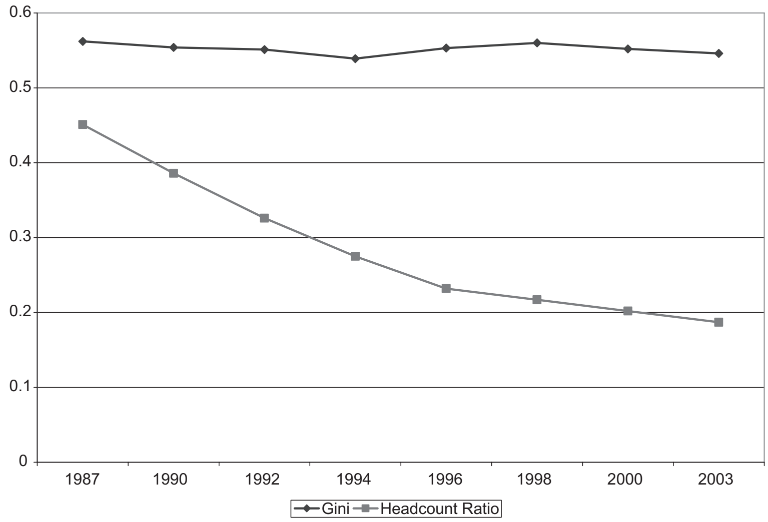

Figure 1. Income Inequality and Poverty in Chile: 1987–2003

many other subsidies, the value of the Water and Sewage Subsidy varies by region, with beneficiaries in Regions I, II, and XI receiving far greater subsidies than households elsewhere, reflecting the cost of purchasing and transporting water in these areas.[11] The average value of the subsidy varies from CH$2,112 in Region VII to CH$7316 in Region II. Weighting household subsidies by the mean number of household members in each region, the total expected monthly value of all subsidies for a representative person ranges from CH$966 in Region XIII to CH$3595 in Region XI; the national average is CH$1,708.

As noted above, public policy that targets poverty may also affect inequality. For example, cash subsidies to poor and indigent families are likely to reduce income inequality by raising incomes at the lower end of the distribution. Still, poor targeting or elite capture may moderate inequality reduction or even lead to increased inequality. Such factors may help to explain why Chile has seen virtually no progress against inequality despite rapid reductions in poverty through targeted programs (Figure 1). Indeed, the persistence of high inequality in Chile has emerged as an important issue of public debate[12] and academic interest (e.g., Contreras, 1996; Beyer, 1997; Contreras and Ruiz-Tagle, 1997; Valdés, 1999; Contreras *et al.*, 2001).

4. Data

The survey employed to impute income as described above is the November 2003 National Survey of Socioeconomic Characterization (*Casen*), administered

[11]For example, the cost of drinking water is up to 66 percent higher than the national average in Region XI despite heavy rainfall in the area.

[12]To wit, each of the three main candidates addressed the issue extensively during the 2006 presidential campaign. In addition, inequality was the explicit focus of one presidential debate.

by the University of Chile on behalf of the Ministry of Planning (*Mideplan*). Unlike the national census, the *Casen* collects detailed income data for individuals and households, including cash transfers from the government. The survey also collects data on demographic characteristics of household members, living conditions, ownership of durable goods, access to sanitation, and health and education characteristics. Before these data are made available, the Economic Commission for Latin America and the Caribbean (ECLAC) undertakes a standardized procedure to correct for reporting errors and discrepancies with national accounts.[13] These procedures are summarized in Appendix 2 and detailed fully in ECLAC, IPEA, and UNDP (2002).

The survey utilizes multistage random sampling with regional stratification and clustering. In the first stage, the country is 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. The sampling frame of the *Casen* is based on the Population and Housing Census and by local records of new construction. In the second stage, households are selected into the sample with equal probability.[14] 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. Although *Mideplan* considers the *Casen* to be representative both at the regional level and at the level of the 301 self-reporting counties, there is no consensus with respect to representativeness at the county level; indeed, many scholars consider the *Casen* to be representative at the national and regional levels only (e.g., Valdés, 1999; Contreras *et al.*, 2001; Pizzolito, 2005).

Using the *Casen* alone to calculate inequality yields results that allow for few conclusions given the magnitude of the errors; for example, the estimated Gini coefficient for Region I is 0.495, but with a standard error of 0.053, the 95 percent confidence interval is [0.392, 0.599]. Following the methodology proposed by Elbers *et al.* (2003), Agostini and Brown (2007) demonstrate that imputing income from the 2003 *Casen* into the April 2002 census affords far more precise estimates of inequality.

The census covered 4,112,838 households composed of 15,545,921 individuals. The data include demographic characteristics for the household members, living conditions, ownership of certain durable goods, access to sanitation, and health and education characteristics, but neither income nor consumption. A set of variables common to both the *Casen* and census is thus required to impute income. Although some explanatory variables are defined identically in both datasets, others were constructed. In such cases, the means and variances of the explanatory variables used in the analysis were evaluated to ensure that they measure the same thing. Using stepwise regression to detect the best fit for each region separately, we determined that household demographics (e.g., the number of household members; the share of young children in the household), characteristics of the household head (e.g., gender; education level; ethnicity), characteristics of the

[13]Although the ECLAC adjustments may theoretically introduce bias, Contreras and Larrañaga (1999) present evidence to the contrary. Regardless, the unadjusted data are not available.

[14]Further methodological details are provided by Pizzolito (2005); see also http://www.mideplan.cl/casen/pdf/Metodologia_%202003.pdf.

house itself (e.g., number of rooms; construction material; type of flooring; water source; sewerage), and asset ownership (e.g., washing machine; water heater; fixed telephone; cellular phone; satellite or cable television; microwave; computer; internet access), were the strongest predictors of household income. Estimates also included location dummies to capture latent cluster-level effects. The predictive ability of the model is high for cross-sectional data, with R^2 values for each region ranging between 0.36 and 0.52; complete summary statistics and the first stage results for each region are reported in Agostini and Brown (2007).

5. Empirical Results

Figures 2–6 depict estimated Gini coefficients for each county derived from the methodology described in Section II. In each, the left panel shows the estimated Gini coefficients based on income prior to the receipt of any transfers from the government. The right panel depicts estimated Gini coefficients for total income, including all five poverty-reduction cash transfers described above. Darker shading indicates higher income inequality.

Based on these figures and on Table 2, it is evident that average pre-transfer income inequality is generally lowest for counties in central Chile, including Regions V, VI, and VII as well as the greater Santiago metropolitan area (Region XIII). Average county-level income inequality is higher in northern Chile (Regions I, II, III, and IV) and higher still south of Region VII. Regions VIII and XIII show the greatest variation in pre-transfer income inequality at the county level. By contrast, variation is extremely low in Regions I, II, and III.

Poverty-reduction transfers have a pronounced impact on estimated inequality at the county level in Regions VIII, IX, and X. Estimated reductions in inequality were quite modest in Regions II, V, VI, and XIII, perhaps not surprising

Figure 2. Pre- and Post-Transfer Gini Coefficients in Northern Chile (Regions I, II, III, and IV)

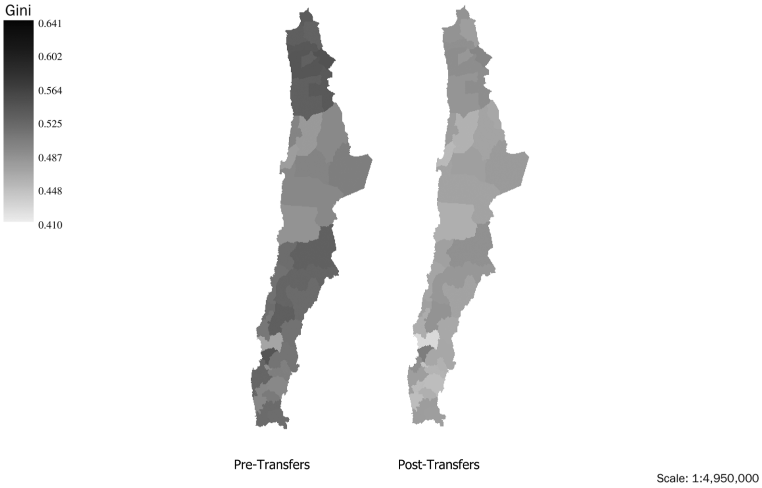

Figure 3. Pre- and Post-Transfer Gini Coefficients in Northern Chile (Regions I, II, III, & IV)

Figure 4. Pre- and Post-Transfer Gini Coefficients in Santiago and Valparaiso (Regions V & XIII)

given the relatively low levels of county-level income inequality in these areas to begin with. However, Region XII also displays extremely modest gains against county-level inequality despite displaying high inequality. Indeed, the estimated Gini coefficients before and after transfers are statistically different in only two of the 11 counties in Region XII at the 90% confidence level and in none at the 99% confidence level (Table 2). By contrast, every county in Regions IV, VII, IX, and X shows statistically significant differences in estimated inequality at the 99% confidence level. Moreover, with the exception of Regions I, II, XI, and XII, estimated inequality falls at the 99% confidence level in at least 70 percent of the counties in each region.

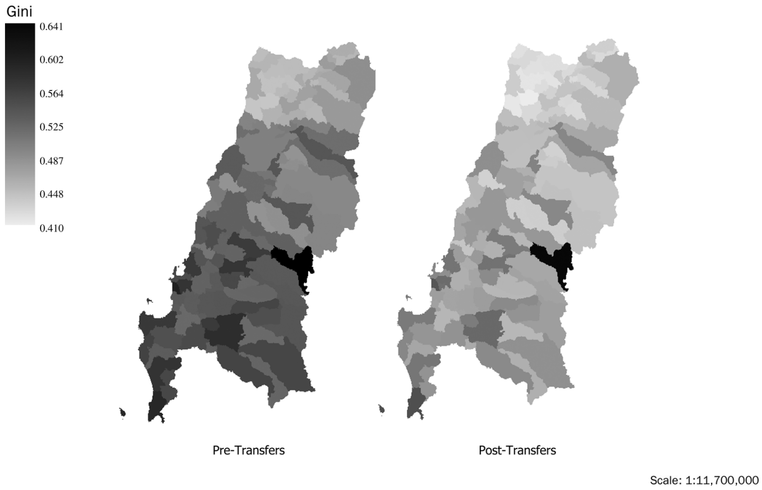

Figure 5. Pre- and Post-Transfer Gini Coefficients in Central Chile (Regions VI, VII, & VIII)

Figure 6. Pre- and Post-Transfer Gini Coefficients in Southern Chile (Regions IX & X)

Confidence intervals for the whole country are depicted in Figure 7. In most cases, the confidence interval of the Gini when including transfers lies completely below the confidence intervals excluding transfers, implying a statistically significant reduction in inequality. For several counties, however, the confidence intervals overlap, implying improvements in inequality based on point estimates but not statistical significance. Overall, poverty-reduction transfers cause the estimated Gini coefficient to fall in 316 of Chile's 342 counties at the 90% confidence level and in 288 counties at the 99% confidence level.

A representative Chilean could expect to receive CH$1708 per month in government subsidies in 2003 (Table 1), although this figure varies widely by

TABLE 2

Changes in Income Inequality by Region

	Region I	Region II	Region III	Region IV	Region V	Region VI	Region VII	Region VIII	Region IX	Region X	Region XI	Region XII	Region XIII
Counties	10	9	9	15	38	33	30	52	31	42	10	11	52
Pre-transfer income inequality													
Maximum	0.544	0.501	0.531	0.541	0.492	0.487	0.540	0.641	0.587	0.577	0.574	0.561	0.556
Minimum	0.527	0.475	0.508	0.467	0.445	0.439	0.483	0.510	0.521	0.495	0.533	0.517	0.442
Average	0.534	0.489	0.519	0.507	0.460	0.458	0.507	0.548	0.549	0.532	0.556	0.538	0.489
Change in estimated Gini													
Average	−9.43%	−4.84%	−9.06%	−8.83%	−4.41%	−6.15%	−10.03%	−11.84%	−11.85%	−11.38%	−11.02%	−3.48%	−2.63%
Std. dev.	0.358%	0.311%	0.324%	0.678%	0.154%	0.430%	0.729%	1.944%	0.810%	0.885%	0.299%	0.138%	0.973%
Counties w/different Gini (90% CI)	10	6	9	15	37	32	30	50	31	42	9	2	43
Counties w/different Gini (95% CI)	10	6	9	15	36	31	30	50	31	42	8	1	40
Counties w/different Gini (99% CI)	6	3	8	15	30	29	30	50	31	42	6	0	38

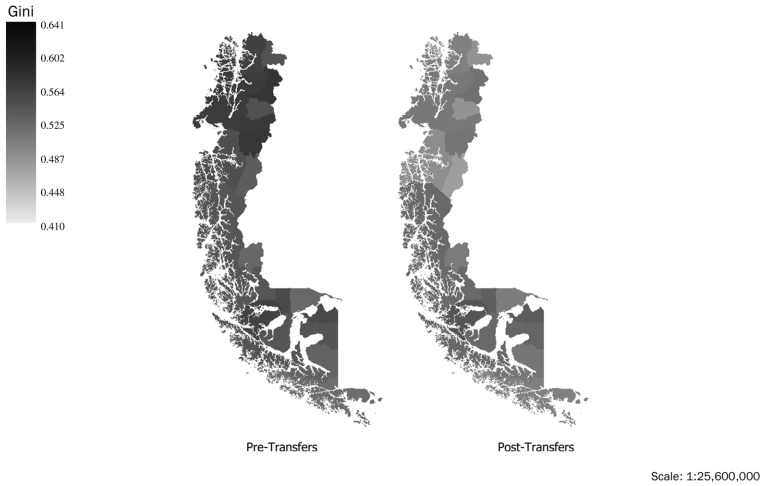

Figure 7. Pre- and Post-Transfer Gini Coefficients in Chilean Patagonia (Regions XI & XII)

region. If targeting is effective and if the benefits of these programs do accrue to the poor, then the greatest reductions in county-level poverty will occur in Regions IV, VII, VIII, IX, X, and XI, where the expected value of transfers exceeds the national average by a wide margin. Clearly, this is the case for Regions IV, VII, IX, and X, in which transfers cause estimated inequality to fall at the 99% confidence level in all counties. In Region VIII, estimated inequality falls in all but two of 52 counties at the 99% confidence level. By contrast, transfers have comparatively little effect on inequality in Region XI, where only 60 percent of counties see statistically significant (at the 99% confidence level) reductions in inequality, suggesting that this area underperforms in terms of anticipated reductions in inequality. Expected transfers to a representative individual are close to the national average in Regions III and VI, and estimated inequality falls in 89 and 88 percent of counties, respectively, suggesting that targeting is effective in these regions. The expected value of transfers is well below the national average in Regions I, II, V, XII, and XIII, resulting in very modest reductions in inequality. In Regions I, II, and V, for example, reductions in estimated inequality are significant at the 99% confidence level in 60, 33, and 79 percent of counties, respectively; in Region XII, transfers do not significantly affect inequality in *any* county at the 99% confidence level. Finally, the expected value of transfers is lowest in Region XIII, yet estimated inequality falls significantly in 38 of the 52 counties, demonstrating that even small transfers may significantly impact inequality if appropriately targeted.

Table 3 depicts changes in inequality associated with poverty-reduction transfers by inequality quintile (ranked low to high). The table demonstrates considerable movement, with approximately 51 percent of counties changing inequality cohorts as a result of the transfers. The most extreme change in inequality occurred in Pedro Aguirre Cerda (Region XIII), which fell from the 2nd to the 5th quintile. Nevertheless, poverty-reduction transfers improve relative income inequality in 95 counties and reduce relative inequality in 73, suggesting that the transfers reduce

TABLE 3
Changes in Inequality by Inequality Decile

		Percentile, Post-Transfer				
		1	2	3	4	5
Percentile, Pre-Transfer	1	84	16	0	0	0
	2	15	38	29	16	2
	3	1	43	25	13	18
	4	0	3	46	38	13
	5	0	0	0	42	68

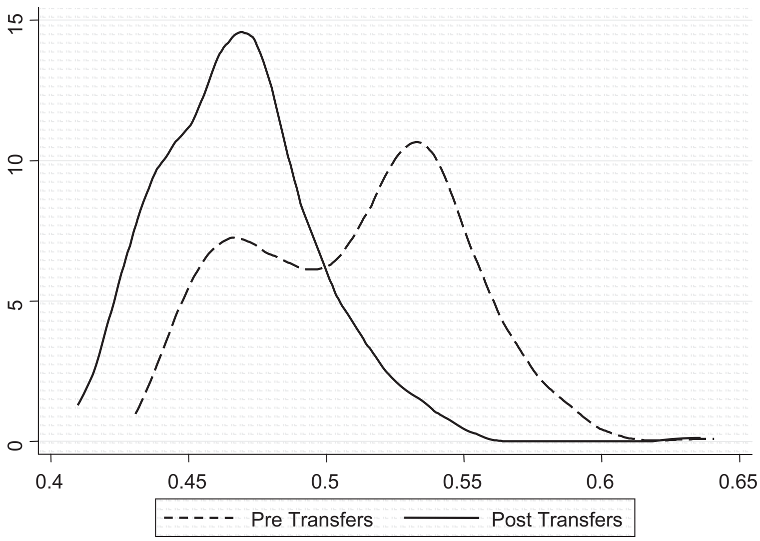

Figure 8. Epanechnikov Kernel Estimation of the Non-Parametric Density of Estimated Gini Coefficients

inequality on balance. Still, the effectiveness of poverty-reduction transfers in reducing inequality is clearly uneven.

To formally examine the impact of poverty-reduction transfers on income inequality at the national level, we estimate the non-parametric density of the county-level Gini coefficients before and after transfers using the Epanechnikov Kernel estimator. The poverty-reduction transfers shift the distribution to the left (Figure 8), implying a reduction in inequality, and the Shapiro–Wilk test for normality strongly rejects the hypothesis that both distributions are normal. Moreover, the Kolmogorov–Smirnov test for equality of distribution functions rejects that the hypothesis that the two distributions come from the same data-generating process.[15]

[15]The first step of the test does not reject the hypothesis that the distribution of Gini coefficients for total income contains smaller values than the distribution of Gini coefficients for autonomous income. The second step of the test rejects the hypothesis that the distribution of Gini coefficients for total income contains larger values than the distribution of Gini coefficients for autonomous income. As a result, the joint test rejects the hypothesis that the two distributions are equal.

As noted above, Chilean law stipulates that taxes cannot be directly tied to expenditures, so poverty-reduction transfers are financed out of total tax revenues. Because over half of total transfers are derived from the Value Added Tax and because confidential income tax data are not available from the Chilean Internal Revenue Service, it is difficult to assess the tax burden of individual households, and thus the impact of taxes on inequality. However, consumption taxes are regressive, suggesting that our estimates of inequality may be biased downward if taxation does affect inequality.

6. Conclusion

The rapid economic growth that Chile has experienced since the 1980s has been accompanied by a rapid decline in poverty rates. The government's fight against poverty revolves around transfers provided to pregnant women, female heads of household, the elderly, the handicapped, the unemployed, the indigent, poor parents, and those unable to purchase sufficient drinking water. Eligibility for most of these transfers is determined by a standardized form that evaluates housing characteristics and household assets.

While these transfers have been instrumental in reducing poverty, inequality at the national level has remained doggedly high, with the Gini coefficient hovering around 0.55 since the late 1980s.[16] Cash transfers to poor, indigent, or vulnerable households can reduce income inequality by increasing the resources available to the lower end of the income distribution, but only if targeting is effective and if the incentive to generate autonomous income is preserved. Understanding the effect of such transfers on inequality at low levels of aggregation is of particular policy importance because local inequality is associated with lower subjective wellbeing, higher rates, worse health outcomes, increased tension between groups, increased incidence of divorce and personal bankruptcy, and other undesirable outcomes.

Fortunately, theoretical advances in poverty mapping allow income to be imputed with a high degree of statistical accuracy, even at very low levels of aggregation. These income estimates then allow us to assess the effect of cash transfers from the government for poverty reduction on local inequality. We find that poverty-reduction transfers reduce the estimated Gini coefficient at the 99% confidence level in 288 of Chile's 342 counties. This is true of all 118 counties in Regions IV, VII, IX, and X, and in all but seven of the 94 counties in Regions III, VI, and VIII. By contrast, just 15 of the 29 counties in Regions I, II, and XI saw statistically significant reductions in income inequality resulting from government transfers. None of the 11 counties in Region XII had statistically significant reductions in inequality with poverty-reductions transfers, although 30 of the 38 counties in Region V and 38 of the 52 counties in Region XIII did.

The expected monthly subsidy was higher than the national average in Regions IV, VII, VIII, IX, and X, suggesting that poverty-reduction transfers were well targeted in these areas. However, the average subsidy was also higher than the

[16]We are grateful to a referee for pointing out that the effectiveness of transfer programs often declines precipitously during periods of high growth, as Paes de Barros *et al.* (1995) observe in Brazil. This pattern is consistent with stagnating inequality in Chile over the last two decades, although not with Chile's concurrent dramatic reductions in poverty.

national average in Region XI, which saw far more modest progress against inequality. Average transfers produced above-average reductions in inequality in Regions III and VI, while below-average transfers nevertheless produced significant reductions in estimated inequality in 76 percent of the counties in Regions V and XIII. In Regions I, II, and XII, low subsidies had very little impact on inequality. These findings suggest that there exist considerable disparities in the effectiveness of poverty targeting across Chile, implying either that housing characteristics and asset ownership are flawed indicators of poverty or that government spending for poverty alleviation is sometimes diverted to alternative purposes.

The government has already taken important steps to better identify poor households by eliminating the CAS-2 card as the determinant of eligibility: because the CAS-2 Card emphasizes housing and asset ownership in identifying the poor, it may have missed transitory poverty and may have penalized borderline households that had had improved their living conditions. Effective April 2007, eligibility is based on the "Social Protection Card" (SPC), which evaluates households based on income stability, educational level, labor experience, age structure, disabilities, health status, number of people (including relative to the size of the housing unit), housing ownership, urban/rural location, and regional unemployment levels. The new criteria will likely result in more effective targeting.

Ideally, we would estimate the overall impact of cash transfers on inequality by also considering their financing through taxes. However, because the Chilean Constitution forbids earmarking revenues, assessing the net impact of cash transfers and tax revenues would require estimating the incidence of the whole tax structure. Although this would be an interesting empirical exercise, the Chilean IRS does not make sufficiently disaggregated data available. Nevertheless, we believe that our results would be robust to the inclusion of transfer financing for two reasons: first, financing for poverty-reduction transfers is drawn from the total budget, of which income taxes comprise a relatively small share; second, Engel *et al.* (1999) show that the impact of taxes on the income distribution in Chile is negligible, even when simulating large tax reforms.

Finally, it is important to acknowledge that cash transfers and taxes may have an intertemporal effect on inequality. This type of dynamic analysis requires a panel of households, which as yet does not exist for Chile, so this remains an important consideration for future research.

Appendix 1

This Appendix provides a brief overview of the methodology proposed by Hentschel *et al.* (2000) and developed by Elbers *et al.* (2003). In the 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):

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

where the error vector u is distributed F(0,Σ). 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.[17] 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 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, bootstrapping 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:

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

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 a 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

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

repeated n times, taking a new set of coefficients β and errors for each simulation; for each geographic area, the mean and the standard deviation of the inequality indicator are calculated over the whole set of simulations, which constitute its point estimate and its standard deviation, 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.:

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

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:

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

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, the methodology again resorts 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:

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

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 $\hat{G}_c$ (computation 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:

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

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 does not 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 as:

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

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.

Appendix 2

This Appendix describes the adjustments to the *Casen* undertaken by ECLAC. See also ECLAC, IPEA, and UNDP (2002).

The first type of adjustment made by ECLAC is related to non-response and invalid answers. In particular, ECLAC makes adjustments in three cases: people who declare themselves as employed but who do not report income from their main occupation; people who declared themselves to be retired or living on a pension but who do not report the amount of the pension; and households living in owner-occupied housing but who do not report an imputed rental value. In the first and second case, ECLAC imputes to each employed and retired person the value of the mean income reported by people of similar characteristics.[18] In the third case, ECLAC imputes an implicit rental value using the "hot deck" technique, wherein the dataset is ordered geographically and households are selected based on the housing tenancy situation, the type of housing and other household

[18]In the case of employed persons, six variables are used to match characteristics: family relationship, gender, educational level, occupational category, type of economic activity, and region. In the case of retired persons, only the first three variables are used.

characteristics. By contrast, when households report a positive value for imputed rent despite not being owners, the value reported is subtracted from the household income.

The second type of adjustment made by ECLAC is related to under- or over-reporting of some types of income. The procedure followed to correct for misreporting basically consists in adjusting income from some specific sources to match the corresponding value in the national accounts. Specifically, the adjustment is made to match the aggregate income of the Households and Expenditures Account of the National Accounts System of the Central Bank of Chile. To do this, the data from National Accounts is converted to match the income categories included in the *Casen*. Then, the total values by each specific income category are compared to the ones in the *Casen* (using expansion factors). Finally, the proportional differences for each income category are imputed uniformly to each individual receiving income in the *Casen*. There are two exceptions to this last step: adjustments to capital income are made only to the top quintile of households, and income from transfers and gifts are not adjusted at all.

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