How well has the Social Protection Scheme Reduced Vulnerability in Chile?

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Abstract

This paper empirically investigates the impact of Chile's social protection's monetary subsidies on vulnerability to poverty during 1996-2006. Using the National Socioeconomic Characterization panel survey data, we adopt the Chaudhuri et al. (2002) method to estimate vulnerability. Since access to monetary subsidies is not random, we use the propensity score matching method to address the problem of selection bias in testing the effect of these transfers. The effect of the social protection transfers on vulnerability is examined both for the entire sample and the poor using Average Treatment Effect on the Treated (ATT) approach and sensitivity analyses. Our results suggest that the impact of the monetary subsidies is limited and mixed. They tend to help lower the vulnerability of those who have access to these subsidies in all three periods covered by the survey, but the subsidies show limited effect on the transitory poor. In general, we find that these subsidies are unable to address the structural causes of vulnerability faced by individuals in Chile.

Keywords: vulnerability, social protection, monetary subsidies, poverty reduction, Chile.

JEL Codes: I31, I32, I38

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1. Introduction

One of the main accomplishments of Chile during the past two decades has been the significant reduction in poverty, from 39% in 1990 to 14% in 2006 (Mideplan, 2010). A number of studies highlight two major reasons for this substantial poverty reduction since Chile's return to democracy in 1990 (Larrañaga, 1994; Contreras, 1996; Contreras, 2001; Pizzolito, 2005). First, there was significant growth in employment and wage earnings that accompanied the overall economic growth (at least until the economic crisis of the late 1990s), a result of the country's adoption of 'growth with equity' development strategy.[3] A second major reason was the increase in government provisioning of social programs since 1990. Since then, Chile has undergone an expansion of social services and provision of monetary transfers to vulnerable groups as a way to eradicate poverty.[4]

The government of Patricio Aylwin first undertook the development and improvement of a number of poverty reduction and social protection programs that provided monetary subsidies to the elderly, indigenous groups, the disabled and women micro-entrepreneurs. Throughout the 1990s and early 2000, the government of Chile continued to improve the quality of the programs and employed better targeting mechanisms (Arellano, 2004). In recent years however, there is growing concern on the extent of vulnerability among low-income households in Chile, particularly on their ability to cope with the multiple risks they face amidst a climate of heightened uncertainty.

Much of this concern is related to the adverse effects of market liberalization policies leading to the persistence of high inequality and employment insecurity. It is estimated that about 30 percent of the population in mid-2000 have incomes within 40 percent above of the official poverty line (Lopez and Miller, 2008). Significant segments

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[3] Investment rate in the 1990s reached up to more that 25 percent of the GDP and domestic savings rate was substantially high as well.

[4] The strong export growth experienced by Chile along with good fiscal management enabled the country to turn its budget deficit during the 1980s into a surplus. Accompanied with tax reforms, new concessions and private-public partnerships (particularly in large infrastructure projects) provided additional financial resources for the social protection scheme. It should be noted that the social programs did not represent a dramatic shift away from the market liberalization and privatization policies adopted in the early eighties. The expanded set of social programs called *Red de Protección Social* (PROTEGE) in the 1990s were established alongside these economic policies.

of the population could fall into poverty if hit by adverse shocks (Solimano, 2009, p. 26). These include loss of stable job, serious illness, increase in schooling expenditures, etc. which can shift their relative asset position and thereby move them into poverty. Non-poor households can also become poor due to a decline in earnings, increased job insecurity, or to their inability to smooth their incomes amidst variability in earnings. These raise the question of whether poverty reduction schemes such as provisioning of monetary subsidies help reduce the vulnerability of households and their members. This issue is important since poverty alleviation is not just about improving economic welfare via increased incomes and consumption. It is also about preventing households from falling into poverty. A focus on vulnerability, rather than merely on observed poverty levels at a given time, can provide a better understanding of poverty as a process and of the ability of households to cope with the multitude of risks that they face.

While a number of studies have examined the impact of Chile's social protection scheme on poverty, none have analyzed its impact on household or individual vulnerability.[5] Our paper attempts to fill in the gap by empirically investigating the effect of Chile's poverty social protection programs during 1996-2006 period on vulnerability. It makes use of the 1996, 2001 and 2006 waves of *Encuesta de Caracterización Socioeconómica Nacional* (CASEN) panel household survey involving 10,287 individual respondents. We define vulnerability to poverty in our paper as a forward-looking measure of the level of exposure to future risks and shocks that can undermine the household's survival and its members' ability to cope. For the non-poor, it refers to the risk of falling into poverty; and among the poor, it refers to the risk of staying poor or becoming even poorer (Kamanou and Morduch, 2005). For our study purpose, we adopt the Chaudhuri, Jalan and Suryahadi, (2002) method for estimating vulnerability. We estimate the Average Treatment Effect on the Treated (ATT) using propensity score matching to evaluate the effect of Chile's monetary transfers on vulnerability.[6] We also examine the effect of these subsidies on two sub-samples: first, the sub-group of those

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[5] See: Arellano (2004); Agostini, Brown and Góngora (2010); Agostini and Brown (2011); Contreras (2003) among others.

[6] Also in Chaudhuri (2003).

who are poor, both chronic and transitory, or have experienced poverty at least in one wave, and, second, the sub-group of transitory poor.[7]

The paper is organized as follows. Section 2 describes Chile's social protection programs during the period 1990-2006. A review of the relevant literature on poverty dynamics and vulnerability is given in Sections 3 and 4. The next section (Section 5) explains the data our methodology used in our empirical analysis and Section 6 presents the results. A summary of the main study findings and their implications for policy and future research concludes the paper in the final section.

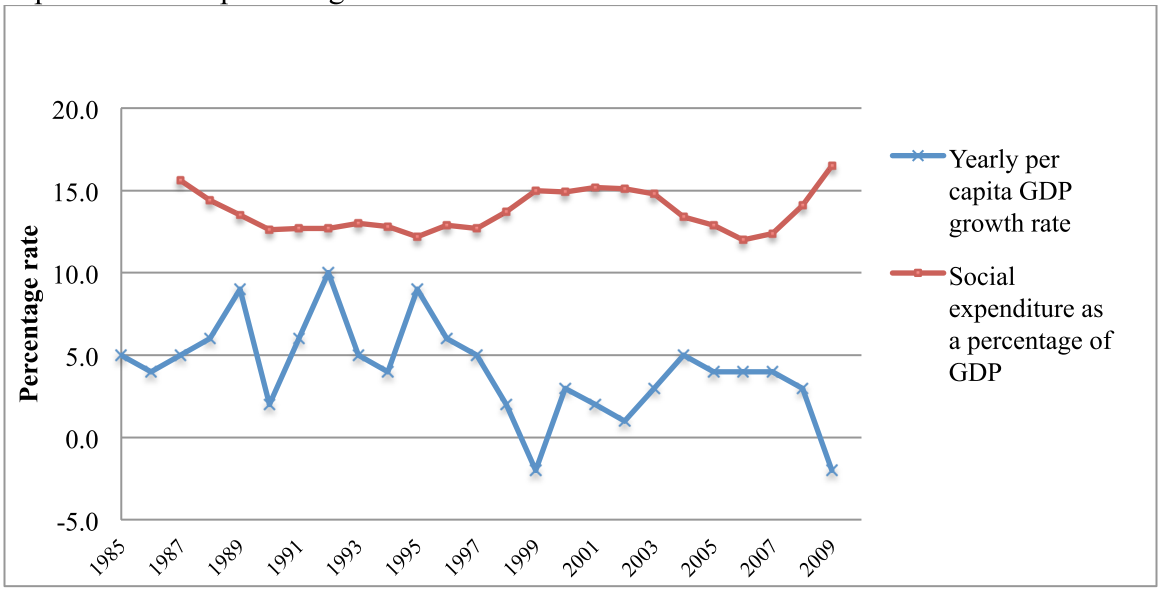
2. Chile's social protection programs after 1990

One of the defining features of the Chilean government policies in the nineties was the expansion of social protection and poverty alleviation programs as part of the "growth with equity" development strategy.[8] Chile's market liberalization policies in the eighties enhanced economic growth but were unable to effectively reduce poverty. Although Chile experienced per capita growth as shown in Figure 1, averaging 5.5 % annually since the mid-eighties, it had a high poverty rate of 39% in 1990.

[7] Transitory poor refers to those individuals being poor in one or two of the three waves, and the chronic poor correspond to those being poor in all three waves.

[8] Chile's social protection scheme encompasses the work of various ministries which implement programs and benefits such as scholarships, monetary transfers, health services, disability and unemployment insurance, etc. (Waissbluth, 2005, p.75)

Figure 1. Chile's per capita gross domestic product growth rate 1985-2009 and social expenditure as a percentage of GDP 1985-2009.



Source: Statistical yearbook for Latin America and the Caribbean, ECLAC (2010), and Estadísticas de las Finanzas Públicas. Dirreccion de Presuppuesto (DIPRES), various years.
Note: Annual percentage growth rate of GDP at market prices based on constant local currency.

For the newly elected Aylwin government and its successors, improved access to social safety nets such as social security, unemployment and disability insurance as well as basic health and social services were deemed critical to prevent those with the least resources from falling (deeper) into poverty and to help generate better opportunities for the poor. Government social expenditures as a percentage of the total government expenditures rose from 58% in 1990 to 67% in 2006 (Rodriguez and Flores, 2010). As percentage share of GDP however, the increase in government social expenditures is more modest; it rose from 12.6% in 1990 to 15.2% in 2001, dropped to 12.2% in 2006 and then increased again to 16.5% in 2009 (See Appendix A).

Much of the increase in public spending was financed by the 1990 tax reforms and increased government revenues resulting from high levels of export and economic growth. The tax reform helped increased Chile's tax revenue from 14% of GDP in 1990 to 16.4% of GDP in 2002, thus providing the needed funds to advance its social policy without incurring large fiscal deficits (Arellano 2004). Moreover, the government not only increased the level of social spending but also implemented reforms aimed at improving the effectiveness and quality of the existing social programs. The importance of social spending in poverty reduction is highlighted in Weyland (1999) and Solimano (2009) who noted that each percentage point of economic growth contributed 50% more towards reducing poverty from 1990 to 1996, under the *Concertación* administrations than under Pinochet's administration.[9]

To allocate monetary subsidies, the government of Chile developed in the eighties a social characterization record card called "*Ficha* CAS". During the period 1990-2005, "*Ficha* CAS" was used to identify the potential beneficiaries of social programs and government assistance by distinguishing poor and non-poor households sorting them according to their needs.[10] This tool applied conventional measures of poverty and made use of several social and economic indicators that were then weighted, yielding a score that ranged from 380 to 770 points.[11] Households that scored below 501 points were considered severely poor, and those with 501-540 points were considered poor. (See Appendix B). The implementation at the municipal level allowed for the decentralization of resource allocation of government assistance, although the Ministry of Planning remained in charge of providing the information for identifying the beneficiaries. The

[9] "Concertación" or *Concertación de Partidos por la Democracia* represents the center-left political parties' coalition founded in 1988, with the purpose to win the presidential elections and end the military government.

[10] The original "Ficha CAS", developed in 1980, was based on the following components: housing characteristics (number of rooms, construction materials, access to water and sanitation, access to electricity and overcrowding), education (household head's years of schooling), occupation (referring to the highest occupational category between spouses or that of household head), household income, and value of assets. This allocation instrument was revised in 1987 and referred to as "Ficha CAS-II". It made use of fifty characteristics which were assessed using principal component and discriminant factor analysis. In 1999, the CAS-II was updated by excluding some variables that were considered ineffective predictors of poverty. See Clert and Wodon (2002) and Larrañaga (2005) for a detailed discussion of "Ficha CAS".

[11] In 2006, the "Ficha CAS II" adopted a new framework, one that is based on the notion of entitlements. The eligibility criteria for accessing social protection programs and government assistance has shifted from being mainly based on income poverty status to a more comprehensive list of vulnerability indicators and adopted a new name "Ficha de Protección Social" (FPS). The FPS identifies vulnerability according to three sources namely: a) access to economic resources, b) household needs, and c) risks faced by households. Economic resources include income generation capacity or work skills of individuals, access to potable water and sewer system, home ownership, and relationship between family size and house size. Needs are based on household size, family composition and related characteristics. Risks include individual-based risks such as health condition, disability and job insecurity, as well as geographical location-based risks such urban-rural area and local unemployment rate. The new instrument, called the Social Protection Record Card or "Ficha de protección social (FPS)", acknowledges the multiple dimensions of poverty. It should be noted however that poverty reduction and social protection programs do not solely base their eligibility on the calculated score; some also specify other requirements that prevails over the estimated FPS score such as disability, old age, childbearing etc.

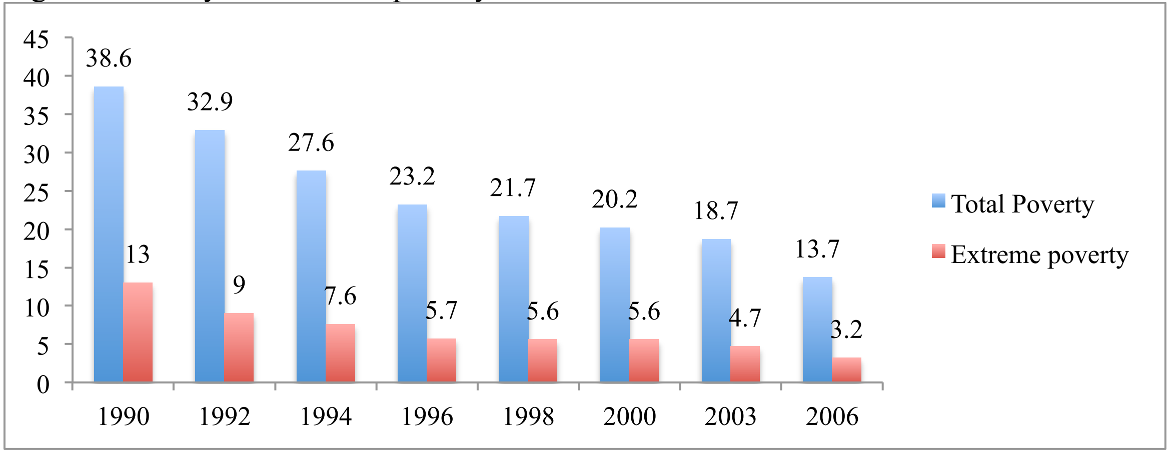
Red de Protección Social involved a number of programs that provided monetary subsidies. (See Appendix C). Household eligibility for these subsidies during the 1996-2006 period was based on their score (in the *Ficha* CAS) that placed them in the first or second quintile of "social vulnerability". Their score was based on an evaluation done at the local government level, using the "*Ficha* CAS" criteria. Hence, there is likely to be some self-selection with regards to access and participation in the social programs. This is an issue that we later address in the methodology section of the paper.

3. Examining poverty reduction in Chile

Several studies have attributed Chile's success in poverty reduction to a number of factors. Arellano (2004) study highlights the role of fiscal prudence and management in enabling the government to increase social spending and reduce poverty. This involved a reduction of the government infrastructure spending by focusing on those projects which have large social benefits and which the private sector was underproviding. The government also reduced the defense budget from 2.3% of GDP in 1990 to 1.2% by 2006.[12] Such efforts to maintain fiscal responsibility contributed to the reduction of the national debt to a quarter of its 1990 level, further freeing up additional resources. It also promoted public-private partnerships in several of its social programs, thereby increasing the financing of (government-guaranteed) education loans, microenterprise development, and housing loans among others. The above initiatives helped expand the coverage and improve the effectiveness of the social programs, thereby reducing income poverty to 23.2% in 1996 and further to 13.7% by 2006 (Figure 2).

[12] Estado de Operaciones del Gobierno Central www.dipres.gov.cl/572/articles-45410_doc_pdf_Funcional 3.pdf

Figure 2.Poverty and extreme poverty rate 1990-2006.



Source: Authors' calculations using CASEN data for each year. Poverty and severe poverty rates are based on the national (income) poverty line and the national (income) severe poverty line respectively. See Mideplan (2009) for estimation.

Larrañaga (1994) and Contreras (2003) argued that poverty reduction in Chile has been due to the pro-poor growth strategies implemented since 1990.[13] By examining quintile-level income changes over time, Contreras, Cooper, Hermann and Neilson (2005) argued that Chile's growth benefited poor people in the sense that they experienced a larger share of the income growth, compared to individuals in higher quintiles. This positive effect is also due to the social protection programs that provided safety nets in the form of cash transfers and subsidies, especially to the lowest quintile. Table 1 shows the percent distribution of monetary transfers and subsidies from 1990 to 2006 by income quintile. The proportion received by those in the lowest quintile increased from 34% in 1990 to 36.2% in 1996 to nearly 50% by 2006. Over the same period, the proportion of total monetary subsidies received by the richest quintile declined from 10.2% in 1990 to 3.2% in 2006.

[13] Using the Datt-Ravallion decomposition, they estimated that economic growth accounted for over 80% of the reduction in poverty in the period 1990-1996.

Table 1. Percentage distribution of total monetary subsidies income quintile 1990-2006.

	Income Quintile				
Year	**I**	**II**	**III**	**IV**	**V**
1990	33.7	23.8	18.5	13.8	10.2
1992	36.6	26.3	17.7	12.0	7.4
1994	38.7	26.2	17.3	12.1	5.7
1996	36.2	27.7	20.5	11.5	4.1
1998	46.3	26.5	15.9	8.5	2.9
2000	45.7	27.4	16.0	8.3	2.6
2003	46.8	25.7	15.7	8.7	3.1
2006	49.3	25.2	14.3	8.0	3.2

Source: Authors' calculations from using CASEN data (Mideplan, 2009).

Other studies however have raised concerns regarding the government provisioning of some basic services. Lopez and Miller (2008) pointed out that public spending in education, health, and environmental protection were modest compared to the potential that Chile could have provided during its period of dynamic economic growth and fiscal abundance. For example, there were substantial differences in the resources spent per student in the public school system compared to those in private schools, a ratio of one to four approximately, which impact student retention and the quality of education. This has reinforced the lack of social mobility and income inequality. There also seems to be an excessive emphasis on targeting, which may have generated unintended exclusions of benefits for 'borderline' individuals including children.

Additionally, some studies have raised the problems associated with the identification of beneficiaries and mismanagement of funds. For instance, Glick and Menon (2008) mentioned that some households might purposely underreport incomes and assets in order to avail themselves of the subsidies. Evidence is provided in Agostini and Brown (2011) who found that a proportionately larger share of monetary transfers (using 2003 data) went to households in the top half of the income distribution. Misrepresentation seems to have occurred at higher levels of aggregation as well.[14]

[14] For example, although municipalities know best what their needs are, decisions regarding development spending are taken at the nation-wide level. As a consequence,"…municipalities have an incentive to exaggerate their list of planned projects…", presumably in order to influence government spending. (Cited in Glick and Menon, 2008).

Hence, the social protection and poverty alleviation programs may not be well targeted and could have been subjected to mismanagement. In addition these social programs did not necessarily represent a dramatic shift away from the market liberalization policies adopted in the early eighties, rather they were establish alongside these economic policies. As a result, social reforms have not been able to address the high levels of inequality, particularly evident in health and educational outcomes.

4. Issue of vulnerability

Poverty is undoubtedly an important concern when monitoring human development progress. However, standard poverty indicators are ex-post measures which overlook the multiple risks that individuals or household may face and their ability/resources (or lack thereof) to cope and avoid becoming poor (or poorer) in the future. There is, by now, some evidence that indicates that a large proportion of the population in developing countries is vulnerable to poverty. The Chronic Poverty Report (2005), for example, indicates that although the estimated population share who are chronic poor in Latin America ranges from 30 to 40 percent, those considered to be transitory poor (i.e., individuals that at least once during the period of study fell below a poverty threshold) appears to be much larger. Income variability that arises from fluctuations in earnings, particularly in temporary or informal employment, can affect households' ability to manage risk and cope with shocks. Poor quality of public services e.g., healthcare, can aggravate household exposure to health shocks. Thus, even though average household incomes do not fall into poverty levels, the degree of household vulnerability can be high, leading to increased debt and sale or pawning of assets. In the long run, it can also affect the vulnerability of later generations through withdrawal of children from school, thereby maintaining the cycle of poverty and capability deprivation.

Given the inadequacy of poverty measures in exploring the risk of becoming poor in the future, a growing number of studies have focused on measuring vulnerability. To date, there exist different vulnerability estimation methods but for the most part, they require longitudinal datasets to explore the dynamics of poverty, which are scarce in developing countries (Günther and Harttgen, 2009; Dercon, 2005). Chaudhuri et al. (2002) propose a method of estimating vulnerability that allows the use of cross sectional data. It assumes that a household's vulnerability level derives from the stochastic properties of the (unobserved) inter-temporal income stream that it faces, and these in turn, depend on pertinent observable and unobservable individual and household characteristics and the characteristics of the environment in which it operates.

The Chaudhuri et al. approach has been utilized in a number of studies of vulnerability. Günther and Harttgen (2009) expanded the Chaudhuri et al. (2002) approach in their multi-level analysis of vulnerability for Madagascar. The study takes into account the effects on household consumption of idiosyncratic and observed covariate shocks in the rural and urban areas. Bourguignon and Goh (2004) estimates vulnerability using repeated cross-sectional data to create a pseudo-panel data and then compared their results with actual panel data. They conclude that under certain assumptions, both estimates are very similar (particularly in trend and average estimates). Their findings indicate job loss as the most important factor affecting vulnerability. Zhang and Wan (2008) also adopted the Chaudhuri et al. model. Using panel data from China they estimate household vulnerability and test the reliability of their estimates. Their findings indicate that vulnerability measures are more reliable when using the $2.00 dollar a day (instead of the $1.25 dollar a day) as poverty line, when the estimation of permanent income assumes a log-normal distribution, and when the vulnerability threshold is set at 50 per cent of probability of being poor in the future. The Chaudhuri et al. method has also been adopted by Imai, Wang and Kang (2009) in their analysis of the impact of taxation on poverty and vulnerability in rural China. Likewise, Jha, Imai and Gaiha (2009) assessed the impact of two public works and food subsidies programs in India on (consumption) poverty and vulnerability. Using an average treatment effect estimator with propensity score matching, the authors found a significant and negative effect of participation on poverty, malnutrition and vulnerability. More recently, Bali-Swain and Floro's (2012) empirical analysis indicates that microfinance programs like the Self Help Group (SHG) program in India can help reduce vulnerability.

Several studies have examined poverty dynamics and income mobility in Chile. The findings of Scott (2000), based on a small rural household panel data from 1968-1986, suggest very small income mobility among the rural population; any poverty reduction during the period was mainly due to social policy transfers and subsidies. Aguilar (2002), using the first wave of the CASEN panel survey for 1996-2001, also analyzed income mobility in Chile and found that household size and lack of or low quality of employment to be main determinants of poverty. He also finds that poor households do not make extensive use of government safety nets when faced with negative shocks; instead, they resort to assistance by kin. Using the same dataset as Aguilar (2002), Castro and Kast (2004) found evidence of income mobility, with 32% of people in Chile having lived below the poverty line at some point during the five year-survey period. Their study also showed negative correlation between poverty and labor market participation, particularly the nature of informal employment. This finding is confirmed by Neilson, Contreras, Cooper and Hermann (2008).[15] Chronic poverty in particular is found to be directly related to unemployment and lack of human capital (as measured by level of education). The effect of household size and composition as well as female headship on poverty and income mobility is pronounced in Zubizarreta (2005).

The issue of vulnerability has been directly examined by Rodriguez, Dominguez, Undurraga and Zubizarreta (2008) and Bronfman (2010), using CASEN panel data for 1996-2001 and 1996-2006 periods respectively. Rodriguez et al. (2008) constructed an adjusted poverty index using vulnerability and explored its determinants. Their results indicate that lack of human capital and certain household characteristics such as household size and proportion of elderly members significantly determine vulnerability. However, this study only looks at the working population in the Metropolitan region. The Bronfman (2010) study confirmed the findings reached by Zubizarreta (2005) and Neilson et al. (2008) regarding movements of large segments of the population in and out of poverty and estimates a large number of individuals as being vulnerable to poverty.

[15] Differentiating between chronic and transitory poor, Neilson et al (2008) estimated that 20,2% and 18.3% of the population were poor in 1996 and 2001 respectively. However, more than 30% of the people lived under the poverty line for at least in one of the periods, and 9% were chronically poor (poor in both years).

More recently, Cruces et al. (2010), in a cross-country study of Latin America, point to a much higher rate of vulnerability compared to poverty estimates, although he argued that aggregate vulnerability in the region has decreased over the early 1990s until the mid 2000.[16]

None of these studies however have examined directly the effect of social protection programs on vulnerability. A few studies that examined the impact of government cash transfers or monetary subsidies in Chile focused solely on poverty. For example, Agostini et al. (2008) and Agostini and Brown (2011) found that monetary subsidies had a positive effect on reducing poverty and inequality at the aggregate level. A later paper by Agostini et al. (2010) emphasized the role of local government finance and strength of government mandates in mediating the effectiveness of monetary subsidies.[17]

Our paper builds on previous work on vulnerability and poverty dynamics in Chile and other developing countries by updating previous vulnerability estimations, and by examining the effect of monetary transfers on vulnerability to poverty in Chile during 1996-2006. In particular, we assess how access to monetary transfers affects vulnerability using propensity score matching-based average treatment on the treated effect (ATT) estimation in order to control for selection and endogeneity bias. We also check the sensitivity of the estimated results using the bound method proposed by Rosenbaum and Rubin (1983) and Rosenbaum (1987).

5. Empirical analysis

a. Data

Our analysis makes use of the 1996, 2001 and 2006 waves of the National Socio Economic Characterization Survey ("*Encuesta de Caracterización Socioeconómica*

[16] The study made use of the \$2 and \$4 per person per day international poverty lines in their poverty estimates.
[17] More specifically, they found evidence regarding the significant impact of public expenditures on the efficiency of monetary transfers and a weak influence by the strength of the mayor's mandate.

Nacional", better known as CASEN) data involving 10,287 survey-respondents.[18] Although the CASEN surveys typically do not have the same household sample for each year, a special sub-sample based on the 1996 version from 4 regions was randomly re-surveyed in 2001(second wave) and 2006 (third wave).[19]

There are two caveats regarding the survey data that need to be mentioned namely, the issue of attrition and the use of income per capita for identifying who are poor. Figure 3 shows the attrition rate associated with the panel survey data, with the number of retained or original (1996) survey respondents in the subsequent (2001, 2006) samples represented by the darker areas. The decline in the number of retained respondents shows the extent of the attrition problem over time. The light gray section of the bar represents the newly added respondents. Since the survey is based on households as well as individuals, new members of original families became part of the latter samples. The attrition rate for the 1996-2001 period is 28.1%, and 50.9% for the 1996-2006 period.[20] To address this issue, the Ministry of Planning and University Alberto Hurtado constructed population and attrition weights. We make use of these weights in order to correct for any attrition bias and to maintain representativeness of the survey sample.[21] The second caveat refers to the choice of poverty measure used in this study. Due to the unavailability of consumption data and the fact that Chile's poverty line, as in many countries, refers to the income level deemed sufficient to satisfy basic needs, we make use of the national per capita income based poverty lines, instead of the alternative per capita consumption, in identifying the poor in our study.

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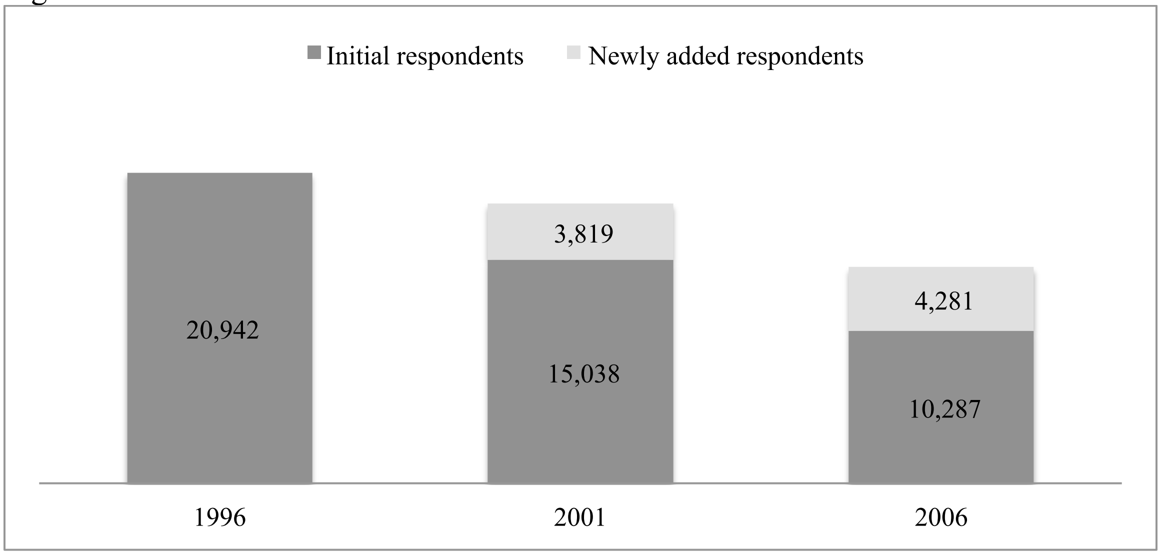
[18] National and regional representative surveys have been conducted every two or three years (1985, 1987, 1990, 1992, 1994, 1996, 1998, 2000, 2003, 2006 and 2009) and are deemed reliable.

[19] Chile has 13 regions at the time of the survey; the 4 regions namely: III, VII, VIII and the Metropolitan Region were covered in the CASEN, representing 60% of total population.

[20] This attrition rate is considered reasonable for a 10-year, three-wave panel data.

[21] For a complete discussion on the panel CASEN attrition problem and data quality, see Bendezú et al. (2007) and PNUD (2009).

Figure 3. Number of interviewed individuals in different waves of the CASEN data.



Source: Bendezú et al. (2007). The "new respondents" came from the original families interviewed in 1996 who have established their own households.

b. Vulnerability estimation

To estimate vulnerability to poverty, we adopt the Chauduri et al. (2002) estimation method, whereby the vulnerability level of a household *h* at time *t*, is defined as the probability that its members become income poor in period *t +1 and implies accounting for the expected (average) income, as well as the fluctuation (variance) of its future income stream*. For our study purpose, we express the vulnerability estimation in per capita terms. Given data limitations, we assume a unitary household and so the vulnerability of the head applies to all individuals in the household.[22]

The stochastic process generating income per capita level depends on the household characteristics, both observed and unobserved, the socio-economic environment in which the household is situated and the shocks that contribute to differential welfare outcomes for households that are otherwise observationally equivalent. It captures the idiosyncratic shocks to income that are identically and independently distributed over time for each household. Hence, any unobservable sources of persistent or serially correlated shocks or unobserved household specific effects over

[22] Given data limitations, we make use of the unitary household model that assumes income and resources are pooled and are shared equally among members of the household.

time on household income are ruled out and the future shocks are assumed to be idiosyncratic. Furthermore, we assume that the variance of the idiosyncratic factors (shocks) depend upon observable household characteristics.

A person's (in household *h*) vulnerability level in terms of its future income can be expressed as a reduced form for per capita income determined by a vector of individual (head) and household characteristics, X_{ht}:

$$LnY_{ht} = \beta_0 + \beta_1 X_{ht} + u_{ht} \tag{1}$$

where $LnY_{h,t}$ represents the log of per capita income at time *t*, X_{ht} represents the set of pertinent characteristics, and u_{ht} is the unexplained part of income per capita. X_{ht} include the sex, lifecycle stage (age, age-squared), and educational attainment, wealth, household size, household composition, presence of children (under 7 years old) and employed members to household size ratio. We also include regional dummy variables to control for region-level fixed effects. Since shocks affect households differently, the variance of the unexplained part of per capita income, μ_{ht} can be estimated as:

$$u_{ht}^2 = \Phi_0 + \Phi_1 X_{ht} + \omega_{ht} \tag{2}$$

which implies that the variance of the error term differs across households and are a function of their characteristics.

The expected mean and variance per capita household income are estimated using Amemiya's (1977) three-step feasible generalized least squares (FGLS) method.[23] The β_1 and Φ_1 estimates that we obtain are then used to directly estimate the expected log per capital income and the variance of log per capita income for each person in household *h*. These serve as our vulnerability estimates.[24] The results of the feasible generalized least squares estimates for expected log per capita income and variance are presented in Appendix E (Tables E1-E3).

To facilitate the comparison of the vulnerability distribution among monetary subsidy and non-monetary subsidy recipients, we estimate two vulnerability measures

[23] For details on the statistical estimation refer to Chauduri et al., 2002.
[24] For more detailed explanation of the vulnerability estimation and its assumptions, see Chaudhuri et al. (2002).

using different thresholds in order to examine the sensitivity of our results to the choice of vulnerability threshold. The first vulnerability threshold used is the observed 1996 poverty rate in the population (23.6%) which is approximately equal to the mean vulnerability level within a group in the absence of aggregate shocks. (Chauduri et al., 2002). Thus, vulnerability levels above the observed poverty rate threshold imply that the individual's risk of poverty is greater than the average risk in the population, thus making it more vulnerable.

The second vulnerability threshold is 0.5. With this cutoff, individuals above a 50% probability of becoming or staying poor in the future are considered *highly vulnerable*. Admittedly, there is some arbitrariness involved in the selection of the vulnerability cutoff, so a comparison of the vulnerability estimates using different vulnerability thresholds shows the sensitivity of the results to the choice of threshold.[25]

c. Propensity score matching

Since access to monetary subsidies is not random, a simple analysis of the difference of means between participants and non-participants will yield biased results due to the selection process and the endogenous targeting method for allocating monetary transfers. Hence, participation in the social protection scheme would depend on the same attributes that also determine the vulnerability of the members in a household.[26]

To address the above concerns created by program selection, we use the propensity score matching (PSM) method to identify the program impact when a random experiment is not implemented and there is no comparable counterfactual or control group. Matching relies on the assumption of conditional independence of potential outcomes and treatment given observables, that is, the selection into the treatment should be driven by factors that can be observed and that are independent of potential outcomes or Conditional Independence Assumption.

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[25] Given the sensitivity of the results to the choice of vulnerability threshold, authors have also estimated vulnerability using other vulnerability thresholds. These are available upon request from authors.

[26] It should be noted that not all eligible households access subsidies for different reasons, stigmatization, proximity to municipalities, lack of information, etc.

To examine the feasibility of using PSM, we checked the data collection method to ensure that the three conditions stated in Heckman et al. (1997) are met. First, the survey questionnaire is the same for the monetary subsidies recipients and non-recipients so that the outcome measures are measured in the same way for both. Second, both groups come from the same area. Third, a rich set of observables for both outcome and participation variables are available for the PSM method to potentially meet the requirements for it to produce reasonable consistent estimates of effect.

The PSM uses the "Propensity Score" or the conditional probability of participation to identify a counterfactual group of non-recipients or non-participants, given conditional independence. This is done by matching the proximity of the household in the treatment group with another in the control group based on observable characteristics.[27] The probability (P(*X*)) of being selected is first determined by a logit equation. This probability (the propensity score) is then used to match the households and by association, the household members. Y_1 is the outcome indicator for the monetary subsidy recipients ($T=1$), and Y_0 is the outcome indicator for the non-recipients ($T=0$), then equation (4) denotes the mean impact:

$$\Delta = E[Y_1 \mid T = 1, P(X)] - E[Y_0 \mid T = 0, P(X)] \qquad (4)$$

where the propensity score matching estimator Δ is the mean difference in the expected outcome of receiving subsidies, over common support, weighted by the propensity score distribution of the recipients.

Since the probability of two households being exactly matched is close to zero, distance measures are used to match households. Following Smith and Todd (2005), we first choose the nearest neighbor (NN) algorithm.[28] This algorithm is the most straightforward and matches partners according to their propensity score. We also use the Kernel method (with bandwidth 0.06), which uses the weighted average of all individuals

[27] In the propensity score matching, we use observable variables that are aligned with those used in the social protection scorecard for determining eligibility.

[28] For further discussion on difference in difference PSM, see Becker and Ichino (2002), Caliendo and Kopeining (2005), Abadie et al. (2004), Abadie and Imbens (2002), Imbens (2004), Heckman, Ichimura, and Todd (1998), and Wooldridge (2002) among others.

in the control group to construct the counterfactual outcome.[29] Bootstrapped standard errors (with 100 repetitions) for the above procedures are estimated as well (Heckman et al., 1997).

6. Results

This section presents both the vulnerability estimations and the effect of monetary transfers on vulnerability in the 1996-2006 period. As mentioned earlier, we take into account the household size and calculate the estimates at the individual (or household member) level. We begin with a discussion of the poverty and vulnerability estimates of the sample, followed by an assessment of the impact of monetary transfers on individual vulnerability using propensity score matching method. We examine the estimated average treatment on treated (ATT) using different matching algorithms.

a. Poverty and vulnerability profile of sample

The poverty profile, in terms of headcount rates, and the vulnerability and high-vulnerability estimates for the CASEN survey rural and urban respondents in 1996, 2001 and 2006 are presented in Table 2. Our results show that a higher proportion of the rural respondents are poor (33.6%) as compared to 22.9% per cent for the urban respondents in 1996. Poverty rates among urban and rural respondents have since declined to 10.2% and 13.0% respectively in 2006.

The vulnerability estimates for rural and urban respondents obtained from the FGLS estimates are also presented in Table 2. Throughout the period 1996-2006, the proportion of the population who are vulnerable is much higher compared to the proportion of poor. In 1996, almost half of the population (48.8%) was vulnerable to poverty, with higher estimates (60.3%) for those living in the rural areas compared to those in the urban areas (47.3%). This declined to 39.8% in 2001 and further to 29.6% in 2006. Since the vulnerability estimate is sensitive to the choice of a threshold, we

[29] Bandwidths are smoothing parameters, which control the degree of smoothing for fitting the local linear regression. We also employed other bandwidths, which gave very similar results to those presented in the paper.

estimate the proportion that is highly vulnerable in terms of being above the vulnerability threshold of 0.5 for a given year. Our estimates in Table 2 show that although urban poverty rates have declined, the fraction of the urban population that is highly vulnerable remained nearly constant throughout the 1996-2006 period. On the other hand, the proportion among the rural population declined significantly from 30.3% in 1996 to 18.2% in 2001, and continued to do so, albeit more slowly, to 16.9% in 2006. There are two plausible explanations for the difference in trends. First, conditions faced by these urban respondents that make them highly vulnerable may have persisted and the introduction of the social protection monetary subsidy programs has neither addressed these conditions nor helped the households to cope. Second, problems associated with the identification of social protection program beneficiaries and/or management of funds may have been especially pronounced in the urban areas.

Table 2. Poverty, vulnerability and high vulnerability estimates.

	1996			**2001**			**2006**		
	Urban	Rural	Total	Urban	Rural	Total	Urban	Rural	Total
Poverty	22.9%	33.6%	23.6%	19.6%	25.1%	20.2%	10.2%	13.0%	10.5%
Vulnerability	47.3%	60.3%	48.8%	39.7%	41.1%	39.8%	29.1%	33.3%	29.6%
High-Vulnerability	17.3%	30.3%	18.8%	16.4%	18.2%	16.6%	17.2%	16.9%	17.2%

Source: Authors' calculations using the CASEN 1996-2001-2006 survey data.
Note: Poverty represents the head count ratio using the national poverty lines for urban and rural areas; Vulnerability represents the vulnerability head count ratio based on a probability of future poverty being equal or higher to 23.6% (the observed poverty rate in 1996); High-vulnerability identifies those individuals with a probability of future poverty equal or above 50%.

b. Assessing program impact on vulnerability using propensity score matching

A simple comparison of the percentage change in vulnerability on the basis of access to and frequency of participation in the social protection programs is likely to suffer from selection bias since local authorities select the recipients based on their household score, which is used as a proxy means-test targeting allocation tool. Therefore any mean differences could be a result of program participants' selection process.

To address the problem, we examine the impact of monetary transfers on vulnerability using multiple algorithms for propensity score matching in order to statistically create the treatment and comparison groups and to estimate the ATT. First, we infer the counter-factual regarding what would have been the value of the outcome indicator in the absence of monetary subsidies by using non-recipients as a comparison group for each year (wave). To obtain a comparable group, the propensity score is estimated using the same set of observable characteristics used by the government in allocating monetary transfers and this score is then applied to identify a similar counterfactual group of non-recipients, given conditional independence. Groups are regarded as comparable if their predicted scores on the outcome indicator (i.e., the predicted house-hold score) are "similar." We use two mechanisms to create "similar", or matching, groups: Nearest Neighbor matching and Kernel matching.

We next estimate the ATT effect by comparing the treatment and control groups in terms of changes in vulnerability estimates over time relative to the outcome observed in pre-intervention baseline.[30] This allows for conditional dependence on the levels arising from additive time-invariant latent heterogeneity.[31] Two different algorithms for propensity score matching identify the comparison groups, namely: a) the Nearest Neighbor matching algorithm (NN) that matches each treated observation to a control observation with the closest propensity score, and b) the Kernel matching method that matches the treated observation with the Kernel weighted average of the outcome of the control units.

The above propensity score matching hinges on the assumption of conditional independence (or unconfoundedness assumption) (CIA) that no unobserved variables affect the participation and the outcome variable simultaneously. If this assumption fails, it may lead to some bias so that the matching estimators may not be valid. Thus, a sensitivity analysis is conducted and the results are reported as well.

Since not all social protection program beneficiaries received monetary transfers throughout the time period under study, we consider the possibility that the effect on vulnerability may vary across households with different levels of access to monetary

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[30] The PSM and ATT were calculated using full Mahalanobis matching for propensity score matching, common support graphing, and covariate imbalance testing methods. Bootstrapped standard errors were computed as well.

[31] The changes over time in the vulnerability estimator will likely contain some heterogeneity in the observables, which would bias an unmatched DID. Propensity score matching addresses possible observable heterogeneity between the two groups.

subsidies. We therefore categorize the individuals in the sample on the basis of household access to and frequency of participation in the program and then identify comparison groups (non-recipients) using the above algorithms for propensity score matching. Group 1 corresponds to those individuals in households that received subsidies once (any one of the three waves), meaning that there were two periods in which they did not receive any subsidy.[32] Group 2 refers to those who received subsidies twice (any two of the three waves) while group 3 refers to individuals who received subsidies throughout the time period (all three waves). The comparison group for all three groups refers to individuals who received no transfers throughout the study period.[33]

The magnitude of the ATT estimates in Table 3 measures the impact of monetary transfers on vulnerability for each group in 2006. The ATT point estimates (both NN and Kernel) are negative but not statistically significant for group 1. This indicates that, after accounting for selection bias, those who received monetary transfers on only one of the three waves are neither more nor less vulnerable compared to non- recipients. Similar results are found for Group 2 individuals. However, the individuals who received monetary transfers in all 3 waves (Group 3) show a significantly lower level of vulnerability compared to the control group, with negative NN and Kernel matching algorithms estimates (9.8% and 6.4% respectively) that are statistically significant at the 5% level. These results suggest that the impact of monetary transfers on vulnerability is cumulative and not immediate. Thus, only individuals in households with continued or regular access to monetary transfers have lower vulnerability compared to those that never received any in 1996-2006.

[32] It could be that individuals in households that first received the monetary subsidies in 2006 are in the beginning of a long spell. We investigated to see if these persons are any different from those individuals who received the monetary subsidies in 1996 or in 2001 and found that there is no significant difference. Hence we combined them in a single group (Group 1).

[33] Appendix H (Tables H1-H3) shows the estimated individual vulnerability for each group category.

Table 3. Average treatment effect on the treated on vulnerability 2006: All sample.

Treatment	Method	n. treat.	n. contr.	ATT	Std. Err.	t
Group 1	Nearest N.	1586	670	-0.006	0.027	-0.212
	Kernel M.	1586	1064	-0.025	0.022	-1.094
Group 2	Nearest N.	2011	588	-0.066	0.037	-1.782
	Kernel M.	2011	1015	-0.044	0.024	-1.835
Group 3	Nearest N.	1995	471	-0.098	0.042	-2.342
	Kernel M.	1995	993	-0.064	0.028	-2.316

Source: Authors' calculations using the CASEN 1996-2001-2006 survey data.

i. Effect of monetary subsidies on poor households

Given the above results, one could argue, that for the population as a whole, and controlling for selection bias, monetary subsidies seem to have no significant effect on vulnerability unless recipients access them on a regular basis. By design however, the social protection programs target poor households, particularly those facing particular conditions such as unemployment, pregnancy, with children under 18 years, old age, disability, etc. Thus, any impact assessment of the program should be focused on them.

Taking the subset of those who experienced poverty at least in one of the periods, the results in Table 4 show a significantly lower vulnerability for groups 2 and 3 compared to non-recipients, controlling for the selection bias. However, for group 1, the results in table 4 show that the ATT estimates (both NN and Kernel) remain negative but they are only statistically significant for the Kernel matching algorithm. The results indicate that having access to monetary transfers only for one year may not be sufficient to lower vulnerability among the subset of poor households.

Table 4. Average treatment effect on the treated on vulnerability 2006: poor sub-sample.

Treatment	Method	n. treat.	n. contr.	ATT	Std. Err.	t
Group 1	Nearest N.	565	178	-0.094	0.054	-1.740
	Kernel M.	565	249	-0.111	0.045	-2.464
Group 2	Nearest N.	926	177	-0.205	0.057	-3.589
	Kernel M.	926	251	-0.147	0.048	-3.055
Group 3	Nearest N.	1067	154	-0.206	0.055	-3.765
	Kernel M.	1067	233	-0.153	0.055	-2.780

Source: Authors' calculations using the CASEN 1996-2001-2006 survey data.

To further our investigation, we take into account the pattern of poverty spells experienced by the poor sub-sample in terms of whether they are transient poor, defined here as being income poor in one or two of the three waves, or chronic poor, defined as being income poor in all three waves.[34] Given issues with identifying a counterfactual group for the chronic poor subsample, we focus our analysis on the effect of the monetary transfers on the transient poor. A majority of the poor fall in this category. Since they move in and out of poverty, it can be argued that these families could certainly benefit from programs and policies that reduce their probability of falling into poverty. Hence, an evaluation of the monetary transfers' impact on their vulnerability can illuminate the social program's effectiveness or limits.

Table 5. Average treatment effect on the treated on vulnerability 2006: transient poor sub-sample.

Treatment	Method	n. treat.	n. contr.	ATT	Std. Err.	t
Group 1	Nearest N.	512	144	-0.031	0.066	-0.475
	Kernel M.	512	220	-0.057	0.046	-1.256
Group 2	Nearest N.	827	148	-0.135	0.072	-1.865
	Kernel M.	827	224	-0.116	0.051	-2.296
Group 3	Nearest N.	881	146	-0.159	0.075	-2.122
	Kernel M.	881	218	-0.080	0.063	-1.281

Source: Authors' calculations using the CASEN 1996-2001-2006 panel data.

[34] Annex G shows the percentage of transitory and chronic poor in Chile in 1996-2001-2006 according to the CASEN panel survey.

The results in Table 5 show that the while the effect on vulnerability is in the intended negative direction, the statistical significance of the estimates is not robust. The ATT point estimates (both NN and Kernel matching) are negative and not statistically significant for the transient poor who received monetary transfers only once during the study period (group 1). These indicate that their vulnerability is not any different from the non-recipients (comparison group). The results for Groups 2 and 3 are mixed and seem to be sensitive to the matching algorithm method used. Although both ATT estimates are negative, their statistical significance varies according to the matching algorithm. Hence, there is need for caution in interpreting the above results, given the lack of robustness in the estimates.

The research on labor markets and inequality in Chile provide some plausible explanation for our results. First, some of the risks faced by a growing number of households are due to worsening labor market conditions, especially for the low and unskilled workers. Unconditional monetary subsidies or cash transfers do not directly address labor market conditions such as precariousness of jobs, employment insecurity, volatility of earnings, etc. that can pull a non-poor into poverty or keep a poor person in it (Aguilar 2002, Castro and Kast 2004, Neilson, Contreras, Cooper and Hermann 2008). Second, households and their members can slide into or remain in poverty due to lack of access to quality health services, leading them to experience more serious health shocks. Public expenditures such as those addressing health risks are found to be important determinants of the ability of households to move out of poverty. However, the level of government expenditures in Chile on general social services has been considered insufficient for providing quality public healthcare services, a consequence of a rather narrow tax base that seriously constrained public revenues (Lopez and Miller, 2008). This also explains the relatively poor quality of public education in Chile, which can either discourage students to continue, or constrain them from obtaining the requisite skills to broaden their knowledge and increase their productivity. Although there has been a gradual increase in education expenditures, the level is still not sufficient "to induce greater access to pre-primary education and good quality of public education… (thereby condemning low-income households)… to under-invest in human capital" (Lopez and

Miller, 2008, p. 6).[35] As with health shocks, monetary subsidies, which represent on average about 4.1-5.2% of household income (as shown in Appendix D), is likely to be inadequate in dealing with education disparities, an important factor in determining one's employment opportunities and in the perpetuation of inequality in Chile.

ii. Sensitivity analysis

As mentioned earlier, the propensity score matching relies on the conditional independence assumption (CIA). Thus results of the estimate of an ATT based on PSM can lead to a hidden bias if there are one or more unobserved variables that simultaneously affect participation and the outcome variable and so the matching estimators may be invalid. Since it is not possible to reject the unconfoundedness assumption directly, several researchers have developed indirect ways of assessing this assumption (Heckman and Hotz, 1989 and Rosenbaum, 1987, Imbens, 2004, Ichino et al. 2007, Nannicini, 2007).[36]

Following Ichino et al. (2007) and Nannicini (2007), we conduct a sensitivity analysis on our ATT estimations. The sensitivity analysis implies that if the CIA is not satisfied given the observables but is satisfied after one observes an additional confounder, then this potential confounder could be simulated in the data and used as an additional covariate with the preferred matching estimator. The comparison of the estimates obtained with and without matching on the simulated confounder shows to what extent the baseline results are robust to specific sources of failure of the CIA. To check the robustness of our ATT estimates, we use two covariates to simulate the confounder namely: unemployed (vs. employed) and low (vs. high) levels of education[37] (both binary variables). These covariates are selected as a way to capture the effect of

[35] Lopez and Miller (2008) also show that Chile is one of the countries that spend the least per student, spending about 50% less than Korea, for example, despite its steady economic growth.

[36] These methods estimate a causal effect that is known to be equal to zero. If the test indicates that the causal effect differs from zero, then the unconfoundedness assumption is considered to be less plausible (Imbens, 2004).

[37] Low level of education is a dummy variable that takes the value of 1 for those individuals 16 years and older who have 8 years or less of formal education.

"unobservables" like ability, motivation, level of information, etc., which may have an impact on a person's participation in the social protection program and on vulnerability. Any dramatic change in the ATT estimates with respect to the confounders, after the simulation, would indicate that our results are not robust. We employ the Kernel matching algorithm with between-imputation standard error, in order to use only the variability of the simulated ATT across iterations.

Table 6 shows the results for both confounders, unemployed and low education. The sensitivity analysis is conducted for the entire sample as well as for the two sub-samples, namely poor and transitory poor, as a way to check the robustness of the results obtained earlier.

Table 6. Simulation-based sensitivity analysis for matching estimators:
ATT Estimation on vulnerability as of 2006 with simulated confounder general multiple-imputation standard errors.

Confounder all sample	(1) ATT	(2) Standard Error	(3) Outcome effect	(4) Selection effect
Group 1				
Unemployed	-0.023	0.030	3.396	0.941
Low Education	-0.031	0.031	0.957	1.105
Group 2				
Unemployed	-0.060	0.035	3.327	1.022
Low Education	-0.070	0.038	0.940	1.388
Group 3				
Unemployed	-0.101	0.045	3.660	0.816
Low Education	-0.116	0.050	0.958	1.802
Confounder poor sub-sample	**(1) ATT**	**(2) Standard Error**	**(3) Outcome effect**	**(4) Selection effect**
Group 1				
Unemployed	-0.066	0.071	8.526	1.086
Low Education	-0.076	0.076	1.923	1.154
Group 2				
Unemployed	-0.202	0.085	12.01	0.974
Low Education	-0.214	0.089	1.982	1.438
Group 3				
Unemployed	-0.198	0.085	98.321	0.845
Low Education	-0.214	0.090	2.017	1.777
Confounder transient poor sub-sample	**(1) ATT**	**(2) Standard Error**	**(3) Outcome effect**	**(4) Selection effect**
Group 1				
Unemployed	-0.064	0.076	116.482	1.156
Low Education	-0.073	0.078	1.776	1.177
Group 2				
Unemployed	-0.164	0.203	17.536	0.892
Low Education	-0.161	0.194	1.669	1.456
Group 3				
Unemployed	.0.214	0.149	19.346	0.894
Low Education	-0.226	0.155	1.569	1.738

Source: Authors' calculations using the CASEN 1996-2001-2006 survey data.
Notes: Based on the sensitivity analysis with kernel matching algorithm with between-imputation standard error. Unemployed confounder variable takes 1 if the person is unemployed and 0 if not, the low education variable is equal to 1 if the individual is has lower than 8 years of schooling and 0 if otherwise.

The simulated ATT estimates are very close to the baseline estimates presented earlier. The outcome and selection effects on vulnerability are positive but not very large for all groups in the total sample and in the transient poor subsamples. There is one exception however in the case of the poor subsample; the outcome effect on group 3 vulnerability for the unemployed confounder is quite large. Thus the sensitivity analysis results indicate that the ATT estimates, for the most part, remain stable with different estimators and the unconfoundedness assumption is therefore more plausible.[38]

7. Concluding remarks

Chile has experienced remarkable achievements in poverty reduction since its return to democracy in 1990. This success is a result of the combination of high economic growth and provisioning of social protection through a variety of monetary subsidies programs. Although Chile has been successful in lowering its poverty rate from 39% in 1990 to 13.7% in 2006, a large proportion of the population appears to be vulnerable to falling into poverty, thus raising the need to also assess the impact of social protection programs on vulnerability. We use propensity score matching to address the potential selection bias that may arise due to unobservable attributes. Using average treatment effect on the treated (ATT) estimations, our results suggest that the impact of the monetary transfers on vulnerability is somewhat mixed. In particular, it has little impact on some segments of the population like the transient poor. For the population as a whole, those who received subsidies in one or two of the periods did not experience a significant improvement, controlling for selection bias. However those who received monetary transfers continuously (in all three waves) had lower vulnerability compared to non-recipients. On the other hand, Chile's social protection schemes indicate that they tend to have some significant effect in reducing the vulnerability of the transient poor individuals but are not robust so that one has to be cautious in drawing inferences. The robustness of the ATT estimations is checked with help of sensitivity analyses and is confirmed by these tests.

Our results indicate that the social protection schemes are limited in helping households reduce their vulnerability; they tend to be more effective when accessed or received on regular basis and over longer time period. Hence those individuals who move in and out of poverty or just above the poverty line and may not be always be eligible to these monetary transfers do not experience any improvement in their

[38] We further test the robustness of our results using the Nearest Neighbor matching approach and found our results to be robust.

vulnerability levels. Moreover, the monetary transfers schemes do not address the structural causes of vulnerability.

The results presented in this study are suggestive; they illustrate the importance of assessing the effect of social policies and poverty reduction programs on vulnerability and not just poverty. Further research is required to understand better the link between vulnerability and the deterioration of labor market conditions and the poor quality of public provisioning in education and health services, which is beyond the scope of the present study.

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Appendices

Appendix A. Components of government social expenditures (as percentage of GDP).

	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Environment Protection[a]	0	0.1	0	0	0	0	0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Housing and Community Services[b]	0.2	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.4
Health Services[c]	2	2.1	2	1.9	2	2.2	2.3	2.4	2.3	2.4	2.4	2.6	2.8	2.8	3	3	3	2.8	2.8	3	3	3.3	4
Recreation, Culture and Religion[d]	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2
Education[e]	3	2.6	2.4	2.3	2.3	2.4	2.5	2.5	2.5	2.8	2.9	3.3	3.8	3.7	3.9	4	3.9	3.6	3.3	3	3.2	3.9	4.4
Social Protection[f]	10.3	9.3	8.8	8.1	8.2	7.8	7.9	7.5	7	7.3	7	7.4	7.9	7.9	7.9	7.7	7.5	6.6	6.4	5.8	5.7	6.3	7.4
Total Government Social Expenditure	15.6	14.4	13.5	12.6	12.7	12.7	13	12.8	12.2	12.9	12.7	13.7	15	14.9	15.2	15.1	14.8	13.4	12.9	12.2	12.4	14.1	16.5

Source: Estadísticas de las finanzas públicas, (Direccion de Presuppuesto (Dipres), various years 2004 – 2010.
[a]Protection of the environment includes reduction of contamination, protection of biological diversity and landscape, and other types of environmental protection.
[b]Health services include public hospitals and public health services.
[c] Recreation, culture and religion include recreational and sporting services and cultural services.
[d] Education includes: preschool and primary and secondary education, tertiary education, education not definable by level, education auxiliary services and education.
[e]Social protection includes: elderly, family and children, unemployment, disability, housing, social protection schemes, research and development related to social protection.

Appendix B. Structure of the "Ficha CAS-II" score and weights.

Factor	Weight	Sub factor	Weight[a]	Variable	Weight[b]
Housing	0.26	Protection from the elements	0.4	Walls	0.35
				Floor	0.35
				Roof	0.3
		Overcrowding	0.22	People to rooms ratio	1
		Sanitation and comfort	0.38	Water	0.35
				Sanitation	0.3
				Shower/bath	0.35
Education	0.25			Years of education HH head	1
Occupation	0.22			Highest occupation category within the couple or HH head	1
Income/Assets	0.27	Income	0.43	Per capita income	1
		Housing	0.13	Owned land and house (Property)	1
		House appliances	0.44	Refrigerator	0.5
				Heating system	0.5

Source: Larrañaga (2005).
a. Total weight of the sub-factor components for a given factor is equal to 1.
b. Total weight of the variable components for a given sub-factor is equal to 1.

Appendix C. List of Monetary Subsidies provided under Chile's social protection scheme.

I. Potable water subsidy (*Subsidio de Agua Potable*, SAP)

Households receive a monetary subsidy that ranges from 50-100% of their water services monthly bill applicable to a 15 m3 of water consumption. The eligibility criteria are: must be permanent resident of the rural or urban area, must be a tenant, owner or usufruct, have a connection to a potable water system, must be able to meet the payments, and must complete an application to the municipality of residency.

II. Welfare pension (*Pension Asistencial,* PASIS)

There are three types of pensions provided:

a) Elderly pension: Consists of unconditional monetary subsidy for senior citizens (65 years and older), whose monthly household per capita income is lower than 50% of the minimum wage.
b) Disabled assistance: Consists of unconditional monetary subsidy for people between 18 to 64 years who have been declared disable by the government medical commission, and whose monthly household per capita income is lower than 50% of the minimum wage.
c) Mentally disabled assistance: This is equal to the disabled subsidy but without the age requirement.

III. Unemployment insurance

Unemployment insurance is mandatory in Chile and it covers formal workers under the labor law. This insurance is financed in part by an individual account, paid by the employee, and in part by a solidarity fund composed by payments done by the employer and the government.

IV. Family subsidy (*Subsidio Úncio Familiar,* SUF)

This is targeted to pregnant women and those with children under the age of 18. In order to receive this subsidy they cannot be recipients of private or public assistance though the PASIS pension system.

Appendix D. Number of recipient-households and amount of subsidies as percentage of before-transfer household income

	Number of recipient households in sample	Amount of subsidies as percentage of before transfer household income
Subsidies 1996	1710	4.0%
Subsidies 2001	1767	5.2%
Subsidies 2006	1942	5.1%

Source: Author's calculations from CASEN 1996-2001-2006 survey data.

Appendix E. FGLS Regression Results

Table E1. FGLS regression estimates for 1996 log per capita income and income per capita variance, Urban and Rural Households.[a]

VARIABLES	Urban Income per capita	Urban Income Variance	Rural Income per capita	Rural Income Variance
Age[b]	0.0108	0.0284**	0.0145	0.0426***
	(0.0073)	(0.0129)	(0.0143)	(0.0151)
Age square	5.41E-05	-0.000314**	4.42E-05	-0.000411***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Education (years of schooling)[b]	0.0689***	-0.00255	0.0494***	0.0248**
	(0.0041)	(0.0106)	(0.0097)	(0.0111)
Home ownership dummy[c]	0.338***	-0.241**	0.253***	-0.143**
	(0.0393)	(0.1100)	(0.0641)	(0.0634)
Unemployed dummy[d]	-0.772***	0.237	-0.372	-0.178
	(0.1130)	(0.2060)	(0.2350)	(0.1570)
Domestic service worker[d]	-0.401***	-0.243**	0.304	-0.434***
	(0.0912)	(0.1220)	(0.1850)	(0.1430)
Self-empl. w/o paid worker dummy[d]	-0.239***	-0.155*	0.0277	-0.116
	(0.0538)	(0.0939)	(0.1310)	(0.1210)
Self-emp. w/ paid worker dummy[d]	0.326***	-0.09	0.787***	-0.362**
	(0.1060)	(0.1100)	(0.2280)	(0.1440)
Wage and salaried employee dummy[d]	-0.165***	-0.156*	-0.0204	-0.302**
	(0.0495)	(0.0863)	(0.1330)	(0.1260)
Sex of household head[e]	0.0966**	0.0196	0.211*	0.0355
	(0.0398)	(0.0583)	(0.1100)	(0.0958)
Couple household dummy[f]	0.00749	-0.032	-0.195**	-0.0293
	(0.0417)	(0.0568)	(0.0984)	(0.1140)
Single person household dummy[f]	0.126**	0.0708	-0.127	-0.0378
	(0.0554)	(0.0750)	(0.1360)	(0.1530)
Household size	-0.0964***	-0.0231	-0.0846***	-0.0705**
	(0.0123)	(0.0226)	(0.0279)	(0.0336)
Young children under 7 years	-0.0675***	-0.0377	-0.092	0.086
	(0.0235)	(0.0426)	(0.0571)	(0.0674)
No. of employed members to HH size ratio	0.840***	-0.0161	0.805***	-0.16
	(0.0672)	(0.1270)	(0.1320)	(0.1160)
7th Region[g]	-0.0959	0.0758	0.229**	-0.129
	(0.0614)	(0.0552)	(0.1070)	(0.1440)
8th Region[g]	-0.0314	0.0477	-0.0185	-0.093
	(0.0555)	(0.0508)	(0.1100)	(0.1510)
Metropolitan Region[g]	0.257***	0.104*	0.399***	-0.205
	(0.0545)	(0.0606)	(0.1180)	(0.1480)
Constant	9.437***	0.159	9.140***	-0.0939
	(0.1820)	(0.2660)	(0.3450)	(0.3170)
Observations	2,299	2,042	552	552
R-squared	0.465	0.018	0.398	0.082

Source: CASEN 1996-2001-2006 panel data. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
[a] This is based on the characteristics of the household head and other household level variables. Some households did not report a household head, thus we re-coded those adults considered as 'partner' as 'head' in 301, 293 and 250 households for 1996, 2001 and 2006 respectively.
[b] Age of household head.
[c] Wealth proxy dummy equals 1 if family owns their dwelling; 0 if otherwise.
[d] Refers to labor force status dummy variables; 0 if not in the labor force.
[e] Equals 1 if head is male; 0 if female.
[f] Refers to household structure dummy variables; 0 if single parent or single adult with dependent household.
[g] Controls for regional fixed effects. The 3rd region is excluded from the regression.

Table E2. FGLS regression estimates for 2001 log per capita income and income per capita variance, Urban and Rural households.

VARIABLES	Urban Income per capita	Urban Income Variance	Rural Income per capita	Rural Income Variance
Age	0.0330***	-0.000276	0.0117	0.00142
	(0.0062)	(0.0066)	(0.0116)	(0.0122)
Age squared	-0.000106*	-2.48E-05	6.96E-05	-2.08E-05
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Education (years of schooling)	0.0683***	0.00507	0.0303***	-0.00385
	(0.0035)	(0.0038)	(0.0081)	(0.0078)
Home ownership dummy	0.388***	-0.110**	0.310***	-0.0912*
	(0.0363)	(0.0485)	(0.0554)	(0.0552)
Unemployed dummy	-0.553***	0.0241	-0.466***	0.0586
	(0.0688)	(0.0876)	(0.1410)	(0.1000)
Domestic service worker dummy	-0.244***	0.064	-0.217	-0.216**
	(0.0898)	(0.1060)	(0.2030)	(0.1020)
Self-employed w/o paid worker dummy	-0.169***	-0.0277	0.0168	0.0594
	(0.0492)	(0.0608)	(0.0962)	(0.0860)
Self-emp. w/ paid worker dummy	0.322***	-0.130*	0.890***	0.34
	(0.0772)	(0.0737)	(0.2750)	(0.2990)
Wage and salaried employee.	-0.0403	-0.169***	0.00438	0.0551
	(0.0436)	(0.0590)	(0.0968)	(0.0942)
Sex of household head	0.0374	0.0451	-0.0267	-0.107
	(0.0371)	(0.0435)	(0.0843)	(0.0790)
Couple household dummy	-0.0551	-0.0241	-0.0663	-0.0723
	(0.0372)	(0.0384)	(0.0808)	(0.0732)
Single person household dummy	0.103**	0.0505	-0.0881	-0.0405
	(0.0458)	(0.0494)	(0.0958)	(0.1280)
Household size	-0.130***	-0.0358***	-0.106***	-0.0484**
	(0.0105)	(0.0104)	(0.0188)	(0.0198)
Young children under 7 yrs.	-0.0109	0.103*	-0.0306	-0.0623
	(0.0424)	(0.0560)	(0.0739)	(0.0665)
Empl. to HH size ratio	0.603***	0.105*	0.572***	0.153
	(0.0523)	(0.0570)	(0.1060)	(0.1090)
7^{th} Region dummy	-0.0952	-0.16	-0.211**	-0.0608
	(0.0685)	(0.1100)	(0.0918)	(0.0899)
8^{th} Region dummy	-0.129**	-0.111	-0.216**	-0.0481
	(0.0653)	(0.1110)	(0.0946)	(0.0919)
Metropolitan Region dummy.	0.0826	-0.192*	0.0805	-0.171*
	(0.0636)	(0.1060)	(0.1010)	(0.0874)
Constant	9.199***	0.757***	9.969***	0.659*
	(0.1760)	(0.2410)	(0.3410)	(0.3970)
Observations	2,547	2,547	635	635
R-squared	0.458	0.035	0.389	0.05

Source: CASEN 1996-2001-2006 panel data. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table E3. FGLS regression estimates for 2006 log per capita income and income per capita variance, Urban and rural households.

VARIABLES	Urban Income per capita	Urban Income Variance	Rural Income per capita	Rural Income Variance
Age	0.0323***	0.000424	0.0227**	0.0081
	-0.00617	-0.00748	-0.0115	-0.0133
Age square	-0.000103*	-3.55E-05	-7.92E-05	-8.10E-05
	-5.55E-05	-6.96E-05	-9.62E-05	-0.000108
Education (years of schooling)	0.0679***	0.0164***	0.0422***	0.00713
	-0.00356	-0.00413	-0.00887	-0.00881
Home ownership dummy	0.312***	-0.158***	0.328***	-0.0867
	-0.0346	-0.0499	-0.0558	-0.0612
Unemployed dummy	-0.343***	0.193	-0.655***	0.0508
	-0.0957	-0.185	-0.19	-0.197
Domestic service worker dummy	-0.274***	-0.274***	-0.349	0.0704
	-0.0794	-0.0725	-0.213	-0.163
Self employed w/o paid worker dummy	-0.141***	-0.0477	0.0423	0.0192
	-0.0492	-0.0517	-0.0949	-0.0887
Self employed w/ paid worker dummy	0.410***	0.0989	0.740***	0.215
	-0.102	-0.105	-0.218	-0.168
Wage and salaried employee dummy	0.0354	-0.172***	-0.029	-0.112
	-0.0452	-0.0549	-0.0866	-0.0893
Sex of household head	-0.0677	0.0991	-0.140*	-0.0199
	-0.0418	-0.0605	-0.0779	-0.0845
Couple household dummy	0.0903**	-0.168***	-0.0795	0.0816
	-0.0425	-0.0615	-0.0838	-0.0961
Single person household dummy	0.147***	0.0763	-0.071	0.274***
	-0.0471	-0.066	-0.0843	-0.0839
Household size	-0.0680***	-0.0244**	-0.103***	0.0106
	-0.0111	-0.0106	-0.0206	-0.0158
Young children under 7 years	-0.0987	-0.0146	-0.119	-0.000516
	-0.062	-0.053	-0.215	-0.114
Employed members to HH size ratio	0.648***	-0.0332	0.533***	0.000674
	-0.0506	-0.0589	-0.0922	-0.103
7th region dummy	-0.215***	0.0354	-0.0111	0.0472
	-0.0633	-0.0687	-0.0917	-0.154
8th region dummy	-0.266***	-0.0336	-0.0825	-0.0629
	-0.0574	-0.0617	-0.0918	-0.161
Metropolitan region dummy	-0.0658	-0.0315	0.272***	-0.0714
	-0.0573	-0.0618	-0.104	-0.161
Constant	9.253***	0.640***	9.905***	0.0787
Observations	-0.182	-0.216	-0.384	-0.486
R-squared	0.374	0.051	0.328	0.049

Source: Based on CASEN 1996-2001-2006 panel data. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Appendix F. Robustness check of vulnerability estimates

We examine the predictive power of the vulnerability estimates by cross-tabulating vulnerability and high-vulnerability in 1996 and 2001 with the observed poverty status in 2001 and 2006 respectively. We present the results in Tables 3 and 4. About 34.8% of those individuals deemed vulnerable in 1996 fell into poverty in 2001; however only 18.1% of those considered vulnerable in 2001 became poor in 2006. Only 6.8% and 5.1% of those identified as not vulnerable in 1996 and 2001 fell into poverty in 2001 and 2006 respectively. The difference in the predictive power of individual vulnerability estimates between the two periods may be due to unexpected shocks faced by households in 1998-99 resulting from the economic crisis and/or to improvements in social protection targeting after 1999, enabling the monetary transfers to better assist those who are deemed vulnerable. Our high-vulnerability estimates yield higher poverty predictive power with 46.7% and 25% of those deemed as highly vulnerable becoming poor in the following wave. The reader should bear in mind that vulnerability and high-vulnerability represents a probability of 24% and 50% or more chance of becoming poor respectively, therefore the predictive power of the identification method seems quite reasonable.

Table F1. Comparison of 1996 estimated individual vulnerability rates and 2001 poverty rates.

	Poor in 2001	
	No	Yes
Vulnerability 1996		
No	93.2%	6.8%
Yes	65.2%	34.8%
High-Vulnerability 1996		
No	86.0%	14.0%
Yes	53.3%	46.7%

Source: Authors' calculations using the CASEN 1996-2001-2006 panel data.

Table F2. Comparison of 2001 estimated individual vulnerability rates and 2006 poverty rates.

	Poor in 2006	
	No	Yes
Vulnerability 2001		
No	94.9%	5.1%
Yes	81.9%	18.1%
High-Vulnerability 2001		
No	92.6%	7.4%
Yes	75.0%	25.0%

Source: Authors' calculations using the CASEN 1996-2001-2006 panel data.

Appendix G. Classification of sample respondents by poverty status (in percent of total)

	1996-2001-2006
Never Poor	64.5%
Transient Poor	31.3%
Chronic Poor	4.2%

Source: Author's calculation from CASEN 1996-2001-2006 survey data.

Appendix H

Table H1. Mean vulnerability and poverty rate estimates for total population, by groups for 1996, 2001 and 2006 (in percentage).

	N	Poverty 1996	Vulnerability 1996	Poverty 2001	Vulnerability 2001	Poverty 2006	Vulnerability 2006
C. Group	1528	8.1%	24.5%	7.7%	23.6%	4.5%	26.5%
Group 1	2362	18.1%	45.5%	16.1%	29.3%	10.6%	25.6%
Group 2	3154	26.5%	54.2%	20.6%	48.7%	10.6%	32.4%
Group 3	3243	39.5%	66.7%	35.3%	55.2%	15.6%	33.5%
Total	1028	23.6%	48.8%	20.2%	39.8%	10.5%	29.6%

Source: CASEN 1996-2001-2006 panel data.

Note: C.group (control group) corresponds to those who did not received any subsidies; group 1 received transfers in any one year, group 2 in any two years; and group 3 in all three years.

Table H2. Mean vulnerability and poverty rate estimates for the transitory poor, by groups for 1996, 2001 and 2006 (in percentage).

	N	Poverty 1996	Vulnerability 1996	Poverty 2001	Vulnerability 2001	Poverty 2006	Vulnerability 2006
C. Group	395	49.9%	58.6%	47.5%	64.6%	27.5%	48.5%
Group 1	969	57.4%	74.9%	51.0%	54.6%	33.5%	43.2%
Group 2	1587	72.1%	82.7%	56.0%	77.4%	28.7%	47.5%
Group 3	1895	71.6%	88.1%	64.0%	81.0%	28.3%	44.8%
Total	4846	66.3%	80.6%	56.9%	72.4%	29.6%	45.6%

Source: CASEN 1996-2001-2006 panel data.

Table H3. Mean vulnerability and poverty rate estimates for the chronic poor, by groups for 1996, 2001 and 2006 (in percentage).

	N	Poverty 1996	Vulnerability 1996	Poverty 2001	Vulnerability 2001	Poverty 2006	Vulnerability 2006
C. Group	41	100%	100%	100%	91.0%	100%	61.7%
Group 1	109	100%	95.6%	100%	90.1%	100%	97.0%
Group 2	203	100%	79.4%	100%	91.6%	100%	83.6%
Group 3	371	100%	97.1%	100%	92.7%	100%	69.1%
Total	724	100%	91.0%	100%	91.8%	100%	73.8%

Source: CASEN 1996-2001-2006 panel data.