Can Institutional Factors Affect Intergenerational Family Transfers?*

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Abstract

This study investigates the impact of a Mexican public health insurance program, *Seguro Popular*, on intergenerational transfers. I implement a machine learning propensity score matching difference-in-difference approach to estimate causal effects. I find that the enrollment in *Seguro Popular* incareses the probability of older adults receiving monetary transfers from their children by $9 - 10\%$, it does not affect the likelihhod of receiving non-monetary transfers, and incraese the amount of monetary transfers by 0.5%. By contrast, the participation in *Seguro Popular* decreases the probability of downward monetary transfers by $8 - 9\%$ and their amount by 0.5%, without affetcing the porbability of sownward non-monetary transfers. These findings contribute to the ongoing debate about how public interventions affect family support dynamics, suggesting a "crowding in" effect where public and private transfers are complementary rather than substitutes. I argue these results are driven by changes in family co-residency status.

JEL Codes: D64 , G51, H55, I13, I18, I38

Keywords: *Seguro Popular*, Upward and Downward Intergenerational Transfers

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1 Introduction

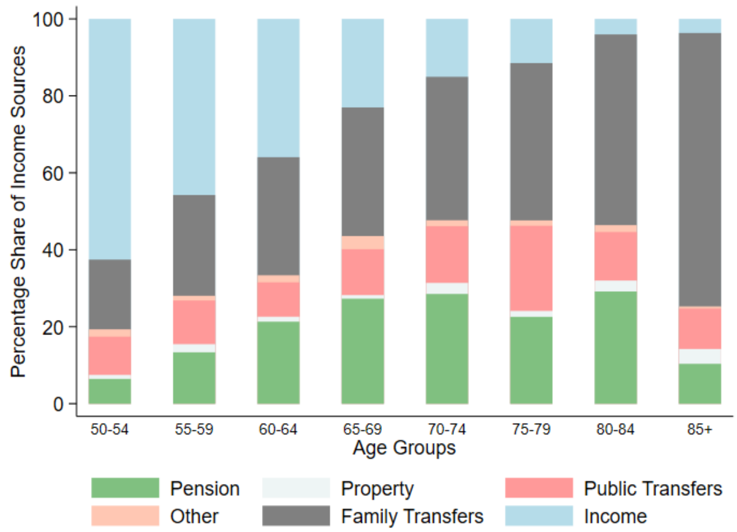
The rapid pace of global population aging poses a significant challenge for countries worldwide. According to the World Health Organization (WHO) (2022), in 2020, the number of individuals aged 60 and older exceeded the population of children under five years old, with a project of doubling before 2050. The aging population creates a challenge for the provision of healthcare services due to the higher frequency of health problems in elderly adults. This challenge is even more evident in Latin America because it is the world's fastest-aging region (Ruano et al., 2021), and access to healthcare is primarily determined by income (Strupat and Klohn, 2018). Consequently, economically disadvantaged households and vulnerable populations depend on informal support networks of family, friends, and neighbors to afford medical treatments (Strupat and Klohn, 2018). These informal support systems are central in offering an insurance mechanism, particularly during vulnerable life stages, such as advanced age. Several countries have responded to this urgent situation by introducing publicly funded health insurance plans to increase coverage and reduce the financial burdens of out-of-pocket medical expenditures (Aranco et al., 2022).

Nevertheless, a crucial question arises: Do these publicly-funded health insurance plans complement (crowd in) or substitute (crowd out) the transfers from informal networks? This study investigates the effect of *Seguro Popular* —a Mexican universal health insurance program —on monetary and non-monetary intergenerational transfers. I explore whether the enrollment in *Seguro Popular* increases (or decreases) upward and downward transfers, with the former defined as transfers from children to their parents and the latter as transfers from parents to children.

Mexico, with its rapidly growing older population and vulnerability to poverty, offers an ideal context to address these questions. As the demographic transition unfolds in Mexico, older citizens are living longer, often with inadequate formal retirement income sources, resulting in financial insecurity for many. Figure 1 underscores that informal mechanisms like family transfers, including remittances, gain importance with age, becoming the primary income source beyond the age of 70 (Aguila et al., 2012; Angel et al., 2017).[1]

[1]In contrast, public transfers, including noncontributory pensions, play a limited role but gradually become more significant at older ages. Wages and business revenue still contribute substantially to income above age 85, indicating that pensions play a modest role overall.

Figure 1: Income Source by Age Group



Source: Author's calculations using the Mexican Health and Aging Study (MHAS) 2001.

This study focuses on older adults and aims to answer a specific question: Does enrollment in *Seguro Popular*, a Mexican universal health insurance program, impact financial transfers from adult children to older adults (upward transfers)? Using data from the Mexican Health and Aging Study (MHAS), which offers comprehensive information on individuals aged 50 and older, including demographic, socioeconomic, family dependency, physical activity, and public/private transfers (INEGI, 2013), this study uses MHAS data from two waves: 2001 (baseline) before *Seguro Popular*'s introduction and 2012 (endline) after its implementation. This research intends to estimate the program's causal effects on financial and in-time transfers. I follow Parker et al. (2018) in identifying the potential "treatment group" as the individuals enrolled in *Seguro Popular* in 2012 and insured with a different plan or without any insurance in 2001. As a robustness check, I define an alternative potential treatment group in which I restrict the sample of respondents enrolled in *Seguro Popular* in 2012 only to individuals with no insurance plan in 2001. The potential control group is defined as all individuals without insurance plans in both years.

I use advanced econometric methods to estimate the causal effect of *Seguro Popular*. First, I addressed the potential selection bias stemming from voluntary enrollment in *Seguro Popular* and the absence of a well-defined eligible population in 2001 by implementing a machine-learning propensity score matching. This procedure consists of two steps. In the first step, I use different machine learning methods —LASSO Regression, Random Forest, and Boosting –to select the relevant observable characteristics that explain the enrollment in *Seguro Popular*. I use the LASSO Regression as the benchmark feature selection method. With the selected variables at hand, I implement a propensity score matching to find a suitable "control group" for the individuals in the "treatment group." This approach accounts for the endogeneity of enrollment decisions, effectively addressing selection bias.

Once the treatment and control groups are identified, I use a difference-in-difference regression model to evaluate to what extent the enrollment in *Seguro Popular* affects monetary and non-monetary intergenerational transfers. I explore the extensive margin, such as the probability of an individual receiving (or giving) transfers from (or to) the children, and the intensive margin, the amount of intergenerational transfers. I implement several model specifications to account for the importance of a large set of control variables found in the literature to determine intergenerational transfer decisions.

I find that enrollment in *Seguro Popular* increases the probability that the treated individuals receive monetary transfers from their children between $9-10\%$. To better understand the magnitude, these estimates imply that 27% of the documented increase in the share of respondents receiving monetary upward transfers in the treatment group relative to those in the control group is due to the enrollment in *Seguro Popular*. By contrast, the diff-in-diff estimates for the probability of giving monetary transfers to the children are negative, ranging, in absolute value, between $8-9\%$. These findings imply that only 10% of the documented drop in the share of respondents giving monetary downward transfers in the control group relative to the treatment group can be explained by the enrollment in *Seguro Popular*. The effect of *Seguro Popular* on non-monetary transfers is negligible. I do not find any statistically significant effects of *Seguro Popular* on upward non-monetary transfers or downward non-monetary ones. These results suggest that the intergenerational time exchange is less sensitive to government interventions.

Finally, I also investigate the effect on the amount of intergenerational transfers. The data lack information about the amount of hours spent helping the parents (or the children). Hence, I only report the estimates for the amount of monetary transfers. I document that the introduction of *Seguro Popular* increases the amount of upward monetary transfers by

0.5%, and decreases the amount of downward monetary transfers by the same percentage.

I evaluate the robustness of the previous findings by implementing a set of robustness checks. First, I use alternative machine learning algorithms as feature selection methods. Second, I define the treatment group as all individuals enrolled in *Seguro Popular* in 2012 and with no insurance in 2001. Finally, I restrict the sample of children to those older than 18 years old. This restriction implies that the probability of receiving (or giving) transfers and the amount of transfers are calculated only based on this restricted sample of children. All these robustness checks return estimates qualitatively and quantitatively consistent with the benchmark results.

This paper significantly contributes to several streams of research. Firstly, it extends the existing body of investigation on the impact of formal insurance on informal transfer networks. Prior studies have explored this relationship, with findings suggesting that formal insurance can crowd out informal transfers (Attanasio and Rios Rull, 2000) (Landmann et al., 2012; Lin, Liu, and Meng, 2014; Lenel and Steiner, 2017; Cecchi, Duchoslav, and Bulte, 2016). Strupat and Klohn (2018) provides empirical evidence that the provision of formal health insurance can lead to a reduction in informal transfers, thus reducing the financial burden on both ill individuals and their network partners. Building on this, my research shows that enrollment in *Seguro Popular*, a form of formal public health insurance, increases the likelihood of older adults receiving financial transfers from their adult children, indicating a crowding-in effect.

Secondly, this paper enriches the debate surrounding the effects of public-funded social benefits on private transfers. Existing literature presents mixed findings, with some studies suggesting that public interventions may crowd out private transfers (Jensen, 2004; Juarez, 2009; Orraca Romano, 2015; Strupat and Klohn, 2018; Smythe, 2022; Dercon and Krishnan, 2003), others argue for crowding-in effects (Brandt and Deindl, 2013; Cheng et al., 2021; Oruč, 2011) or neither of the two (Geng et al., 2018) or both (Mukherjee, 2018; Landmann et al., 2020; Ongudi et al., 2023). In the context of Mexico, where social norms play a central role, my study provides fresh insights into this debate.

Thirdly, this paper adds to the literature on the interaction between social policies and intergenerational transfers[2].Most of the previous research has investigated intergenerational

[2]See, for example, Umberson (1992), Whitbeck et al. (1994), Klaus (2019), Fingerman et al. (2020), Thomas and Dommermuth (2020), and Orozco Rocha et al. (2021).

transfers from parents to children —downward transfers (among others, Brandt and Deindl, 2013). In contrast, this paper studies transfers from children to parents —upward transfers (Sloan et al., 2002; Attias Donfut et al., 2005; Orraca Romano, 2015; Mukherjee, 2018; Smythe, 2022). Compared to previous works, my study presents causal estimates of the effect of *Seguro Popular* on intergenerational transfers and provides new interesting patterns in the connection between enrollment in *Seguro Popular* and intergenerational transfers.

Fourthly, this study contributes to the literature on the effects of *Seguro Popular*. This literature can be divided into two groups. The first group of studies explores the effects of *Seguro Popular* on directly targeted outcomes such as, for example, the use of health services (Barros et al., 2008; Parker et al., 2018; Turrini et al., 2018), the quality of health outcomes (King et al., 2009; Beltrán Sánchez et al., 2015), the probability of catastrophic health expenditures (Galárraga et al., 2010), infant mortality (Pfutze, 2014; Conti and Ginja, 2023), adult mortality (Arenas et al., 2023), and nutrition (Costa Font et al., 2020). The second group, instead, focuses on untargeted outcomes like labor supply and informality (Aterido et al., 2011; Azuara and Marinescu, 2013; Bosch and Campos Vazquez, 2014), school enrollment and academic performance (Alcaraz et al., 2017), domestic violence (Beleche, 2019), and intergenerational transfers (Orraca Romano, 2015). My study fits in this second group and contributes to a limited literature on a better understanding of the effect of universal health coverage on family dynamics and intergenerational transfers.[3]

Finally, this study contributes to the literature on altruism and monetary transfers in the household. Altruism and reciprocity are critical motivators behind private transfers (Soldo and Hill, 1993) within informal networks, serving as crucial mechanisms of insurance during times of hardship (Tsai and Dzorgbo, 2012). My research adds to this literature by analyzing older adults' families and exploring the possible channels behind the increase in the likelihood of receiving upward transfers.

In terms of policy, this research opens avenues for critical discourse on the broader social and economic repercussions of public health interventions. It raises questions about the burdens placed on primary caregivers, often women, and the intersection of gender and age within these dynamics. Furthermore, it examines the persistence of support following a spouse's death and the effectiveness of non-familial caregiving settings, ultimately pondering

[3] In this respect, the closest paper to mine is Orraca Romano (2015). Although we use different approaches and sample, this paper also studies the effect on intergenerational transfers due to the introduction of *Seguro Popular*.

the potential unintended consequences of such policies on the wealth-building capacities of adult children.

The subsequent sections of this paper are structured as follows: Section 2 provides a brief review of the theoretical framework, Section 3 outlines the main features of *Seguro Popular*, Section 4 introduces the data and describes their main features. Section 5 discusses the two econometric strategies and addresses potential identification challenges, Section 6 presents the empirical findings and discusses their economic implications, and finally, Section 7 offers the concluding remarks.

2 Conceptual Framework

A vast theoretical literature has examined the underlying reasons for intra-household transfers. Economic theories have primarily identified three motives: altruism (Becker, 1974; Barro, 1974), exchange (Bernheim et al., 1985; Cox, 1987), and cultural or social norms (Guttman, 2001).[4] Altruistic remittances occur when donors prioritize the welfare of recipients. Conversely, exchange-motivated remittances are essentially payments for services provided by the recipient.[5] Finally, individuals may transfer because they receive a positive utility from giving away or because social norms require such behaviors, especially in the case of upward intergenerational transfers. Public interventions like universal health insurance may lead to different outcomes depending on the motive for the intra-household transfers (Cox, 1987).

Within the altruistic paradigm, if public programs increase recipients' disposable income and donors' income decreases or increases by less than recipients' income, private transfers may decrease because the recipients are no longer in need of financial help. Under this scenario, the "crowding out" effect dominates, and public spending substitutes for private transfers, potentially dampening the impacts of public spending (Juarez, 2009).

Under the exchange approach, results are more ambiguous. An increase in recipients' income implies that donors are less dependent on their recipients' transfers. Thus, recipients will ask for a higher price for providing the services to the donors, and the effect of public interventions on private transfers will depend on the elasticity of the donors' demand for

[4] Other drivers have also been explored in the literature. For example, Lucas and Stark (1985) or Arrondel and Masson (2006) study the strategic role of upward transfers to secure family assets like inheritance. Lee and Xiao (1998) justify upward transfers to re-pay the investment and sacrifices that parents made for their children at their young ages.

[5] The altruism and exchange motives both are grounded on the Life Cycle Model, initially proposed by Modigliani and Brumberg (1954) that provides a theoretical foundation for understanding savings, consumption, and intergenerational wealth transfers.

the services provided by recipients. When services are irreplaceable and demand is inelastic, rises in income could generate larger private transfers that amplify the impact of the policy. This scenario is called the "crowding in" effect.

Social norms may prescribe donors to transfer income to the recipients. On the one hand, if public programs do not change social norms, donors will still face the prescription of transferring money to the recipients. On the other hand, if public interventions that boost a recipient's disposable income change social norms (Bau, 2021), private transfers may either increase or decrease. In this case, it remains uncertain whether the "crowding out" effect dominates the "crowding in" effect or vice versa.

The interrelation between public policies and intergenerational transfers is complex, emphasizing the interplay between public and private support systems. Furthermore, the relative importance of these motives may vary between upward and downward intergenerational transfers, implying that a public intervention might increase one type of transfers and decrease the other. As a consequence, public policies might indirectly create intergenerational trade-offs.

Such a dynamic relationship underscores the need for more comprehensive research in economies with limited or inexistent social security systems. A thorough understanding of these dynamics is essential to develop policies and strategies that boost welfare and promote effective intergenerational wealth transfers. Finally, with changing demographics, evolving social norms, and varying state provisions, it's critical to continually reassess and refine our understanding of these mechanisms.

3 Institutional Background: *Seguro Popular*

In Mexico, as in many other countries in the region, the healthcare system faces inefficiencies and generates inequalities. Before the creation of *Seguro Popular*, only employees in the formal sector had access to social security and health insurance through their employers.[6] This share accounted for less than 50% of the Mexican population.[7] The majority of the population —self-employed, underemployed, and unemployed —either could use partially-funded health coverage through the Secretaría de Salubridad y Asistencia (SSA) or pay for

[6]The health insurance plans were provided through social security institutions such as Instituto Mexicano del Seguro Social (IMSS) or Instituto de Seguridad y Servicios Sociales de los Trabajadores del Estado (ISSSTE).

[7]In 2000, 33% of Mexico's residents were covered by IMSS, 6% by ISSSTE and 2.2% by another public or private health insurer. The remaining 57.8% of the population did not have health coverage (Frenk et al., 2006).

private care out-of-pocket.[8] Indeed, in 2003, healthcare expenditures paid out-of-pocket accounted for 58% of the total health expenditures in Mexico (Pérez Rico et al., 2005).

The financial burden of paying for health treatments out-of-pocket is likely to lead people to postpone or avoid regular checkups and screenings, especially among poor households that had unstable or informal jobs and could not receive health insurance through their employers. The high out-of-pocket costs of medical treatment are likely to disincentivize the prevention of diseases but also to inhibit compliance with treatment plans when illnesses are diagnosed, leading to higher mortality rates. Furthermore, the absence of universal public health coverage magnifies the inequality between rich and poor households, with the latter suffering even worse economic conditions when they have to face unexpected health shocks and, consequently, the costs of medical treatments.

To address these issues, in October 2001, the Mexican government introduced a pilot phase of the *Seguro Popular* in five states (Aguascalientes, Campeche, Colima, Jalisco, and Tabasco),[9] but it was formally implemented in 2004 when it became part of the System of Social Protection in Health. The program gradually expanded throughout Mexico according to resource availability.[10] At the end of 2004, 30 out of 32 states had signed an agreement with the federal government formalizing their participation in *Seguro Popular*. The last two states, Durango and Mexico City, joined the program in 2005.

The *Seguro Popular* is a funding mechanism that aims to guarantee universal access to health services, especially for the most vulnerable populations without social security, and reduce out-of-pocket health expenditures.[11] In the ten years after the adoption of *Seguro Popular*, the rate of individuals without health insurance drops significantly by 45 percentage points (from 58% in 2002 to 13% in 2012), meaning that over 50 million people enrolled in the program (Knaul et al., 2013). The adoption of *Seguro Popular* was also accompanied by an increase in public health expenditures in the first decade of the 2000s. The SSA budget increased by 142% to provide an adequate supply of medical services to the increasing number

[8]The SSA was underfunded as it was financed through a combination of federal and state resources that were not sufficient to cover the needs.

[9]The selection of these states was based on their social security coverage, their capacity to provide the health services and their urban concentration.

[10]With the adoption of *Seguro Popular*, the Mexican government also established the rules for the future selection of states into the program. The selection of a state would be based on the proportion and number of uninsured people at the bottom of the income distribution, the incidence of diseases, the existence of adequate health facilities, the demand for the program, and per capita federal contributions. In practice, other factors played a role in the participation order, among them political interests Diaz Cayeros et al. (2006) or the size of the states (Bosch and Campos Vazquez, 2014).

[11]Other developing countries, among them Thailand, Indonesia, and Ghana, have introduced similar programs to guarantee universal health coverage. These programs, although have a similar scope, differ in their functioning and funding strategy.

of patients (Knaul et al., 2013). Furthermore, in terms of per capita health expenses, the gap between individuals covered by social security institutions and the uninsured population narrowed significantly. On the other hand, the Mexican government has also undergone massive investments to strengthen the health infrastructure and provide an adequate supply of medical services.

To enroll in the *Seguro Popular*, applicants must reside in Mexico,[12] not be eligible for coverage from other social security institutions and present a birth certificate or unique registration code.[13] The enrollment requires a visit to the nearest registration center that conducts a socioeconomic evaluation of the applicant.[14] The evaluation aims to classify households into two groups. The bottom 40% in terms of income are enrolled in the program without the need to pay the enrollment fee. The remaining 60%, instead, are required to pay an annual enrollment fee that increases with their income.[15]

Each state's health service administration is responsible for the provision of services included under the *Seguro Popular*.[16] These services include primary, secondary, and more advanced medical interventions, as well as access to medications and laboratory clinical studies. The treatments are grouped into six categories —public health, general family health and specialty services, dentistry, emergency hospitalization and general surgery —that account for more than 90% of all hospital interventions. Furthermore, *Seguro Popular* covers 58 interventions contained in the Fondo de Protección contra Gastos Catastróficos, which includes treatment for prematurely-born babies, childhood leukemia, cervical cancer, and HIV. Overall, as of 2012, the *Seguro Popular* program covers 284 interventions as well more than $1,500$ illnesses. Households enrolled in the program can access all these treatments free of charge, apart from the enrollment fee.

One important aspect in the design of the *Seguro Popular* that matters for the evaluation

[12] They must provide a utility bill as verification of their address.

[13] Affiliation is not conditioned on health status or pre-existing illness.

[14] As noticed by Parker et al. (2018), the socioeconomic evaluation was mainly a formal requirement. In practice, the registration centers did not evaluate the socioeconomic status of the applicants but simply verified whether the applicants were affiliated with other social security institutions.

[15] Enrollement fees may go from the lowest of USD150 for households in the fifth decile of the income distribution to USD1000 for households in the top decile. (Knaul et al., 2013) document that a small share of households, approximatively 0.5%, pays an enrollment fee, meaning either the sample of the population enrolled in *Seguro Popular* over-represents the bottom of the distribution or households systematically under-report their incomes. Furthermore, states have incentives to enroll as many people as possible to receive a large share of the federal budget.

[16] The funding of the *Seguro Popular* is split among the federal government, states, and households. The federal government provides most of the funding through two components: (i) Social Contribution (Cuota Social) equivalent to 3.92% of the annual minimum wage, and (ii) Federal Contribution (Aportación Solidaria Federal) equivalent to 1.5 times the Social Contribution. States contribute 0.5 times the Social Contribution. Enrolled households pay an enrollment fee based on their estimated income. See Pueblita (2013) for further details about the funding structure of *Seguro Popular*.

of the effect of access to universal health coverage on inter-generational family transfers is that affiliation is voluntary. Thus, the comparison between affiliates and non-affiliates is problematic because people who choose to affiliate may be different compared to people who choose not to affiliate. In Section 5, I tackle this selection bias issue and estimate an unbiased causal effect by implementing a difference-in-difference combined with propensity score matching on observed characteristics, as in Parker et al. (2018), among others.

4 Data

4.1 Sample

The main data source for this study is the Mexican Health and Aging Study (MHAS), sponsored by the National Institutes of Health/National Institute of Aging in the United States and the National Institute of Statistics and Geography (INEGI) in Mexico.[17] The MHAS is the first national longitudinal study of adults 50 years and older in Mexico.[18] The MHAS was designed to evaluate the aging process, the impact of diseases, and the capacity of individuals to carry out activities of daily living (ADLs) and Instrumental Activities of Daily Living (IADLs). The MHAS collects a wide range of information, such as demographic and socioeconomic characteristics, family dependency, physical activity, and public and private transfers. This information provides a rich picture of family dynamics and status (INEGI, 2013).[19]

The first wave was collected in 2001 with a nationally representative sample of individuals born in or earlier than 1951. The sample is distributed across the 32 Mexican states, representing both rural and urban areas.[20] The sample of residents for the 2001 wave was selected from the Encuesta Nacional de Empleo. The eligible households had at least one resident aged 50 years or older. If a selected household had more than one person of 50 years or older without any marital tie, then one of these was selected randomly as the respondent for the study. If, instead, the selected person was married or in a consensual union with a partner younger or older than 50 years old, the partner was included in the MHAS regardless of the age restriction. The follow-up surveys were collected in 2003, 2012, 2015, 2018, and 2021. However, the analysis in this paper is based on the waves in years 2001 and 2012.

[17] See Wong et al. (2017) for an extensive discussion about the creation of the MHAS and its features.

[18] One additional advantage of the MHAS that I do not exploit in this paper is that the study also enables cross-national comparisons. Indeed, similar datasets are also available in other countries, including the US.

[19] Data were collected from the Mexican Health and Aging Study.

[20] The survey oversamples households from the six states accounting for 40% of Mexican migrants to the US.

The 2001 wave is the first wave available before the introduction of *Seguro Popular*, while the 2012 wave is chosen because the MHAS only collects information about *Seguro Popular* in that wave. The 2012 wave included all age-eligible individuals present in previous waves and a new nationally representative sample of individuals born between 1952 and 1962, as well as their spouses regardless of age.[21]

The MHAS collects a rich set of information for three generations of individuals: the person who participates in the survey (the "respondent"), the respondent's parents, and the respondent's children. For the scope of this study, the unit of observation is the respondent. I restricted the sample to respondents 50 years old or older at the moment of the first data collection (2001) and participated in the surveys of 2001 and 2012.[22] The balanced panel after these filters consists of 3,473 observations for each wave. I also apply standard filters common in the literature; for example, I drop observations with incomplete or incongruent information in any variable of interest for the analysis. This sample constitutes the basis for the matching procedure described in Section 5 in which individuals enrolled in *Seguro Popular* are matched to their correspondent counterfactual that acts as the control group. Specifically, the panel nature of the dataset allows me to identify in the baseline (2001) the individuals who have enrolled in *"Seguro Popular"* health insurance based on the follow-up survey in 2012 (endline), and their counterfactual based on a rich set of observable characteristics (INEGI, 2013; Wong et al., 2017).

The MHAS has three main advantages for the purpose of this study. First, it reports the type of insurance in which individuals are enrolled in each wave.[23] This feature is important for identifying the treatment and control groups. Second, the survey collects information about monetary and non-monetary transfers through retrospective questions.[24] Finally, the

[21] As expected, given the sample population consists of elderly adults, about 25% of them are only present in the first wave. The main cause of attrition is the respondents' death (55% of the attrited individuals).

[22] I consider only the main respondent for each household. In other words, we exclude spouses or partners if present in the survey.

[23] The insurance in which a respondent is enrolled is defined based on the following question: "*Do you have the right to medical attention in i) IMSS; ii) ISSSTE; iii) Pemex, Defensa o Marina; iv) Private medical insurance; v) Other; vi) Seguro Popular; vii) None?*"

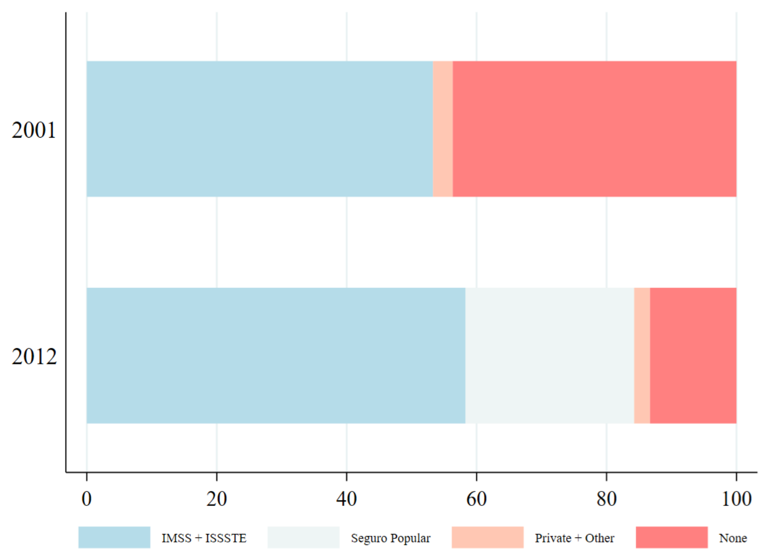
[24] Regarding monetary transfers, the questionnaire asks: "*In the last two years, have you (or your spouse) received financial or in-kind support from any of your children and/or grandchildren (and those of your spouse)?*" and "*In the last two years, have you (or your spouse) given financial or in-kind support to any of your children and/or grandchildren (and those of your spouse)?*" Regarding non-monetary transfers, the questionnaire asks: "*In the last two years, have your (and your spouse's) children/their spouses/grandchildren spent at least one hour a week helping you with household chores, errands, transportation, etc.?*" and "*In the last two years, have your children/their spouses/grandchildren spent at least one hour a week helping you (and your spouse's) with household chores, errands, transportation, etc.?*". These questions refer to help with household tasks, errands, and so forth that the respondent's (or their spouse's) children and immediate family have provided within the last two years. The questions aim to capture an approximate level of assistance. If the respondent states that they have received help only sporadically, such as once a month, then that assistance is not considered. If the respondent indicates that the level of

survey collects information about the amounts of upward and downward monetary transfers. I will use this information to provide insights into the intensive margin.

4.2 Descriptive Statistics

Figure 2 shows the shares of individuals enrolled in each insurance type by wave. In 2001, only 53% was enrolled in plans provided by either IMSS or ISSSTE. 44% of the sample was not covered by any health insurance plan. The scenario drastically changes with the introduction of *Seguro Popular*. In 2012, the share of individuals without insurance drops from 44% to 13%, mirroring the 25% enrollment rate in *Seguro Popular*. Regardless of the year, a negligible share of the population is covered by "Private + Other" insurance plans, with 3% in 2001 and 2.4% in 2012.

Figure 2: Types of Insurance by Year



Notes: The balanced panel consists of $3,473$ observations for each wave. The first category, "IMSS + ISSSTE" also includes Pemex, Defensa, and Marina, which account for a marginal share of health insurance plans. The shares are computed as weighted shares by the individual survey weights.

The enrollment rates in the different types of health insurance plans show significant heterogeneity. Figure B.1 in the Appendix reports the share of individuals enrolled in each insurance category by type of location and gender. The first two panels highlight considerable differences in health insurance coverage by type between individuals living in urban and rural areas. In 2001, in urban areas, 70% of individuals were under insurance plans provided

help varies, efforts are made to determine what occurs most frequently or on average. The goal of the questions is to capture substantial assistance, defined as, on average, at least one hour per week.

through their private or public employers (IMSS or ISSSTE), and less than a third had no access to health insurance. Rural areas had these figures completely reversed, with only 37% covered by insurance plans provided by their employers and 60% uncovered. The introduction of *Seguro Popular* has changed this discrepancy in coverage between rural and urban areas, with a higher share of rural residents enrolled in *Seguro Popular* than urban residents. Indeed, 39% of rural residents were affiliated with *Seguro Popular* by 2012 compared to 13% in urban areas. These figures mirror the economic structure of Mexico, where there is a higher share of informal workers in rural areas than in urban areas, implying that before the adoption of *Seguro Popular*, a larger share of rural inhabitants were unprotected against illnesses and health shocks. By contrast, I do not document any striking differences between women and men.

Table 1: Transition Shares between Insurance Types

Insurance Type in 2001	Insurance Type in 2012			
	IMSS + ISSSTE	Seguro Popular	Private + Other	None
IMSS + ISSSTE	0.883	0.063	0.017	0.037
Private + Other	0.234	0.430	0.260	0.076
None	0.236	0.492	0.016	0.257

Notes: The balanced panel consists of 3,473 observations for each wave. The first category, "IMSS + ISSSTE" also includes Pemex, Defensa, and Marina, which account for a marginal share of health insurance plans. The shares are computed as weighted shares by the individual survey weights.

As showed in Table C.1 in the Appendix, 54% of the sample was enrolled in a health insurance plan (public or private) in 2001 and 2012, while 11% remained uncovered in both years. 32% of the sample was under a health insurance plan only in 2012, while only 2.2% of the sample was covered in 2001 and not in 2012. These statistics are calculated regardless of the type of insurance, and they also suggest, in conjunction with the findings from Figure 2, that interesting transition patterns between types of insurance occurred between 2001 and 2012. Table 1 digs into this analysis by investigating the transition patterns between types of insurance. The statistics report the share of individuals transitioning from an insurance type in 2001 to another insurance in 2012 relative to the number of individuals in that insurance type in 2001.

Almost the totality (88%) of individuals enrolled in either IMSS or ISSSTE in 2001 remains covered by the same type of insurance in 2012. By contrast, only 26% individuals without any insurance in 2001 were without any insurance in 2012 as well. The main reason for this drop is that 49% of uninsured individuals in 2001 were enrolled in *Seguro Popular* in 2012. The remaining 24% of individuals without any insurance in 2001 received in 2012 a health insurance plan through IMSS or ISSSTE, implying that those individuals were able to find a job in the formal labor market.

Based on the statistics from Table C.2 in the Appendix, the share of respondents that receive monetary transfers from their children increased between 2001 and 2012 regardless of their insurance statuses. Indeed, in the aggregate, the share of respondents that receive monetary transfers from children rose from 33% in 2001 to 43% in 2012 (column 2). By contrast, the share of respondents that receive help with house chores from their children slightly declined from 49% in 2001 to 41% in 2012 (column 4). The share of respondents that make downward transfers remained unchanged between 2001 and 2012 (column 1), while the share of respondents that help their children with non-monetary transfers declined by 17 percentage points (column 3).[25] These figures fit well with a life-cycle pattern. On the one hand, as children grow up, they become financially more independent. Thus, they need less financial support from their parents, and they start to help them with monetary transfers. As a consequence, as children grow up, monetary upward transfers increase. On the other hand, non-monetary transfers are only slightly affected by the children's aging process. The types of chores children perform at different ages are likely different; while young children living at home often assist with household chores, adult children tend to focus on helping their aging parents with activities of daily living. These findings highlight the importance of controlling for factors like age and living and marital status to evaluate the impact of *Seguro Popular* on inter-generational transfers.

Table 2 reports the share of respondents that receive monetary or non-monetary transfers from their children by year and by the transition between types of insurance. Specifically, I first identify respondents that have transited between types of insurance between 2001 and 2012. These shares are shown for both 2001 and 2012. Then, I calculate each cell of

[25] The question included in the survey asks whether the respondent (or their spouse) has spent at least one hour a week helping their children or their children's nuclear families, as well as taking care of grandchildren or great-grandchildren, cooking, shopping, etc.

Table 2: Share of Upward Transfer Respondents

Monetary Transfers

Panel A: Share of Transfer Respondents in 2001

Type Insurance in 2001	Insurance Type in 2012: IMSS + ISSSTE	Seguro Popular	Private + Other	None
IMSS + ISSSTE	0.347	0.330	0.176	0.340
Private + Other	0.296	0.510	0.187	0.538
None	0.307	0.280	0.578	0.364

Panel B: Share of Transfer Respondents in 2012

Type Insurance in 2001	Insurance Type in 2012: IMSS + ISSSTE	Seguro Popular	Private + Other	None
IMSS + ISSSTE	0.409	0.636	0.325	0.341
Private + Other	0.577	0.530	0.397	0.618
None	0.433	0.456	0.305	0.437

Non-Monetary Transfers

Panel C: Share of Transfer Respondents in 2001

Type Insurance in 2001	Insurance Type in 2012: IMSS + ISSSTE	Seguro Popular	Private + Other	None
IMSS + ISSSTE	0.505	0.557	0.442	0.337
Private + Other	0.221	0.458	0.376	0.215
None	0.463	0.481	0.577	0.491

Panel D: Share of Transfer Respondents in 2012

Type Insurance in 2001	Insurance Type in 2012: IMSS + ISSSTE	Seguro Popular	Private + Other	None
IMSS + ISSSTE	0.406	0.327	0.367	0.409
Private + Other	0.327	0.346	0.521	0.581
None	0.428	0.415	0.659	0.409

Notes: The balanced panel consists of 3,473 observations for each wave. The first category, "IMSS + ISSSTE" also includes Pemex, Defensa, and Marina, which account for a marginal share of health insurance plans. The shares are computed as weighted shares by the individual survey weights.

Table 2 as the share of respondents that receive transfers from their children relative to the number of respondents that have changed their types of insurance between 2001 and 2012. These statistics aim to quantify whether *Seguro Popular* has increased (decreased) the share of respondents that receive monetary or non-monetary transfers between 2001 and 2012 by more (or less) than other insurance statuses.

As previously mentioned, the share of respondents enrolled in "Private + Other" insurance is negligible. Hence, we abstract from discussing this set of results. The largest increase in the share of respondents that receive transfers from their children between 2001 and 2012 is for respondents that are enrolled in *Seguro Popular* in 2012 regardless of their insurance status in 2001. Indeed, the share of respondents enrolled in employer-based health insurance plans in 2001 and in *Seguro Popular* in 2012 receiving money from their children doubled between those two years, going from 33% to 64%. Similarly, the share of respondents without any insurance in 2001 and enrolled in *Seguro Popular* in 2012 receiving monetary transfers from their children rose by 19 percentage points, from 28% in 2001 to 47% in 2012. I also document that the share respondents either enrolled in both employer-based insurance plans or without insurance plans receiving monetary transfers from their children increased by 6 between 2001 and 2012.

The results of non-monetary transfers show that the share of respondents who receive help from their children decreased for all pairs of insurance types, except respondents enrolled in employer-based insurance plans in 2001 and with no insurance in 2012 (7 percentage points increase). The drops for the other pairs of insurance types are significant, with a peak of 23 percentage points for respondents in employer-based insurance plans in 2001 and were in *Seguro Popular* in 2012.

Table 3: Share of Downward Transfer Respondents

Monetary Transfers

Panel A: Share of Transfer Respondents in 2001

Type Insurance in 2001	Insurance Type in 2012: IMSS + ISSSTE	Seguro Popular	Private + Other	None
IMSS + ISSSTE	0.153	0.076	0.091	0.092
Private + Other	0.165	0.045	0.348	0.042
None	0.151	0.109	0.048	0.084

Panel B: Share of Transfer Respondents in 2012

Type Insurance in 2001	Insurance Type in 2012: IMSS + ISSSTE	Seguro Popular	Private + Other	None
IMSS + ISSSTE	0.125	0.125	0.073	0.262
Private + Other	0.039	0.086	0.075	0.470
None	0.140	0.110	0.025	0.178

Non-Monetary Transfers

Panel C: Share of Transfer Respondents in 2001

Type Insurance in 2001	Insurance Type in 2012: IMSS + ISSSTE	Seguro Popular	Private + Other	None
IMSS + ISSSTE	0.523	0.560	0.481	0.540
Private + Other	0.241	0.196	0.437	0.275
None	0.522	0.449	0.473	0.416

Panel D: Share of Transfer Respondents in 2012

Type Insurance in 2001	Insurance Type in 2012: IMSS + ISSSTE	Seguro Popular	Private + Other	None
IMSS + ISSSTE	0.319	0.357	0.387	0.429
Private + Other	0.287	0.170	0.542	0.587
None	0.281	0.293	0.354	0.347

Notes: The balanced panel consists of 3,473 observations for each wave. The first category, "IMSS + ISSSTE" also includes Pemex, Defensa, and Marina, which account for a marginal share of health insurance plans. The shares are computed as weighted shares by the individual survey weights.

Table 3 reports the share of respondents that monetary or non-monetary transfers to their children. The share of respondents making downward monetary transfers remains substantially unchanged for most combinations of insurance types in 2001 and 2012. The only two surprising exceptions are the increases in the share of respondents giving monetary transfers to their children who were enrolled in the employer-funded insurance plans in 2001 and without any insurance in 2001 (9% vs. 26%) and for respondents without any insurance in both periods (8% vs. 18%). Regarding downward non-monetary transfers, I document a decline in the share of respondents helping their children with time for all combinations of insurance types, ranging between 20 and 7 percentage points.

Table 4: Amount of Monetary Transfers

Upward Transfers

Panel A: Amount of Transfers in 2001

Type Insurance in 2001	Insurance Type in 2012			
	IMSS + ISSSTE	Seguro Popular	Private + Other	None
IMSS + ISSSTE	2.500	2.384	1.368	2.227
Private + Other	2.367	3.297	1.483	3.557
None	2.147	1.980	4.156	2.546

Panel B: Amount of Transfers in 2012

Type Insurance in 2001	Insurance Type in 2012			
	IMSS + ISSSTE	Seguro Popular	Private + Other	None
IMSS + ISSSTE	1.963	2.017	1.459	1.124
Private + Other	2.688	2.125	1.924	3.179
None	2.366	1.957	1.906	2.114

Downward Transfers

Panel C: Amount of Transfers in 2001

Type Insurance in 2001	Insurance Type in 2012			
	IMSS + ISSSTE	Seguro Popular	Private + Other	None
IMSS + ISSSTE	1.108	0.539	0.760	0.553
Private + Other	1.282	0.303	2.993	0.442
None	1.065	0.718	0.309	0.564

Panel D: Amount of Transfers in 2012

Type Insurance in 2001	Insurance Type in 2012			
	IMSS + ISSSTE	Seguro Popular	Private + Other	None
IMSS + ISSSTE	0.710	0.370	0.573	1.085
Private + Other	0.256	0.548	0.445	1.594
None	0.651	0.466	0.240	1.091

Notes: The balanced panel consists of 3,473 observations for each wave. The first category, "IMSS + ISSSTE" also includes Pemex, Defensa, and Marina, which account for a marginal share of health insurance plans. The amounts are computed as weighted amounts by the individual survey weights.

In addition to the extensive margins, I also investigate the changes along the intensive margin. Both the amounts of upward and downward transfers were larger in 2001 than in 2012. Indeed, the average upward monetary transfer in 2001 was 2353 USD, and 2010 USD in 2012, while the average downward monetary transfer in 2001 was 0.924 USD, and 0.680 USD in 2012. Table 4 digs further into these figures and reports the average monetary transfer from children to parents by the transition between health insurance types.[26] Upward

[26] I cannot calculate the changes in the average number of hours that children dedicate to helping their parents because the question is not asked in 2001.

transfers decrease by a similar amount for all combinations of insurance types between 2001 and 2012. I also document a similar pattern for downward transfers, except for respondents who switched from any insurance in 2001 to no insurance in 2012. In those cases, the downward transfers doubled between the two years.[27]

Overall, I document that the most marked changes in upward transfers come from children whose parents were enrolled in *Seguro Popular* in 2012, regardless of their status in 2001. These findings strongly point to an effect of *Seguro Popular* in changing the behaviors of children of enrolled parents. Although these descriptive statistics show interesting patterns, we cannot draw at this point any causal conclusions. First, the statistics have been computed as unconditional statistics without accounting for a rich set of cofounders that may affect these patterns. Second, as mentioned, participation in *Seguro Popular* is voluntary, and affiliates may differ from non-affiliates. Section 5 presents an identification strategy that allows us to estimate the causal effect of *Seguro Popular* on intergenerational transfers. In this respect, the survey design and the quality of the data collected provide an ideal setting for investigating this question.

5 Empirical Strategy

The main issue to draw causal inference on the effect of *Seguro Popular* on intergenerational transfers is that the affiliation to the public program is voluntary, making the comparison of affiliates with non-affiliates problematic due to the selection bias as people choosing to affiliate may be different compared to non-affiliates in observed characteristics that could be associated with outcomes of interest. Addressing this potential estimation problem is necessary to get unbiased estimates.

In this paper, I leverage the panel nature of the data, and I address the selection bias by estimating a difference-in-difference propensity score matching model using individual-level information from the survey waves before and after the introduction of *Seguro Popular*, i.e., 2001 and 2012. The choice of 2012 as the endline is due to the fact that the question related to the enrollment in *Seguro Popular* was included in the MHAS questionnaire for the first time in 2012. The estimation strategy consists of two stages.

In the first stage, I address the methodological issue of selecting a valid counterfactual that takes into account the endogeneity of the enrollment decision. The treatment group

[27] Individuals enrolled in "Private + Other" plans are very few. Hence, the variance in their transfers is very high.

consists of survey respondents enrolled in *Seguro Popular* in the follow-up survey from 2012 (endline). This definition of the treatment group implies that those individuals in 2001 could be either insured with a different plan or without any insurance. As a robustness check, I define an alternative treatment group in which I restrict the sample of respondents enrolled in *Seguro Popular* in 2012 only to individuals with no insurance plan in 2001.[28] Given the panel nature of the dataset, I can track the individuals enrolled in *Seguro Popular* in 2012 back to the baseline survey (2001). This strategy allows me to observe the characteristics of the individuals in the treatment group in the baseline. I define the potential control group as all individuals without any insurance plan in both 2001 and 2012.[29] Following Parker et al. (2018), I construct a properly selected control group such as the observed characteristics of the treated individuals in baseline match with those of the untreated included in the potential control group. This approach allows me to overcome the selection bias and estimate causal effects.

This approach consists of various steps. First, I use machine learning algorithms to select the relevant variables for modeling the program-participation decision. To evaluate the performance of the different algorithms, I split the sample into two sub-samples, separately for the potential treatment and control groups (Sendhil Mullainathan and Jann Spiess, 2017). The training sample with 80% of the observations is used to calibrate and estimate the algorithm. The testing sample with 20% of the observations is used to test the out-of-sample performance.

The first feature selection method is the LASSO (Least Absolute Shrinkage and Selection Operator) Regression (Hastie et al., 2015). This method adds a penalization term to the OLS objective function:

$$\hat{\beta}(\lambda) = \underset{\beta \in \mathcal{R}^{+}}{\operatorname{argmin}} \sum_{i+1}^{n} \Big(y_i - x_i \beta \Big)^2 + \lambda \sum_{j=1}^{k} |\beta_j| \tag{1}$$

where k is the number of potential predictors, and λ is the penalization term. In practice, the LASSO algorithm selects variables with high predictive power and shrinks their coefficients while constraining all other variables to have zero coefficients. The penalty parameter λ is

[28] The figures reported in Section 4 suggest that the differences between the two definitions of the treatment group are marginal as only a small share of individuals with an insurance plan in 2001 enrolled in *Seguro Popular* in 2012.

[29] Alternative potential control groups could be defined. For example, one might define it as all individuals without insurance in 2012. This comparison group would like to underestimate the effect of *Seguro Popular* because a share of those individuals could be covered in 2001 by another insurance plan.

chosen via cross-validation.[30]

The second machine learning algorithm used for feature selection is the random forest (Breiman, 2001). In a random forest algorithm, multiple decision trees are trained on random subsets of the training data, where a decision tree is a random subset of the data. There are two levels of randomness: in the choice of the observations and variables to include in each tree. Each tree produces a prediction. These predictions are combined to make the final prediction. The idea is that by combining multiple predictions, the errors made by individual trees are reduced, leading to a more accurate prediction.

The last feature-selection algorithm is the Boosting (also called Boosted Regression) method (Friedman et al., 2000). Like the random forest algorithm, the boosting method combines the predictions of multiple random trees. There are two main differences between random forest and boosting: i) boosting combines trees sequentially, implying that observations misclassified in previous iterations receive a larger weight in the following iteration; ii) boosting uses shorter trees, implying the overall prediction combines more individual predictions than the random forest algorithm. I improve the algorithm's performance by using bagging, which consists of using only a random subset of the training data to define the tree in each iteration. Furthermore, the algorithm could estimate models that fit well the training sample but have poor out-of-sample performance. To avoid the risk, I include a shrinkage parameter that reduces the contribution of each additional tree and decreases the risk of over-fitting the model.

When the relevant predictors are selected, I compute the propensity score for all individuals in the treatment and in the potential control group. The propensity score is estimated using a probit model. Finally, I implement a Local Linear Regression (LLR) estimator to generate the control group for the treated units (Heckman et al., 1997). LLR estimator uses a weighted average of all observations within the common support region, with the weight of a comparison unit inversely proportional to the distance from the treated unit and the inclusion of a linear term in the weighting function to avoid bias. I discard the nonparametric regression results in regions where the density of the propensity score in the control group is small. In other words, I exclude the observations outside the common support (Frölich, 2004; Chabé Ferret, 2015). In order to estimate the standard errors correctly, I use bootstrapping,

[30] Section A.2 in the Appendix explains in detail the cross-validation strategy to choose the number of folds and penalty coefficient.

which consists of drawing repeated samples from the original sample and estimating for each repeated sample the properties of the estimates like the standard errors (Heckman et al., 1998). The use of bootstrapping is necessary because the estimated variance of the treatment effect should also include the variance attributable to the derivation of the propensity score, the determination of the common support, and the order in which treated individuals are matched (Caliendo and Kopeinig, 2008).

In the second stage of the estimation strategy, I infer the causal effect of *Seguro Popular* on intergenerational transfers. To achieve this goal, I combine the difference-in-difference approach and the matching estimator technique using the above-defined treatment and control groups (Bellak et al., 2006; Buscha et al., 2012; Chabé Ferret, 2015; Heckman et al., 1997, 1998; Parker et al., 2018). Specifically, I estimate the following linear probability model:

$$y_{it} = \alpha + \beta_1 T_t + \beta_2 SP_i + \beta_3 T_t \cdot SP_i + \delta X_{it} + \nu_t + \varepsilon_{it} \tag{2}$$

where y_{it} is the outcome variable for individual i in year t. y_{it} is a binary variable that takes the value of one if the respondent receives monetary or non-monetary transfers from its adult children, zero otherwise. Monetary transfers are defined as financial help, while non-monetary transfers are defined as time dedicated to helping the parents.[31]

The variable T_t is a binary variable that takes the value of one if the reported year is 2012 (endline) and zero if the collected information refers to 2001 (baseline). This variable captures the change in transfers between 2001 and 2012 independent from the effect of *Seguro Popular*. The variable SP_i is an indicator variable equal to one if an individual i was enrolled in *Seguro Popular* in 2012 (treatment group), and zero if the individual has no health insurance plan in 2001 (baseline) and in 2012 (endline). This regressor captures the differences in transfers for individuals included in the treatment and in the control groups.

The interaction term $T_t \cdot SP_i$ is the main regressor and is the product of the above-defined indicator variables. The coefficient β_3 is the difference-in-difference estimate and measures the effect of the universal health insurance program on intergenerational transfers. A positive (negative) β_3 implies that the probability of receiving transfers for an older adult from its adult children has increased (decreased) for the treatment group by $100 \cdot \beta_3\%$ after the

[31] I also run some specifications where the outcome variables are downward monetary and non-monetary transfers rather than upward transfers.

introduction of *Seguro Popular*. The remaining terms of Equation (2) are control variables that absorb the heterogeneity across observations along observable dimensions. X_{it} is a set of individual-level, household and family characteristics.[32] Finally, ε_{it} is the error term. I cluster the standard errors at the individual level. The estimates are calculated using the inverse probability weights (Alberto Abadie, 2005).

I will now turn to discuss the potential threats to identification. First, *Seguro Popular* may have affected the participation in the MHAS 2012 follow-up survey.[33] If attrition is correlated with participation in the program, our results would be biased. For example, if access to *Seguro Popular* reduces the mortality of the less-healthy individuals in 2001 that need more support from their children, then the program may affect the composition of the sample in 2012 and the estimated results.[34] Parker et al. (2018) use a comparable sample to mine and they implement a careful analysis of the effect of *Seguro Popular* on attrition. They find little support for the hypothesis that the introduction of the universal health insurance plan affected the probability of responding to the survey questions. These findings point out that attrition is uncorrelated with participation in the program.

A second limitation of the data is that we cannot identify the duration of the enrollment in *Seguro Popular* or in any other health insurance plan. This data limitation may affect our estimates in two ways. First, the control group is constructed from individuals with no insurance plan in both 2001 and 2012. As we do not have information between these two years, apart from 2003, we may include in the control group individuals who were enrolled in *Seguro Popular* or in other health insurance plans between those years. As argued by Parker et al. (2018), it is likely that individuals without any insurance plans in 2001 and 2012 were also uncovered between those two years. Second, the effect of *Seguro Popular* on intergenerational transfers may change with the length of exposure. As shown in Section 4, most of the individuals participating in *Seguro Popular* in 2012 were without any insurance plan in 2001. As argued in Section 3, enrolling in *Seguro Popular* was practically free for all participants. Thus, uninsured individuals in 2001 who joined in *Seguro Popular* had strong incentives to join as soon as possible, making it likely that all individuals have been enrolled

[32] Section 6.3 will discuss in details the characteristics included in the regression specification.

[33] The follow-up survey does not contain any information about the individuals who left the sample, neither the reason for not being in the follow-up survey nor their health insurance status nor their transfers.

[34] The main reason for attrition is mortality. Individuals may not be included in the 2012 follow-up wave also because either they cannot be located or because they may refuse to answer the survey.

in the program for a similar period. Overall, although it seems to be a minor issue, it is definitely a caveat in the analysis carried out in this paper.

Finally, the effectiveness of the propensity score matching procedure relies on the degree to which observed characteristics determine participation in the program. This feature of this approach is its main advantage, but also its main potential drawback. If observe characteristics drive participation in the program, then propensity score matching is a valid strategy to provide a valid comparison group and derive causal estimates.[35] Although this condition is not directly testable, the richness of individual, household, and children characteristics included in the propensity score matching algorithm and previous studies, such as , suggest my specification includes most of the factors driving program participation. Nevertheless, it is important to mention this potential limitation and keep it in mind when we interpret the causal estimates.

6 Results

This section is structured in three parts. I first discuss the results from the machine learning algorithm in selecting the variables for modeling the program-participation decision. Next, I present the propensity score matching results and discuss comparing the treatment and the control groups. Finally, I present the difference-in-difference results.

6.1 Feature Selection

To implement the feature selection —the process of selecting a subset of relevant variables to explain enrollment in *Seguro Popular* —I feed the model with a large set of potential variables.[36] Table A.1 in the Appendix lists the variables initially fed into the model, while Table A.2 reports the list of the selected variables by each algorithm.

To evaluate whether the selected variables by the machine learning algorithm are good predictors of the probability of program participation, I construct out-of-sample goodness-of-fit measures. Several measures have been proposed in the literature to evaluate the goodness of fit of binary outcomes, such as the enrollment in *Seguro Popular*. These measures compare the predicted outcomes of the machine learning algorithm and the actual values for the testing sample. Table 5 simplifies the exposition of the potential cases by reporting the confusion

[35] By contrast, if the selection bias comes from unobserved characteristics, the propensity score matching generates a comparison group that differs from the treatment group.

[36] The cross-validation approach, used to select the number of folds and the penalty coefficient for implementing the LASSO algorithm, returns that the optimal number of folds is 10 and the optimal penalty coefficient is 0.5.

matrix, which summarizes the predicted and actual outcomes in a matrix form.

Table 5: Confusion Matrix

		Predicted Values	
		0	1
Actual Values	0	True Negative (TN)	False Positive (FP)
	1	False Negative (FN)	True Positive (TP)

The top-left and the bottom-right cells represent the cases in which the machine learning algorithm correctly predicts the actual outcomes —non-participation and participation, respectively. The remaining two cells are cases where the machine learning algorithm wrongly predicts the outcomes. Based on the comparison between predicted and actual outcomes, I construct a few measures of goodness of fit. The first statistic is the accuracy and measures the share of observations correctly predicted by the algorithm:

$$\text{Accuracy} = \frac{TN + TP}{\#Observations}. \tag{3}$$

The second statistic, the recall rate, is used in the case of imbalanced data. In other words, when the number of positive values is much larger than the number of negative values or vice-versa. In these scenarios, the accuracy may not perform well in assessing model out-of-sample goodness of fit. In our study, the number of untreated is about one-third of the treated. The recall rate is calculated as:

$$\text{Recall} = \frac{TP}{TP + FN}. \tag{4}$$

Intuitively, in the case of imbalanced data, an algorithm should focus on identifying the relevant cases, i.e., the treated individuals. The recall measures the ability of the algorithm to classify those relevant cases correctly.

If the algorithm predicts that all individuals are enrolled in *Seguro Popular*, the recall will equal one. Nevertheless, the classification may be problematic because there is a trade-off between recall and precision. The precision measures the ability of an algorithm to identify only the relevant cases. In other words, it measures the proportion of the predicted relevant cases that were indeed relevant. The precision is calculated as:

$$\text{Precision} = \frac{TP}{TP + FP}. \tag{5}$$

Finally, as a trade-off exists between recall and precision, the last metric, the F1-score, summarizes both recall and precision. The F1-score is calculated as a harmonic mean between precision and recall:[37]

$$\text{F1-Score} = 2\,\frac{Precision * Recall}{Precision + Recall}. \tag{6}$$

The LASSO and Boosting algorithms, in the cases of binary outcomes, predict the probabilities without reporting the classification of an observation. I followed the standard practice in the literature and classified an observation as treated as the predicted probability is greater than or equal to 0.5 and zero otherwise. The Random Forest algorithm, instead, returns the binary classification for each observation. Table 6 reports the out-of-sample performance.

Table 6: Model Comparison - Goodness of Fit

	Accuracy	Recall	Precision	F1-Score
Full Model	0.726	0.952	0.743	0.835
Lasso	0.721	0.993	0.725	0.838
Random Forest	0.716	0.966	0.731	0.832
Boosted Regression	0.726	1.000	0.726	0.841

Notes: The performance metrics are calculated using the testing sample that consists of 20% of the data. These statistics are measures of out-of-sample performance.

The first row of Table 6 reports the performance statistics for the model that includes all variables as predictors. These statistics represent the benchmark comparison to evaluate the performance of the machine learning algorithms. The remaining three rows of Table 6 show the statistics for the three machine learning methods. All models perform very well in explaining the program participation. The out-of-sample accuracy rates range between 71% and 73%. This implies that the algorithms correctly classify an observation about three-fourths of the time. The second column highlights that all algorithms tend to classify all observations in the testing sample as treated. Nevertheless, high recall rates do not seem

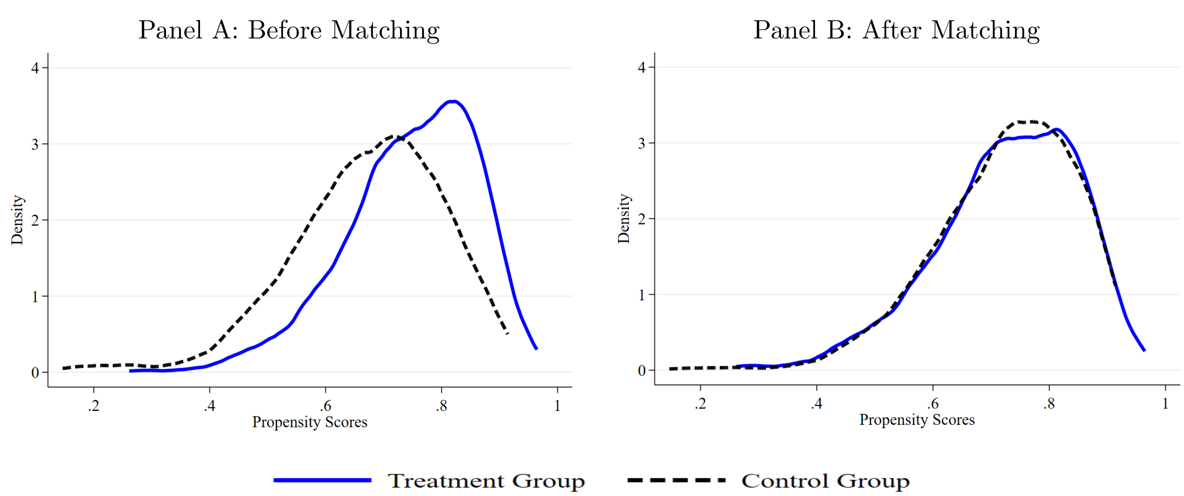
[37] The harmonic mean punishes extreme values differently from the simple mean. Furthermore, the F1 score gives equal weight to both metrics.

problematic because the precision rates remain high. Indeed, about 73% of the observations classified as treated are actual treated units. Finally, the four column reports the F1-Score. The F1-Score ranges between 0 and 1 with a score of 1 indicating perfect precision and recall and 0 instead of poor performance of the model in at least one of the two dimensions. The estimates for the F1-Score are over 0.83, implying that all models have high precision and recall. Overall, these results highlight all models properly classify observations. I chose the set of variables selected by the LASSO algorithm for the benchmark estimation, and the estimates for the set of variables selected by the other algorithms will be reported as robustness checks.

6.2 Propensity Score Matching

The Propensity Score Matching (PSM) algorithm matches untreated observations in the potential control group with the treated units and creates a valid control group. In this respect, the procedure successfully matches the individuals enrolled in *Seguro Popular* with their respective counterfactuals.

Figure 3: Common Support



Notes: The Kernel densities are computed based on the propensity scores computed in 2001. The propensity scores are calculated using the variables selected by the LASSO regression method. The treatment group is defined as all individuals enrolled in *Seguro Popular* in 2012 and with any or no insurance in 20001. The control group is defined as all individuals with no insurance in both 2001 and 2012. Panel A uses all units in the potential treatment and control groups. Panel B uses only the matched units weighted by the inverse probability weights calculated after the matching.

Figure 3 shows the kernel density of the propensity scores for the individuals enrolled in *Seguro Popular* in 2012 (treatment group) and potential control groups.[38] This figure

[38]Figures B.2 and B.3 in the Appendix show the common supports based on the variables selected by the Boosting Regression

aims to show the common support between these two groups and that there exists a range of scores in which it is possible to find a match between the treated and the untreated individuals and, consequently, construct a valid control group. Panel A shows that the solid blue line representing the propensity scores for the treatment group and the dashed black line representing those for the potential control group are largely distributed over a common domain. These results highlight a large common support area where one can match treated and untreated units and construct a valid control group (Smith and Todd, 2005). Panel B highlights that the observations matched in the treatment and control groups have a similar density distribution. The only noticeable difference is that the mass of treated units concentrated around the mode of distribution is slightly less than the mass of the untreated units.

I evaluate the quality of the matching by exploring if the balancing property is satisfied (Becker and Ichino, 2002). The balancing property states that the matched treated and control units, based on their propensity scores, have the same distribution of the observed covariates. Table 7 reports the averages for a set of observable characteristics for the treatment and control groups.[39] All the statistics reported in the table are weighted by the inverse probability weights.

Panel A of Table 7 reports the probabilities of receiving or giving monetary and non-monetary transfers. The first two measure the share of respondents that receive monetary or non-monetary transfers from their children, while the remaining two measure the share of respondents that give monetary or non-monetary transfers to their children. The shares of respondents receiving monetary or non-monetary transfers from children range between 35% and 40%. By contrast, only a 10% of the respondents transfer money to their children. Most of the help the children receive is in terms of non-monetary transfers, likely time spent in taking care of the grandchildren.

Panel B presents the averages for the respondent's characteristics. Along most of these dimensions, the treatment and the control groups do not present any statistically significant differences, except for the importance of religion and health status. About one-third of the sample considers its health status excellent or good. The matched sample comprises respon-

and the Random Forest methods, respectively.

[39] Tables C.3 and C.4 in the Appendix show the comparison between treatment and control groups based on the variables selected by the Boosting Regression and the Random Forest methods, respectively.

Table 7: Balancing Property Test

	Mean		t-test	p-value
	Enrolled	Non-enrolled		
Panel A: Outcome Variables				
Received monetary transfer from children	0.367	0.416	-1.929	0.054
Received non-monetary transfer from children	0.421	0.379	1.602	0.109
Gave monetary transfer to children	0.107	0.067	2.696	0.007
Gave non-monetary transfer to children	0.405	0.364	1.612	0.107
Panel B: Respondent Characteristics				
Age	59.195	59.116	0.190	0.849
Women (Share)	0.553	0.538	0.577	0.564
Married/Union (Share)	0.667	0.648	0.771	0.441
No Education (Share)	0.337	0.358	-0.823	0.410
Primary Education (Share)	0.592	0.595	-0.106	0.915
Secondary Education (Share)	0.059	0.037	1.960	0.050
Tertiary Education (Share)	0.012	0.011	0.244	0.808
Has some Disease (Share)	0.411	0.356	2.153	0.031
Not Employed (Share)	0.295	0.263	1.341	0.180
Religion is very important (Share)	0.711	0.652	2.416	0.016
Religion is somewhat important (Share)	0.262	0.327	-2.759	0.006
Religion is not important (Share)	0.262	0.327	-2.759	0.006
Very Good health (Share)	0.033	0.022	1.281	0.200
Good health (Share)	0.325	0.312	0.505	0.614
Fair Health (Share)	0.484	0.560	-2.938	0.003
Poor Health (Share)	0.159	0.105	3.019	0.003
Earnings and Wages (USD)	136.614	204.922	-2.986	0.003
Pensions (USD)	4.024	4.031	-0.004	0.997
Government Subsidies (USD)	22.237	23.279	-0.140	0.889
Properties (USD)	5.762	4.704	0.286	0.775
Capital Assets (USD)	1.414	0.766	0.970	0.332
At least a parent died (Share)	0.903	0.904	-0.088	0.930
At least a parent lives in the house (Share)	0.029	0.026	0.320	0.749
Raised kids alone (Share)	1.130	1.242	-0.792	0.428
Health Problems before 10 (Share)	0.114	0.062	3.527	0.000
Speaking indigenous languages (Share)	0.597	0.527	0.714	0.475
Panel C: Household Characteristics				
HH has radio (Share)	0.829	0.884	-2.988	0.003
HH has TV (Share)	0.863	0.845	0.963	0.336
HH has piped water (Share)	0.584	0.573	0.423	0.672
HH has toilet with water connection (Share)	0.447	0.408	1.480	0.139
HH has water heater (Share)	0.248	0.248	0.000	1.000
Rural Area (Share)	0.605	0.623	-0.698	0.485
Location more than 15,000 Inhabitants (Share)	0.484	0.479	0.157	0.875
Panel D: Kid Characteristics				
Number of Kids	5.818	6.245	-2.667	0.008
Kids' Age (Average)	29.007	28.946	0.138	0.890
Kids older than 16 years (Share)	0.930	0.928	0.243	0.808
Kids older than 18 years (Share)	0.890	0.885	0.534	0.594
Kids older than 24 years (Share)	0.703	0.699	0.192	0.848
Daughters (Share)	0.494	0.522	-2.253	0.024
Kids with grandkids (Share)	0.622	0.606	0.935	0.350
Married/Union (Share)	0.639	0.646	-0.385	0.700
Not Employed (Share)	0.385	0.412	-1.741	0.082
Kids No Education (Share)	0.042	0.046	-0.587	0.557
Kids Primary Education (Share)	0.445	0.442	0.178	0.859
Kids Secondary Education (Share)	0.436	0.432	0.186	0.852
Kids Tertiary Education (Share)	0.077	0.080	-0.225	0.822
Excellent or Very Good Financial Situation (Share)	0.014	0.007	1.863	0.063

Notes: The treatment group is defined as all individuals enrolled in *Seguro Popular* in 2012 and with any or no insurance in 20001. The control group is defined as all individuals with no insurance in both 2001 and 2012. Observations are weighted by the inverse probability weights calculated after the propensity score matching using the set of variables selected by the LASSO Regression method. Errors are clustered at the respondent level.

dents with an average age of around 59 years old, mostly female (55%) and married or in a civil union (67%). The education levels among the two groups are pretty comparable, with over 90% of the observations in both groups having completed at most primary education. Financially, the two groups have the same amount of income from all sources except earnings and wages, which is higher for the untreated group.

Panel C reports the characteristics of the household. Along all these dimensions, the two groups are highly similar, with no statistical differences except for the share of households having a radio in the house. These statistics emphasize that a relatively large share of households has no access to basic services such as piped water (42%), a toilet with water connection (55%), or a water heater (75%). Most households live in rural areas (60%) and locations with less than $15,000$ inhabitants (52%).

Finally, the last panel reports the kids' characteristics. Also, in this case, there are almost no significant differences between the two groups. The average age of the respondent's children is 29 years old, with marginal shares of young children (only 7% below 16 years old, and 11% below 18). More than 60% of the respondent's children are married or in a civil union and have their children. As expected, the education level of the children is higher than that of the respondents, with less than 45% children with at most primary education compared to 90% of the respondents.

Overall, the balancing property tests confirm that the samples in the treatment and the control groups have similar characteristics in the baseline. Hence, the control group is a valid comparison for the treatment based on the baseline characteristics.

6.3 Difference-in-Difference Results

This subsection studies the effect of *Seguro Popular* on intergenerational transfers.[40] First, I discuss the results of the extensive margins, i.e., the probability of receiving (giving) transfers from (to) children. Then, I present the findings about the intensive margin that consists of the amount of transfers that respondents receive (give) from (to) children.

Table 8 reports the estimates for the extensive margins. These probabilities are estimated using a linear regression model. Panel A shows the results for the probability of receiving upward intergenerational transfers, while Panel B shows the downward intergenerational transfers. Columns (1) - (5) show the findings for monetary transfers, while columns (6)-(10) show the results for non-monetary transfers. For each of these outcome variables, I

[40] As we explore the effect of *Seguro Popular* on various outcomes, I opt to use a fixed set of control variables. This decision highly simplifies the exposition. Choosing relevant variables by machine learning algorithms would imply that each outcome variable would have a different set of controls. The comparison across estimates would become less straightforward.

implement five specifications. The first specification includes only the dummy that takes the value of one if the wave corresponds to the endline and zero otherwise (T_t), the dummy that takes the value of one if an observation is in the treatment group and zero if it is in the control group (SP_i), and the interaction between the two previous binary variables ($T_t \cdot SP_i$) that captures the difference-in-difference effect. The remaining specifications sequentially include additional control variables, such as respondent characteristics, household characteristics, kid characteristics, and respondent fixed effects.

Table 8: Extensive Margins: Probability of Receiving or Giving Tranfers

	Monetary Transfers					Non-monetary Transfers				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Upward Transfers										
Time	-0.015	-0.093*	-0.062	-0.093*	-0.380*	-0.050	-0.047	-0.109**	-0.104*	-1.048***
	(0.041)	(0.047)	(0.050)	(0.050)	(0.226)	(0.048)	(0.053)	(0.053)	(0.053)	(0.266)
Seguro Popular	-0.037	-0.029	-0.030	-0.022		-0.015	-0.014	-0.015	-0.013	
	(0.038)	(0.036)	(0.036)	(0.036)		(0.038)	(0.037)	(0.037)	(0.037)	
Time * Seguro Popular	0.096**	0.090*	0.093*	0.099**	0.097**	-0.002	-0.004	-0.008	0.001	0.028
	(0.048)	(0.048)	(0.048)	(0.047)	(0.046)	(0.054)	(0.053)	(0.052)	(0.053)	(0.051)
Observations	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006
Respondent Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Kid Controls	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Individual FE	No	No	No	No	Yes	No	No	No	No	Yes
Panel B: Downward Transfers										
Time	0.073***	0.130***	0.118***	0.122***	0.074	-0.080*	0.033	-0.040	-0.037	-0.224
	(0.026)	(0.032)	(0.034)	(0.034)	(0.117)	(0.042)	(0.052)	(0.054)	(0.054)	(0.307)
Seguro Popular	0.035*	0.033*	0.032*	0.033*		0.042	0.046	0.046	0.048	
	(0.020)	(0.019)	(0.019)	(0.019)		(0.037)	(0.037)	(0.036)	(0.036)	
Time * Seguro Popular	-0.094***	-0.095***	-0.093***	-0.086***	-0.091***	-0.019	-0.030	-0.035	-0.018	-0.031
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.049)	(0.049)	(0.048)	(0.048)	(0.047)
Observations	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006
Respondent Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Kid Controls	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Individual FE	No	No	No	No	Yes	No	No	No	No	Yes

Notes: The estimates are computed from Equation (2). The treatment group is defined as all individuals enrolled in *Seguro Popular* in 2012 and with any or no insurance in 20001. The control group is defined as all individuals with no insurance in both 2001 and 2012. Observations are weighted by the inverse probability weights calculated after the propensity score matching using the set of variables selected by the LASSO Regression method. Errors are clustered at the respondent level.

The estimates in Panel A for the binary variable that identifies the wave of the survey (T_t) are negative in all specifications. The significance level varies across specifications. These results suggest that, independently from other factors, respondents had a lower probability of receiving upward transfers in 2012 than in 2001. Panel B highlights a different story for downward transfers. The probability of a respondent giving monetary transfers to its children has increased in 2012 relative to 2001, while the probability of helping them in terms of time has remained substantially unaffected between the baseline and endline.

The coefficients for the dummy corresponding to being enrolled in *Seguro Popular* are negative in all specifications when the outcome variable is the probability of receiving upward transfers and positive when the dependent variable is the probability of downward transfers. Most of these estimates are not significant or marginally significant at the 10% significance level, implying no statistical difference in the probability of upward and downward transfers between the treatment and the control groups. This finding is an additional validation that the two groups do not differ from each other in the probabilities of receiving (or giving) transfers from (to) their children.

Let's now turn to the difference-in-difference effects ($T_t \cdot SP_i$), representing the central findings of the paper. Three main findings stand out. First, while I document significant effects of *Seguro Popular* on the probability of upward or downward monetary transfers, the estimates on non-monetary transfers are negative but close to zero and highly non-significant. These findings emphasize that enrollment in *Seguro Popular* does not change the time that children dedicate to help their parents or the other way around. Let's now dig into the impact on monetary transfers.

The probability of receiving monetary transfers from the children significantly increases for respondents enrolled into *Seguro Popular* compared to individuals without any insurance plans. The magnitude of the coefficients is sizable. Indeed, being enrolled in *seguro Popular* increases the probability of receiving upward transfers between $9-10\%$. To better understand the magnitude of these estimates, I compute the percentage points increase based on the 2001 figures (see Table C.6 in the Appendix). In 2001, 30% of the respondents in the treatment group received monetary transfers from their children. In 2012, the share of respondents in the treatment group receiving upward transfers was 48%, with an increase of 18 percentage points. In the case of the control group, the share of respondents receiving upward transfers was 36% in 2001 and 44% in 2012, with an increase of 7 percentage points. The share of respondents in the treatment group receiving upward transfers increased by more than 11 percentage points than those in the control group. An estimate of 9.7% (column 5 in Panel A of Table 8) implies an increase of the share of respondents receiving monetary transfers from their children of about 2.9 percentage points relative to the share of 2001. These calculations imply that 27% of the documented increase in the share of respondents receiving monetary upward transfers in the treatment group relative to those in the control group is due to the enrollment in *Seguro Popular*.

Last but not least, the probability that an individual enrolled in *Seguro Popular* gives monetary transfers to its children declined by 9% compared to the individuals in the control group. The estimates are strongly significant at the 1% significance level. Similarly to the calculation for upward transfers, in 2001, 10% of the respondents in the treatment group give financial help to their children. This share slightly increased in 2012 by one percentage point. In the case of the control group, the share of respondents giving monetary help to their children more than doubled, from 8% to 17%. A decline of 9% due to *Seguro Popular* implies a decline of the share of respondents that give monetary downward transfers of about 0.9 percentage points. The share of respondents in the treatment increased by less than those in the control group, and the participation in the *Seguro Popular* account for 10% of the smallest increase for the treatment group.

Table 9: Intensive Margins: Amount of Monetary Transfers

	Upward Transfers					Downward Transfers				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Time	-1.145***	-1.590***	-1.344***	-1.504***	-2.914*	0.133	0.403**	0.322*	0.333*	-0.399
	(0.270)	(0.321)	(0.333)	(0.340)	(1.526)	(0.143)	(0.161)	(0.188)	(0.191)	(0.794)
Seguro Popular	-0.296	-0.244	-0.257	-0.209		0.212	0.189	0.185	0.193	
	(0.274)	(0.258)	(0.256)	(0.252)		(0.137)	(0.133)	(0.133)	(0.131)	
Time * Seguro Popular	0.559*	0.510	0.542*	0.591*	0.568*	-0.503***	-0.519***	-0.504***	-0.473***	-0.490***
	(0.314)	(0.315)	(0.315)	(0.313)	(0.312)	(0.170)	(0.171)	(0.171)	(0.173)	(0.174)
Observations	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006
Respondent Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Kid Controls	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Individual FE	No	No	No	No	Yes	No	No	No	No	Yes

Notes: The estimates are computed from Equation (2). The treatment group is defined as all individuals enrolled in *Seguro Popular* in 2012 and with any or no insurance in 20001. The control group is defined as all individuals with no insurance in both 2001 and 2012. Observations are weighted by the inverse probability weights calculated after the propensity score matching using the set of variables selected by the LASSO Regression method. Errors are clustered at the respondent level.

To provide a complete picture of the effects of *Seguro Popular* on intergenerational transfers, Table 9 reports the change in the amount of upward and downward monetary transfers. The Mexican Health and Aging Study (MHAS) does not collect information on the amount of hours spent by parents and children in helping each other. I can use only information about the size of the monetary transfers to study the intensive margin. As many respondents respond that they receive zero transfers, I convert the outcome variable using the inverse hyperbolic sine transformation to retain an elasticity interpretation of the estimates. These estimates can be interpreted as percentage changes.

The first five columns report the estimates for the amount of money given by the children to their parents, while the remaining columns present different specifications of the effect of *Seguro Popular* on the amount of downward transfers. Individuals enrolled in *Seguro Popular* increase the amount of monetary transfers they receive from their children by $5-6\%$ compared to their counterparts without any insurance plans in both 2001 and 2012. Similarly, also the size of the downward monetary transfers decreases by 5%.

Overall, the results indicate that *Seguro Popular* changes the intergenerational dynamics, favoring a larger financial flow from children to parents. By contrast, non-monetary transfers remain unaffected by the introduction of *Seguro Popular*. The estimates suggest sizable effects, implying that *Seguro Popular* has played a central role in the changes in the probability and amount of intergenerational transfers documented between 2001 and 2012.

6.4 Robustness Checks

This section will present two types of robustness checks. First, I will discuss the previous estimates using the set of variables for the propensity score matching identified by alternative machine learning algorithms —random forest and boosting regression. The second set of robustness will use an alternative definition of the treatment group. Finally, the third robustness check restricts the sample of children making (or receiving) transfers to those at least 18 years old.

The use of different machine learning algorithms in choosing the relevant variables may affect the diff-in-diff results in two ways. First, a different set of variables may lead to a different matching between treated and untreated observations, with some that may not be matched. Second, different algorithms may assign different inverse probabilistic weights to each matched observation. In our case, the latter is more relevant than the former in driving the differences in the diff-in-diff estimates because the sets of matched units overlap.

Table 10 shows the results for the diff-in-diff regression using the Boosted Regression to select the relevant variables in the model, while Table 11 reports the coefficients using the Random Forest method. The diff-in-diff estimates calculated using the inverse probability weights calculated using the Boosted Regression to predict the relevant variables for the participation in *Seguro Popular* are qualitatively and quantitatively comparable to those in the previous section. If any, the magnitude of the estimates in Table 10 are slightly bigger

Table 10: Extensive and Intensive Margins: Boosting Feature Selection

	Probability Monetary Transfers					Probability Non-monetary Transfers					Amount Monetary Transfers				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
								Panel A: Upward Transfers							
Time	-0.000	-0.086*	-0.072	-0.102**	-0.377*	-0.060	-0.063	-0.122**	-0.117**	-0.943***	-1.107***	-1.612***	-1.449***	-1.602***	-3.043**
	(0.041)	(0.048)	(0.050)	(0.050)	(0.203)	(0.046)	(0.052)	(0.052)	(0.053)	(0.261)	(0.263)	(0.314)	(0.333)	(0.335)	(1.335)
Seguro Popular	-0.025	-0.027	-0.029	-0.027		-0.022	-0.024	-0.024	-0.021		-0.219	-0.262	-0.260	-0.255	
	(0.037)	(0.036)	(0.036)	(0.036)		(0.038)	(0.037)	(0.036)	(0.036)		(0.270)	(0.260)	(0.258)	(0.253)	
Time * Seguro Popular	0.080*	0.081*	0.085*	0.096**	0.094**	0.008	0.004	-0.001	0.007	0.033	0.489	0.508*	0.538*	0.609**	0.617**
	(0.048)	(0.048)	(0.048)	(0.048)	(0.047)	(0.052)	(0.052)	(0.051)	(0.052)	(0.050)	(0.307)	(0.307)	(0.310)	(0.308)	(0.313)
Observations	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006
Respondent Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Kid Controls	No	No	No	Yes	Yes	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Respondent FE	No	No	No	No	Yes	No	No	No	No	Yes	No	No	No	No	Yes
								Panel B: Downward Transfers							
Time	0.078***	0.136***	0.125***	0.128***	0.080	-0.088**	0.021	-0.053	-0.044	-0.145	0.150	0.447***	0.378**	0.381**	-0.387
	(0.026)	(0.031)	(0.034)	(0.034)	(0.115)	(0.041)	(0.051)	(0.053)	(0.053)	(0.306)	(0.148)	(0.166)	(0.188)	(0.193)	(0.791)
Seguro Popular	0.031	0.034*	0.034*	0.035*		0.037	0.038	0.040	0.040		0.180	0.184	0.184	0.193	
	(0.020)	(0.020)	(0.019)	(0.019)		(0.037)	(0.037)	(0.036)	(0.037)		(0.140)	(0.137)	(0.137)	(0.133)	
Time * Seguro Popular	-0.097***	-0.100***	-0.099***	-0.093***	-0.102***	-0.011	-0.017	-0.024	-0.009	-0.026	-0.511***	-0.548***	-0.540***	-0.509***	-0.546***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.048)	(0.049)	(0.047)	(0.048)	(0.047)	(0.174)	(0.176)	(0.177)	(0.180)	(0.176)
Observations	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006
Respondent Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Kid Controls	No	No	No	Yes	Yes	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Respondent FE	No	No	No	No	Yes	No	No	No	No	Yes	No	No	No	No	Yes

Notes: The estimates are computed from Equation (2). The treatment group is defined as all individuals enrolled in *Seguro Popular* in 2012 and with any or no insurance in 20001. The control group is defined as all individuals with no insurance in both 2001 and 2012. Observations are weighted by the inverse probability weights calculated after the propensity score matching using the set of variables selected by the Boosting method. Errors are clustered at the respondent level.

than those previously discussed.

Table 11: Extensive and Intensive Margins: Random Forest Feature Selection

	Probability Monetary Transfers					Probability Non-monetary Transfers					Amount Monetary Transfers				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
								Panel A: Upward Transfers							
Time	0.018	-0.058	-0.039	-0.064	-0.436**	-0.064	-0.068	-0.117**	-0.112**	-0.877***	-0.852***	-1.324***	-1.167***	-1.295***	-3.370**
	(0.036)	(0.045)	(0.049)	(0.049)	(0.216)	(0.042)	(0.049)	(0.052)	(0.052)	(0.256)	(0.251)	(0.314)	(0.336)	(0.341)	(1.517)
Seguro Popular	0.004	-0.003	-0.011	-0.003		-0.018	-0.019	-0.013	-0.010		0.002	-0.046	-0.079	-0.040	
	(0.036)	(0.035)	(0.035)	(0.035)		(0.037)	(0.037)	(0.036)	(0.036)		(0.258)	(0.251)	(0.251)	(0.249)	
Time * Seguro Popular	0.062	0.065	0.074*	0.081*	0.071	0.010	0.007	-0.009	-0.001	0.025	0.215	0.240	0.316	0.377	0.354
	(0.044)	(0.044)	(0.045)	(0.044)	(0.045)	(0.048)	(0.049)	(0.049)	(0.050)	(0.049)	(0.297)	(0.302)	(0.306)	(0.305)	(0.306)
Observations	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006
Respondent Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Kid Controls	No	No	No	Yes	Yes	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Respondent FE	No	No	No	No	Yes	No	No	No	No	Yes	No	No	No	No	Yes
								Panel B: Downward Transfers							
Time	0.072**	0.123***	0.112***	0.117***	0.031	-0.097**	0.006	-0.057	-0.050	-0.355	0.107	0.370**	0.292	0.310	-0.569
	(0.028)	(0.034)	(0.036)	(0.036)	(0.131)	(0.040)	(0.050)	(0.054)	(0.054)	(0.256)	(0.162)	(0.184)	(0.206)	(0.212)	(0.936)
Seguro Popular	0.017	0.021	0.024	0.027		0.032	0.027	0.036	0.039		0.088	0.119	0.138	0.165	
	(0.021)	(0.020)	(0.020)	(0.020)		(0.036)	(0.037)	(0.036)	(0.036)		(0.147)	(0.142)	(0.141)	(0.139)	
Time * Seguro Popular	-0.088***	-0.093***	-0.093***	-0.087***	-0.085***	0.001	0.000	-0.020	-0.005	-0.018	-0.448**	-0.500***	-0.503***	-0.484**	-0.459**
	(0.032)	(0.032)	(0.032)	(0.032)	(0.031)	(0.047)	(0.048)	(0.047)	(0.047)	(0.046)	(0.184)	(0.187)	(0.189)	(0.190)	(0.185)
Observations	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006
Respondent Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Kid Controls	No	No	No	Yes	Yes	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Respondent FE	No	No	No	No	Yes	No	No	No	No	Yes	No	No	No	No	Yes

Notes: The estimates are computed from Equation (2). The treatment group is defined as all individuals enrolled in *Seguro Popular* in 2012 and with any or no insurance in 20001. The control group is defined as all individuals with no insurance in both 2001 and 2012. Observations are weighted by the inverse probability weights calculated after the propensity score matching using the set of variables selected by the Random Forest method. Errors are clustered at the respondent level.

The estimates in Table 11 point out in the same direction as the estimates previously discussed. In other words, participation in *Seguro Popular* increases the probability of receiving and the amount of upward monetary transfers and decreases the probability of giving and the amount of downward monetary transfers. By contrast, the probability of upward and downward non-monetary transfers remains unaffected. Although the magnitude of the estimates is comparable with those previously discussed, the estimates in Table 11 are statistically less significant. Overall, the qualitative differences in the significance levels do not invalidate the previous findings.

The second set of robustness consists of defining an alternative treatment group. In the benchmark specification, I define the treatment group as all individuals with *Seguro Popular* in 2012, and with or without any insurance plan in 2001.[41] The alternative definition of the treatment group is more restrictive and considers only individuals with no insurance plans in 2001. The results are reported in Table 12.

Table 12: Extensive and Intensive Margins: Alternative Treatment Group

	Probability Monetary Transfers					Probability Non-monetary Transfers					Amount Monetary Transfers				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
								Panel A: Upward Transfers							
Time	-0.000	-0.083*	-0.055	-0.079	-0.401*	-0.051	-0.055	-0.122**	-0.111**	-1.064***	-1.033***	-1.511***	-1.318***	-1.433***	-3.001**
	(0.039)	(0.047)	(0.050)	(0.050)	(0.226)	(0.048)	(0.053)	(0.054)	(0.054)	(0.270)	(0.259)	(0.320)	(0.335)	(0.338)	(1.527)
Seguro Popular	-0.018	-0.014	-0.016	-0.005		-0.004	-0.008	-0.008	-0.003		-0.135	-0.117	-0.141	-0.082	
	(0.039)	(0.037)	(0.036)	(0.036)		(0.039)	(0.038)	(0.037)	(0.037)		(0.274)	(0.258)	(0.258)	(0.253)	
Time * Seguro Popular	0.074	0.070	0.073	0.079*	0.076*	-0.001	0.001	-0.004	0.003	0.027	0.381	0.347	0.384	0.428	0.420
	(0.047)	(0.047)	(0.047)	(0.046)	(0.045)	(0.054)	(0.053)	(0.053)	(0.053)	(0.051)	(0.306)	(0.308)	(0.310)	(0.306)	(0.303)
Observations	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978
Respondent Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Kid Controls	No	No	No	Yes	Yes	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Respondent FE	No	No	No	No	Yes	No	No	No	No	Yes	No	No	No	No	Yes
								Panel B: Downward Transfers							
Time	0.070***	0.121***	0.110***	0.115***	0.088	-0.076*	0.038	-0.042	-0.035	-0.250	0.164	0.420**	0.331*	0.357*	-0.269
	(0.025)	(0.030)	(0.034)	(0.034)	(0.115)	(0.044)	(0.054)	(0.054)	(0.054)	(0.306)	(0.146)	(0.164)	(0.195)	(0.197)	(0.800)
Seguro Popular	0.036*	0.033*	0.032*	0.033*		0.043	0.043	0.044	0.048		0.223*	0.199	0.196	0.208	
	(0.019)	(0.019)	(0.019)	(0.019)		(0.038)	(0.037)	(0.036)	(0.036)		(0.134)	(0.130)	(0.130)	(0.129)	
Time * Seguro Popular	-0.093***	-0.092***	-0.090***	-0.084***	-0.086***	-0.020	-0.030	-0.035	-0.021	-0.032	-0.534***	-0.539***	-0.525***	-0.494***	-0.488***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.051)	(0.051)	(0.049)	(0.049)	(0.047)	(0.172)	(0.173)	(0.174)	(0.175)	(0.175)
Observations	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978	1,978
Respondent Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Kid Controls	No	No	No	Yes	Yes	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Respondent FE	No	No	No	No	Yes	No	No	No	No	Yes	No	No	No	No	Yes

Notes: The estimates are computed from Equation (2). The treatment group is defined as all individuals enrolled in *Seguro Popular* in 2012 and with no insurance in 20001. The control group is defined as all individuals with no insurance in both 2001 and 2012. Observations are weighted by the inverse probability weights calculated after the propensity score matching using the set of variables selected by the LASSO Regression method. Errors are clustered at the respondent level.

The set of estimates for the treatment, including only individuals with no insurance plans in 2001 are qualitatively consistent with the previous results. The diff-in-diff estimates for the effect of *Seguro Popular* on the probability of receiving upward transfers lose some statistical significance. Indeed, while in Table 8 the coefficients under all specifications were significant, in Table 12 they are significant only when introducing the kids' characteristics as controls. Another difference between the estimates using the most restrictive definition of the treatment and the benchmark definition is that the estimates for the amount of upward monetary transfers return significance levels slightly higher 10%. The remaining findings are

[41] Figure B.4 show the common support and the weighted distribution of the treated and untreated observations. Table C.5 presents the differences in the means between the treated and untreated groups.

qualitatively and quantitatively comparable with the previous estimates. Overall, the definition of the treatment does not highly affect the effects of *Seguro Popular* on intergenerational family dynamics.

The last robustness check restricts the sample of children to those at least 18 years old. This restriction implies that I consider only transfers received (or given) from (or to) children at least 18 years old. It is plausible that the transfer decisions differ between young and adult children. This restriction allows me to isolate the effect from (and to) adult children. Results are reported in Table 13. The results are quite consistent with the benchmark findings. Regarding upward transfers, I find a positive and significant effect on the probability of receiving monetary transfers, while no statistically significant effect on the probability of receiving non-monetary transfers. Different from the benchmark results, the effect on the amount of upward monetary transfer is positive but not significant at any standard significance levels. Regarding downward transfers, there are two main differences compared to the benchmark findings. The effect on downward non-monetary transfers is negative and significant, while in the benchmark specification, it was not significant. The effect on the amount of downward monetary transfer turns out to be non-significant. Although there are these differences in the significance levels, the magnitude of the estimates is comparable with the benchmark results.

Table 13: Extensive and Intensive Margins: Only Children older than 18

	Probability Monetary Transfers					Probability Non-monetary Transfers					Amount Monetary Transfers				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Panel A: Upward Transfers															
Time	-0.015	-0.094**	-0.065	-0.095*	-0.378*	-0.001	-0.024	-0.107**	-0.105**	-1.058***	-1.211***	-1.510***	-1.314***	-1.406***	-2.257*
	(0.041)	(0.047)	(0.050)	(0.050)	(0.225)	(0.049)	(0.054)	(0.053)	(0.053)	(0.264)	(0.204)	(0.243)	(0.251)	(0.254)	(1.198)
Seguro Popular	-0.040	-0.031	-0.033	-0.025		-0.002	-0.001	-0.003	0.001		-0.179	-0.145	-0.153	-0.117	
	(0.038)	(0.036)	(0.036)	(0.036)		(0.037)	(0.037)	(0.036)	(0.036)		(0.206)	(0.195)	(0.193)	(0.190)	
Time * Seguro Popular	0.099**	0.093*	0.096**	0.102**	0.098**	-0.014	-0.017	-0.020	-0.014	0.013	0.315	0.277	0.302	0.338	0.327
	(0.048)	(0.048)	(0.048)	(0.047)	(0.046)	(0.054)	(0.053)	(0.053)	(0.053)	(0.052)	(0.236)	(0.238)	(0.238)	(0.238)	(0.237)
Observations	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006
Respondent Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Kid Controls	No	No	No	Yes	Yes	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Respondent FE	No	No	No	No	Yes	No	No	No	No	Yes	No	No	No	No	Yes
Panel B: Downward Transfers															
Time	0.073	0.174*	0.112	0.111	-0.392	0.077***	0.113***	0.105***	0.107***	0.103	-0.055	0.042	-0.031	-0.031	-0.182
	(0.092)	(0.101)	(0.118)	(0.122)	(0.552)	(0.024)	(0.029)	(0.031)	(0.031)	(0.109)	(0.042)	(0.053)	(0.053)	(0.053)	(0.310)
Seguro Popular	0.084	0.068	0.065	0.072		0.019	0.017	0.016	0.016		0.044	0.048	0.048	0.052	
	(0.082)	(0.082)	(0.082)	(0.081)		(0.017)	(0.017)	(0.017)	(0.016)		(0.036)	(0.036)	(0.035)	(0.035)	
Time * Seguro Popular	-0.252**	-0.259**	-0.249**	-0.241**	-0.235**	-0.064**	-0.063**	-0.061**	-0.057**	-0.058**	-0.018	-0.029	-0.034	-0.021	-0.032
	(0.109)	(0.110)	(0.110)	(0.111)	(0.111)	(0.028)	(0.028)	(0.028)	(0.027)	(0.028)	(0.049)	(0.050)	(0.048)	(0.048)	(0.047)
Observations	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006	2006
Respondent Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Kid Controls	No	No	No	Yes	Yes	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Respondent FE	No	No	No	No	Yes	No	No	No	No	Yes	No	No	No	No	Yes

Notes: The estimates are computed from Equation (2). The treatment group is defined as all individuals enrolled in *Seguro Popular* in 2012 and with any or no insurance in 20001. The control group is defined as all individuals with no insurance in both 2001 and 2012. Observations are weighted by the inverse probability weights calculated after the propensity score matching using the set of variables selected by the LASSO Regression method. The sample for the transfers is restricted only to children at least 18 years old. Errors are clustered at the respondent level.

This set of robustness checks confirms that the results remain qualitatively, and in most cases also quantitatively, robust to the alternative selection of relevant variables for the program participation, the treatment definition,a nd the measurement of the outcome variables.

7 Conclusion

In this paper, I show that older adults who receive *Seguro Popular* have a higher probability of receiving monetary transfers from their children. The effects are not only statistically significant but also economically sizeable. I document that 27% of the documented increase in the share of respondents receiving monetary upward transfers in the treatment group relative to those in the control group is due to the enrollment in *Seguro Popular*.

By contrast, the effect of *Seguro Popular* on downward monetary transfers is negative and significant. The estimates imply that only 10% of the documented drop in the share of respondents giving monetary downward transfers in the control group relative to the treatment group can be explained by the enrollment in *Seguro Popular*.

I also show the *Seguro Popular* has no significant effects on the probability of upward or downward non-monetary transfers. These results suggest that the intergenerational time exchange is less sensitive to government interventions.

Regarding the intensive margin, I find that the introduction of *Seguro Popular* increased the amount of upward monetary transfers and decreased the amount of downward monetary transfers.

These findings also have implications for guiding economic theory. Indeed, they show that the "crowding in" effect dominates the "crowding out" effect, implying that public interventions are not substitutes for private transfers but rather complementary. In this respect, my results contradict the prediction of the altruism models that state the existence of "crowding out" effects. By contrast, they provide strong support for the exchange models that argue that public transfers amplify private transfers.

Finally, these findings have clear policy implications. First, public insurance plans and private transfers are complementary. Therefore, a relatively small increase in public health coverage for older adults may have large improvements in their health status due to changes in the propensity of intergenerational transfers. Second, in cases in which children lack resources to support their older adults, public insurance plans provide alleviation for adult children of the burden of maintaining their parents.

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Appendix

A. Data

A.1. Variables Description

A.2. LASSO Cross-Validation Algorith

The selection of the optimal number of folds K and the penalty coefficient λ for the LASSO regression is achieved via cross-validation. The following steps describe the computational algorithm.

1. I select the optimal number of folds for the cross-validation analysis. I chose different number of folds, and I estimated the model for any of these numbers of folds using the training sample. I computed the deviance and the deviance ratio for the training and testing samples. I select the optimal number of folds as the one with the lowest deviance and highest deviance ratio for the testing sample.

2. Given the selected number of folds, I select the optimal penalty parameter via cross-validation. The cross-validation consists of randomly dividing the data randomly into K of folds. For a given λ, I train the algorithm on the $K-1$ folds, and I predict the probability of enrolling in *Seguro Popular* for the individuals in the Kth fold. I repeated the procedure for all K folds, and I computed the average performance across the folds. I repeat the algorithm for each of the λ parameter values. I chose the optimal λ as the one that minimizes the deviance and maximizes the deviance ratio.

3. Given the selected number of folds and penalty parameter, I select the variables to include as predictors of the probability of being enrolled in *Seguro Popular* by estimating the algorithm with the training sample and the quality of the out-of-sample performance using the testing sample.

A.3. Variables for Feature Selection

Table A.1: Variables for Feature Selection

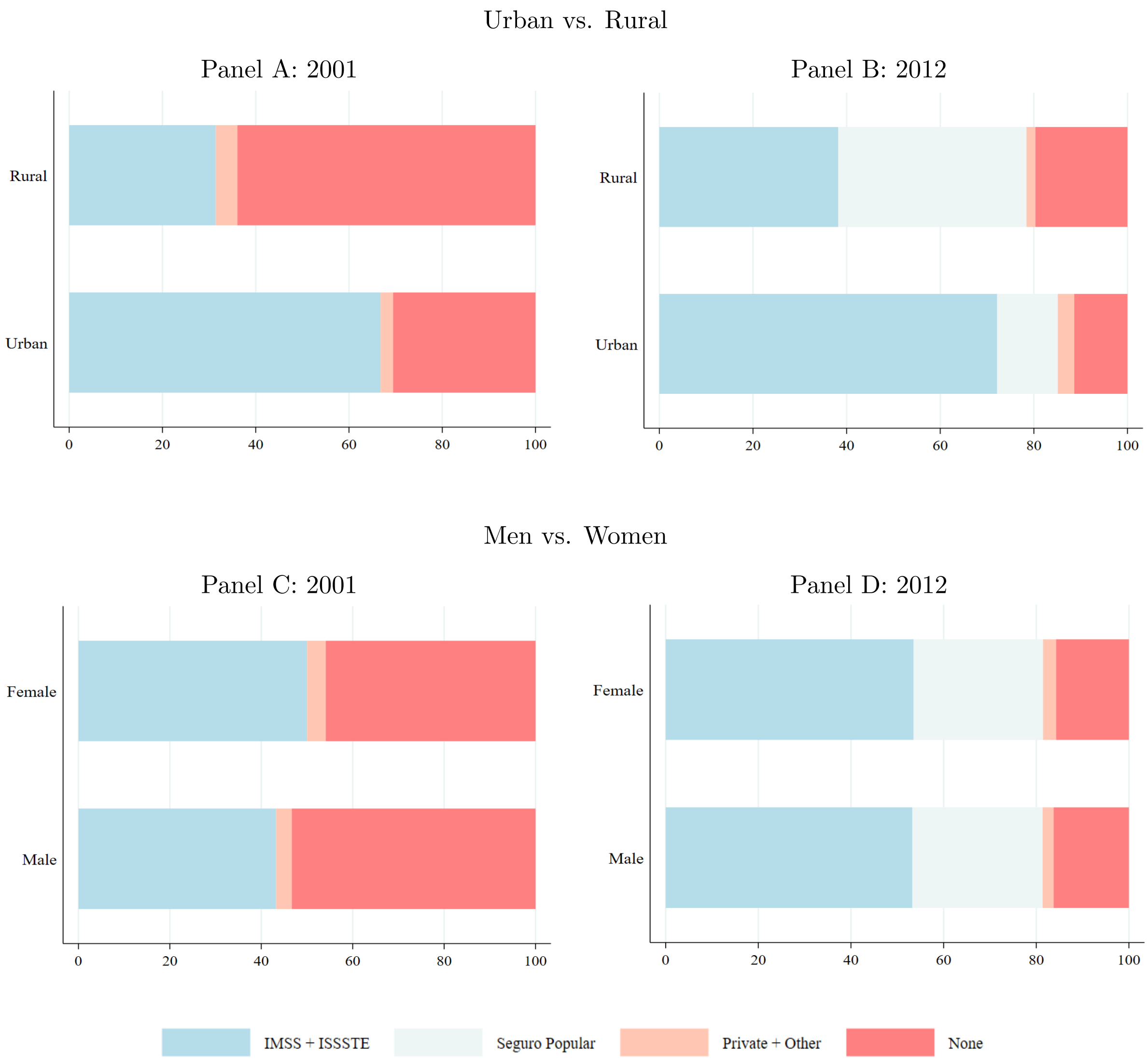
	Respondent
1	Dummy for not Employed
2	Age
3	Dummy for Gender
4	Dummy for having a partner
5	Dummy for No Education
6	Dummy for Primary Education
7	Dummy for Secondary Education
8	Dummy for Tertiary Education
9	Dummy for Health Status being very good
10	Dummy for Health Status being good
11	Dummy for Health Status being fair
12	Dummy for Health Status being poor
13	Dummy for Health Pre-conditions (heart attack, diabetes, blood pressure)
14	Dummy for Health Problems before 10
15	Income from Earnings and Wages
16	Income from Pensions
17	Income from Government Subsidies
18	Income from Properties
19	Income from Capital Assets
20	Dummy for Income being in the bottom two quintiles
21	Dummy for at least one parent died
22	Dummy for at least one parent lives at home
23	Dummy for having raised the kids alone
24	Dummy for indigenous heritage
25	Dummy for religion being very important
26	Dummy for religion being somewhat important
27	Dummy for religion being not important
	Household
28	Dummy for HH with piped water
29	Dummy for HH with toilet with water connection
30	Dummy for HH with radio
31	Dummy for HH with tv
32	Dummy for HH with water heater
33	Dummy for HH in the rural area
34	Dummy for localities with more than 15,000 inhabitants
	Kids
35	Number of Kids
36	Average Age
37	Share of kids at least 16 years old
38	Share of kids at least 18 years old
39	Share of kids at least 24 years old
40	Share of kids with kids
41	Share of Female kids
42	Share of kids with a partner
43	Share of kids with No Education
44	Share of kids with Primary Education
45	Share of kids with Secondary Education
46	Share of kids with Tertiary Education
47	Share of kids not employed
48	Share of kids with excellent or very good financial situation

Table A.2: Selected Variables

	LASSO	Random Forest	Boosting
1	Age	Age	Age
2	Dummy for Gender	Dummy for Gender	Dummy for Gender
3	Share of kids with kids	Share of kids with kids	Share of kids with kids
4	Share of kids with Secondary Education		Share of kids with Secondary Education
5		Number of Kids	Number of Kids
6	Dummy for localities with more than 15,000 inhabitants		Dummy for localities with more than 15,000 inhabitants
7	Dummy for not Employed	Dummy for not Employed	
8	Dummy for religion being somewhat important	Dummy for religion being somewhat important	
9		Average Kids' Age	Average Kids' Age
10		Dummy for having raised the kids alone	Dummy for having raised the kids alone
11		Share of Female kids	Share of Female kids
12		Income from Earnings and Wages	Income from Earnings and Wages
13	Dummy for Health Pre-conditions	Dummy for Health Pre-conditions	
14	Income from Government Subsidies		Income from Government Subsidies
15	Dummy for having a partner	Dummy for having a partner	
16	Share of kids with Tertiary Education		Share of kids with Tertiary Education
17	Income from Capital Assets		Income from Capital Assets
18	Share of kids not employed		Share of kids not employed
19	Share of kids at least 16		Share of kids at least 16
20		Dummy for good Health Status	
21			Share of kids with a partner
22		Dummy for No Education	
23	Dummy for at least one parent died		
24			Share of kids at least 18
25		Dummy for poor Health Status	
26		Share of kids at least 24	
27		Dummy for religion being not important	
28	Dummy for HH with water heater		
29		Dummy for fair Health Status	
30		Dummy for Secondary Education	
31	Dummy for Tertiary Education		
32		Dummy for Health Problems before 10	
33		Dummy for Income being in the bottom two quintiles	
34			Share of kids with Primary Education
35		Dummy for HH with piped water	
36		Dummy for religion being very important	
37		Dummy for Primary Education	
38	Dummy for very good Health Status		

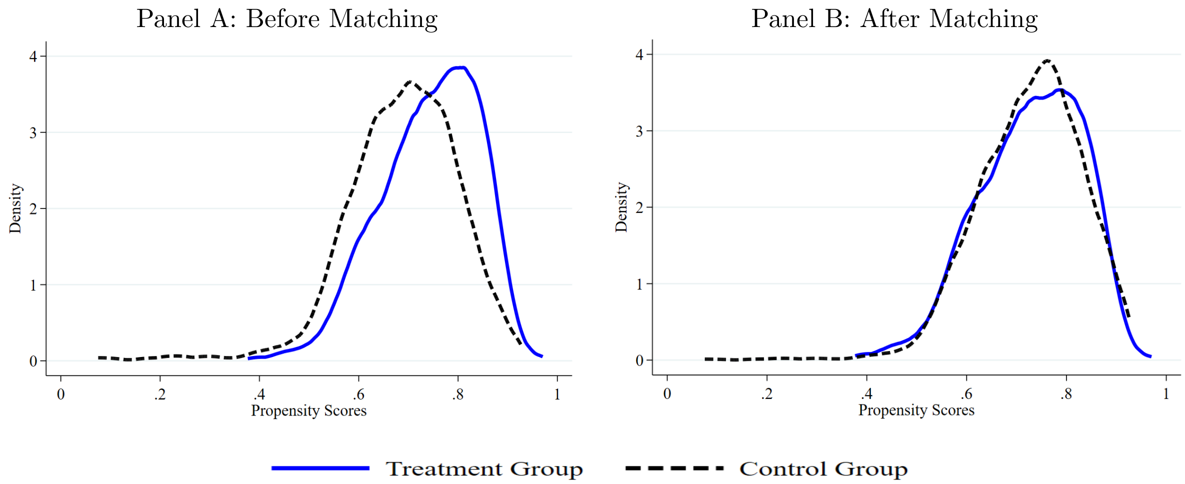
B. Figures

Figure B.1: Types of Insurance by Gender and Year



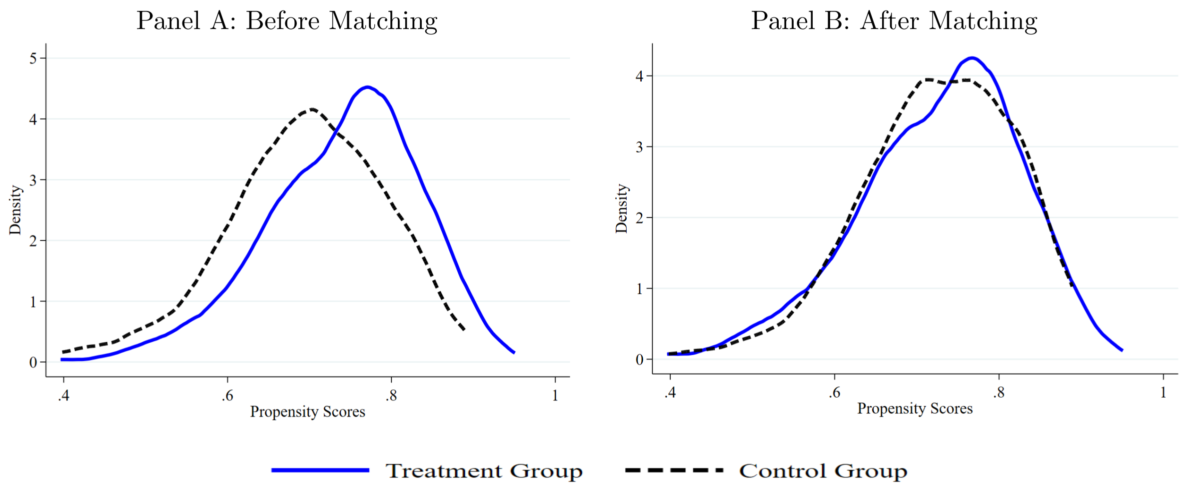
Notes: The balanced panel consists of 3,473 observations for each wave. The first category, "IMSS + ISSSTE" also includes Pemex, Defensa, and Marina, which account for a marginal share of health insurance plans. The shares are computed as weighted shares by the individual survey weights.

Figure B.2: Common Support



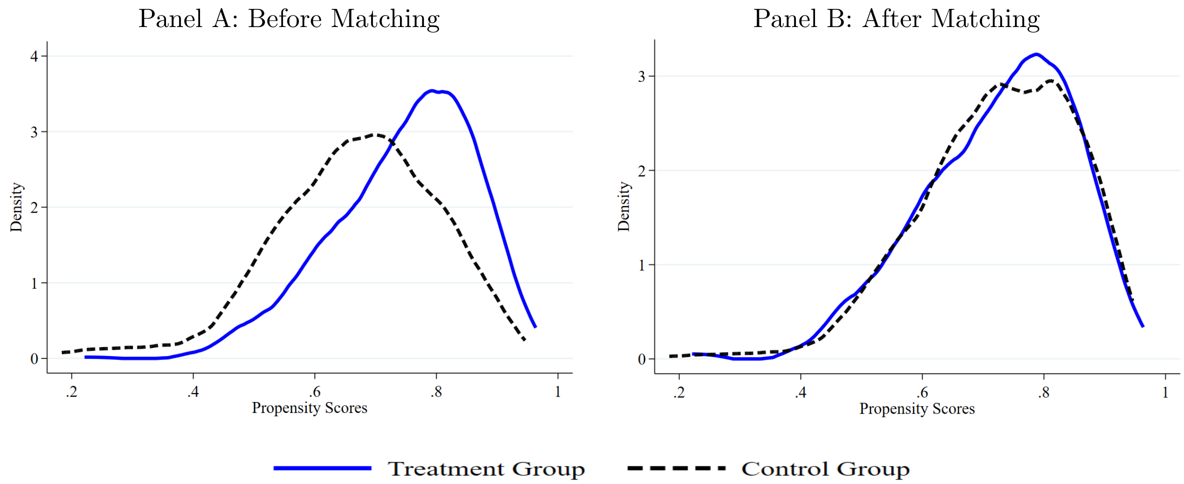
Notes: The Kernel densities are computed based on the propensity scores computed in 2001. The propensity scores are calculated using the variables selected by the Boosting Regression method. The treatment group is defined as all individuals enrolled in *Seguro Popular* in 2012 and with any or no insurance in 20001. The control group is defined as all individuals with no insurance in both 2001 and 2012. Panel A uses all units in the potential treatment and control groups. Panel B uses only the matched units weighted by the inverse probability weights calculated after the matching.

Figure B.3: Common Support



Notes: The Kernel densities are computed based on the propensity scores computed in 2001. The propensity scores are calculated using the variables selected by the Random Forest method. The treatment group is defined as all individuals enrolled in *Seguro Popular* in 2012 and with any or no insurance in 20001. The control group is defined as all individuals with no insurance in both 2001 and 2012. Panel A uses all units in the potential treatment and control groups. Panel B uses only the matched units weighted by the inverse probability weights calculated after the matching.

Figure B.4: Common Support



Notes: The Kernel densities are computed based on the propensity scores computed in 2001. The propensity scores are calculated using the variables selected by the LASSO Regression method. The treatment group is defined as all individuals enrolled in *Seguro Popular* in 2012 and with no insurance in 20001. The control group is defined as all individuals with no insurance in both 2001 and 2012. Panel A uses all units in the potential treatment and control groups. Panel B uses only the matched units weighted by the inverse probability weights calculated after the matching.

C. Tables

Table C.1: Share of Insured Respondents by year

Insurance in 2001 and 2012	No Insurance in 2001 and 2012	Insurance in 2001, No Insurance in 2012	No Insurance in 2001, Insurance in 2012
0.543	0.112	0.022	0.323

Notes: The balanced panel consists of $3,473$ observations for each wave. The shares are computed as weighted shares by the individual survey weights.

Table C.2: Share of Upward and Downward Transfers by year

Year	Gave any financial transfer to children	Received any financial transfer from children	Gave time to children	Received time from children
2001	0.130	0.331	0.489	0.488
2012	0.130	0.432	0.317	0.410

Notes: The balanced panel consists of $3,473$ observations for each wave. The shares are computed as weighted shares by the individual survey weights.

Table C.3: Balancing Property Test

	Mean		t-test	p-value
	Enrolled	Non-enrolled		
Panel A: Outcome Variables				
Received monetary transfer from children	0.367	0.441	-2.884	0.004
Received non-monetary transfer from children	0.421	0.440	-0.739	0.460
Gave monetary transfer to children	0.107	0.075	2.092	0.037
Gave non-monetary transfer to children	0.405	0.366	1.558	0.119
Amount of monetary transfer from children (USD)	536.698	581.315	-0.421	0.674
Amount of monetary transfer to children (USD)	314.410	210.240	0.540	0.590
Panel B: Respondent Characteristics				
Age	59.195	59.514	-0.742	0.458
Women (Share)	0.553	0.582	-1.108	0.268
Married/Union (Share)	0.667	0.611	2.234	0.026
No Education (Share)	0.337	0.410	-2.871	0.004
Primary Education (Share)	0.592	0.534	2.216	0.027
Secondary Education (Share)	0.059	0.042	1.431	0.153
Tertiary Education (Share)	0.012	0.014	-0.231	0.818
Has some Disease (Share)	0.411	0.389	0.854	0.393
Not Employed (Share)	0.295	0.312	-0.739	0.460
Religion is very important (Share)	0.711	0.795	-3.713	0.000
Religion is somewhat important (Share)	0.262	0.193	3.128	0.002
Religion is not important (Share)	0.262	0.193	3.128	0.002
Very Good health (Share)	0.033	0.025	0.938	0.348
Good health (Share)	0.325	0.288	1.532	0.126
Fair Health (Share)	0.484	0.526	-1.622	0.105
Poor Health (Share)	0.159	0.162	-0.142	0.887
Earnings and Wages (USD)	136.614	137.942	-0.070	0.944
Pensions (USD)	4.024	2.958	0.626	0.531
Government Subsidies (USD)	22.237	11.370	1.914	0.056
Properties (USD)	5.762	2.496	1.437	0.151
Capital Assets (USD)	1.414	0.507	1.435	0.152
At least a parent died (Share)	0.903	0.862	2.436	0.015
At least a parent lives in the house (Share)	0.029	0.016	1.584	0.113
Raised kids alone (Share)	1.130	1.168	-0.289	0.773
Health Problems before 10 (Share)	0.114	0.093	1.288	0.198
Speaking indigenous languages (Share)	0.597	0.484	1.190	0.234
Panel C: Household Characteristics				
HH has radio (Share)	0.829	0.890	-3.399	0.001
HH has TV (Share)	0.863	0.849	0.745	0.457
HH has piped water (Share)	0.584	0.549	1.319	0.187
HH has toilet with water connection (Share)	0.447	0.407	1.533	0.125
HH has water heater (Share)	0.248	0.286	-1.655	0.098
Rural Area (Share)	0.605	0.627	-0.860	0.390
Location more than 15,000 Inhabitants (Share)	0.484	0.463	0.785	0.432
Panel D: Kid Characteristics				
Number of Kids	5.818	5.949	-0.824	0.410
Kids' Age (Average)	29.007	29.262	-0.601	0.548
Kids older than 16 years (Share)	0.930	0.937	-0.765	0.444
Kids older than 18 years (Share)	0.890	0.896	-0.554	0.579
Kids older than 24 years (Share)	0.703	0.717	-0.872	0.384
Daughters (Share)	0.494	0.509	-1.187	0.236
Kids with grandkids (Share)	0.622	0.607	0.917	0.359
Married/Union (Share)	0.639	0.621	1.144	0.253
Not Employed (Share)	0.385	0.373	0.836	0.403
Kids No Education (Share)	0.042	0.061	-2.026	0.043
Kids Primary Education (Share)	0.445	0.459	-0.680	0.497
Kids Secondary Education (Share)	0.436	0.410	1.333	0.183
Kids Tertiary Education (Share)	0.077	0.070	0.676	0.499
Excellent or Very Good Financial Situation (Share)	0.014	0.016	-0.326	0.745

Notes: The treatment group is defined as all individuals enrolled in *Seguro Popular* in 2012 and with any or no insurance in 20001. The control group is defined as all individuals with no insurance in both 2001 and 2012. Observations are weighted by the inverse probability weights calculated after the propensity score matching using the set of variables selected by the Boosted Regression method. Errors are clustered at the respondent level.

Table C.4: Balancing Property Test

	Mean		*t-test*	*p-value*
	Enrolled	Non-enrolled		
Panel A: Outcome Variables				
Received monetary transfer from children	0.367	0.405	-1.504	0.133
Received non-monetary transfer from children	0.421	0.430	-0.370	0.711
Gave monetary transfer to children	0.107	0.084	1.515	0.130
Gave non-monetary transfer to children	0.405	0.378	1.071	0.284
Amount of monetary transfer from children (USD)	536.698	503.431	0.318	0.750
Amount of monetary transfer to children (USD)	314.410	200.395	0.591	0.555
Panel B: Respondent Characteristics				
Age	59.195	58.310	2.210	0.027
Women (Share)	0.553	0.552	0.053	0.958
Married/Union (Share)	0.667	0.703	-1.464	0.144
No Education (Share)	0.337	0.382	-1.799	0.072
Primary Education (Share)	0.592	0.547	1.743	0.082
Secondary Education (Share)	0.059	0.048	0.930	0.353
Tertiary Education (Share)	0.012	0.023	-1.582	0.114
Has some Disease (Share)	0.411	0.403	0.319	0.750
Not Employed (Share)	0.295	0.311	-0.683	0.495
Religion is very important (Share)	0.711	0.727	-0.698	0.485
Religion is somewhat important (Share)	0.262	0.244	0.782	0.434
Religion is not important (Share)	0.262	0.244	0.782	0.434
Very Good health (Share)	0.033	0.040	-0.699	0.485
Good health (Share)	0.325	0.277	1.997	0.046
Fair Health (Share)	0.484	0.479	0.157	0.875
Poor Heatlh (Share)	0.159	0.204	-2.241	0.025
Earnings and Wages (USD)	136.614	130.591	0.273	0.785
Pensions (USD)	4.024	3.714	0.181	0.856
Government Subsidies (USD)	22.237	17.652	0.819	0.413
Properties (USD)	5.762	3.101	0.749	0.454
Capital Assets (USD)	1.414	5.300	-1.817	0.069
At least a parent died (Share)	0.903	0.825	4.369	0.000
At least a parent lives in the house (Share)	0.029	0.012	2.215	0.027
Raised kids alone (Share)	1.130	1.085	0.337	0.736
Health Problems before 10 (Share)	0.114	0.108	0.333	0.739
Speaking indigenous languages (Share)	0.597	0.582	0.153	0.878
Panel C: Household Characteristics				
HH has radio (Share)	0.829	0.841	-0.634	0.526
HH has TV (Share)	0.863	0.797	3.353	0.001
HH has piped water (Share)	0.584	0.574	0.370	0.711
HH has toilet with water connection (Share)	0.447	0.484	-1.416	0.157
HH has water heater (Share)	0.248	0.405	-6.499	0.000
Rural Area (Share)	0.605	0.573	1.275	0.202
Location more than 15,000 Inhabitants (Share)	0.484	0.567	-3.203	0.001
Panel D: Kid Characteristics				
Number of Kids	5.818	6.003	-1.150	0.250
Kids' Age (Average)	29.007	28.191	1.904	0.057
Kids older than 16 years (Share)	0.930	0.925	0.676	0.499
Kids older than 18 years (Share)	0.890	0.888	0.248	0.804
Kids older than 24 years (Share)	0.703	0.677	1.492	0.136
Daughters (Share)	0.494	0.479	1.194	0.233
Kids with grandkids (Share)	0.622	0.604	1.053	0.293
Married/Union (Share)	0.639	0.632	0.429	0.668
Not Employed (Share)	0.385	0.332	3.558	0.000
Kids No Education (Share)	0.042	0.029	1.810	0.071
Kids Primary Education (Share)	0.445	0.385	2.990	0.003
Kids Secondary Education (Share)	0.436	0.467	-1.629	0.103
Kids Tertiary Education (Share)	0.077	0.118	-3.498	0.000
Excellent or Very Good Financial Situation (Share)	0.014	0.013	0.221	0.825

Notes: The treatment group is defined as all individuals enrolled in *Seguro Popular* in 2012 and with any or no insurance in 20001. The control group is defined as all individuals with no insurance in both 2001 and 2012. Observations are weighted by the inverse probability weights calculated after the propensity score matching using the set of variables selected by the Random Forest method. Errors are clustered at the respondent level.

Table C.5: Balancing Property Test

	Mean		t-test	p-value
	Enrolled	Non-enrolled		
Panel A: Outcome Variables				
Received monetary transfer from children	0.372	0.397	-0.975	0.330
Received non-monetary transfer from children	0.421	0.440	-0.745	0.456
Gave monetary transfer to children	0.104	0.039	4.840	0.000
Gave non-monetary transfer to children	0.404	0.331	2.850	0.004
Amount of monetary transfer from children (USD)	545.263	466.273	0.728	0.467
Amount of monetary transfer to children (USD)	318.097	36.373	1.695	0.090
Panel B: Respondent Characteristics				
Age	59.304	59.628	-0.793	0.428
Women (Share)	0.560	0.553	0.265	0.791
Married/Union (Share)	0.662	0.634	1.104	0.270
No Education (Share)	0.343	0.365	-0.882	0.378
Primary Education (Share)	0.591	0.599	-0.322	0.747
Secondary Education (Share)	0.054	0.018	3.686	0.000
Tertiary Education (Share)	0.013	0.018	-0.858	0.391
Has some Disease (Share)	0.416	0.429	-0.480	0.631
Not Employed (Share)	0.298	0.273	1.050	0.294
Religion is very important (Share)	0.713	0.717	-0.175	0.861
Religion is somewhat important (Share)	0.259	0.270	-0.478	0.633
Religion is not important (Share)	0.259	0.270	-0.478	0.633
Very Good health (Share)	0.032	0.021	1.314	0.189
Good health (Share)	0.322	0.247	3.166	0.002
Fair Health (Share)	0.485	0.499	-0.527	0.598
Poor Heatlh (Share)	0.162	0.234	-3.453	0.001
Earnings and Wages (USD)	136.442	130.737	0.279	0.780
Pensions (USD)	4.092	1.986	1.357	0.175
Government Subsidies (USD)	21.671	29.456	-1.066	0.287
Properties (USD)	5.858	17.763	-1.672	0.095
Capital Assets (USD)	1.437	1.025	0.441	0.659
At least a parent died (Share)	0.904	0.884	1.199	0.231
At least a parent lives in the house (Share)	0.028	0.032	-0.464	0.643
Raised kids alone (Share)	1.149	1.561	-2.614	0.009
Health Problems before 10 (Share)	0.116	0.177	-3.293	0.001
Speaking indigenous languages (Share)	0.595	0.848	-2.245	0.025
Panel C: Household Characteristics				
HH has radio (Share)	0.827	0.795	1.550	0.121
HH has TV (Share)	0.865	0.809	2.861	0.004
HH has piped water (Share)	0.584	0.536	1.807	0.071
HH has toilet with water connection (Share)	0.447	0.400	1.815	0.070
HH has water heater (Share)	0.247	0.223	1.057	0.291
Rural Area (Share)	0.606	0.656	-1.968	0.049
Location more than 15,000 Inhabitants (Share)	0.485	0.440	1.693	0.091
Panel D: Kid Characteristics				
Number of Kids	5.868	6.206	-2.077	0.038
Kids' Age (Average)	29.279	29.370	-0.210	0.834
Kids older than 16 years (Share)	0.944	0.938	0.826	0.409
Kids older than 18 years (Share)	0.905	0.896	1.001	0.317
Kids older than 24 years (Share)	0.714	0.715	-0.024	0.981
Daughters (Share)	0.492	0.516	-1.871	0.061
Kids with grandkids (Share)	0.632	0.616	1.029	0.304
Married/Union (Share)	0.649	0.624	1.540	0.124
Not Employed (Share)	0.377	0.357	1.313	0.189
Kids No Education (Share)	0.042	0.038	0.616	0.538
Kids Primary Education (Share)	0.445	0.501	-2.723	0.007
Kids Secondary Education (Share)	0.434	0.360	3.869	0.000
Kids Tertiary Education (Share)	0.079	0.101	-1.918	0.055
Excellent or Very Good Financial Situation (Share)	0.015	0.017	-0.452	0.651

Notes: The treatment group is defined as all individuals enrolled in *Seguro Popular* in 2012 and with no insurance in 20001. The control group is defined as all individuals with no insurance in both 2001 and 2012. Observations are weighted by the inverse probability weights calculated after the propensity score matching using the set of variables selected by the LASSO Regression method. Errors are clustered at the respondent level.

Table C.6: Magnitude of the estimates

Year	Gave any financial transfer to children	Received any financial transfer from children	Gave time to children	Received time from children
	Treatment Group			
2001	0.102	0.298	0.451	0.489
2012	0.111	0.483	0.295	0.400
$\Delta^{T}_{12,01}$	0.009	0.185	-0.156	-0.089
	Control Group			
2001	0.084	0.364	0.416	0.491
2012	0.178	0.437	0.347	0.409
$\Delta^{C}_{12,01}$	0.095	0.072	-0.070	-0.082
	Magnitude of the effect			
Coefficient	-0.091	0.097	-0.031	0.028
Magnitude Treatment	-0.009	0.029	-0.014	0.014
$\Delta^{T}_{12,01} - \Delta^{C}_{12,01}$	-0.086	0.113	-0.086	-0.007
Share (%)	10.47	26.66	16.28	-200