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The evolution of consumption inequality and risk-insurance in Chile☆

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ABSTRACT

Using micro survey data, I show that income and consumption inequality fell substantially in Chile since 1987. Consumption inequality between and within groups fell substantially over the last 35 years, especially for within groups. During this period, households' use of financial services increased substantially. Estimating a standard consumption model, the results reject both the autarky and the full risk sharing frameworks. It is found that for services and non-durable goods, consumption is almost half-way between autarky and full risk-sharing. However, purchases of Semi-Durables, Durables, Medical, Insurance, and other financial products are strongly affected by income fluctuations.

1. Introduction

Income inequality has fallen in Chile consistently since the 1980s, with the income Gini coefficient dropping from 56.2% in 1987 to 44.4% in 2017 (World Bank, 2021), due to multiple factors such as an expansion in education (De Gregorio and Lee, 2002), a fall in poverty (Sanhueza et al., 2010), a reduction of the experience and education wage premia (Azevedo et al., 2013) and expansive fiscal policy during the commodity boom (Guerra-Salas, 2016). Income inequality in Chile fluctuated at levels above 55% between 1987 to 1998 but fell sharply in the 2000s (Parro and Reyes, 2017), with the Gini coefficient dropping from 55.5% in 1998 to 46% in 2011 (World Bank, 2021). Furthermore, inequality has increased across the world (World Bank, 2021). The relevance of socioeconomic inequality is receiving a great amount of attention in Chile due to the "Social Explosion" event in October 18 of 2019 with massive political protests and social demands (Madeira, 2022).

However, many variations in income are transitory and its effects depend on the credit and insurance markets available to smooth income, therefore income dispersion does not automatically translate into consumption and welfare (Krueger and Perri, 2006). Chile had a significant expansion of its financial system since the 1980s, with robust expansions in terms of consumer insurance products and household credit, such as mortgages and consumer loans (Berstein and Marcel, 2019). The welfare impact of the income inequality reduction over the last decades therefore depends on the interaction of households with the financial system and the expansion of social programs during this period. For this reason it is important to analyze the consumption dispersion and risk-sharing in Chile, in a similar way as studies for other countries such as the USA, Canada, UK, Germany, Sweden, Italy, Spain, Russia and Mexico (Krueger et al., 2010). This work also relates to the literature relating economic inequality to the lack of access to finance (Demirgüç-Kunt and Levine, 2009; Cihak and Sahay, 2020) and to how inequality and income volatility impact the business cycle and financial stability (García and Pérez, 2017).

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To analyze the distribution and growth of consumption in Chile I use the Chilean Household Expenditure Survey (in Spanish, *Encuesta de Presupuestos Familiares*, hence on EPF) between the years of 1987 to 2017. Using micro survey data, I show that both household income and consumption inequality declined substantially in Chile since 1987. This makes Chile an unique case, since both income and consumption inequality increased strongly in North America, and Europe (with the exception of Russia in the 2000s) over the last 30 years (Krueger et al., 2010). I also show that consumption inequality in Chile declined at a much faster rate than income inequality, which is evidence of an improvement in households' access to financial instruments that allow for income smoothing and insurance against idiosyncratic shocks. In fact, consumption inequality in Chile is now much lower than income inequality. In the most recent survey of 2017, in the Great Santiago region the Gini coefficient for income is around 47.5%, while the Gini for total consumption (durable plus non-durable expenditures) and total non-durables (non-durable and semi-durable goods and services) was 42% and 40%, respectively. The same result is found by using other measures of income and consumption inequality, such as the variance or the ratio between the top (the richest) and bottom (the poorest) percentiles. This evidence is consistent with the fall in real interest rates and the improvement in households' access to financial products (Berstein and Marcel, 2019). Furthermore, both the inequality of consumption between groups (households of different age, education and professional occupations) and within groups has fallen substantially, showing that households are now less subject to both permanent and temporary income frictions (Katz and Autor, 1999). This is particularly true for the consumption inequality within similar groups, represents the source of frictions that can be more easily smoothed by households using asset markets or social safety net programs (Krueger and Perri, 2006). This result confirms that Chilean households' welfare is now much less impacted by the heavy fluctuations in income and consumption that affected them in previous decades. The EPF survey shows that nowadays households spend a greater share of their income on insurance products and "out of the pocket" medical expenses. However, their expenses with non-insurance financial products such as banking fees dropped significantly due to the great gains in the efficiency of the banking sector (Berstein and Marcel, 2019).

In a world with perfect assets for each contingency (negative health, unemployment, income shocks), the individual consumption would only be affected by aggregate shocks and not by individual factors (Townsend, 1994). Therefore the degree to which personal consumption depends on the current income is a proxy for the efficiency of the risk-sharing implied by the financial and insurance markets plus the social safety net of government programs (Attanasio and Davis, 1996). In a perfect risk-sharing economy the coefficient of income would be zero, while an autarky economy (one without any risk-sharing) would have a coefficient of one. Using the cohorts, region and education groups from the EPF surveys, I apply the pseudo-panel methodology proposed by Attanasio and Davis (1996) to test whether households in Chile have some degree of risk-sharing relative to fluctuations in permanent income, unemployment risk and income volatility.

The consumption model estimates reject both the perfect risk-sharing (a coefficient of zero for income) and the autarky with no-risk sharing (a coefficient of one for income). However, total consumption and non-durable expenditures are not affected by unemployment risk and income volatility. The consumption of Non-durable goods and Services have coefficients around 0.5 to 0.6 for the fluctuations of income, which shows a substantial degree of consumption smoothing and risk-sharing for these kinds of goods. However, the consumption of Semi-Durables and Durables have coefficients for income around 1.3 and 2, which shows that these goods are strongly pro-cyclical and affected by income fluctuations, perhaps because these expenditures are made for large items which are infrequently purchased and can therefore be reduced during a negative period for the household (Browning and Crossley, 2009; Cerletti and Pijoan-Mas, 2017). Another evidence that shows income frictions are much more important for Semi-Durables and Durable goods is that the inequality across income levels for these goods is much higher than for Services and Non-Durable goods. However, the inequality in the consumption of Durables fell substantially until 2007, showing that financial frictions for these purchases is now reduced, perhaps due to the greater access to consumer debt. In the same way, the pseudo-panel consumption regressions show that households' medical expenses, insurance and financial goods' purchases are still subject to heavy income frictions and there is much greater inequality in terms of medical and financial expenses than for other goods. This result makes sense because our survey dataset only allows us to study consumption from out of the pocket expenses and therefore does not cover consumption from government subsidized goods, such as use of public hospitals. Therefore it makes sense that in a world with imperfect asset markets, the consumers will reduce substantially the payments on medical expenses that have a lower degree of public reimbursement and use more of the less expensive services covered by the state. The reduction in the consumption of insurance and financial goods after negative income shocks is also expected because insurance contracts and financial goods such as mortgages and consumer loans are complementary to the purchases of durable goods such as homes, vehicles and furniture. Therefore a big elasticity (in absolute value) of insurance and financial goods' consumption with respective to income is to be expected, because the consumption of durable goods is easier to be reduced by consumers in a world with imperfect markets (Browning and Crossley, 2009, Cerletti and Pijoan-Mas, 2017).

This paper fits into a larger literature that uses microdata to study household finance issues (Cifuentes et al., 2020; Madeira, 2018), saving and consumption decisions (Sim and Lee, 2020), inequality (Krueger and Perri, 2006; Attanasio and Pistaferri, 2016), consumers' financial access (Cifuentes et al., 2020; Lu et al., 2020), with a focus on a comparison over long periods of time (Attanasio and Davis, 1996; Attanasio and Szekely, 2004). Consumption inequality is a particularly relevant topic for developing economies (Cifuentes et al., 2020, Lu et al., 2020), where there are few studies in this area due to the lack of adequate panel data (Krueger et al., 2010). It is relevant to note that there are several surveys of consumption and expenditures at a five or ten year frequency across many developing countries and emerging markets (Deaton, 2019; FAO and World Bank, 2018). Several of the earliest studies of consumption using microdata to test smoothing of income shocks, risk-sharing across households, poverty and demand for different goods were implemented in developing economies, in particular Asian countries, such as Thailand, India, Pakistan, China, Vietnam and other countries (Paxson, 1993; Townsend, 1994; Alderman, 1996; Gibson et al., 2003; Gibson and Kim, 2015; Deaton, 2019). Chile is one of the highest income countries in Latin America, therefore providing a useful comparison study for its regional neighbors.

This work also expands the consumption literature by considering the evolution of risk-sharing in Chile across three decades and by relating the changes in risk-sharing to the higher access of financial products and insurance contracts. This study, therefore, fits well with the recent literature showing a higher degree of financial access across many emerging markets and developed countries, both as a result of the expansion of the banking sector, the use of formal and informal financial services, or from new FinTech players (Demirgüç-Kunt et al., 2021).

Finally, it is increasingly important for economists to understand the welfare consequences of economic shocks for household consumption and how agents can insure shocks through either social networks, government transfers or financial products (Attanasio and Weber, 2010). Consumption relative to GDP has been growing across many developing economies and emerging markets over the last decade, even if it fell slightly for the OECD and the World economy as a whole. Consumption to GDP between 2010 and 2019 increased from 58.5%, 62.1%, and 64.4% to 64.1%, 62.3%, and 68.2% for, respectively, South Asia, Latin America and Caribbean, and Sub-Saharan Africa (World Bank, 2021), making consumption more relevant for the stabilization of the business cycle and welfare.

This paper is organized as follows. Section 2 summarizes the survey data, while Section 3 shows the evolution of the consumption inequality in Chile across different demographic groups and Section 4 shows the distribution of expenditures according to purpose and durability of the goods. Section 5 shows the estimates of the risk-sharing model for total consumption and expenditures according to purpose and durability. Finally, Section 6 concludes with a summary of the policy implications.

2. Data and empirical strategy

2.1. The welfare and consumption optimization model

As proposed in Townsend, 1994 and Attanasio and Davis, 1996, a test for full-insurance requires showing that the marginal utility of consumption is only affected by aggregate economy shocks and not by idiosyncratic factors (such as shocks to personal income or individual health):

$$U_c\left(c_{i,t}(s_t), z_{i,t}(s_t)\right)\lambda_i\beta_i = \mu(s_t) \tag{1}$$

with $c_{i,\ t}$ being the individual consumption of household i at time t, $z_{i,\ t}$ being a vector of individual time-varying characteristics (which can be observable or unobservable) that affect the utility of consumption (such as health, marriage or the number of children), and s_t denotes the aggregate state of the economy. λ_i is the Pareto-weight given by the social planner to individual i in the maximization problem, β_i is the discount factor for individual i, and $\mu(s_t)$ is the Lagrange multiplier associated with the aggregate resource constraint when the state of the world is s_t. One can develop this expression further by taking logs of both sides and taking time-differences between t and another period t^* to eliminate the constant unobserved factors $\lambda_i\beta_i$:

$$ln\left(\frac{U_c\left(c_{i,t}(s_t), z_{i,t}(s_t)\right)}{U_c\left(c_{i,t^*}(s_{t^*}), z_{i,t^*}(s_{t^*})\right)}\right) = ln\left(\frac{\mu(s_t)}{\mu(s_{t^*})}\right) \tag{2}$$

For simplicity, consider a CRRA utility function: $U\left(c_{i,t}(s_t), z_{i,t}(s_t)\right) = \frac{c_{i,t}^{1-\gamma}}{1-\gamma}exp\left(z_{i,t}\right)$. Assume that the vector $z_{i,\ t}$ can be decomposed into observable ($x_{i,\ t}$) and unobservable factors ($\varepsilon_{i,\ t}$), with $\lambda_i\beta_i$ being an idiosyncratic random term uncorrelated with $z_{i,\ t}$. Then one can estimate the full risk-sharing condition in expression 1) from cross-sectional data:

$$ln\left(c_{i,t}\right) = \widetilde{c}_{i,t} = \alpha_t + \theta x_{i,t} + \varepsilon_{i,t} + ln(\lambda_i\beta_i) \tag{3}$$

with $\widetilde{c}_{i,t}$ being the individual log-consumption and α_t being dummy variables to account for the aggregate states in each period t.

The regression model implied by Eq. (3)) can be further relaxed by using panel data to difference the constant unobserved factor ln ($\lambda_i\beta_i$). However, household surveys with consumption data are often expensive and are only available in cross-sectional form (Attanasio and Davis, 1996). Therefore one can take advantage that this welfare optimization model is still valid for an aggregation of a group g of i different households and one can use a pseudo-panel of households with groups of households composed by cohort, education level and geographical area.

Let us define $y_{g,t} = \frac{1}{n_g}\sum_{i\in g}y_{i,t}$ as the average of a variable across all individuals in the group g, therefore being the group average equivalent of the same variables for the individuals. Assuming that individuals do not often migrate between groups (say, if household heads are unlikely to gain more education after a certain age or move to other regions), then one can aggregate the condition of expression 1) for all individuals in the group g, divide by the number in group g to obtain the group average, and again take the differences in logs to obtain:

$$\sum_{i\in g} ln\left(c_{i,t}\right) - \sum_{i\in g} ln\left(c_{i,t^*}\right) = n_g(\alpha_t - \alpha_{t^*}) + \theta\sum_{i\in g}\left(x_{i,t} - x_{i,t^*}\right) + \sum_{i\in g}\left(\varepsilon_{i,t} - \varepsilon_{i,t^*}\right) \Leftrightarrow \tag{4}$$

$$\widetilde{c}_{g,t} - \widetilde{c}_{g,t^*} = d_t + \theta\left(x_{g,t} - x_{g,t^*}\right) + \zeta_{g,t} \tag{5}$$

with $d_t = (\alpha_t - \alpha_t^*)$ and $\zeta_{g,t} = \frac{1}{n_g}\sum_{i\in g}\left(\varepsilon_{i,t} - \varepsilon_{i,t^*}\right)$. Expression 5) can then be estimated using a pool of cross-sections to obtain a pseudo-panel dataset based on well-defined groups.

In a world with perfect risk-sharing, then the coefficients θ for the variables x would be zero, since only aggregate shocks (d_t) cannot be insured by assets and contracts between agents. The model is easier to interpret if one includes income in the control vector $x_{i,\ t}$. In a perfect risk-sharing economy the coefficient of income would be zero, while an autarky economy (one without any risk-sharing) would have a coefficient of one. One can also observe whether there is risk-sharing for some variables (for instance, temporary unemployment) but not for others (ex: permanent income). Note, however, that this regression only evaluates the degree of risk-sharing, but not the welfare of the agents, because the model has a very general utility function as defined in Eq. (1)) and it is, therefore, robust to a wide range of specifications (Townsend, 1994). A welfare analysis would require a specific utility function and other assumptions on market arrangements, therefore it is outside the scope of this article (Attanasio and Weber, 2010).

2.2. Estimating the model from survey data

This study uses the Chilean Expenditure Survey (*Encuesta de Presupuestos Familiares*, hence on EPF) for the waves 1987, 1997, 2007, 2012 and 2017. This survey was implemented only every 10 years until 2007[1] and once every 5 years since then, covering around 10,000 urban households. In particular, the EPF survey collected information from 5076, 8445, 10,092, 10,473 and 15,239 households in the years of 1987, 1997, 2007, 2012 and 2017. This study will use the pooled cross-section waves between 1987 and 2017, with a total of 49,325 household observations. Since expenditure surveys are expensive, requiring a mix of recall and diary measurement of expenditures (Battistin et al., 2020), the 1987 and 1997 waves only cover the Great Santiago area of the capital region, which concentrates around 40% of the country's population, but with survey waves since 2007 collecting around 1/3 of their samples in the regions outside of the capital. The EPF survey provides a high quality measure of durable and non-durable expenditures classified for a list of 1570 product categories, with interviewers visiting households multiple times during a period of one month, asking for their bills and receipts from expenditures, plus memory reports of non-receipt expenses made during the period and of infrequent expenses, similar to the best international procedures (Attanasio and Weber, 2010; Battistin et al., 2020).

To obtain comparable measures of income and consumption across households, I express all household income and consumption variables in terms of their equivalized measures (Krueger et al., 2010; Attanasio and Szekely, 2004). The equivalized measures are similar to a "per capita" measure, but, instead of dividing by the total number of household members n_i, the equivalized measures take into account that there are some scale economies in terms of the consumption of joint goods within the household. In this paper I apply the OECD-modified scale (OECD, 2008), which assigns a value of 1 to the household head, 0.5 to each additional adult member (above age 15) and 0.3 to each child: $ne_i^{OECD} = 1 + 0.5(adults_i - 1) + 0.3(children_i)$. Other measures are possible, with for instance some articles using the square-root of all household members ($ne_i = \sqrt{n_i}$) or the Oxford scale which assigns a value of 1 to the first household member, 0.7 to each additional adult and 0.5 to each child ($ne_i^{Oxford} = 1 + 0.7(adults_i - 1) + 0.5(children_i)$). The results in this article are qualitatively similar if one uses the Oxford or the square-root household equivalence measures.

For simplicity, the analysis in this article is limited to households of working age, therefore I restrict the sample to household heads between age 25 and 64. This choice is standard for studying consumption models and it is widely used in the previous literature (Attanasio and Davis, 1996; Attanasio and Brugiavini, 2003; Attanasio and Szekely, 2004). The reason is that most workers retire at age 65 and retired workers may have a different model of consumption due to the higher possibilities of spending in leisure and using time to search for lower prices (Attanasio and Weber, 2010). Like many countries, Chile has a retirement age for workers at age 65, which includes both contributory pensions accumulated by the workers and also public non-contributory pensions given by the government as a support for poor households in their old age. For this reason, I follow the standard sample selection used in the literature of analyzing only households with heads between 25 and 64 years of age. This sample selection applies to all the figures and tables in this article (except for Fig. 4, which uses aggregate data).

To analyze the consumption of different goods in real value over time, I apply different CPI indexes to each good (Krueger and Perri, 2006). This option is made to take into account that some goods may have decreased or increased their prices relative to the general CPI, with for example computers becoming cheaper, while healthcare and education becomes more expensive. There is not an individual CPI for each product category (1570 product categories), therefore I match each product category to one of the 144 CPI categories published by Carlomagno et al. (2021) with a standardization of 1 in december of 2007. Therefore the consumption of household i at time t for each product j is calculated as: $c_{i,j,t} = \frac{exp_{i,j,t}}{CPI_{j,t} \times ne_i^{OECD}}$ and the total consumption of household i at time t is given by $c_{i,\ t} = \sum_j c_{i,\ j,\ t}$. Another reasonable option is to calculate the total consumption standardized by the CPI of the period t (instead of the individual CPIs): $\widehat{c}_{i,t} = \frac{\sum_j exp_{i,j,t}}{CPI_t \times ne_i^{OECD}}$. However, both measures of consumption, $c_{i,\ t}$ and $\widehat{c}_{i,t}$, are very similar, showing a correlation coefficient of 98.6% for the pooled EPF dataset (1987–2017).

To estimate the consumption models in expressions 3) and 5), the vector $x_{i,\ t}$ includes variables such as five year dummies for the age of the household head, demographics (number of children, adults and senior-aged members in the household), but also the logarithm of income (which can be either the current observed income $Y_{i,\ t}$ or the permanent household income $P_{i,\ t}$), labor income volatility ($\overline{\sigma}_{i,t}$) and unemployment risk ($\overline{u}_{i,t}$). The coefficients of labor income volatility $\overline{\sigma}_{i,t}$ and unemployment risk $\overline{u}_{i,t}$ are expected to be negative due to precautionary savings motives (Gourinchas and Parker, 2002; Attanasio and Weber, 2010; Madeira, 2019a). The permanent income of household i in period t, $P_{i,\ t}$, is then the sum of non-labor income $a_{i,\ t}$ (such as government subsidies, returns from financial assets or real estate) plus the expected labor income of each of its k adult members, $P_{k,\ i,\ h}$:

[1] There were also EPF surveys in 1967 and 1977, but the microdata for those waves is no longer available.

$$P_{i,t} = a_{i,t} + \sum_k lfp_{k,i,t} P_{k,i,h}, \text{ with } P_{k,i,t} = W_{k,i,t}\left(1 - u_{k,i,t} + u_{k,i,t} RR_{k,i,t}\right) \tag{6}$$

with $lfp_{k,\ i,\ t}$ being a dummy variable for whether member k of household i at time t is in the labor force, $W_{k,\ i,\ t}$ being the labor income of that member while employed, while workers in unemployment receive an income proportional to their wage earnings $RR_{k,\ i,\ t}$, with both wages ($W_{k,\ i,\ t}$) and the income replacement ratio ($RR_{k,\ i,\ t}$) being heterogeneous according to their characteristics $x_{k,\ t}$. The unemployment risk and labor income volatility of each household i is given by a weighted average according to the labor income of each member k in the household: $\overline{u}_{i,t} = \sum_k \frac{P_{k,i,t}}{\sum_h P_{h,t}} u_{k,i,t}$ and $\overline{\sigma}_{i,t} = \sum_k \frac{P_{k,i,t}}{\sum_h P_{h,i,t}} \sigma_{k,i,t}$.

To estimate the permanent income, unemployment risk and labor income volatility of the households of the EPF surveys, I use the Chilean Employment Survey (*Encuesta Nacional de Empleo*, hence on ENE), which covers around 80,000 workers from 35,000 homes each quarter to calibrate the labor market dynamics' parameters of unemployment risk and income volatility ($u_{k,\ t}$, $\sigma_{k,\ t}$) conditional on the workers' characteristics $x_{k,\ t}$, which consist of over 500 mutually exclusive worker types expressed by $x_k = \{$Santiago Metropolitan area or not, Industry (primary, secondary, tertiary sectors), Gender, Age (3 brackets, ≤ 35, $35-54$, ≥ 55), Education (secondary school or less, technical degree, college), and Household Income quintile$\}$. The empirical estimation of $u_{k,\ t}$ is obtained as $Pr\left(U_{k,t} = 1 | x_{k,t}\right) = \frac{\sum_v 1\left(U_{v,t}=1, x_{v,t}=x_{k,t}\right)}{\sum_v 1\left(x_{v,t}=x_{k,t}\right)}$. Besides measuring labor participation, unemployment and formal work status in each quarter, the ENE also measures respondents' labor income $W_{k,\ t}$ in the fourth quarter of every year. Using a pooled set of two-year panel data samples, it is possible to estimate the income volatility as $\sigma_{k,t} = \sqrt{\frac{\sum_v 1\left(x_{v,t}=x_{k,t}\right)\left(ln\left(W_{v,t}/W_{v,t-1}\right)\right)^2}{\sum_v 1\left(x_{v,t}=x_{k,t}\right)}}$ and the replacement ratio of income during unemployment as $RR_{k,t} = \frac{\sum_v W_{v,t} 1\left(x_{v,t}=x_{k,t}, U_{k,t}=1\right) / \sum_v 1\left(x_{v,t}=x_{k,t}, U_{v,t}=1\right)}{\sum_v W_{v,t} 1\left(x_{v,t}=x_{k,t}, U_{k,t}=0\right) / \sum_v 1\left(x_{v,t}=x_{k,t}, U_{v,t}=0\right)}$. Readers can refer to a full treatment in Madeira (2015) for the estimation of the parameters ($u_{k,\ t}$, $RR_{k,\ t}$, $\sigma_{k,\ t}$), the heterogeneity of its distribution and its historical evolution.

Participation in the EPF and ENE is compulsory by law and therefore non-response rates are low. The EPF and ENE surveys are designed with population weights (or expansion factors), due to a higher probability of selecting poorer urban areas. For this reason all the results in this paper - whether tables, graphics or regressions - are estimated with population weights.

2.3. Robustness of the grouped estimator

The demeaned linear estimator for consumption obtained in expression 5) is an example of a grouped estimator. As outlined by Moffitt, 1993, the grouped estimators have the advantage of being a special case of an instrumental variables method, with the grouped variables (such as cohort and other fixed characteristics like gender) being instruments for the variables of individuals that may have measurement error (Verbeek and Nijman, 1993). The regression 5) is an example of a broad class of grouped estimators, which can be summarized as:

$$y_{g,t} = \theta z_{g,t} + \zeta_{g,t} \tag{7}$$

with g denoting the group and t time. The error term plus the endogenous and exogenous variables are obtained from group averages: $h_{g,t} = \frac{1}{n_{g(t)}} \sum_{i=1}^{n_{g(t)}} h_{i,t}$, with h denoting a variable such as y, z and ζ. In the specific case application of this article (expressed in Eq. (5))), $z_{g,\ t}$ includes the time dummies for each year (d_t) and the differenced grouped characteristics ($x_{g,\ t} - x_{g,\ t^*}$) relative to another period t^* (which can be, for instance, the first period in the survey t_0). The groups are given by the cohorts based on 5-year groups across education levels (secondary school or less, technical education, college or more) and regions (Great Santiago Region or not).

It is relevant to note that for the traditional case in which observations are iid across i and $z_{i,\ t}$ is uncorrelated with the error term $\zeta_{i,\ t}$ (i.e., $E[z_{i,\ t}\zeta_{i,\ t}] = 0$), then both the regression with individual observations ($y_{i,\ t} = \theta z_{i,\ t} + \zeta_{i,\ t}$) and the grouped regression given by expression 7) are asymptotically consistent for θ and with the traditional variance-covariance matrix (which would be $V(\theta^i) = \sigma_\zeta^2 (Z^{i'} Z^i)$ for the estimator with the individual outcomes i and $V(\theta^g) = \frac{\sigma_\zeta^2}{n_g}(Z^{g'} Z^g)$ for the grouped estimator). In that simple case, then the grouped estimator is less efficient because the estimator with individual outcomes has n observations and the estimator with grouped variables has $\frac{n}{n_g}$ observations, with n_g being the size of each group. If the observations have heterogeneity, then one can apply the Robust Huber-White Variance-Covariance matrix.

However, there are cases in which the grouped estimator (with the vector Z^g) can be more efficient than the estimator with the individual variables, such as the case of measurement error (Verbeek and Nijman, 1993; Hausman, 2001). Suppose that the individual outcomes are:

$$y_{i,t} = \theta\left(z_{i,t} - \eta_{i,t}\right) + \zeta_{i,t} \tag{8}$$

with the observed variable $z_{i,t}$ being a measurement with error ($z_{i,t} = \widetilde{z}_{i,t} + \eta_{i,t}$) of the true outcome ($\widetilde{z}_{i,t}$). In this case the estimator with the individual outcomes is biased, with the estimated coefficients in absolute value ($|\widehat{\theta}^{i}|$) converging to a lower value than the true parameters ($|\theta|$), which is a classic case of mismeasured regressors (Hausman, 2001). However, in this case the grouped estimator ($\widehat{\theta}^{g}$) is still consistent and converges to the true parameters (θ) as the group size increases ($n_g \to \infty$):

$$y_{g,t} = \theta\left(z_{g,t} - \eta_{g,t}\right) + \zeta_{g,t} \tag{9}$$

with the measurement error becoming negligible as group size increases, that is, $\eta_{g,t} = \frac{1}{n_{g(t)}}\sum_{i=1}^{n_{g(t)}} \eta_{i,t} \to 0$ as $n_{g(t)} \to \infty$. Therefore, as group size increases, the measurement error can be ignored and the model can be consistently estimated from the grouped average variables. How large should one require the groups to be? Simulations by Verbeek and Nijman, 1993 suggest that for most parametrizations, the measurement error in grouped regressions can be ignored with just 100 observations per group or even less under some conditions. Table A.2 of the appendix summarizes the distribution of the number of observations for each group across the entire sample and for the most recent wave of 2017, showing that the median group has more than 150 observations. Even the smallest groups are not extremely small, since the smallest groups have 12 observations if one considers all the survey waves and 56 observations for the most recent wave in 2017. This suggests that the analysis in this article is an appropriate setting to obtain consistent results from a grouped regression (Verbeek and Nijman, 1993).

It is worth noting, however, that the pooled cross-section dataset for Chile in this article has a five year periodicity (or even 10 years for the oldest waves) between waves. For this reason, I account for fixed-effects in the preferences of the households or other kinds of fixed unobservables by using first-differences relative to the previous survey wave (which is valid as argued by the result obtained from the risk-sharing model in Section 2.1), but the data does not allow for estimating a dynamic model of how income or consumption shocks develop from year to year such as an AR(1) or MA(1) structure (Moffitt, 1993). In the case of the analysis in this article, there are no tests for habit formation (Attanasio and Weber, 2010) and other model parametrizations which require observing the individual consumption during the previous year.

Note that the use of micro-data and grouped cohorts provides a clear identification of the impact of income on consumption (Attanasio, 1999). Identification is difficult in the national accounts' aggregate data, because for a representative agent its income and consumption can be mingled (for example, the economy produces agricultural food and then consumes those same products). However, this does not happen in the micro-data, because a given household receives income and then buys consumption goods from the rest of the economy. This reasoning is also valid in a grouped regression (say, the cohort of college educated households with age 25–29 buys its consumption goods mostly from the other cohorts, not from persons of their own age and education).

2.4. *Decomposing the sources of inequality*

I also decompose the change in income and consumption inequality into changes in between- and within-group inequality. Between-group inequality is attributable to fixed observable characteristics of the household head (sex, age, education, professional category, plus interaction terms between age and education). Although between-group inequality changes over time (as in the case of the increase in the college premium), it is unlikely that households can insure against these changes (Krueger and Perri, 2006). Therefore changes in between-group income inequality should translate into similar increases in between-group consumption inequality. Within-group income inequality is a residual measure that can be (at least partly) attributable to an increase in the volatility of idiosyncratic income shocks. The better households can insure against these shocks the less we expect within-group consumption inequality to increase in response to income shocks.

Following the decomposition methodology of Katz and Autor, 1999 and Krueger and Perri, 2006, I regress the income and consumption of each wave on the reference person's characteristics: sex, race, years of education, age, interaction terms between age (a proxy for labor market experience) and education, dummies for managerial and professional occupations, plus dummies for the Great Santiago region. These characteristics explain about 50% and 45% of the cross-sectional variation of the permanent income and consumption in 1987. The cross-sectional variance explained by these characteristics is the "between-group" inequality and the residual variance is the "within-group" inequality. By construction the two variances sum to the total variance.

The definitions of total ($Tvar_t$), between ($Bvar_t$) and within ($Wvar_t$) variances for each variable Y (which can be total consumption, non-durable consumption and permanent income) are:

$$Tvar_t = \frac{1}{n_t}\sum_{i=1}^{n_t}\left(Y_{i,t} - \overline{Y}_t\right)^2 \tag{10}$$

$$Wvar_t = \frac{1}{n_t}\sum_{i=1}^{n_t}\widehat{e}_{i,t}^2 \tag{11}$$

$$Bvar_t = Tvar_t - Wvar_t \tag{12}$$

with $\overline{Y}_t = \frac{1}{n_t}\sum_{i=1}^{n_t} Y_{i,t}$ denoting the average value of each year, n_t the total number of households in each survey wave, and $\widehat{e}_{i,t} = Y_{i,t} - \beta_t x_{i,t}$ being the residuals of a linear (OLS) regression with different parameters β_t in each year t. The vector $x_{i,t}$ with demographic characteristics of the household head includes dummy variables for gender, region (Santiago Metropolitan region or not), 5 year age dummies (26–30, …, until 61–65), education (secondary or less, technical education, college or more), industry of occupation (out of the labor force, primary, secondary, tertiary sectors), occupational category,[2] occupation group,[3] plus dummies for all the interaction terms between the three education levels and the 5 year age dummies. This methodology as exposed in Katz and Autor, 1999 is quite flexible, because it accounts for both changes in the distribution of the observable workers' characteristics ($x_{i,\ t}$) and changes to the returns of observable variables (β_t).

3. Evolution of income and consumption inequality

Fig. 1 shows the Gini coefficient of the income and consumption plus the variance of the log of income and consumption across the Chilean population since 1987. In 2017 the Gini coefficient of income for the Great Santiago region was around 47.5%, while the Gini for total consumption (durable plus non-durable expenditures) and total non-durables (non-durable and semi-durable goods and services) was 42% and 40%, respectively. The Gini coefficient in Chile dropped for income, permanent income, total consumption and non-durables between 2007 and 2012, but the dispersion in total consumption and non-durables increased again in 2017, while income and permanent income remained stable. In the Great Santiago area the Gini coefficient of income, permanent income, total consumption and non-durables remained stable until 2007 and then fell significantly afterwards. The Gini coefficient has a problem of being too sensitive to outliers since it gives a lot of weight to the units with the largest values, therefore some researchers prefer the variance of log-income and consumption as a better inequality measure (Attanasio and Pistaferri, 2016). The Gini coefficient and the variance for the income and consumption differ somewhat in their evolution between 1987 and 2017, possibly due to the presence of outliers. However, both the Gini and the variance measures are consistent in showing that income has a higher dispersion than either total consumption or non-durables, which makes sense due to the consumption smoothing goal of the households (Attanasio and Weber, 2010). Finally, as shown in the Fig. 1, the dispersion measures for the current income or the permanent income (whether Gini or variance) are very similar, therefore in the rest of this article I will focus just on the permanent income measures.

The evolution of the variance of log income and consumption is much smoother and easier to interpret than the Gini coefficient. The variance of log income and consumption in Chile remained stable between 2007 and 2012, before falling in 2017. In the Great Santiago area the dispersion in both income and consumption is falling since 1987, while again experiencing a steep fall in the recent year of 2017. For instance, the variance of log income and permanent income dropped from 90% in 1987 to just 70% in 2017, while the variance of total consumption and non-durable dropped from 90% and 81% in 1987 to 62% and 51% in 2017, respectively. These values represent a significant fall in the inequality of both income and consumption. Fig. 1 also shows (in a similar way as Fig. 2 and Fig. 3) that household inequality, whether in terms of consumption or income, increased slightly between 2007 and 2012 before resuming its downward trend in 2017. This result could be explained by the large earthquake that Chile faced in 2010, which could have affected more the poorer neighborhoods and owners with worse insurance policies (Micco et al., 2012), with García and Pérez, 2017 also finding a shock to income inequality around the time of the earthquake.

Fig. 2 shows other measures of dispersion given by the ratio between households enjoying high consumption or income (those in the percentiles 90 or 75), the middle class (the percentile 50 of consumption and income), and the poor (those in the percentiles 25 and 10). The qualitative conclusions are similar to those obtained from the variance of the log income and consumption in Fig. 1. The dispersion for income is somewhat larger than for total consumption and non-durables, which confirms the consumption smoothing motive (Attanasio and Weber, 2010). Again, there was a steady fall in the dispersion of income, total consumption and non-durables since 1987, which is qualitatively similar across all the percentile ratios. The percentile ratio 90–10 (the most common percentile measure of dispersion) for total consumption, non-durables and permanent income fell from 2.40, 2.35, 2.48 in 1987 to 2.10, 1.85, 2.20 in 2017, respectively. Just like most other countries (Krueger et al., 2010; Attanasio and Pistaferri, 2016), Chile has a much higher income and consumption inequality at the top between the rich and the middle class (percentile ratio 90–50) than at the bottom between the middle class and the poor (percentile ratio 50–10).

The decomposition of the total log variance in between groups (a measure of permanent differences) and within groups (a proxy for temporary shocks) shows that both the between and within variance components fell significantly in the Great Santiago area between 1987 and 2017 (Fig. 3). However, the drop in inequality was larger for the within groups variance, which can be an indicator that households in recent years are better able to smooth such transitory shocks in terms of their consumption (perhaps due to the expansion in financial access, as documented by Berstein and Marcel, 2019). An explanation for the decline in within group inequality is the reduction in both the unemployment rate (therefore, a lower fraction of people with an extremely negative shock) and labor income volatility since the 1990s (Madeira, 2015; García and Pérez, 2017). Stronger social security nets for health costs also decreased inequality in both consumption (Sapelli, 2004; Sanhueza et al., 2010). The total variance of the log of permanent income and consumption fell from around 110% in 1987 to just 62% in 2017, although the dispersion of income was substantially higher than the dispersion for consumption between 1997 and 2012. It is noticeable, however, that the inequality between groups is much lower for

[2] Occupational category classifies workers in 9 mutually exclusive categories, according to their main occupation (although some workers can have multiple occupations): 0 - Doesn't answer or doesn't apply (outside of the labor force), 1 - Employer or boss, 2 - Self employed, 3 - employee in the private sector, 4 - employee in the public sector, 5 - domestic worker living within the household, 6 - domestic worker living outside of the household, 7 - non remunerated worker (ex: voluntary worker, relative or family member).

[3] Occupation group includes 11 mutually exclusive categories, according to the main occupation: 0 - Doesn't answer or doesn't apply (outside of the labor force), 1 - Directors, Managers or Administrators, 2 - Scientific and Intellectual Professionals, 3 - Technicians and Intermediate Level Professionals, 4 - Administrative Support Staff, 5 - Service workers, retail and salesmen, 6 - Agriculturers or farmers, 7 - Craftsman and trade specialists, 8 - Infrastructure and machine operators, 9 - Basic occupations, 10 - Non identified groups.

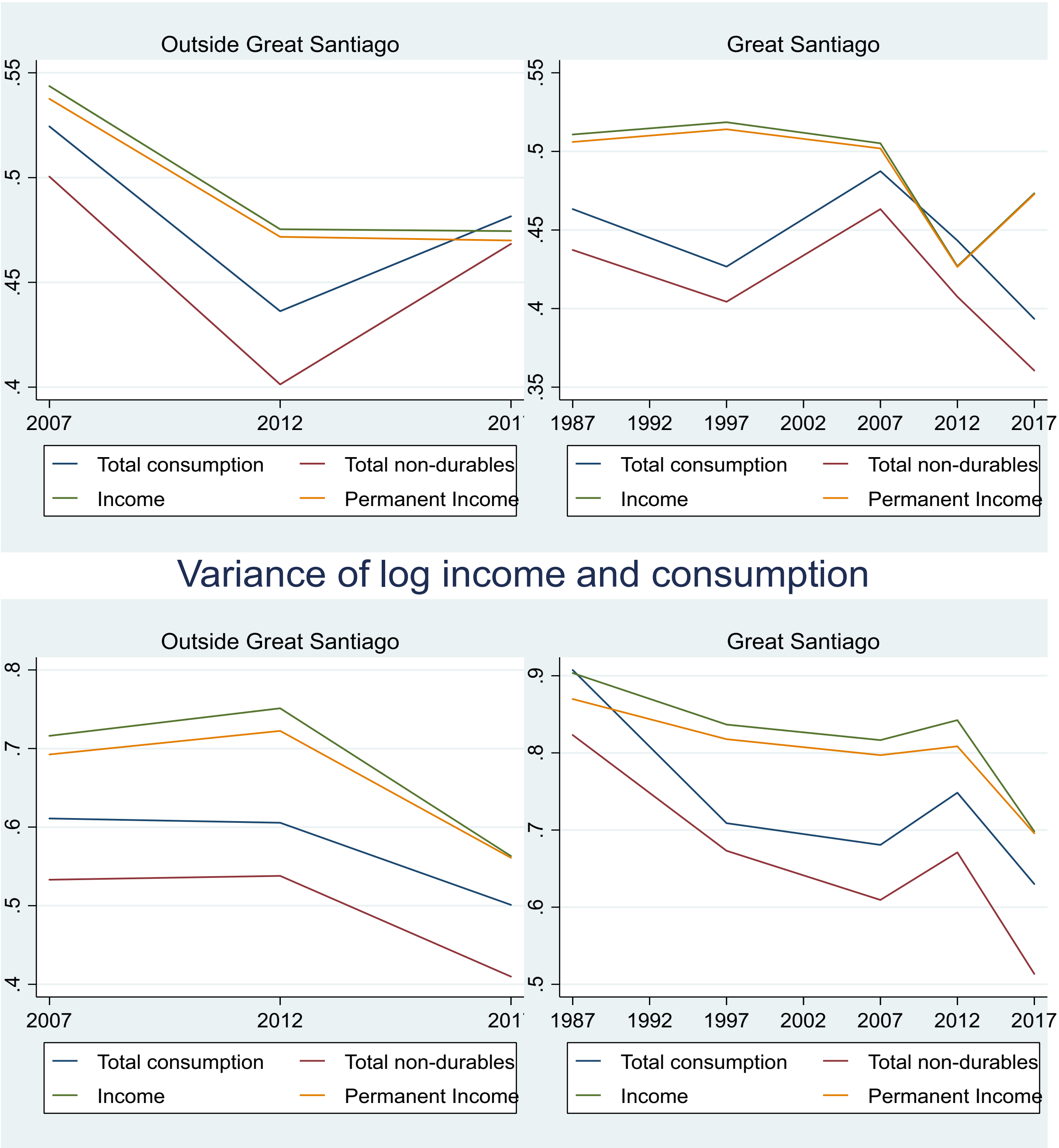

Fig. 1. Inequality of equivalized income and consumption in Chile (1987–2017).

consumption than for the permanent income, being about 10% lower throughout most of the last 35 years. Between inequality for income and consumption fell from 54% and 44% in 1987 to 37% and 31% in 2017, respectively, although consumption showed a brief increase in inequality in 2012. The within inequality had an even stronger decrease over this period. Within groups variance inequality for income and consumption fell from 55% and 64% in 1987 to 30% and 32% in 2017, respectively, with a steady decline throughout the whole period. It is curious to observe that in Chile the within inequality of consumption was higher than that for income in 1987, which is perhaps a reflection that households had to accumulate more precautionary savings in that period to face against idiosyncratic shocks (Attanasio and Weber, 2010). The reduction of within inequality over the last 35 years was much stronger. Within inequality for both income and consumption was higher than between inequality in 1987, but it was lower after 2012. The within inequality fell in 25% for both income and consumption, while the reduction in between inequality for income and consumption was just 17% and 13%, respectively.

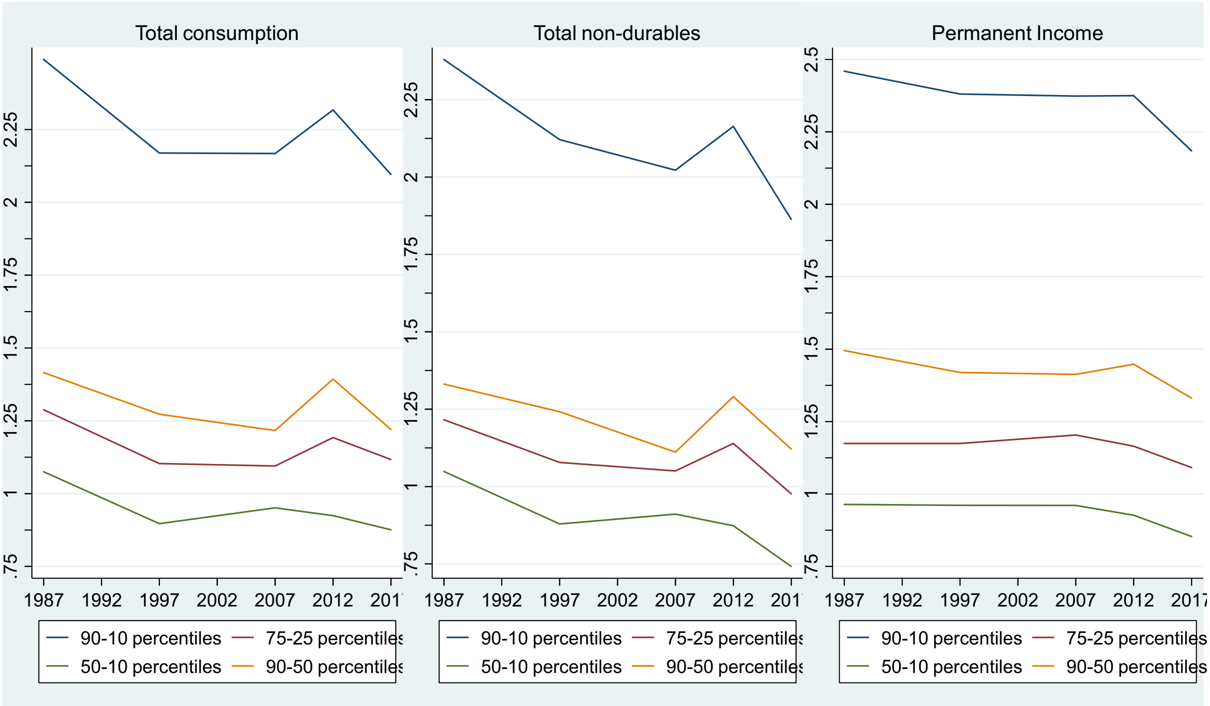

Fig. 2. Ratios of the percentiles for the logarithm of the equivalized total consumption, non-durable expenditures and permanent income in the Great Santiago.

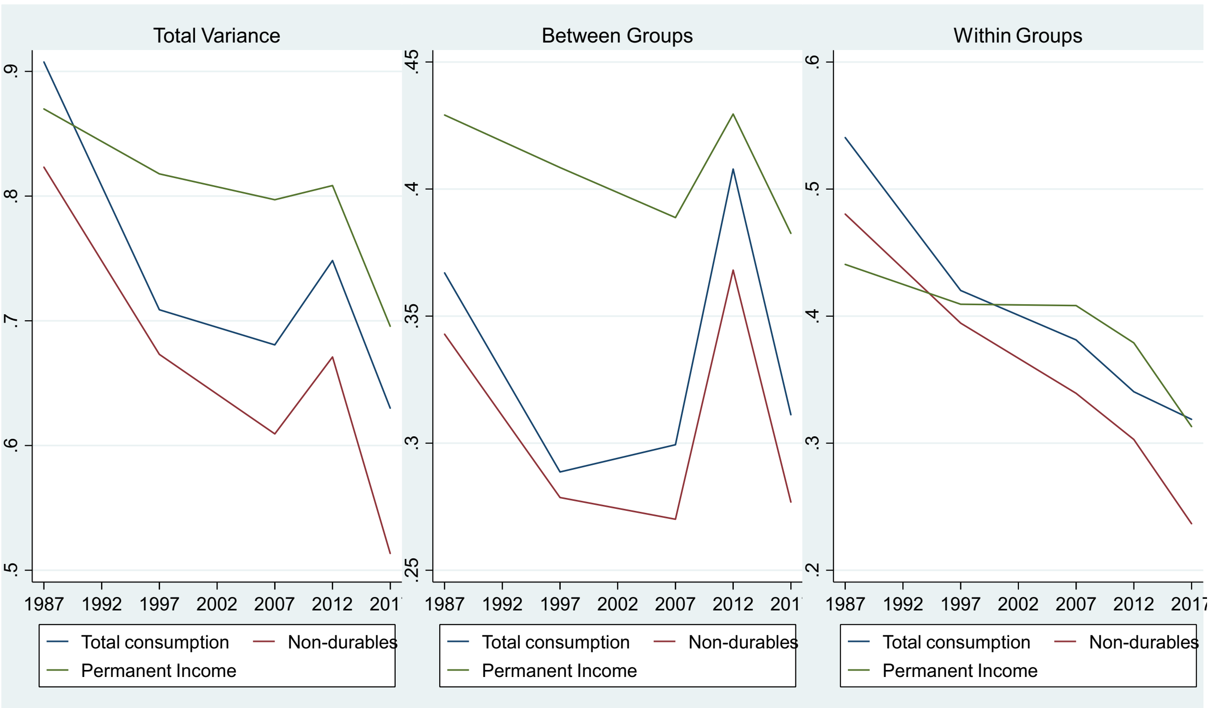

Fig. 3. Variance between and within groups in the Great Santiago (1987–2017).

Overall, the robust economic growth, greater access to finance in the last 35 years and the risk reduction implied by the increased government subsidies and social security (Berstein and Marcel, 2019) may have had an effect on reducing both the between and the within inequality in Chile.

4. Share of consumption according to purpose and durability

Fig. 4 shows the evolution of 7 aggregate time series between 1990 to 2020. In one panel it is shown the evolution of the aggregate consumption plus the banking loans for mortgages, and consumer debt (source: Central Bank of Chile). Aggregate consumption has floated around 60% of the GDP during the entire period, although with a significant drop during 1998 to 2005 after Chile was negatively hit by the Asian crisis. Mortgages, however have grown steadily from 6.4% of the GDP in 1990 to 28.8% in 2020. Consumer loans also grew substantially from 1.8% of the GDP in 1990 to 10.4% in 2019, although it experience a significant fall after the Asian crisis and more recently during the Covid pandemic in 2020. The other panel shows the size of the payments in insurance premia for Property and Life/Health accidents (World Bank - Global Financial Development database), the financial sector's GDP, plus the out-of-the-pocket household medical expenses (OECD - Global Health Expenditure Database) and the government plus compulsory private insurances' medical expenditures (OECD - Global Health Expenditure Database). The financial sector's GDP in Chile has fluctuated around a stable value of 4.5% of the total GDP, although with a significant fall after the Asian crisis in 1998 and after the dot-com crisis in 2002. In terms of medical expenditures, the government plus compulsory insurance payments have grown from 3.8% in 2000 to 5.4% in 2019. Therefore in the recent decades the Chilean government increased both the income transfers (Sanhueza et al., 2010) and the direct payments to households such as medical expenditures, which is a significant improvement in the social safety net in Chile (Sapelli, 2004, Sanhueza et al., 2010).

I then classify the product lists in terms of three purposes: medical expenses, financial, insurance. Table 1 shows the share of expenditures dedicated to these 3 different uses as a fraction of the total household consumption in the Great Santiago area, according to the households' education level. The fraction of household heads in Chile with secondary education or less fell from 69.7% to 59% between 2007 and 2017, while the share of household heads with a college education increased from 21.5% to 28.5%, according to Table A.1 in the appendix.

Table 1 shows that households dedicate a stronger fraction of their consumption to medical expenses since 1987, with this share increasing from 2.4% to 4.2% for the average household. Furthermore, since 1987 more than 60% of the households put some out of the pocket expenditures for medical consumption. Although the share of households with some out of the pocket medical expenditures fell between 1987 and 1997 due to the expansion of the state-sponsored medical program FONASA (Sapelli, 2004), the share of households with medical expenditures grew again in 2007, 2012 and 2017, reaching 84.8% of the households in the Great Santiago Metropolitan region. Table A.3 in the appendix shows that similar values are valid for Chile as a whole, with 83.6% of the population making out of the pocket medical expenditures.

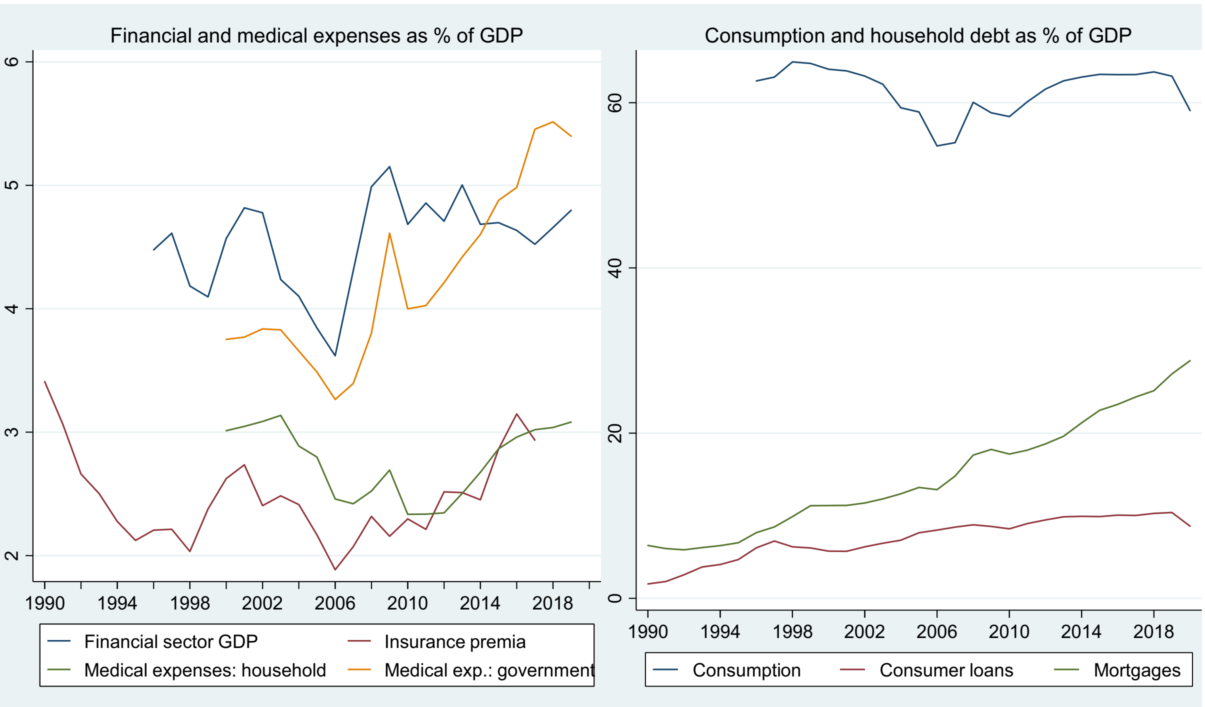

Fig. 4. Aggregate time series for the weight of the household debt, aggregate consumption, financial sector and medical expenses in GDP (in %).

Table 1
Consumption dedicated to medical, financial and insurance as a fraction of the total household consumption (in %) in the Great Santiago region - mean statistics for all the households and according to the education level (secondary school or less, technical education, college or more) of the household head. Sample includes only household heads aged 25–64.

Year	Education	Consumption as a fraction of total consumption (in %)			Fraction of households with positive consumption (in %)		
		Medical	Financial	Insurance	Medical	Financial	Insurance
1987	All households	2.4	2.5	0.3	74.9	59.5	11.9
1997	All households	3.9	1.4	0.4	63.1	51.3	24.1
2007	All households	3.8	1.4	0.6	66.3	61.5	35.6
2012	All households	3.7	2.0	0.6	71.2	73.6	38.1
2017	All households	4.2	1.5	0.7	84.8	91.1	44.5
1987	Secondary or less	1.9	2.0	0.1	67.8	55.1	4.1
1997	Secondary or less	3.1	0.9	0.2	55.7	41.7	18.5
2007	Secondary or less	3.2	1.4	0.5	60.6	59.2	28.8
2012	Secondary or less	3.1	1.5	0.4	64.2	68.2	29.3
2017	Secondary or less	3.7	1.2	0.3	78.7	89.3	28.2
1987	Technical educ.	2.8	3.1	0.3	83.7	65.0	16.1
1997	Technical educ.	4.0	1.5	0.3	65.2	56.1	24.5
2007	Technical educ.	3.9	1.6	0.7	76.9	68.0	44.0
2012	Technical educ.	5.1	2.5	0.9	84.9	82.5	52.9
2017	Technical educ.	4.9	1.6	0.7	92.6	92.2	48.5
1987	College or more	3.7	3.5	0.9	89.2	68.3	36.7
1997	College or more	5.6	2.3	0.8	76.5	66.2	35.5
2007	College or more	5.3	1.2	1.0	77.8	65.6	51.1
2012	College or more	5.0	3.2	1.1	88.6	87.9	61.1
2017	College or more	4.9	2.2	1.3	92.4	93.8	71.4

The share of financial expenditures in total consumption actually dropped substantially from 2.5% in 1987 to 1.4% in 1997 and then persisting at a similar level afterwards, with a value of 1.5% in 2017. Therefore financial products became less important relative to other goods, which makes sense, since financial products are mostly an expense made by households in order to transfer income to other time periods. If households can now devote less expenses to such products due to their relative decreasing costs over time, then this implies a welfare gain. In fact, the share of households with some financial expenses grew throughout this period from 59.5% of the households in 1987 to 91.1% in 2017, therefore there is more widespread access to financial services now. The fraction of consumption dedicated to insurance products increased from 0.3% in 1987 to 0.7% in 2017, while the fraction of households with insurance products grew from 11.9% in 1987 to 44.5% in 2017. In summary, this shows that in 2017 there is more widespread access to both

Table 2
Fraction of the households (in %) purchasing different financial and insurance products in the Great Santiago region. Sample includes only household heads aged 25–64.

Year	Education	Financial products			Insurance products			
		Mortgages & Bank Loans	Credit cards, Retail & other lenders	Bank accounts & other products	Life & Health	Home	Vehicle & Travel	Other (ex: loan insurance)
1987	All levels	46.1	28.9	0.3	4.5	1.8	4.0	0.3
1997	All levels	26.5	35.4	1.1				
2007	All levels	24.0	54.6	0.0				
2012	All levels	24.5	67.2	29.6	5.8	2.8	9.7	31.1
2017	All levels	22.6	80.8	51.7	24.4	6.0	22.1	19.9
1987	Secondary or less	39.2	30.2	0.0	1.2	0.3	0.9	0.1
1997	Secondary or less	21.4	26.3	0.1				
2007	Secondary or less	16.2	55.1	0.0				
2012	Secondary or less	16.3	62.9	24.8	2.5	0.8	2.9	26.2
2017	Secondary or less	12.5	77.1	58.7	13.4	2.0	8.5	13.0
1987	Technical educ.	52.5	32.6	0.2	6.5	3.1	4.3	0.5
1997	Technical educ.	30.1	37.7	1.2				
2007	Technical educ.	29.2	62.4	0.0				
2012	Technical educ.	37.4	72.1	38.0	11.8	4.0	15.2	42.1
2017	Technical educ.	25.9	82.4	57.1	28.7	5.8	20.3	18.7
1987	College or more	63.5	17.1	1.8	14.9	5.6	16.1	0.9
1997	College or more	33.2	52.0	3.0				
2007	College or more	43.2	50.1	0.0				
2012	College or more	46.8	79.4	42.1	14.2	9.2	30.7	42.8
2017	College or more	39.0	86.5	37.3	42.2	13.2	46.7	32.5

insurance products (44.5% of the population) and other financial products (91.1% of the population) in the Great Santiago Metropolitan region. Table A.3 in the appendix shows similar results for Chile.

Finally, the consumption of medical goods and services, financial products, and insurance is increasing with the education of the household head, even taking into account that values are standardized as a fraction of the total household consumption. The share of medical, financial and insurance products in total consumption in 2017 was 4.9%, 2.2%, 1.3% for the college educated, 4.9%, 1.6%, 0.7% for those with technical education, and 3.7%, 1.2%, 0.3% for those with secondary degrees or less. The out-of-the-pocket medical expenses grew for all the education groups between 1987 and 2017, in the same way as the insurance expenses increased over this period. Since Life and Health insurance are related to medical expenses, then the ageing of the Chilean society could be a factor pushing up both the consumption of medical and insurance goods (Sapelli, 2004). However, it is also noticeable that the consumption of financial goods (as a share of the total consumption) fell 0.8% to 1.5% across all education levels, with a sharper fall for the technical education household heads (from 3.1% in 1987 to 1.6% in 2017). This fall in the consumption of financial goods could be explained by a reduction in fees for such goods and services over the last few decades. Furthermore, there was a significant increase across all education levels in the fraction of households using financial goods and services between 1987 and 2017, with such users growing from 59.5% to 91.1% among all households. In particular, the fraction of users of financial services increased from 55.1% to 89.3% for the household heads with secondary education or less, showing a greater access to financial services. The share of households with out-of-the-pocket medical expenses was high already in 1987, but it dropped significantly in 1997 across all education levels (perhaps due to the expansion of the FONASA) and has since grown again with the higher demand of medical services among the population. Finally, the fraction of households consuming insurance products grew from 11.9% in 1987 to 44.5% in 2017, a steady increase in the use of insurance with each wave. However, the fraction of insurance users fell slightly between 2012 and 2017 for the household heads with less than a college education.

Table 2 goes a step further by showing the fraction of households that use different kinds of financial products (Mortgages & Bank Loans; Credit cards, Retail & other lenders; Bank accounts & other products) and Insurance (Life, health and personal accidents; Home and property; Automobiles, vehicles and travel; Other, ex: loan insurance). In 1987 the most common type of financial products were "Mortgages and Bank Loans", which were used by 46.1% of the households, while "Credit cards, retail loans, and other non-bank lenders" were used by 28.9% of the families. By 2017 the use of "Credit cards, retail loans, and other non-bank lenders" had grown to 80.8% of the population, while "Bank accounts and other financial products" grew from almost 0% (between 1987 to 2007) to 51.7% of the population. However, the share of households paying mortgages or other bank loans in the Santiago capital area had fallen from 46.1% in 1987 to 26.5% in 1997 and 22.6% in 2017. This pattern was similar across all education levels and it is explained because between the 1960s and 1990s there were several government programs subsidizing mortgages for houses of low appraisal value (Micco et al., 2012). The share of families using "Mortgages and other bank loans" fell substantially (especially among the low educated), while the share of users of "Credit cards, retail loans, and other non-bank lenders" and "Bank accounts and other financial products" grew significantly. Table A.4 in the appendix shows similar values for Chile.

In terms of insurance, there are no categories in 1997 and 2007 because the EPF survey questionnaire was reduced substantially in

Table 3
Consumption (in %) dedicated to Services (non-durable), Non-Durable Goods, Semi-Durable and Durable Goods in the Great Santiago region - mean statistics for all the households and according to the education level (secondary school or less, technical education, college or more) of the household head. Sample includes only household heads aged 25–64.

Year	Education	Consumption as a fraction of total consumption (in %)				Households with positive Durables consumption (in %)
		Services	Non-Durable	Semi-Durable	Durable	
1987	All levels	25.3	40.0	28.8	5.9	53.7
1997	All levels	34.2	53.0	9.3	3.5	49.4
2007	All levels	42.7	41.1	6.8	9.3	75.6
2012	All levels	52.6	29.4	8.0	10.0	73.8
2017	All levels	51.1	25.1	11.2	12.5	75.3
1987	Secondary or less	22.5	45.7	27.1	4.7	39.9
1997	Secondary or less	30.0	58.2	9.0	2.9	39.8
2007	Secondary or less	39.9	45.4	6.5	8.3	71.9
2012	Secondary or less	51.1	33.0	7.5	8.5	67.5
2017	Secondary or less	48.8	29.3	11.2	10.7	65.7
1987	Technical educ.	27.7	34.8	30.3	7.1	65.8
1997	Technical educ.	33.9	52.4	10.0	3.7	52.3
2007	Technical educ.	44.5	37.4	7.3	10.7	78.9
2012	Technical educ.	53.2	25.1	9.8	11.9	85.6
2017	Technical educ.	52.6	22.8	11.1	13.6	81.7
1987	College or more	32.9	25.0	33.1	9.0	90.0
1997	College or more	43.6	42.7	9.2	4.5	66.7
2007	College or more	50.0	30.9	7.5	11.7	84.8
2012	College or more	57.6	19.3	8.8	14.3	89.7
2017	College or more	54.7	18.7	11.3	15.3	89.5

those waves and there is not enough detail to know which insurance products were being used. The two most popular insurance products are Life and Vehicles. The results show that all the types of insurance products grew substantially between 1987 to 2012 and 2017. Life and Health insurance grew from 4.5% of the households in 1987 to 5.8% in 2012 and 24.4% in 2017. Vehicle and Travel insurance grew from 4.0% of the families in 1987 to 9.7% in 2012 and 22.1% in 2017. Home and other insurance products grew respectively from 1.8% and 0.3% in 1987 to 6.0% and 19.9% in 2017, although the category of other loan insurance fell a bit since 2012. This drop in the use of other insurance since 2012 is consistent with the fall in the use of consumer loans in recent years, perhaps as a result of the lower interest rate ceiling introduced in 2013 and which substantially reduced the use of high cost small loans

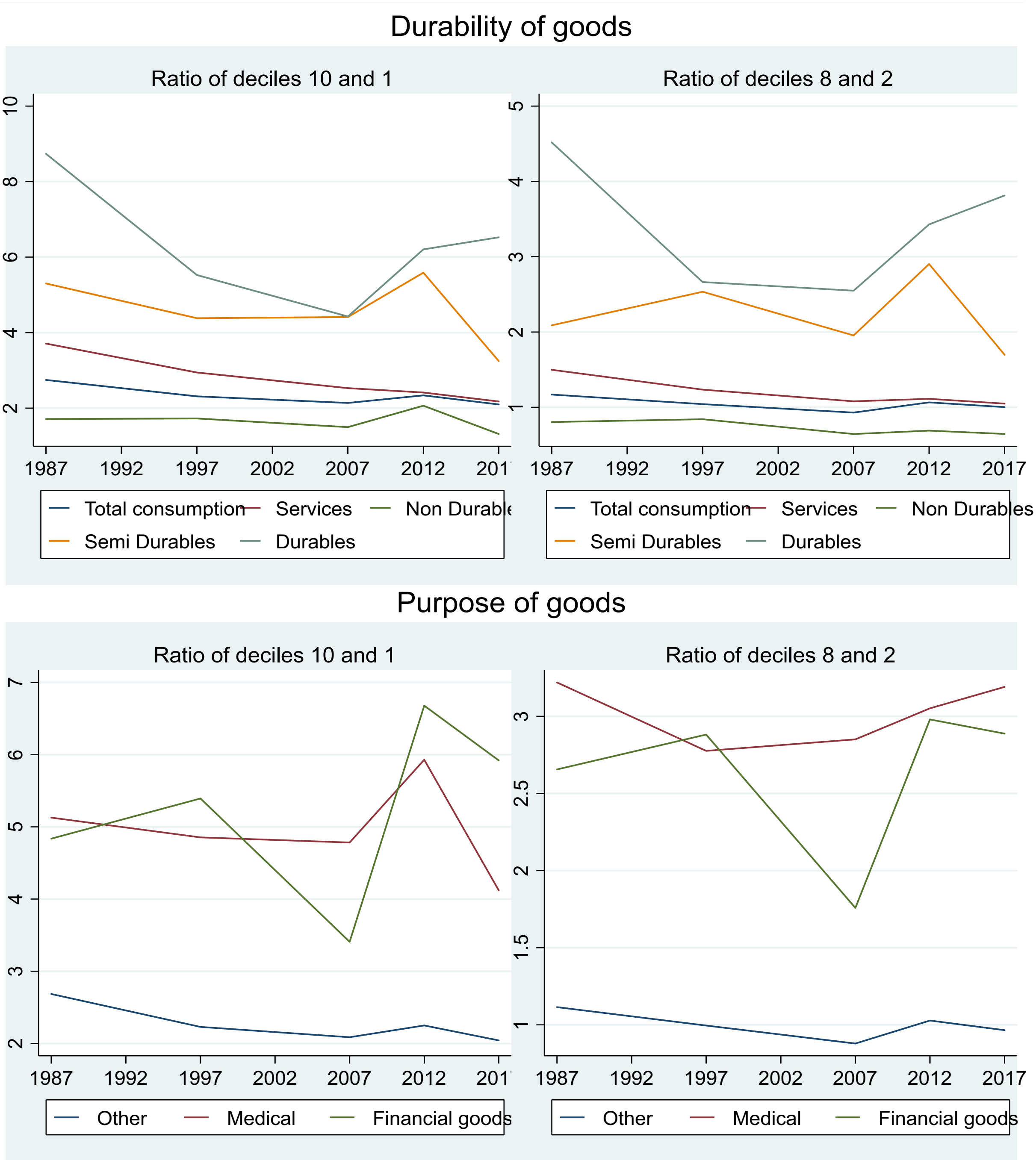

Fig. 5. Ratios across different income deciles of the average consumption of goods across different categories in the Great Santiago.

(Madeira, 2019b).

Are households able to purchase more durable goods in recent years due to their access to finance? To answer this question I classify the product lists of the EPF surveys in terms of their durability: Services (non-durable), Non-Durable goods, Semi-Durable goods (goods that can last more than one year but less than 3 years), Durable (goods that can last more than 3 years). Durable goods are more affected by financial conditions, because these products are more expensive, infrequently purchased and their use must be smoothed over longer periods. Table 3 confirms that the share of durable goods increased from 5.9% of the consumption in 1987 to 12.5% in 2017, while the number of households with positive consumption of durable goods increased from 53.7% in 1987 to roughly 75% during the period of 2007 to 2017. The share of non-durables and semi-durables in consumption decreased between 1987 and 2017, although the share of services increased substantially. This pattern is similar across all education levels, with the share of durables in consumption roughly doubling between 1987 and 2017. The share of college educated families consuming durables remained roughly constant around 90% during this period, while the share of families with positive durables consumption increased significantly from 39.9% and 65.8% in 1987 to 65.7% and 81.7% in 2017 for the secondary or less and the technical education households, respectively. This is an indicator that financial access and credit constraints fell significantly in Chile during this period, especially among the low educated and more disadvantaged families. Furthermore, Table A.5 in the appendix shows that similar values are valid for Chile nationwide.

Now Fig. 5 shows the ratio of the consumption of different goods across families in different deciles. Whatever the measure is - whether the ratio between deciles 10 and 1 (a measure of inequality between the richest and the poor) or the ratio between deciles 8 and 2 (a measure of inequality closer to the center of the distribution) - the results show that inequality is the highest for Durables and then Semi-Durables, with Services and Non-Durables having a much lower degree of inequality. Services tends to have a stronger inequality than non-durables because services tend to be normal goods with an increasing level of consumption relative to income (Attanasio and Pistaferri, 2016). It is easy to observe that between 1987 and 2007 there was a strong decline in the consumption of Durables, although there was also a moderate decline in the consumption of Semi-Durables and Services. However, the inequality in Services has kept falling after 2007, while the inequality in Durables increased again somewhat since then.

Fig. 5 shows a small reduction in the inequality of financial goods and out-of-the-pocket medical services until 2007 and an increase afterwards, while the inequality in the consumption of the other goods (that is, non-financial and non-medical consumption) has

Table 4

Regressions of the risk-sharing model for the equivalized consumption using levels and first differences (OLS): cohorts based on 5-year groups across education levels and regions (Great Santiago and outside). Time period is from 1987 to 2017 for the levels and from 1997 to 2017 for the first-differences. Sample includes only household heads aged 25–64.

	Total consumption		Total non-durables		Non-Durable goods	
Controls	Levels	Differences	Levels	Differences	Levels	Differences
$\ln(P_{i,t})$	0.890***	0.630***	0.863***	0.632***	0.670***	0.545***
	(0.0194)	(0.0865)	(0.0181)	(0.0756)	(0.0229)	(0.0736)
$u_{i,t}$	0.847	1.317	0.445	1.270	0.834	1.232
	(0.804)	(1.097)	(0.719)	(0.974)	(0.799)	(1.055)
$\sigma_{i,t}$	−0.248	−0.541	−0.279	−0.474	0.293	0.0599
	(0.302)	(0.363)	(0.266)	(0.332)	(0.270)	(0.333)
Observations	192	120	192	120	192	120
R-squared	0.981	0.636	0.982	0.662	0.944	0.885
	Services		Semi-Durables		Durables	
Controls	Levels	Differences	Levels	Differences	Levels	Differences
$\ln(P_{i,t})$	1.046***	0.754***	1.592***	1.149***	2.535***	1.447***
	(0.0260)	(0.109)	(0.0942)	(0.395)	(0.165)	(0.530)
$u_{i,t}$	1.048	2.104*	−0.101	0.00511	5.619	1.052
	(0.872)	(1.063)	(2.779)	(4.921)	(5.067)	(5.782)
$\sigma_{i,t}$	−0.661*	−0.483	−3.219**	−4.868***	1.635	−0.400
	(0.379)	(0.436)	(1.388)	(1.645)	(2.326)	(2.443)
Observations	192	120	192	120	192	120
R-squared	0.984	0.754	0.898	0.803	0.900	0.768
	Financial services		Insurance		Medical expenses	
Controls	Levels	Differences	Levels	Differences	Levels	Differences
$\ln(P_{i,t})$	1.367***	2.138***	2.181***	2.877***	2.132***	2.646***
	(0.111)	(0.482)	(0.145)	(0.481)	(0.124)	(0.498)
$u_{i,t}$	2.897	3.796	−7.330*	0.0833	2.598	3.951
	(3.719)	(5.373)	(4.124)	(5.654)	(4.876)	(4.756)
$\sigma_{i,t}$	−6.047***	−4.607**	2.097	6.024**	−2.415	−0.144
	(1.576)	(2.210)	(1.949)	(2.594)	(1.677)	(1.875)
Observations	192	120	192	120	192	120
R-squared	0.894	0.652	0.852	0.517	0.892	0.561

Other controls (all regressions): Average number of children, adults and senior members per household, five-year age dummies of the household head, time dummies.

Robust Standard-errors in (). ***,**,* denote 1%, 5% and 10% statistical significance.

persistently declined since 1987 until now. Finally, the inequality in the consumption of financial goods and medical services is much higher than for other products, with the ratio on 2017 between the deciles 10 and 1 being around 6 for financial goods, 4 for medical services and just 2 for the other products.

5. Estimates of the risk-sharing model

I first present the results of the model in levels (Eq. (3)) and first differences (Eq. (5)), using all the EPF survey waves. For this reason the cohorts must be based on 5-year groups, since in 1997 and 2007 the age of each household head is available only in 5-year brackets. Table 4 presents the results based on cohorts using 5 year age groups, education levels (secondary or less, technical, college education) and region (Santiago capital, outside of the capital), which assumes there is little migration and change in education levels in adulthood after age 25 (Attanasio and Davis, 1996). Furthermore, since households retire after age 65, the regressions are limited to the sample of household heads between age 25 and 64 (Attanasio and Weber, 2010).

Estimating the log-linear consumption regressions clearly rejects the perfect risk-sharing model, since the coefficient for the log-permanent income for either the total consumption or the total non-durables (services, non-durable goods and semi-durable goods) is statistically positive. While both the models in levels and in first-differences reject the hypothesis of perfect risk-sharing, the models in differences present a coefficient for the log-permanent income around 0.630, which is substantially below the 0.890 of the models in levels. This shows the importance of using the pseudo-panel to correct for unobservable fixed-factors that affect different cohorts and groups of household with different education and region of residence. The unemployment risk and the income volatility of the households do not significantly impact total consumption or total non-durables (the sum of services, non-durables and semi-durables), which could show that the Chilean social security income safety net is adequate to smooth such shocks (Madeira, 2015).

Similar to studies in other countries (Krueger and Perri, 2006; Krueger et al., 2010; Attanasio and Davis, 1996; Attanasio and Szekely, 2004), Chile is an economy with neither perfect risk-sharing or financial autarky. Since the coefficient in first-differences is around 0.6, then there is some limited form of risk-sharing due to access to social security subsidies, transfers among relatives and the use of financial products such as the households' own savings (Attanasio and Weber, 2010).

Table 4 also shows that the coefficient for log-permanent income in terms of consumption is smaller for Non-Durables (0.5 in the

Table 5

Regressions of the risk-sharing model for the equivalized consumption using levels and first differences (OLS) for the waves 1987, 2012 and 2017: cohorts based on 1-year groups across education levels and regions (Great Santiago and outside). Time period is 1987, 2012 and 2017 for the levels and 2012 to 2017 for the first differences (data for 1987 is the first lag). Sample includes only household heads aged 25–64.

	Total consumption		Total non-durables		Non-Durable goods	
Controls	Levels	Differences	Levels	Differences	Levels	Differences
$\ln(P_{i,t})$	0.862***	0.617***	0.822***	0.561***	0.638***	0.521***
	(0.0237)	(0.0659)	(0.0226)	(0.0581)	(0.0181)	(0.0660)
$u_{i,t}$	−0.774	−0.255	−0.701	0.0325	−0.456	0.733
	(0.590)	(0.685)	(0.481)	(0.529)	(0.662)	(0.797)
$\sigma_{i,t}$	−0.410*	−0.305	−0.434**	−0.420	0.206	0.298
	(0.228)	(0.297)	(0.219)	(0.274)	(0.201)	(0.347)
Observations	599	253	599	253	599	253
R-squared	0.945	0.752	0.947	0.770	0.839	0.393
	Services		Semi-Durables		Durables	
Controls	Levels	Differences	Levels	Differences	Levels	Differences
$\ln(P_{i,t})$	0.969***	0.590***	1.574***	1.313***	2.827***	2.217***
	(0.0336)	(0.0717)	(0.0901)	(0.337)	(0.130)	(0.462)
$u_{i,t}$	−0.753	−0.865	0.203	−0.915	−7.744	−10.22
	(0.602)	(0.687)	(2.811)	(3.715)	(5.651)	(6.803)
$\sigma_{i,t}$	−0.690**	−0.609*	−2.927**	−6.637***	3.070**	7.345***
	(0.317)	(0.355)	(1.372)	(1.804)	(1.495)	(2.361)
Observations	599	253	599	253	599	253
R-squared	0.956	0.896	0.694	0.644	0.678	0.311
	Financial services		Insurance		Medical expenses	
Controls	Levels	Differences	Levels	Differences	Levels	Differences
$\ln(P_{i,t})$	1.482***	1.614***	2.441***	2.702***	2.098***	1.532***
	(0.105)	(0.323)	(0.107)	(0.423)	(0.106)	(0.257)
$u_{i,t}$	0.399	−0.455	−10.88***	0.465	−0.178	0.467
	(2.588)	(4.079)	(3.842)	(5.839)	(3.258)	(3.310)
$\sigma_{i,t}$	−1.740	−1.474	2.345*	9.036***	−2.277	−5.633***
	(1.261)	(1.668)	(1.287)	(2.627)	(1.412)	(1.698)
Observations	599	253	599	253	599	253
R-squared	0.699	0.293	0.706	0.373	0.683	0.295

Other controls (all regressions): Average number of children, adults and senior members per household, five-year age dummies of the household head, time dummies.
Robust Standard-errors in (). ***,**,* denote 1%, 5% and 10% statistical significance.

first-differences regression) and Services (0.7 in the first-differences regression) than for Semi-Durables (1.1 in the first-differences regression) and Durables (1.2 in the first-differences regression). This makes sense, because Semi-Durables and Durables are the most expensive items and the ones that are purchased less frequently, therefore these are the kinds of goods more subject to credit constraints and financial frictions that depart from consumption smoothing. Finally, the models (in levels or first-differences) show that the coefficients of log-income for financial goods and services consumption, medical services and insurance products are above 2. This can be an indicator that these products are luxury goods, which are only obtained when households purchase houses, vehicles or private medical services that are expensive.

As a robustness check, I report the results from one year age cohorts plus education level and region in Table 5, which excludes the survey waves of 1997 and 2007. Despite the exclusion of 2 survey waves, there are more observations due to the sample having one year age groups instead of five-year brackets. The results are qualitatively similar to those reported with the five-year age groups (Table 4). Both the models in levels and first-differences clearly reject the perfect risk-sharing model. The models in first-differences again report lower coefficients than the levels, but still the estimated coefficients of permanent income for total consumption and total non-durables (the sum of services, non-durables and semi-durables) are 0.62 and 0.56, both statistically different from zero at the 1% significance level. Again, however, the coefficients for unemployment risk and the labor income volatility are not statistically different from zero for total consumption and non-durables in the first-differences regression, which shows that the social safety nets and households' precautionary savings could be adequate to protect from such risks. Again, I also find that risk-sharing is more efficient for non-durable goods and services (which have income coefficients of 0.52 and 0.59) rather than Semi-Durables and Durables (which have income coefficients around 1.3 and 2.2). Finally, the models (in levels or first-differences) show that the coefficients of log-income for financial goods and services consumption, medical services and insurance products are quite above 1, which again is an indicator that these are luxury goods which are more frequently purchased at higher income levels.

6. Conclusions

Using the Family Expenditures Survey (EPF) waves, I show that consumption inequality fell substantially in Chile since 1987. This evidence is consistent with the strong drop in income inequality, plus the reduction in real interest rates and the improvement in households' access to financial products (Berstein and Marcel, 2019). I also show that both the inequality between and within groups fell substantially in all these decades, especially for the within groups consumption inequality. Estimating a standard consumption model, the results reject both the autarky (no risk-sharing between households) and the full risk sharing hypothesis. For services and non-durable goods, consumption is almost half-way between autarky and full risk-sharing. However, purchases of Semi-Durables and Durables goods are strongly affected by income fluctuations. The consumption of medical services, insurance, and other financial products is strongly increasing with income, which can denote that these are luxury goods. Out of the pocket medical expenses and insurance strongly increased since 1987, perhaps due to ageing demographics (Sapelli, 2004) and the expansion of mortgages among households (with home and fire-earthquake insurance being popular products). It is noticeable that consumption of financial goods and services as a fraction of the total consumption of the households fell significantly over the last 35 years, but the fraction of households using financial products increased from 59.5% in 1987 to 91.1% in 2017. This is an indicator that financial goods and services are now cheaper with families spending less on such products and at the same time much more accessible across the population. At the same time the share of durable goods (which are large items and infrequently purchased, therefore requiring more financing) increased from 5.9% to 12.5% between 1987 and 2017, while the number of families making durables purchases increased from 53.7% to 75.3%. Therefore the financial expansion in Chile during this period could have contributed towards reducing certain inequalities for purchasing goods and services across the population (Berstein and Marcel, 2019; Cihak and Sahay, 2020).

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CRediT authorship contribution statement

Carlos Madeira: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The author has declared that no competing interests exist.

Data availability

Users can download (at no cost) the raw data of all the EPF and ENE surveys from the website of the Chilean Institute of National Statistics.

ENE: https://www.ine.cl/estadisticas/sociales/mercado-laboral/ocupacion-y-desocupacion.

EPF: https://www.ine.cl/estadisticas/sociales/ingresos-y-gastos/encuesta-de-presupuestos-familiares.

All the codes required to replicate the analysis in this article are publicly available through the Mendeley Data repository (see the link https://data.mendeley.com/datasets/mjcdpy5z2d/1): Madeira (2022), " Codes for replicating " The evolution of consumption inequality and risk-insurance in Chile"", *Mendeley Data*, V1, doi: https://doi.org/10.17632/mjcdpy5z2d.1

Appendix A. Appendix

Table A.1
Fraction of the population with different education levels in Chile (2007–2017). Sample includes only household heads aged 25–64.

Year	Education	% of population
2007	Secondary or less	69.7
2012	Secondary or less	67.8
2017	Secondary or less	59.0
2007	Technical educ.	8.9
2012	Technical educ.	10.7
2017	Technical educ.	12.5
2007	College or more	21.5
2012	College or more	21.5
2017	College or more	28.5

Table A.2
Number of observations for each cohort, with cohorts given by 5 year birth cohorts, education (secondary or less, technical education, college or more) and region (Santiago Metropolitan Region or outside of the capital). Sample includes only household heads aged 25–64.

Percentile	All years	2017
min	12	56
1	18	56
5	34	74
10	48	79
25	89	104
50	158	178
75	289	299
90	407	509
95	494	563
99	634	647
max	647	647

Table A.3
Consumption dedicated to medical, financial and insurance as a fraction of the total household consumption (in %) in Chile - mean statistics for all the households and according to the education level (secondary school or less, technical education, college or more) of the household head. Sample includes only household heads aged 25–64.

Year	Education	Consumption as a fraction of total consumption (in %)			Fraction of households with positive consumption (in %)		
		Medical	Financial	Insurance	Medical	Financial	Insurance
2007	All households	3.6	1.6	0.6	64.8	64.9	36.3
2012	All households	3.8	2.1	0.6	72.6	75.9	42.7
2017	All households	4.2	1.6	0.6	83.6	89.9	47.0
2007	Secondary or less	3.0	1.6	0.5	59.4	62.8	30.5
2012	Secondary or less	3.2	1.6	0.5	65.5	70.8	34.6
2017	Secondary or less	3.6	1.3	0.3	77.7	87.7	34.4
2007	Technical educ.	4.0	1.7	0.8	73.6	70.2	43.3
2012	Technical educ.	5.0	2.5	0.8	86.2	84.5	54.5
2017	Technical educ.	4.8	1.6	0.7	90.6	91.1	51.8
2007	College or more	5.3	1.3	1.0	78.8	69.2	52.2
2012	College or more	5.1	3.3	1.1	88.2	87.8	62.6
2017	College or more	5.0	2.1	1.1	92.8	93.9	71.1

Table A.4
Fraction of the households (in %) purchasing different financial and insurance products in Chile. Sample includes only household heads aged 25–64.

Year	Education	Financial products			Insurance products			
		Mortgages & Bank Loans	Credit cards, Retail & other lenders	Bank accounts & other products	Life & Health	Home	Vehicle & Travel	Other (ex: loan insurance)
2007	All levels	22.8	59.2	0.0				
2012	All levels	26.2	68.8	33.1	6.1	4.1	9.3	36.2
2017	All levels	22.6	78.5	53.2	27.9	6.6	16.9	21.9
2007	Secondary or less	15.4	59.6	0.0				
2012	Secondary or less	17.9	64.8	28.1	3.1	2.2	3.3	31.1
2017	Secondary or less	13.8	75.4	57.0	18.7	3.9	6.6	16.4
2007	Technical educ.	29.0	65.4	0.0				
2012	Technical educ.	37.1	73.7	41.2	10.3	6.3	12.6	44.5
2017	Technical educ.	27.1	78.8	57.4	32.6	8.1	17.7	22.6
2007	College or more	44.1	55.5	0.0				
2012	College or more	47.2	78.8	44.6	13.4	9.0	26.8	47.9
2017	College or more	39.1	84.7	43.4	45.0	11.7	37.8	33.1

Table A.5
Consumption (in %) dedicated to Services (non-durable), Non-Durable Goods, Semi-Durable and Durable Goods in Chile - mean statistics for all the households and according to the education level (secondary school or less, technical education, college or more) of the household head. Sample includes only household heads aged 25–64.

Year	Education	Consumption as a fraction of total consumption (in %)				Households with positive Durables consumption (in %)
		Services	Non-Durable	Semi-Durable	Durable	
2007	All levels	42.0	41.6	6.7	9.7	75.6
2012	All levels	52.4	28.2	8.5	10.9	76.0
2017	All levels	50.0	25.3	11.9	12.9	75.8
2007	Secondary or less	39.5	45.3	6.5	8.7	71.9
2012	Secondary or less	51.3	31.2	8.0	9.6	70.1
2017	Secondary or less	48.4	28.3	11.9	11.4	68.0
2007	Technical educ.	45.4	37.3	6.9	10.4	79.3
2012	Technical educ.	52.8	24.7	9.9	12.6	85.4
2017	Technical educ.	50.4	23.3	11.9	14.4	82.4
2007	College or more	48.9	31.2	7.3	12.5	85.8
2012	College or more	56.0	20.5	9.3	14.3	90.1
2017	College or more	53.0	19.8	11.8	15.5	89.1

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