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Micro-Evidence on the Consumption Impact of Income-Support Policies During COVID-19

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ABSTRACT: Income-support policies can boost consumption during a catastrophic episode like the COVID-19 pandemic. Using data on Chilean municipalities, we investigate the impact on private consumption of income-support policies, such as lump-sum trans-fers and withdrawals of funds from the contributors' mandatory pension accounts. We find that both emergency income and pension withdrawals had statistically sig-nificant effects with an estimated average marginal propensity to consume of about 20 percent. Consumption of durable goods is more sensitive to these policies than other goods, especially in the programs' initial stages. Higher educational attainment and financial leverage, proxying better access to bank credit, are associated with weaker consumption reaction across municipalities.

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1 Introduction

The COVID-19 pandemic shock triggered a need to implement mobility constraints to restrict social interactions and limit the spread of the virus. At the same time, however, the mobility constraints led to a significant decline of economic activity and a deterioration of labor market conditions, manifested through a rise in unemployment and a fall in wage earnings across various parts of the world. In this context, many countries deployed income-support programs to mitigate the negative impact of the pandemic and the related restrictions on households and firms.

Policymakers in Chile introduced policies targeting people's mobility to limit the spread of the virus at the early stage of the pandemic. From April 2020 until the end of July 2020, the government instituted a system of *Rotating lockdown*: depending on the rate of contagiousness, a given municipality was subjected to a lockdown. The mobility constraint after July evolved into a five-step plan, *Step by step plan*, where the first two steps involved some degree of confinement measures, and the last three did not restrict mobility.

As the mobility constraints and the fear of social interaction were resulting in large economic losses, the government implemented income-support programs to mitigate the pandemic's negative effect on the household sector. In May 2020, the government started executing the Emergency Family Income program, whose main feature was to provide lump-sum transfers to individuals in the most vulnerable segments of the society. Initially thought to last four months, the program faced several extensions into 2021. Another measure aimed at supporting household incomes was the policy that allowed the contributors to the private pension system to withdraw up to ten percent of their mandatory accounts on three different occasions: August 2020, December 2020, and April 2021. As these funds are property of the contributor to the pension system, these withdrawals would be expected to have a null effect on consumption if Ricardian equivalence were to hold. In fact, one of the key findings of this paper is that the evidence resoundingly rejects that supposition.

In this paper, we quantify the impact of Emergency Family Income, and pension withdrawal programs (jointly referred to as income-support policies) as well as mobility constraints on consumption during the peak phase of the pandemic (2020-21). We exploit the cross-municipality exposure to these policies to identify the effect on consumption.[1] The lowest level of aggregation that we observe in consumption data is at the municipal-

[1]Other studies that use a similar level of aggregation to tackle related questions are, in the context of the US Great Recession, Mian et al. (2013) and Giroud and Mueller (2016). In the context of the COVID-19 pandemic see, e.g., Chetty et al. (2020) and Andersen et al. (2022).

ity level, and we construct municipality level consumption data using retailers' debit and credit card spending information. All the other variables we employ in the analysis are also based on a similar level of aggregation.

Our strategy relies on accounting for pre-pandemic historical cross-municipality heterogeneity to mitigate challenges and strengthen identification of the income-support policies' effects. Given that income-support policies were determined by pre-pandemic municipality-household characteristics, their impact could vary according to these initial conditions and thus bias our results. For example, pension withdrawal programs depend on the cumulative funds in individual pension accounts, whereas the Emergency Family Income applies to households classified among the 60 percent most vulnerable segments of the population. To address this concern, we remove historical cross-municipality heterogeneity from the variables under analysis, ensuring that pre-pandemic differences in municipality characteristics do not drive our findings. In addition, although the pension withdrawals include a selection component—only individuals with pension funds are eligible—most entitled individuals took advantage of the withdrawals, so selection bias is unlikely to affect our identification strategy.[2]

We find that the income-support policies had a significant impact on consumption. We estimate an average marginal propensity to consume (MPC) out of the income-support policies of about 20 percent. Pension withdrawals have resulted in consumption jumps in the months in which these programs were implemented. Overall, the different income-support programs seem to have similar effects on consumption. Except for the months when the pension withdrawals took place, we do not find statistical differences between the impact of the Emergency Family Income and the pension withdrawals when estimating the effects of the policies month-over-month. The magnitude of the MPC of the first pension withdrawal is massive, around 0.6, and it descends to roughly two-thirds of this value for the second withdrawal. Following a peak during the month when withdrawals occur, the effects can extend up to three months later. The effect of the Emergency Family Income is rather stable over time. We find that these initial differences across programs and time horizons are due to the effect on consumption of durable goods. Indeed, when we zoom in on the consumption of durables, we find that its effect is larger but mainly due to a higher initial effect (in the earlier months of the Emergency Family Income program and when the first and second pension withdrawals occur).

We extend the empirical analysis by studying whether the heterogeneity across municipalities along important dimensions, such as average educational attainment and level of indebtedness or financial leverage, determines the effect of the income-support programs

[2]In fact, 88 percent of those eligible to withdraw funds chose to do so (see Fuentes et al. (2022)).

on consumption. The literature that studies the determinants of consumption focuses on how demographics, wealth, the degree of indebtedness, or behavioral considerations affect the size of the MPC from transitory income shocks. We find that municipalities with relatively higher levels of education or financial leverage experienced relatively smaller increases in consumption out of income-support programs.

Finally, we also document the impact of mobility constraints on consumption. The mobility constraints during the most acute phase of the pandemic (Rotating Lockdowns) are associated with a massive 60 percent drop in goods consumption relative to municipalities that do not experience any constraints. The impact is lower during the *Step by step plan*, dropping by half or more.

Our work builds on the literature that studies the effects of income shocks on consumption, such as those summarized in Jappelli and Pistaferri (2010). One of the novelties of our work is its focus on the pension withdrawals, providing evidence about the impact on consumption of a wealth-neutral policy (allowing people access to a portion of their pension funds as a source of current, rather than future disposable income). Ganong et al. (2022) study the increase in unemployment insurance benefits in the US during the COVID-19 pandemic: using individual bank account data, they find a one-month MPC ranges of 25 to 45 percent. Chetty et al. (2020) study the impact of direct payments to households (made under the Coronavirus Aid, Relief, and Economic Security Act) on consumption: using debit and credit card data aggregated at the ZIP code level, the authors find that transfers are an effective tool to boost consumption, detecting heterogeneous effects across zip codes in payments made at the late stages of the pandemic. In this context, exploiting cross-municipality spending data from debit and credit card transactions, which include online sales, we find that drawing from the own pension funds, on average, was associated with a significant increase in consumption.

Our findings relate to the literature on how the MPC depends on wealth. For instance, in Carroll and Kimball (1996), the MPC is decreasing in the individuals' wealth level. Kaplan and Violante (2014) give some nuance to the Carroll and Kimball prediction: households with a higher share of illiquid wealth would also behave as financially constrained agents. On the empirical side, using the responses to a survey about how households would spend an unexpected windfall, Christelis et al. (2019) find that the consumption response to income shocks declines with economic resources. In the global financial crisis context, Mian et al. (2013) find that ZIP codes with poorer households have higher MPC out of shocks in housing wealth. To the extent higher education is associated with higher wealth, we find consistent evidence: in municipalities with a larger share of educated individuals, consumption exhibited a lower sensitivity to the income programs than in municipalities with less educated individuals.

Municipalities with higher financial leverage, serving as a proxy for better access to borrowing from financial institutions, exhibit lower sensitivity in consumption following the windfall. As Zeldes (1989) argues, borrowing constraints are a key factor in understanding consumption patterns. However, during periods of financial stress, high leverage can create a need to deleverage, which reduces the effectiveness of income-support policies. For instance, during the US Great Recession, Mian and Sufi (2010) and Mian et al. (2013) find that consumption experiences a more significant drop in geographical areas with high leverage. In our analysis of Chile, we find that municipalities with higher household financial leverage responded less to income-support programs. Given the large number of credit programs deployed at the onset of the pandemic, the interpretation that higher financial leverage signals lower liquidity constraints appears to be the most plausible.[3]

Studies investigating the impact of withdrawals from pension funds on consumption are scarce. Using cross-sectional data, Kreiner et al. (2019) examine the Special Pension payout, a stimulus policy designed to stabilize the Danish economy during the financial crisis. This policy allowed individuals to access part of their pension funds, which would otherwise be inaccessible until age 65. To measure the impact on consumption, the authors survey the program beneficiaries, asking for changes in their total spending due to the payout. The study finds that consumers with more liquidity constraints predict a greater propensity to spend following the payout. Hamilton et al. (2023) use an event study research design to study the effect on consumption of the early pension withdrawal that occurred in Australia during the Covid-19 pandemic, finding that allowing individuals to withdraw funds from their pension account is effective in increasing consumption. Our work contributes to this literature by studying the Chilean pension withdrawal case and providing evidence that the effects of the withdrawals are more intense at the earliest stage of the program and can account for cross-municipality differences in consumption spending beyond the first month of the intervention.

Our work also touches upon the relation between mobility constraints and consumption. The magnitude of the effects we find is broadly comparable with Goolsbee and Syverson (2021) and Alexander and Karger (2021), who analyze the impact of the pandemic shock on consumption, finding that most of the consumption drop was due to individuals' voluntary decisions to disengage from shopping rather than government-imposed restrictions on activity. We find that the mobility constraints similarly affect

[3]For a review of the liquidity programs conducted over the period see Central Bank of Chile (2020).

consumption in Chile as in the US.[4] However, in our case, we cannot isolate how much of the effect can be attributed to the policies or what portion of it operates through consumers avoiding exposure to the virus by self-isolation.

The rest of the paper is organized as follows. Section 2 discusses the methodology of our empirical exercises. Section 3 describes the data used in the analysis and presents background information on the policies implemented in Chile over the period. Section 4 presents the empirical results about the effect of the different income-support policies. Section 5 concludes.

2 Methodology

2.1 The effects of the policies on consumption

We quantify the impact of mobility constraints and income-support policies on consumption during the pandemic. We follow a similar approach to the empirical literature that estimates the effect of tax rebates on consumption (see, for example, Johnson et al. (2006) and Misra and Surico (2014)), and the literature that estimates MPC (see, for instance, Luengo-Prado and Sørensen (2008) and Jappelli and Pistaferri (2010)). We use municipalities as our panel cross-sectional units. We exploit cross-municipality variation within region-period-specific units to identify the effects of the policies on consumption, and distinguish them from aggregate region-specific shocks. This implies that any aggregate shock happening at the regional level does not contaminate our estimates of the effects of the policies on consumption. Thus, we include region-time-specific dummies ($\mu_{r,t}$) in the empirical model, and estimate the following panel regression specification:

$$\Delta c_{r,m,t} = \beta_{inc} \Delta income_{r,m,t} + \beta_{sup} income\,programs_{r,m,t} + \beta'_{mob} mobility_{r,m,t} + \mu_{r,t} + \epsilon_{r,m,t}. \tag{1}$$

Our consumption and income variables are based on changes relative to the pre-pandemic period. We denote $\Delta \ln \mathrm{C}_{r,m,t}$ as the log change of retail sales in region r, municipality m at month t, relative to the same month a year prior ($\Delta \mathrm{X}_{r,m,t} = \mathrm{X}_{r,m,t} - \mathrm{X}_{r,m,t-12}$); and $\Delta \ln \mathrm{INCOME}_{r,m,t}$ as the corresponding log change of labor income. We remove the historical cross-municipality heterogeneity from these variables to ensure the ex-ante (pre-pandemic) heterogeneity does not drive our results. In order to do that, as our cross-sectional variation comes from municipalities we cannot simply demean the variables as

[4] For Denmark, Andersen et al. (2022) find quantitative results that closely follow our estimates.

that would eliminate the municipalities' exposure to the income-support policies. Hence, our consumption variable would be $\Delta c_{r,m,t} = \Delta \ln C_{r,m,t} - \overline{\Delta \ln C_{r,m}}$, where $\overline{\Delta \ln C_{r,m}}$ is the average growth rate in the pre-pandemic period (2015-19). We perform the same demeaning procedure for labor income, denoting $\Delta income_{r,m,t}$.

We consider three alternative measures for income-support policies that include the two main programs that occurred over the period:

1. The size of cumulative withdrawals from pensions funds up to time t relative to labor income one year prior: $withdrawal_{r,m,t} = \ln\left(1 + \frac{\text{WITHDRAWAL}_{r,m,t}}{\text{INCOME}_{r,m,t-12}}\right)$;
2. The size of the cumulative Emergency Family Income program up to time t relative to labor income one year prior: $efi_{r,m,t} = \ln\left(1 + \frac{\text{EFI}_{r,m,t}}{\text{INCOME}_{r,m,t-12}}\right)$;
3. The sum of the cumulative withdrawals and Emergency Family Income funds up to time t relative to the labor income one year prior: $benefits_{r,m,t} = \ln\left(1 + \frac{\text{WITHDRAWAL}_{r,m,t}+\text{EFI}_{r,m,t}}{\text{INCOME}_{r,m,t-12}}\right)$.

The primary coefficient of interest is β_{sup}, our measure of the MPC from the income-support policies. The coefficient measures how much of a shock equivalent to one percent of monthly labor income translates into consumption increases.

The vector *mobility* summarizes the main mobility constraints over the period, with each component indicating the percentage of days that a specific municipality is under a type of mobility constraints. We consider three different mobility constraints. First, for the period from April to July 2020, we use (i) *lockdown* which reflects the municipalities that had full lockdown. From August 2020 onward, we employ: (ii) *step* 1 which captures municipalities which had a lockdown-like constraint; and (iii) *step* 2 which is a restriction only on weekends. We do not control for steps that do not impose lockdown, hence all the coefficients for the mobility constraints should be interpreted relative to non-lockdown municipalities.

2.2 Heterogeneity

In order to assess possible heterogeneous effects of income-support programs depending on municipalities characteristics, we interact the income-support program variables with five variables (fixed at pre-pandemic values, averaged over the period 2015-2019) which could induce different consumption-savings decisions. We include three controls related to wealth considerations: labor income, schooling of the income-support recipients, and the ratio of consumption credits to labor income. We include two demographic controls:

age and gender (the latter being measured by the share of males living in the municipality). We augment Equation (1) by considering the heterogeneity dimension to estimate the following regression model:

$$
\begin{aligned}
\Delta c_{r,m,t} =& \beta_{inc}\Delta income_{r,m,t} + \beta_{sup} support\, income_{r,m,t} + \beta'_{mob} mobility_{r,m,t} + \\
& \beta'_{hsup}(h_{r,m} - h) \times support\, income_{r,m,t} + \mu_{r,t} + \epsilon_{r,m,t}
\end{aligned}
\tag{2}
$$

where $h_{r,m}$ is a vector with the aforementioned five variables; h is the cross-sectional average of $h_{r,m}$. We remove h from $h_{r,m}$ to keep comparable the scale of the β_{sup} coefficient between Equations 1 and 2. We omit the individual terms for the five dimensions, as they are captured by the historical heterogeneity that has been removed from the construction of the consumption and labor variables.

These characteristics have been discussed in the literature as affecting consumption. Wealth can have different effects on how people spend an unexpected increase in disposable income. For instance, Carroll and Kimball (1996) show that in the absence of perfect risk-sharing, the MPC out of transitory income decreases with the level of wealth, which we proxy with years of schooling. In a quantitative framework, Kaplan and Violante (2014) argue that distinguishing between liquid and illiquid wealth is fundamental to understanding the behavior of consumption out of increases in disposable income. Illiquid assets earn an exogenously higher rate of return than liquid assets but can be accessed only by paying some form of transaction cost. In this setting, households holding sizable amounts of illiquid wealth may behave similarly to those under liquidity constraints and optimally choose to consume more of their transitory windfall. Hence, a lower MPC in wealth would be predicted except if wealthy municipalities had a high share of illiquid assets. As in Zeldes (1989), consumers with the ability to borrow against future income should react less to new sources of income. Thus, in municipalities where household leverage is higher, consumption should be less sensitive to the income support programs. Education can also be associated with financial sophistication. Christelis et al. (2019) show that consumers lacking financial sophistication have a higher marginal propensity to consume out of the transitory income.

With respect to the role of gender, Duflo (2012) surveys the literature that documents differences in consumption patterns between males and females of conditional transfer programs targeted at women. To control for different spending patterns across cohorts of different ages, we include age as an additional regressor, proxied by the weighted average of the beneficiaries recipients age.

3 Data and background information

To address the empirical question of this paper, we combine several datasets from private and administrative sources that track information at a granular level. As in Chetty et al. (2020), to preserve the privacy of the reporters, all the data we handle in this work is anonymized or already aggregated at the municipality level to meet the privacy protection requirements of using household level data.

3.1 Retail sales

To build our measure of consumption, we use information at the municipality level from the leading provider of point-of-sale terminals for processing credit and debit card payments at retail locations as well as online sales. This information is available daily, but we aggregate it monthly to match it with the labor income data. The dataset contains an identifier of the type of retailers selling the products, which allows us to explore the effect of the policies on different types of consumption goods: retailers that sell durable as opposed to other goods. In Appendix Figures 10a and 10b, we show how the evolution of debit and credit cards co-moves with consumption data from the national accounts. Appendix Table 12 reports a high correlation of the data with their national accounts counterpart and significant coverage of households' goods consumption. After dropping outliers, of 346 municipalities distributed in 13 regions, the cleaning procedure leaves a dataset with 290 municipalities.[5] Appendix A describes the cleaning procedure for municipalities' data.

3.2 Labor income

We use information from the Administrator of Severance Payments Funds to calculate labor income. We start from data on labor earnings for each employee. As for each employee we have the information about the municipality they live in, we collapse labor earnings at the monthly-municipality level.

Table 1 presents descriptive statistics of labor income. In the years before the pandemic, labor income grew at an annual average growth rate of 5%. During 2020 it collapsed to negative -1% to bounce back to 10% in 2021. Across municipalities, income distribution presents the typical asymmetric pattern observed at the household level. Appendix Figure 11a shows the pre-pandemic income distribution: the mass of the distribution concentrates on the left, with a long right tail. During the pandemic, the income

[5] We remove the complete municipality if a single value is missing or outlier.

distribution does not change much relative to the pre-pandemic dynamics, as visible from Appendix Figure 11b.

3.3 Mobility constraints

Rotating lockdown: On March 18, the President of Chile declared a state of national catastrophe due to the pandemic. On March 22, a curfew began throughout Chilean territory, prohibiting citizens from circulating between 10:00 p.m. and 5:00 a.m. On March 25, there was an announcement of a system of *Rotating lockdown*. According to the epidemiological situation of each municipality, the national authority imposed a focused lockdown over limited periods. The mobility constraints of the period were an all-or-nothing situation in which a municipality was either in lockdown or not.

Step by step we take care of ourselves plan: On July 19, 2020, the Chilean government considered a five steps plan to overcome the worst of the Covid-19 pandemic. The plan ranged from lockdown to opening face-to-face activities. The plan's first step was a lockdown. It considered limited mobility to minimize the spread of the virus. The more notorious restriction was the need for government permits to perform essential activities such as shopping or attending work. This step considered the suspension of non-essential face-to-face activities.[6] The second step was characterized by a reduction in the degree of confinement. There were no mobility constraints on weekdays, but mandatory lockdown held for those over 75 and on weekends and holidays. Non-essential face-to-face activities were not allowed. From the third-to-fifth step, there was no lockdown for the general population. Social and recreational activities were allowed over the week with a maximum of 50 people, and mobility was allowed. Differences across the third-to-fifth step involved different degrees of maximum capacity for non-essential activities. For our empirical analysis, we do not distinguish among the last three steps of the plan because of the lack of lockdown and the difficulties in implementing controls for the varying degrees of capacity for non-essential activities.

Data: Data on lockdown and steps of *Rotating lockdown* and *Step by step we take care of ourselves plan* is from the Ministry of Science. We use the percentage of days of the month that a municipality was under each mobility restriction: $Lockdown$ is the variable that captures the constraints over the *Rotating lockdown* period; $step\,1$ and $step\,2$ are the variables used to capture the first two steps of the *Step by Step Plan* period. The municipality nature of the mobility constraints is an advantage for our work because it allows

[6] They include, for example, the closure of schools and restaurants and the prohibition of events of more than 50 people.

us to exploit cross-sectional variation at the municipality level to identify the effect of the constraints on the evolution of municipality sales of goods.

3.4 Income-support programs

3.4.1 Pension fund withdrawals

To mitigate the negative impact of COVID-19, Chile's Congress passed three laws that allowed the affiliates of the private pension system to voluntarily withdraw for a one-time up to 10 % of their mandatory contributions fund. The government enacted the laws on July 30, 2020, December 10, 2020, and April 28, 2021.[7] The laws established a maximum withdrawal amount of 150 Unidades de Fomento (UF) and a minimum of 35 UF.[8] If 10 % of the fund was less than 35 UF, the affiliate could withdraw up to the available amount. The affiliate could withdraw the entire fund if it was less than 35 UF. Affiliates had a time limit of 365 days to request their funds, and the withdrawn amount was tax-exempt (except for the second withdrawal).

Data: The Chilean Pensions Supervisor collected data at the affiliated-daily level for the amount withdrawn from the pension fund. Appendix Figure 12 shows the daily information on the withdrawal amount. Most withdrawals concentrated during the early days the law operated; this suggests the need for liquidity by the households. We aggregate the information at the municipality-monthly level to match it with data on labor income at the same aggregation level.

Table 1 reports descriptive statistics about the distribution of the withdrawals. In 2020, the average withdrawal is equivalent to roughly 50% of the 2019 labor income and in 2021 to approximately 40%. The standard deviation of the withdrawals is around a quarter of the dispersion of labor income. The low dispersion of the withdrawals highlights the relatively higher importance of the withdrawal for poorer municipalities (Figure 2a). For poorer municipalities, the withdrawal accounted for as much as 50% of their annual labor income. In contrast, for the wealthiest municipalities, it accounted for up to 20% of their income. We also identify the effect of withdrawals on consumption by exploiting the differential exposure of the municipalities to the withdrawals. Table 2 shows the coverage of the withdrawals as a percentage of the working-age population. Across municipalities, on average 73% (64%) of the working age population withdrew funds from their pension accounts in 2020 (2021).

[7] Laws 21,248, 21,295 and 21,330.

[8] Unidades de Fomento is an inflation adjusted index widely used in Chile to convert nominal values in comparable units over time.

3.4.2 Emergency Family Income

On May 14, 2020, the government enacted Law 21,230 to grant an Emergency Family Income for middle- and low-income households. The households had to meet two requirements to be beneficiaries: the Ministry of Social Development must classify them as belonging to the 60% most vulnerable populations; their legal-age members must not receive labor income, severance payments, or pension benefits. If they qualified, the amount of each contribution would be equivalent to the difference between the Emergency Family Income and the sum of the households' income.[9] Households made up of at least one beneficiary of solidarity pensions for disability or old age were entitled to receive the Emergency Family Income. The policy initially consisted of four monthly payments; given the hurdles of the period, the government later extended the program to include two additional payments. Thus, according to the scheme summarized in Table 15, the Emergency Family Income provided six payments. In addition, the Ministry of Social Development also delivered a bonus on Christmas to those households that receive the sixth payment of the program. During the first three months of 2021, the Emergency Family Income became conditional on the municipality's stage in the *Step by Step Plan*. As of April 2021, the Emergency Family Income was extended to the 80% most vulnerable populations.

Data: Emergency Family Income program data is from the Ministry of Social Development. Table 1 reports descriptive statistics about the distribution of the program. In 2020, the average withdrawal was equivalent to roughly 10% of the labor income in 2019, and in 2021 it increased to more than 40%. As with the withdrawals, the standard deviation of the Emergency Family Income program is around a quarter of the dispersion of labor income, so Figure 2b shows that the importance of the program benefits disproportionately more the lower income municipalities, in addition to showing the higher importance of the program in 2021. Table 2 shows the increasing coverage in terms of the percentage of the working-age population, in 2021, relative to 2020.

3.4.3 Characteristics of the Emergency Family Income and Withdrawals recipients

We compare how the Emergency Family Income program and the withdrawals from the pension funds are distributed among the programs' recipients. To do so, we compute the weighted average, by the size of each emergency income program and their sum, of income, schooling, credit, and demographics within municipalities; then, we focus on how this statistic is distributed across municipalities. Table 3 and Figure 3 show the

[9] For further details on how the Emergency Family Income operates, see Law 21,230.

results. Panel a) and Charts (a) to (c) show that while the withdrawals affected both ends of the distribution, the Emergency Family Income distinctly targeted the lower end. Panel b) and Charts (d) to (f) present the results for educational attainment (years of schooling). In Chile, twelve years of schooling is equivalent to finishing high school. The Emergency Family Income benefited those with lower educational attainment more than the withdrawals from the pension funds. On average, the recipients of the Emergency Family Income completed half a year of education on top of their high school education. Those who withdraw pension funds have one year and a half in addition to their high school years. Panel c), Charts (g) to (i) show a wide dispersion in indebtedness across those that withdraw pensions funds. On the contrary, the recipients of the Emergency Family Income are characterized by a lower degree of indebtedness or access to credit.[10]

Panel d) and e), Charts (j) to (o), show the distribution of the programs across different demographic characteristics. As for age, younger population groups benefited slightly more from the Emergency Family Income than the Withdrawals. However, the differences are minor in the upper end of the distribution. As for gender, the Emergency Family Income distinctly benefited females more than males.

4 Results

4.1 The narrative of the pandemic and the income-support programs

Before turning to a formal regression analysis, we provide a graphical description of the evolution of income, consumption, and the income-support programs during the pandemic in Figure 4a. There are several important insights conveyed in this figure. First, labor income and consumption both collapsed at the onset of the pandemic in March 2020. Second, while labor income remained roughly flat in the following months through September 2020, consumption began to recover faster, sustained by the inception of the Emergency Family Income program during the early phase of the pandemic (Figure 4b). Third, the consumption recovery strengthened further starting from August, when the withdrawals of up-to 10% from the individual pension fund accounts started to kick in (Figure 4c); consumption jumped markedly also at the time of the second and third withdrawal from the pensions funds. Fourth, labor income started to gradually recover as the mobility constraints began to ease (Figure 4d). Overall, these figures convey one important message – the timing of the widening of the wedge between consumption and

[10] Data on educational attainment is from the Ministry of Education. Data on indebtedness is from the Financial Market Commission.

labor income coincides with the timing of the Emergency Family Income and the pension withdrawals.

Going beyond these aggregate movements, Figure 5 shows that there is substantial cross-municipality heterogeneity in consumption growth over time. We exploit this heterogeneity with the idiosyncratic exposure of each municipality to the income-support programs, mobility constraints, and labor income to estimate the effect of each municipality-specific factor on consumption, as well as with the interaction with municipalities characteristics.

4.2 Regression analysis

Having provided some initial insights from the graphical description, we now turn to quantify the effects of the mobility constraints and income-support policies on consumption. We then analyze differences in the effects between durable and non-durable consumption goods and focus on whether different municipalities' characteristics account for different MPC out of the support income programs.

4.2.1 The effects of the mobility constraints and the income programs

In this section, we quantify the effects of the mobility constraints and income-support policies on households' spending. We first estimate the effect of income growth on consumption growth, and subsequently we add one policy variable at a time to isolate the extent to which these policies explain the joint dynamics between consumption and income. We end up with a fully-fledged empirical model that considers all the covariates simultaneously, pinning down the contribution of each policy. Table 4 presents the results of this exercise.[11]

First, column (1) shows that consumption and income dynamics are tightly associated. A coefficient significantly lower than one indicates that agents internalize part of the shocks affecting their income during the pandemic as transitory. .[12]

Second, column (2) shows the effect of the mobility constraint policies conditional on income. The lockdown variable captures the effect of the constraint during the most acute stage of the pandemic. Municipalities under lockdown suffer a staggering 60% drop in goods consumption relative to municipalities that do not experience any constraint. Over time, the effect of lockdown policies is less severe. For instance, during the *Step by Step Plan*, the impact of the most stringent constraint, *step* 1, accounts for less than half

[11]The correlation matrix of the variables entering in the regressions are reported in Appendix Table 13.

[12]For instance, for the US, see Luengo-Prado and Sørensen (2008), Demyanyk et al. (2019).

the effect at the onset of the pandemic (as instead captured by the lockdown variable). Nevertheless, consumption suffers a severe drop of about 30% relative to municipalities with fewer constraints. A lower level of mobility constraints, *step* 2, presents a milder effect on consumption of about 10%.

Third, columns (3) and (4) show that the income-support policies have a coefficient of about 0.2-0.3, while the income coefficient remains significant and of similar magnitude. The decline in the coefficient for income resulting from adding income-support policies (columns 3 and 4) is smaller than the decline from adding the mobility restrictions (column 2), which is consistent with the fact that income-support programs did not target municipalities based on their income fluctuations. The coefficients of the individual income-support programs remain significant after controlling for the various restrictions measures (columns 5 and 6), albeit their magnitude declines slightly, to about 0.15-0.25.

Finally, when we enter all explanatory variables together in column (7) we see that they are all significant and with the expected sign. Given the very high correlation of the two income-support policies, it is not surprising to see that their coefficients become smaller when they are jointly introduced. Interestingly, it also becomes identical in size. Hence, in column (8) we add the two variables together in a single income-support policies (labeled as benefits) and find a coefficient of 0.2, consistent with columns 5 and 6 with all variables and one program at the time.

We consider column 8, with the two income programs joint together as one variable, as our baseline regression, when comparing it to other exploratory exercises.

Sequence of monthly cross-sectional regressions: We also estimate our baseline Equation 1 via a cross-sectional regression for each month, rather than pooling the data for the full-period. The impact over time of the mobility constraints and the income-support policies is depicted in Figures 6 and 7 , which plot the estimated coefficients for the different specifications. The upper panel in Figures 6a and 7a show that municipalities with stricter mobility constraints suffer a large drop in consumption spending than municipalities with moderate constraints, consistent with the findings presented in Table 4.

The lower panels show that the income-support programs have especially large impact in the initial period, which moderates over time. Moreover, the impact of the different programs–Emergency Family Income and withdrawals–converges toward a similar value of about 0.2 over time. Figure 6b shows the Emergency Family Income and the withdrawals coefficients as individual regressors: except for the periods where the withdrawals take place, the coefficients present similar magnitude and are indistinguishable from each other. Figure 7b shows the results when summing the Emergency Family

Income and the withdrawals into the variable named "benefits", which remains always significant. In terms of size, the effect of the income programs is very large in the initial period, then it decays gently. In all cases, the month-by-month estimates turn out to be less precisely estimated than pooling the data and running regressions exploiting the panel dimension.

4.2.2 The effect on durable and non-durable consumption goods

We switch to analyze the effects of the mobility constraints and the income-support policies over durable and non-durable consumption, based on a distinction of durability at the sectoral level. Table 5 shows the results of estimating Equation 1, as estimated in column 8 of Table 4, considering consumption of durable and non-durable goods as left-hand-sided variables.

Consumption of durable goods seems to be more sensitive to income, mobility constraints, and income-support policies than non-durable goods. When instead of pooling the entire period and performing panel regressions, we undertake our empirical analysis via monthly cross-sectional regressions, Figure 8 shows that the higher MPC for durables is present mainly in the first period. To some extent, the higher sensitivity of consumption of durable goods to income may come as a surprise since there is an extensive literature showing that a random walk can generally approximate the consumption of durable goods and the result of the excess sensitivity of non-durable consumption to income in the consumption literature.[13] However, Mian et al. (2013) and Parker et al. (2013) find a higher sensitivity of durable goods to wealth and disposable income shocks, respectively, a result which is consistent with ours. In our context, one possible explanation behind the higher sensitivity of durable goods consumption may be related to borrowing constraints distinctly affecting households' consumption of durable goods, given the documented importance of financing for the purchase of durable goods, see Chah et al. (1995) and Mian et al. (2013). A second possible explanation may arise from the peculiarities of the Covid-19 shock and the associated uncertainty about the future, which drives a bias in favor of spending on durable goods. As we will see in the next section, we offer evidence consistent with the borrowing constraint argument: in tables 7, we can see that better access to bank credit, captured by the financial leverage variable, is stronger and more robust for durable goods.

[13] Mankiw (1982) and Caballero (1990) are two references for the statistical properties of consumption of durable goods. For the excess sensitivity of non-durable consumption to income see Galí (1993) and Luengo-Prado and Sørensen (2008).

4.2.3 Heterogeneous effects across municipalities

To what extent the characteristics of the recipients of the income-support policies generate differences in the degree of spending out of the income programs? Understanding whether there is heterogeneity in the programs' MPCs is essential, both to assess their aggregate effect and to make informed decisions about the policy design. We focus on five possible sources of heterogeneity: gender (share of males), age, income, schooling of the recipients (all weighted by the amount of the programs they receive), and municipality financial leverage (defined as ratio of consumption credit to labor income, averaged over 2015-2019).[14] We estimate the baseline Equation 2 and present the results in Table 6, keeping in all regressions the interactions based on demographics, while exploring alternatively the interaction with other explanatory variables income, schooling, or leverage (given their high correlation we introduce these three one at the time).[15]

The key sources of heterogeneity in determining the size of the MPC are educational attainment, financial leverage, age, and income. In particular, two findings stand out. First, the interaction term with educational attainment (column 2) suggests that municipalities with relatively less educated recipients spend a higher share of their windfall than municipalities with relatively more educated beneficiaries. This is consistent with Christelis et al. (2019) showing that consumers lacking financial sophistication have a higher marginal propensity to consume out of their transitory income. To the extent higher education is associated with higher wealth, this result is consistent with an MPC that decreases with wealth. Second, municipalities where financial leverage is higher experience lower MPC out of the income-support programs (column 3). The lower MPC implies that the income-support programs are less likely to affect activity in the more leveraged municipalities since households allocate a lower share of their windfall to current spending, which is consistent with the idea that in these municipalities, households have more access to borrowing from financial institutions, therefore, are less likely to be liquidity constrained.

When considering the role of heterogeneity across municipalities for durables and non-durables, Table 7, we find that the impact of benefits upon spending on durable goods is positively affected mainly by weak leverage, younger age, and higher male presence. Given the importance of financing for the purchase of durable goods, the higher sensitivity of durable goods consumption reinforces the link between the effect of the

[14] We also tried alternative measures of leverage (mortgage loans to labor income as well as the sum of consumption credit and mortgage loans to labor income) and the results are similar.

[15] The correlation matrix of the interacted variables entering in the regressions are reported in Appendix Table 14.

programs generating a larger effect in municipalities where households are less likely to borrow against future income. The impact of benefits upon spending on non-durables is positively affected mainly by relatively lower education. Note that the various lockdown measures continue to remain stronger than for non-durables as in the Table 5.

4.3 Robustness

We analyze how sensitive our results are to modifications in our baseline strategy. We assess the sensitivity of our results to considering different reference periods for consumption in place of year-over-year growth rates and we evaluate whether our results are driven by central municipalities within each region by dropping them from the sample.

Changing the reference period: In tables 8 and 9, we show that our results are robust when defining our variables in alternative ways and extending the estimation sample until the end of 2021. In one table, growth variables are defined as a 2-year growth rate, to avoid the large denominator effect from the pandemic when moving in the 2021 regression sample. In the other table we use the average 2019 value as denominator, for income and income policies. Overall, the coefficient of the benefits in the usual column 8 is about 0.22-0.23, remarkably close to the baseline value of 0.2.

Dropping central municipalities: We drop municipalities where people are unlikely to reside in, as their registered consumption pattern may be driven by factors prevalent in other municipalities, and estimate back Equation 1. We define central municipalities as the capital of each Chilean region. We drop a total of thirteen municipalities. Table 10 displays the results, which are almost identical to our baseline of Table 4.

4.4 Support income programs and income smoothing

The previous sections show that income-support policies are highly effective in stimulating consumption. However, from a welfare standpoint, a feature transfers programs should satisfy is smoothing income fluctuations to isolate the municipalities from their idiosyncratic shocks. The smoothing goal implies that the income-support policies should differently benefit municipalities more affected by adverse income shocks. Asdrubali et al. (1996) provide a formal decomposition about the role of income programs to smooth income fluctuations.[16] In the spirit of this decomposition, we assess the extent to which the income policies provide insurance against the municipalities' income fluctuations by plotting the size of the Emergency Family Income and Withdrawals (relative to pre-pandemic income) with flipped sign, $-\frac{\text{EFI}_{r,m}}{\text{INCOME}_{r,m,2019}}$ and $-\frac{\text{WITHDRAWAL}_{r,m}}{\text{INCOME}_{r,m,2019}}$, against income

[16]In their framework, these programs would embed into programs the fiscal authority implements.

fluctuations, $\Delta income_{r,m}$. If the programs provide income smoothing, we should expect the sign of this relation to be significantly positive.

Figure 9 shows the sign of this relation for the two programs comparing 2020 to 2019, 2021 to 2019, and the sum of the programs in 2020-2021 relative to 2019. The result is striking; the income-support policies did not provide insurance against income fluctuations in all cases. We attribute the lack of income insurance to the design of the programs, in which there is no consideration of the size of income fluctuations for determining the amount of benefit to which households are entitled. Although beneficial to boost consumption, our empirical application shows that unconditional income-support programs correlate with the wrong sign with income fluctuations. As long as income smoothing is a goal of the support income programs, conditioning the policies on the size of labor income fluctuations is something to consider in the programs' design.

5 Conclusion

The analysis in this paper contributes to understanding the impact on private consumption of the unprecedented set of policies implemented in response to the pandemic. We use microdata on Chilean municipalities to investigate the impact of mobility constraints and income-support programs–such as income transfers and pension withdrawals–on private consumption during the pandemic. It sheds light on a set of empirical findings, including on the characteristics of the program's recipients that are crucial to understanding the effects of the programs.

First, income-support policies, such as the family emergency income and pension withdrawals, had significant and economically meaningful effects on private consumption. Their effects were similar, with MPC out of each measure estimated at about 0.2. In fact, the relative importance of these measures depended on the exact timing, with the effect being the strongest at the beginning and then moderating roughly in similar fashion over time. Such measures helped mitigate the profound impact of the mobility restrictions on consumption, with the municipalities under lockdown estimated to have suffered a drop of about 60 percent in goods consumption relative to municipalities that did not experience any constraint.

Second, the mobility constraints, emergency income program and pension withdrawals have not had a uniform impact across categories of goods. Distinguishing between durable and non-durable goods, the analysis finds that consumption of durables is relatively more sensitive to mobility constraints and income-support programs, especially in the programs' initial stages.

Finally, the effects of income-support policies seem to be highly heterogeneous across municipalities. In particular, the recipients' educational attainment and the degree of municipality leverage seem to the be the key factors explaining the heterogeneity in consumption responses. Municipalities with relatively higher educational attainment of its residents or relatively higher degree of financial leverage seem to be associated with a relatively weaker impact on consumption. The latter likely reflects the higher effect of the income-support programs in municipalities where households experience higher borrowing constraints.

References

Alexander, Diane and Ezra Karger, "Do Stay-at-Home Orders Cause People to Stay at Home? Effects of Stay-at-Home Orders on Consumer Behavior," *The Review of Economics and Statistics*, 09 2021, pp. 1–25.

Andersen, Asger Lau, Emil Toft Hansen, Niels Johannesen, and Adam Sheridan, "Consumer responses to the COVID-19 crisis: evidence from bank account transaction data," *The Scandinavian Journal of Economics*, 2022, *124* (4), 905–929.

Asdrubali, Pierfederico, Bent E. Sørensen, and Oved Yosha, "Channels of Interstate Risk Sharing: United States 1963–1990," *The Quarterly Journal of Economics*, 11 1996, *111* (4), 1081–1110.

Caballero, Ricardo J., "Expenditure on Durable Goods: A Case for Slow Adjustment," *The Quarterly Journal of Economics*, 1990, *105* (3), 727–743.

Carroll, Christopher D. and Miles S. Kimball, "On the Concavity of the Consumption Function," *Econometrica*, 1996, *64* (4), 981–992.

Central Bank of Chile, "Monetary policy report September 2020," *Central Bank of Chile*, 2020.

Chah, Eun Young, Valerie A. Ramey, and Ross M. Starr, "Liquidity Constraints and Intertemporal Consumer Optimization: Theory and Evidence from Durable Goods," *Journal of Money, Credit and Banking*, 1995, *27* (1), 272–287.

Chetty, Raj, John N. Friedman, Nathaniel Hendren, Michael Stepner, and The Opportunity Insights Team, "The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data," NBER Working Papers 27431, National Bureau of Economic Research, Inc June 2020.

Christelis, Dimitris, Dimitris Georgarakos, Tullio Jappelli, Luigi Pistaferri, and Maarten van Rooij, "Asymmetric Consumption Effects of Transitory Income Shocks," *The Economic Journal*, 2019, *129* (622), 2322–2341.

Demyanyk, Yuliya, Dmytro Hryshko, María José Luengo-Prado, and Bent E. Sørensen, "The Rise and Fall of Consumption in the 2000s: A Tangled Tale," *Economica*, July 2019, *86* (343), 495–531.

Duflo, Esther, "Women Empowerment and Economic Development," *Journal of Economic Literature*, 2012, *50* (4), 1051–1079.

Fuentes, Olga, Ximena Quintanilla Domínguez, Alexandra Rueda Restrepo, Eugenio Salvo Cifuentes, Diego Herrera Astorga, and Maria Fernanda Toledo Badilla, "Retiro de Fondos de Pensiones: Resultados y efectos," Technical Report, Superintendencia de Pensiones 2022.

Galí, Jordi, "Variability of Durable and Nondurable Consumption: Evidence for Six O.E.C.D. Countries," *The Review of Economics and Statistics*, 1993, *75* (3), 418–428.

Ganong, Peter, Fiona E Greig, Pascal J Noel, Daniel M Sullivan, and Joseph S Vavra, "Spending and Job-Finding Impacts of Expanded Unemployment Benefits: Evidence from Administrative Micro Data," Working Paper 30315, National Bureau of Economic Research August 2022.

Giroud, Xavier and Holger M. Mueller, "Firm Leverage, Consumer Demand, and Employment Losses During the Great Recession," *The Quarterly Journal of Economics*, 10 2016, *132* (1), 271–316.

Goolsbee, Austan and Chad Syverson, "Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020," *Journal of Public Economics*, 2021, *193*, 104311.

Hamilton, Steven, Geoffrey Liu, Jorge Miranda-Pinto, and Tristram Sainsbury, "Early pension withdrawal as stimulus," *Available at SSRN 4389699*, 2023.

Jappelli, Tullio and Luigi Pistaferri, "The Consumption Response to Income Changes," *Annual Review of Economics*, 2010, *2* (1), 479–506.

Johnson, David S., Jonathan A. Parker, and Nicholas S. Souleles, "Household Expenditure and the Income Tax Rebates of 2001," *American Economic Review*, December 2006, *96* (5), 1589–1610.

Kaplan, Greg and Giovanni L. Violante, "A Model of the Consumption Response to Fiscal Stimulus Payments," *Econometrica*, 2014, *82* (4), 1199–1239.

Kreiner, Claus Thustrup, David Dreyer Lassen, and Søren Leth-Petersen, "Liquidity Constraint Tightness and Consumer Responses to Fiscal Stimulus Policy," *American Economic Journal: Economic Policy*, February 2019, *11* (1), 351–79.

Luengo-Prado, María José and Bent E. Sørensen, "What Can Explain Excess Smoothness and Sensitivity of State-Level Consumption?," *The Review of Economics and Statistics*, 02 2008, *90* (1), 65–80.

Mankiw, N.Gregory, "Hall's consumption hypothesis and durable goods," *Journal of Monetary Economics*, 1982, *10* (3), 417–425.

Mian, Atif and Amir Sufi, "Household Leverage and the Recession of 2007–09," *IMF Economic Review*, 2010, *58* (1), 74–117.

_ , Kamalesh Rao, and Amir Sufi, "Household Balance Sheets, Consumption, and the Economic Slump," *The Quarterly Journal of Economics*, 09 2013, *128* (4), 1687–1726.

Misra, Kanishka and Paolo Surico, "Consumption, Income Changes, and Heterogeneity: Evidence from Two Fiscal Stimulus Programs," *American Economic Journal: Macroeconomics*, October 2014, *6* (4), 84–106.

Parker, Jonathan A., Nicholas S. Souleles, David S. Johnson, and Robert McClelland, "Consumer Spending and the Economic Stimulus Payments of 2008," *The American Economic Review*, 2013, *103* (6), 2530–2553.

Zeldes, Stephen P., "Consumption and Liquidity Constraints: An Empirical Investigation," *Journal of Political Economy*, 1989, *97* (2), 305–346.

Table 1: Descriptive statistics: Labor income and income-support policies

Year	Mean	Std. Dev.	Min	10%	50%	90%	Max
Panel a) Labor income							
2015	88.42	42	20.79	47.41	81.2	133.8	329.42
2016	91.99	41.77	22.87	51.47	84.36	133.65	343.19
2017	93.63	42.52	23.08	51.91	85.86	135.76	353.86
2018	97.66	43.13	25.33	55.22	89.26	139.84	361.7
2019	101.43	43.17	28.94	58.39	93.06	143.59	362.54
2020	96.53	39.06	28.41	55.33	89.28	135.31	334.21
2021	105.31	41.98	31.06	62.64	98.06	149.61	361.04
Panel b) Income support policies 2020							
Benefits	59.87	7.87	31.71	49.48	59.84	69.47	86.21
Withdrawals	49.64	8.34	21.62	39.27	49.87	59.08	78.27
Emergency Family Income	10.23	2.61	1.76	6.94	10.08	13.69	18.34
Panel c) Income support policies 2021							
Benefits	46.55	9.35	22.44	36.5	45.91	57.47	93.42
Withdrawals	39.96	9.99	16.11	28.78	39.31	50.86	92.45
Emergency Family Income	6.58	2.25	0.97	4.27	6.14	9.7	13.78

Notes: Summary statistics of Labor Income, Withdrawals, and Emergency Family Income. Labor income represents annual labor income of all participants in the formal labor market. Withdrawals, Emergency Family Income, and Benefits represents annual withdrawals, Emergency Family Income, and the sum of the two of them of the policies benefits. All values are aggregated at the municipality level and expressed in real terms (Unidades de Fomento, an inflation adjusted index widely used in Chile to express nominal values in real terms).

Table 2: Descriptive statistics: Coverage of income-support policies as percentage of working age population

	Mean	SD	Min	P10	P50	P90	Max
Panel a) 2020							
Benef. of the two programs	90,74	11,18	48,96	75,3	92,33	102,96	115,37
Benef. Withdrawals	75,67	9,26	41,74	63,56	76,18	86,57	98,62
Benef. Emergency Family Income	38,11	10,16	7	24,92	38,28	51,19	65,83
Panel b) 2021							
Benef. of the two programs	89,51	9,82	46,53	77,28	91,11	100,36	112,19
Benef. Withdrawals	66,31	8,71	34,61	54,76	66,99	76,49	88,23
Benef. Emergency Family Income	49,6	9,92	9,57	35,7	50,76	60,1	77,12

Notes: This table presents summary statistics for the ratio of population that benefited from programs to working age population (the ratio could be larger than one as there could be more beneficiaries than working age population) by the support programs in our sample. ”Benef. Withdrawals” represent the share of people in a municipality that withdrew pension funds in 2020 (2021). ”Benef. Emergency Family Income” represent the share of people in a municipality that obtained Emergency Family Income in 2020 (2021). ”Benef. of the two programs” represent the share of people in a municipality that withdrew pension funds andor obtained Emergency Family Income in 2020 (2021).

Table 3: Descriptive statistics according to characteristics of income-support policies' beneficiaries

	Mean	SD	Min	P10	P50	P90	Max
Panel a) Monthly income (UF)							
Benefits	15,89	7,91	3,45	7,81	14,36	25,13	56,45
Withdrawals	17,55	8,36	4,54	8,97	15,91	27,34	58,83
Emergency Family Income	6,32	2,99	0,65	2,51	6,17	10,05	17,6
Panel b) Years of schooling							
Benefits	13,35	0,71	12,01	12,64	13,23	14,19	16,95
Withdrawals	13,49	0,72	12,08	12,77	13,39	14,39	16,98
Emergency Family Income	12,2	0,41	10,73	11,76	12,19	12,74	14,02
Panel c) Credit to labor income (leverage)							
Benefits	15,89	7,91	3,45	7,81	14,36	25,13	56,45
Withdrawals	17,55	8,36	4,54	8,97	15,91	27,34	58,83
Emergency Family Income	6,32	2,99	0,65	2,51	6,17	10,05	17,6
Panel d) Age (years)							
Benefits	41,52	0,97	37,13	40,29	41,58	42,65	44,5
Withdrawals	41,83	0,98	37,57	40,5	41,91	42,92	44,94
Emergency Family Income	38,55	1,2	33,9	37,13	38,65	39,85	42,36
Panel e) Sex (share of males)							
Benefits	64,42	4,81	49,65	58,48	64,2	71,08	77,06
Withdrawals	66,71	4,94	52,84	60,7	66,55	73,7	78,83
Emergency Family Income	43,5	7,04	26,34	35,18	42,61	52,96	63,9

Notes: Descriptive statistics. Weighted average of monthly labor income, years of schooling (people between 24-38 years old, 12 years is equivalent to complete high-school) across municipalities of, Age and sex (the share of males living in the municipality), credit relative to the municipality income. The weights are the individual shares of income received from the respective program (Withdrawals, Emergency Family Income, and Benefits which is the sum of two programs in 2020 and 2021) in total income received from that program All variables are computed as the average between 2015-2019. Unidades de Fomento (UF) is an inflation adjusted index widely used in Chile to express nominal values in real terms

Table 4: Determinants of goods consumption during the pandemic

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta income$	0.64***	0.27*	0.56***	0.63***	0.23*	0.29**	0.27*	0.26*
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
$lockdown$		−0.59***			−0.59***	−0.57***	−0.57***	−0.56***
		(0.05)			(0.05)	(0.05)	(0.05)	(0.05)
$step\,1$		−0.32***			−0.29***	−0.29***	−0.29***	−0.29***
		(0.02)			(0.02)	(0.02)	(0.02)	(0.02)
$step\,2$		−0.11***			−0.08***	−0.08***	−0.08***	−0.08***
		(0.02)			(0.02)	(0.02)	(0.02)	(0.02)
$withdrawal$			0.28***		0.22***		0.10*	
			(0.03)		(0.03)		(0.05)	
efi				0.21***		0.15***	0.10***	
				(0.02)		(0.02)	(0.03)	
$benefits$								0.20***
								(0.02)
$Observations$	3190	3190	3190	3190	3190	3190	3190	3190
R^2	0.35	0.43	0.36	0.37	0.44	0.44	0.44	0.45

Notes: Each column reports the beta coefficients from regressions $\Delta c_{r,m,t} = \beta_{inc}\Delta income_{r,m,t} + \beta_{sup} income\,programs_{r,m,t} + \beta'_{mob} mobility_{r,m,t} + \mu_{r,t} + \epsilon_{r,m,t}$, where the row's name indicates the variables included as regressors. $\Delta c_{r,m,t}$ is $\Delta \ln C_{r,m,t} - \overline{\Delta \ln C_{r,m}}$, where $C_{r,m,t}$ is consumption in region r, municipality m, month t, Δx_t is $x_t - x_{t-12}$, $\overline{\Delta \ln C_{r,m}}$ is the average growth rate in the pre-pandemic period. We perform the same demeaning procedure for labor income growth, $\Delta income_{r,m,t}$. $withdrawal_{r,m,t}$ is $\ln\left(1 + \frac{\text{Withdrawal}_{\text{r,m,t}}}{\text{INCOME}_{r,m,t-12}}\right)$; $efi_{r,m,t}$ is $\ln\left(1 + \frac{\text{EFI}_{\text{r,m,t}}}{\text{INCOME}_{r,m,t-12}}\right)$, and $benefits_{r,m,t}$ is $\ln\left(1 + \frac{\text{WITHDRAWAL}_{r,m,t} + \text{EFI}_{r,m,t}}{\text{INCOME}_{r,m,t-12}}\right)$; $\text{WITHDRAWAL}_{r,m,t}$ and $\text{EFI}_{r,m,t}$ are cumulative withdrawals from pensions funds and Emergency Family Income receipts up-to period t. $lockdown$, $step\,1$, and $step\,2$ are the percentage of days the municipality is under each type of constraint policy in a period. All regressions include region-time-fixed effects, $\mu_{r,t}$. The estimation period is May 2020 to March 2021.

Standard errors, robust to heteroscedasticity, in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5: Heterogeneity across goods

	(1) Durable goods stores	(2) Other stores
$\Delta income$	0.61**	0.15
	(0.20)	(0.11)
$lockdown$	−1.54***	−0.27***
	(0.10)	(0.04)
$step\,1$	−0.73***	−0.17***
	(0.04)	(0.02)
$step\,2$	−0.17***	−0.06***
	(0.03)	(0.02)
$benefits$	0.29***	0.18***
	(0.04)	(0.02)
$Observations$	2959	3168
R^2	0.52	0.32

Notes: Each column reports the beta coefficients from regressions $\Delta c^{type}_{r,m,t} = \beta^{type}_{inc}\Delta income_{r,m,t} + \beta^{type}_{ben} benefits_{r,m,t} + \beta^{type'}_{mob}\, mobility_{r,m,t} + \mu^{type}_{r,t} + \epsilon^{type}_{r,m,t}$, where $\Delta c^{type}_{r,m,t}$ is $\Delta \ln C^{type}_{r,m,t} - \overline{\Delta \ln C^{type}_{r,m}}$, where $C^{type}_{r,m,t}$ is consumption in stores that sell durable or non-durable goods in region r, municipality m, month t, Δx_t is $x_t - x_{t-12}$, $\overline{\Delta \ln C^{type}_{r,m}}$ is the average growth rate in the pre-pandemic period. We perform the same de-meaning procedure for labor income growth, $\Delta income_{r,m,t}$. $benefits_{r,m,t}$ is $\ln\left(1 + \frac{\text{WITHDRAWAL}_{r,m,t} + \text{EFI}_{r,m,t}}{\text{INCOME}_{r,m,t-12}}\right)$; $\text{WITHDRAWAL}_{r,m,t}$ and $\text{EFI}_{r,m,t}$ are cumulative withdrawals from pensions funds and Emergency Family Income receipts up-to period t. $lockdown$, $step\,1$, and $step\,2$ are the percentage of days the municipality is under each type of constraint policy in a period. All regressions include region-time-fixed effects, $\mu_{r,t}$. The estimation period is May 2020 to March 2021.
Standard errors, robust to heteroscedasticity, in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6: Heterogeneity across municipalities

	(1)	(2)	(3)
$\Delta income$	0.17	0.11	0.16
	(0.11)	(0.11)	(0.11)
$lockdown$	-0.57^{***}	-0.58^{***}	-0.57^{***}
	(0.05)	(0.05)	(0.05)
$step\,1$	-0.28^{***}	-0.27^{***}	-0.29^{***}
	(0.02)	(0.02)	(0.02)
$step\,2$	-0.06^{***}	-0.06^{***}	-0.07^{***}
	(0.02)	(0.02)	(0.02)
$benefits$	0.17^{***}	0.04	0.17^{***}
	(0.04)	(0.03)	(0.02)
$Income \times benefits$	0.01		
	(0.03)		
$Schooling \times benefits$		-0.06^{***}	
		(0.01)	
$Leverage \times benefits$			-0.20^{***}
			(0.05)
$Age \times benefits$	-0.01^{***}	-0.00	-0.01^{**}
	(0.00)	(0.00)	(0.00)
$Gender \times benefits$	0.46^{***}	0.10	0.30^{***}
	(0.07)	(0.08)	(0.08)
$Observations$	3190	3190	3190
R^2	0.46	0.47	0.46

Notes: Each column reports the beta coefficients from regressions $\Delta c_{r,m,t} = \beta_{inc}\Delta income_{r,m,t} + \beta_{ben} benefits_{r,m,t} + \beta'_{mob} mobility_{r,m,t} + \beta'_{hben}(h_{r,m} - h) \times benefits_{r,m,t} + \mu_{r,t} + \epsilon_{r,m,t}$ where the row's name indicates the variables included as regressors. Except for the interactions, all variables are defined as in Table 4. $h_{r,m}$ is vector that includes labor income, schooling, the ratio credit to labor income, age, and gender (the share of males living in the municipality); h is the cross-sectional average of $h_{r,m}$. We remove h from $h_{r,m}$. We omit the individual terms for the five dimensions, as they are redundant given the variable demeaning process. The estimation period is May 2020 to March 2021.

Standard errors, robust to heteroscedasticity, in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 7: Heterogeneity across municipalities: Durable and other goods stores

	Durables			Other stores		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta income$	0.30	0.18	0.23	0.08	0.03	0.07
	(0.20)	(0.20)	(0.20)	(0.11)	(0.11)	(0.11)
$lockdown$	-1.56^{***}	-1.58^{***}	-1.56^{***}	-0.28^{***}	-0.29^{***}	-0.28^{***}
	(0.10)	(0.10)	(0.10)	(0.04)	(0.04)	(0.04)
$step1$	-0.68^{***}	-0.68^{***}	-0.71^{***}	-0.16^{***}	-0.15^{***}	-0.17^{***}
	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)
$step2$	-0.13^{***}	-0.12^{***}	-0.15^{***}	-0.06^{***}	-0.05^{**}	-0.06^{***}
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
$benefits$	0.23^{*}	-0.01	0.24^{***}	0.13^{**}	0.04	0.16^{***}
	(0.09)	(0.06)	(0.04)	(0.04)	(0.03)	(0.02)
$Income \times benefits$	-0.00			-0.02		
	(0.06)			(0.03)		
$Schooling \times benefits$		-0.11^{***}			-0.06^{***}	
		(0.01)			(0.01)	
$Leverage \times benefits$			-0.63^{***}			-0.16^{**}
			(0.09)			(0.05)
$Age \times benefits$	-0.02^{***}	-0.00	-0.01	-0.01^{**}	0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
$Gender \times benefits$	1.36^{***}	0.69^{***}	0.88^{***}	0.34^{***}	-0.00	0.22^{**}
	(0.12)	(0.15)	(0.13)	(0.07)	(0.08)	(0.08)
$Observations$	2959	2959	2959	3168	3168	3168
R^2	0.53	0.54	0.54	0.33	0.35	0.33

Notes: Each column reports the beta coefficients from regressions $\Delta c^{type}_{r,m,t} = \beta^{type}_{inc}\Delta income_{r,m,t} + \beta^{type}_{ben} benefits_{r,m,t} + \beta^{type'}_{mob} mobility_{r,m,t} + \beta^{type'}_{hben}(h_{r,m} - h) \times benefits_{r,m,t} + \mu^{type}_{r,t} + \epsilon^{type}_{r,m,t}$ where $C^{type}_{r,m,t}$ is consumption in stores that sell durable or non-durable goods in region r, municipality m, month t and the row's name indicates the variables included as regressors. Except for the interactions all variables are defined as in Table 5. $h_{r,m}$ is vector that includes labor income, schooling, the ratio credit to labor income, age, and gender (the share of males living in the municipality); h is the cross-sectional average of $h_{r,m}$. We remove h from $h_{r,m}$. We omit the individual terms for the five dimensions, as they are redundant given the variable demeaning process. The estimation period is May 2020 to March 2021.
Standard errors, robust to heteroscedasticity, in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 8: Determinants of goods consumption, bi-annual growth rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta income$	0.71^{***}	0.47^{***}	0.57^{***}	0.61^{***}	0.35^{***}	0.40^{***}	0.37^{***}	0.36^{***}
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)	(0.09)	(0.08)
$lockdown$		-0.53^{***}			-0.54^{***}	-0.51^{***}	-0.52^{***}	-0.51^{***}
		(0.05)			(0.05)	(0.05)	(0.05)	(0.05)
$step\,1$		-0.26^{***}			-0.24^{***}	-0.24^{***}	-0.24^{***}	-0.24^{***}
		(0.02)			(0.02)	(0.02)	(0.02)	(0.02)
$step\,2$		-0.10^{***}			-0.07^{***}	-0.08^{***}	-0.07^{***}	-0.07^{***}
		(0.02)			(0.02)	(0.02)	(0.02)	(0.02)
$withdrawal$			0.28^{***}		0.26^{***}		0.11^{**}	
			(0.02)		(0.02)		(0.04)	
efi				0.19^{***}		0.17^{***}	0.11^{***}	
				(0.01)		(0.01)	(0.02)	
$benefits$								0.23^{***}
								(0.02)
$Observations$	5800	5800	5800	5800	5800	5800	5800	5800
R^2	0.32	0.36	0.34	0.34	0.37	0.37	0.38	0.38

Notes: Each column reports the beta coefficients from regressions $\Delta_{24}c_{r,m,t} = \beta_{inc}\Delta_{24}income_{r,m,t} + \beta_{sup}income\,programs_{r,m,t} + \beta'_{mob}mobility_{r,m,t} + \mu_{r,t} + \epsilon_{r,m,t}$, where the row's name indicates the variables included as regressors. $\Delta_{24}c_{r,m,t}$ is $\Delta_{24}\ln C_{r,m,t} - \overline{\Delta_{24}\ln C_{r,m}}$, where $C_{r,m,t}$ is consumption in region r, municipality m, month t, $\Delta_{24}x_t$ is $x_t - x_{t-24}$, $\overline{\Delta_{24}\ln C_{r,m}}$ is the average growth rate in the pre-pandemic period. We perform the same demeaning procedure for labor income growth, $\Delta_{24}income_{r,m,t}$. $withdrawal_{r,m,t}$ is $\ln\left(1+\frac{\mathrm{Withdrawal}_{r,m,t}}{\mathrm{INCOME}_{r,m,t-24}}\right)$; $efi_{r,m,t}$ is $\ln\left(1+\frac{\mathrm{EFI}_{r,m,t}}{\mathrm{INCOME}_{r,m,t-24}}\right)$, and $benefits_{r,m,t}$ is $\ln\left(1+\frac{\mathrm{WITHDRAWAL}_{r,m,t}+\mathrm{EFI}_{r,m,t}}{\mathrm{INCOME}_{r,m,t-24}}\right)$; $\mathrm{WITHDRAWAL}_{r,m,t}$ and $\mathrm{EFI}_{r,m,t}$ are cumulative withdrawals from pensions funds and Emergency Family Income receipts up-to period t. $lockdown$, $step\,1$, and $step\,2$ are the percentage of days the municipality is under each type of constraint policy in a period. All regressions include region-time-fixed effects, $\mu_{r,t}$. The estimation period is May 2020 to December 2021.

Standard errors, robust to heteroscedasticity, in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 9: Determinants of goods consumption relative to pre-pandemic

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta income$	0.57^{***}	0.37^{***}	0.48^{***}	0.52^{***}	0.30^{***}	0.34^{***}	0.31^{***}	0.31^{***}
	(0.09)	(0.08)	(0.08)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)
$lockdown$		-0.58^{***}			-0.58^{***}	-0.56^{***}	-0.57^{***}	-0.56^{***}
		(0.05)			(0.05)	(0.05)	(0.05)	(0.05)
$step\,1$		-0.28^{***}			-0.26^{***}	-0.26^{***}	-0.26^{***}	-0.25^{***}
		(0.02)			(0.02)	(0.02)	(0.02)	(0.02)
$step\,2$		-0.09^{***}			-0.07^{***}	-0.07^{***}	-0.07^{***}	-0.07^{***}
		(0.02)			(0.02)	(0.02)	(0.02)	(0.02)
$withdrawal$			0.27^{***}		0.25^{***}		0.14^{***}	
			(0.03)		(0.03)		(0.04)	
efi				0.17^{***}		0.15^{***}	0.08^{***}	
				(0.01)		(0.01)	(0.02)	
$benefits$								0.22^{***}
								(0.02)
Observations	5800	5800	5800	5800	5800	5800	5800	5800
R^2	0.3	0.34	0.31	0.31	0.35	0.35	0.35	0.35

Notes: Each column reports the beta coefficients from regressions $\Delta' c_{r,m,t} = \beta_{inc}\Delta' income_{r,m,t} + \beta_{sup} income\,programs_{r,m,t} + \beta'_{mob} mobility_{r,m,t} + \mu_{r,t} + \epsilon_{r,m,t}$, where the row's name indicates the variables included as regressors. $\Delta' c_{r,m,t}$ is $\Delta' \ln C_{r,m,t} - \overline{\Delta' \ln C_{r,m}}$, where $C_{r,m,t}$ is consumption in region r, municipality m, month t, $\Delta' x_t$ is $x_t - \tilde{x}$, $\tilde{x}$ is the average value of x on 2019. $\overline{\Delta' \ln C_{r,m}}$ is the average growth rate in the pre-pandemic period. We perform the same demeaning procedure for labor income growth, $\Delta' income_{r,m,t}$. $withdrawal_{r,m,t}$ is $\ln\left(1 + \frac{\mathrm{Withdrawal_{r,m,t}}}{\overline{\mathrm{INCOME}}_{r,m,2019}}\right)$; $efi_{r,m,t}$ is $\ln\left(1 + \frac{\mathrm{EFI_{r,m,t}}}{\overline{\mathrm{INCOME}}_{r,m,2019}}\right)$, and $benefits_{r,m,t}$ is $\ln\left(1 + \frac{\mathrm{WITHDRAWAL}_{r,m,t} + \mathrm{EFI}_{r,m,t}}{\overline{\mathrm{INCOME}}_{r,m,2019}}\right)$; $\mathrm{WITHDRAWAL}_{r,m,t}$ and $\mathrm{EFI}_{r,m,t}$ are cumulative withdrawals from pensions funds and Emergency Family Income receipts up-to period t. $lockdown$, $step\,1$, and $step\,2$ are the percentage of days the municipality is under each type of constraint policy in a period. All regressions include region-time-fixed effects, $\mu_{r,t}$. The estimation period is May 2020 to December 2021.
Standard errors, robust to heteroscedasticity, in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 10: Determinants of goods consumption excluding central municipalities

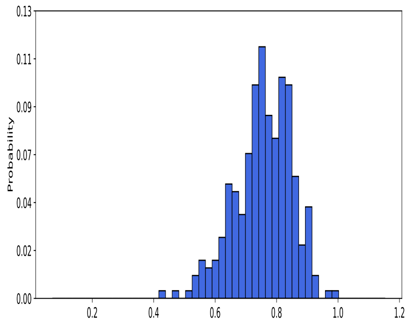
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta income$	0.52***	0.22*	0.48***	0.54***	0.20	0.25*	0.23*	0.22*
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
$lockdown$		−0.57***			−0.57***	−0.55***	−0.56***	−0.54***
		(0.05)			(0.05)	(0.05)	(0.05)	(0.05)
$step\,1$		−0.29***			−0.28***	−0.28***	−0.28***	−0.28***
		(0.02)			(0.02)	(0.02)	(0.02)	(0.02)
$step\,2$		−0.10***			−0.08***	−0.08***	−0.08***	−0.08***
		(0.02)			(0.02)	(0.02)	(0.02)	(0.02)
$withdrawal$			0.24***		0.19***		0.10*	
			(0.03)		(0.03)		(0.05)	
efi				0.18***		0.13***	0.08**	
				(0.02)		(0.02)	(0.03)	
$benefits$								0.18***
								(0.02)
$Observations$	3036	3036	3036	3036	3036	3036	3036	3036
R^2	0.34	0.42	0.36	0.36	0.43	0.43	0.43	0.43

Notes: We replicate the exercise of Table 4 but excluding central municipalities. We define central municipalities as the capital of each Chilean region. We drop a total of thirteen municipalities. The estimation period is May 2020 to March 2021.
Standard errors, robust to heteroscedasticity, in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

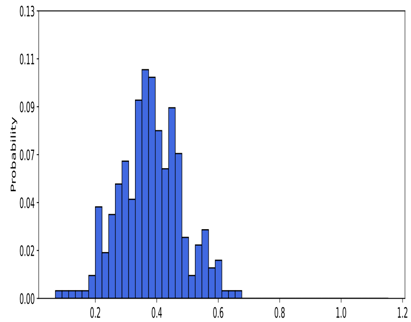
Figure 1: Coverage income-support policies

Year 2020

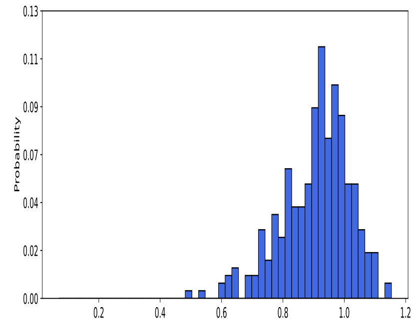
(a) withdrawals



(b) Emergency Family Income

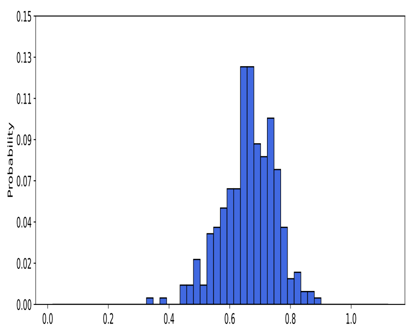


(c) Sum of income-support policies

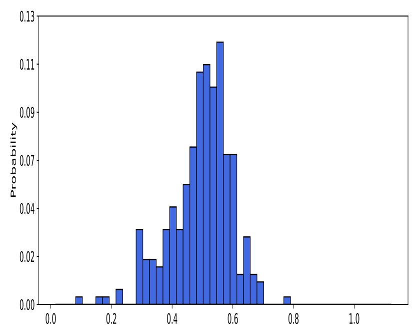


Year 2021

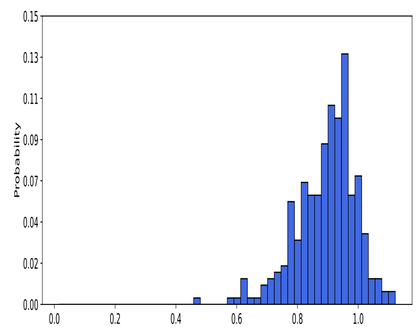
(d) Withdrawals



(e) Emergency Family Income



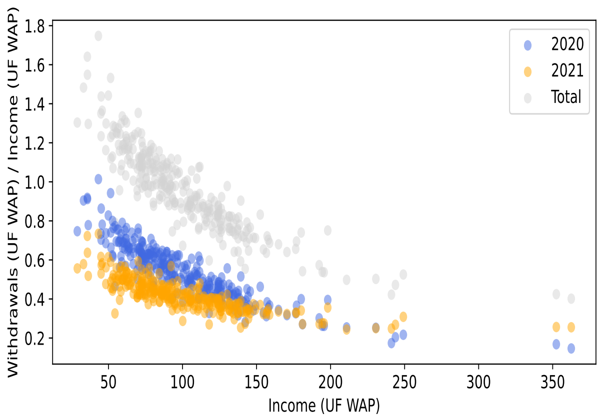
(f) Sum of income-support policies



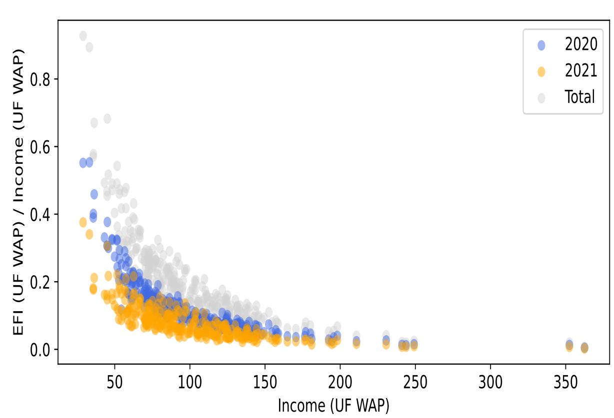
Notes: The figures present histograms for the ratio of population that benefited from the support programs to working age population in our sample. Withdrawals represent the share of people in a municipality that withdrew pension funds in 2020 (2021). Emergency Family Income represent the share of people in a municipality that obtained Emergency Family Income in 2020 (2021). Beneficiaries represent the share of people in a municipality that withdrew pension funds and/or obtained Emergency Family Income in 2020 (2021).

Figure 2: Income-support policies and income levels

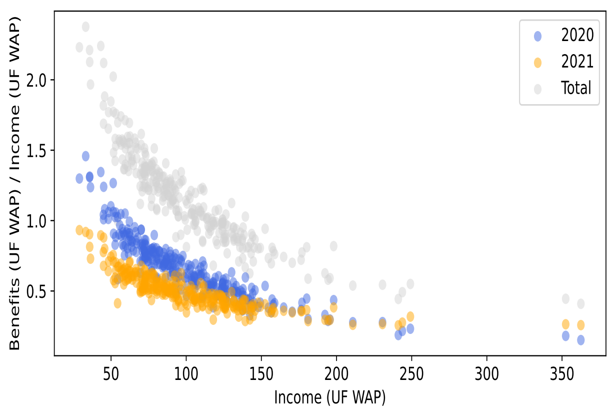
(a) Withdrawals



(b) Emergency Family Income



(c) Sum of income-support policies

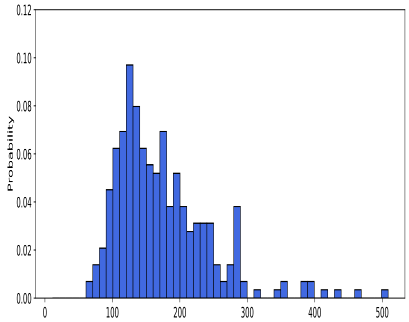


Notes: The scatterplot relates Withdrawals, Emergency Family Income, and the sum of the benefits as a share of labor income in 2019 (y-axis) relative to labor income in 2019 (x-axis). Oranges dots are pair of values in 2020, blue dots values in 2021, and grey dots the sum of 2020 and 2021.

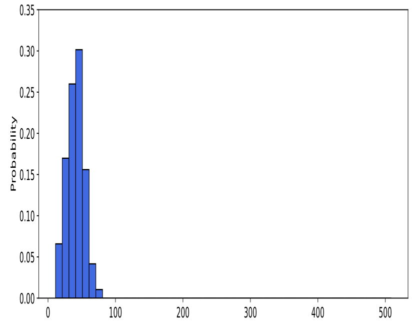
Figure 3: Histogram of the five interacting of variables weighted by policies.

Income

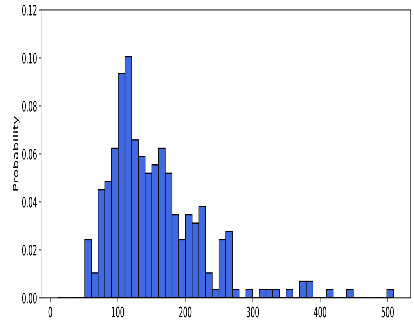
(a) Withdrawals



(b) Emergency Family Income

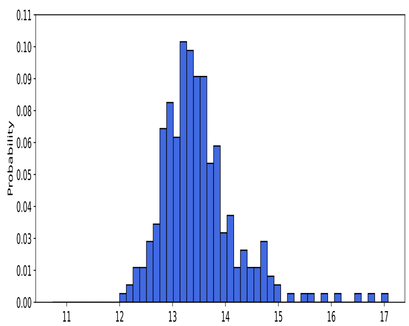


(c) Sum of income-support policies

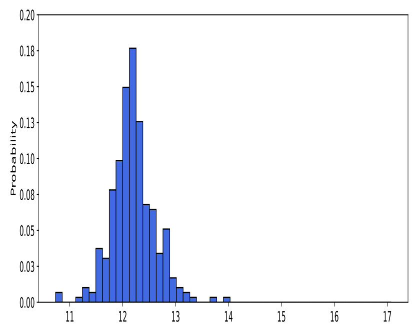


Schooling

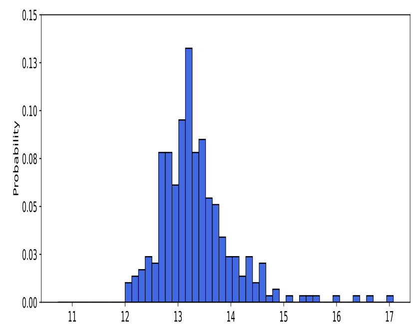
(d) Withdrawals



(e) Emergency Family Income

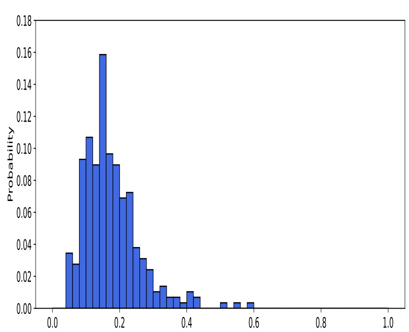


(f) Sum of income-support policies

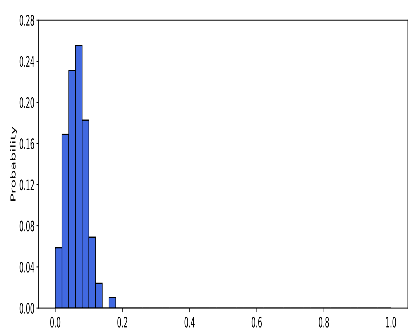


Credit to labor income (leverage)

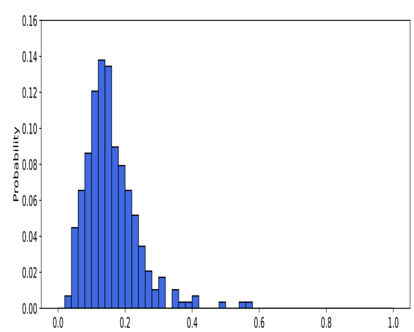
(g) Withdrawals



(h) Emergency Family Income

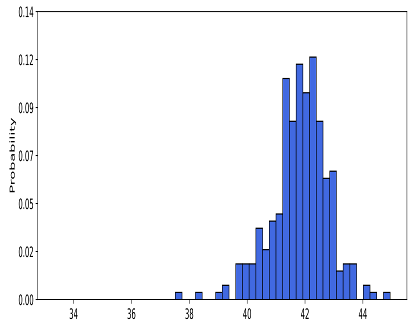


(i) Sum of income-support policies

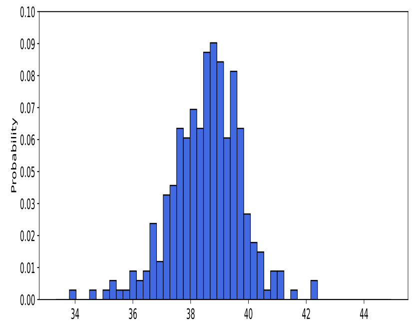


Age

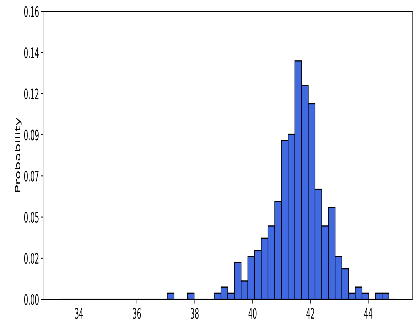
(j) Withdrawals



(k) Emergency Family Income

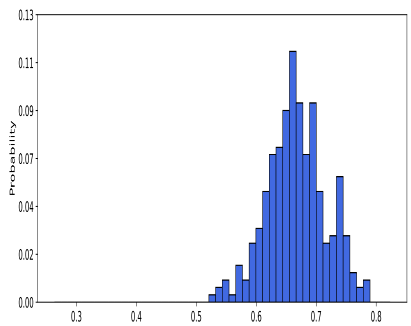


(l) Sum of income-support policies

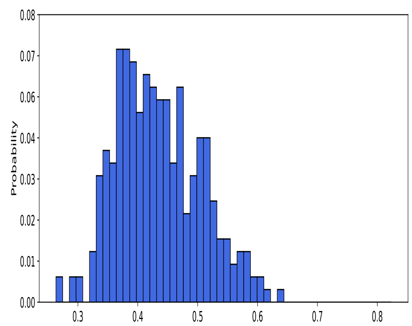


Gender

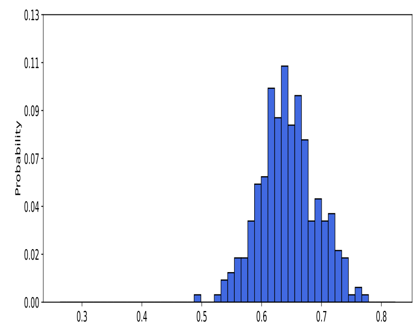
(m) Withdrawals



(n) Emergency Family Income



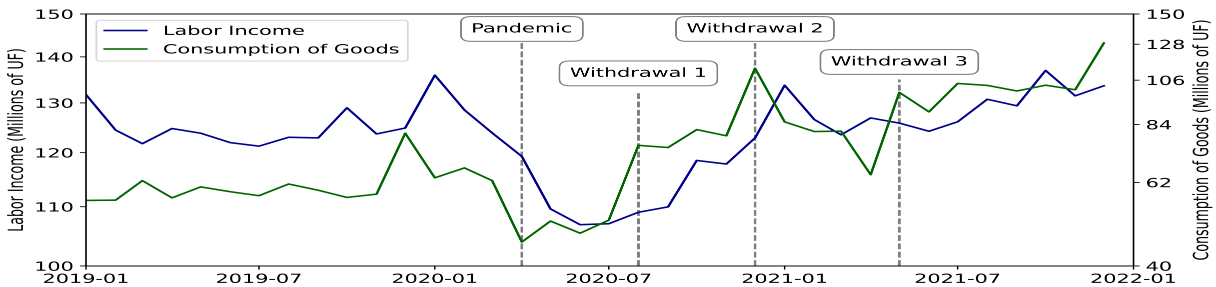
(o) Sum of income-support policies



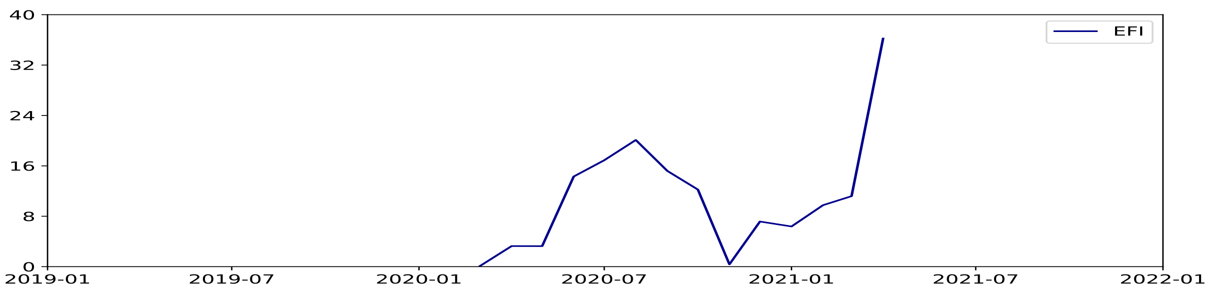
Notes: Histograms across municipalities of weighted average (by the size of the withdrawal, Emergency Family Income, and the sum the two programs in 2020 and 2021) of labor income, years of schooling (people between 24-38 years old, 12 years is equivalent to complete high-school), credit relative to the municipality income, age and gender (the share of males living in the municipality). All variables are computed as the average between 2015-2019.

Figure 4

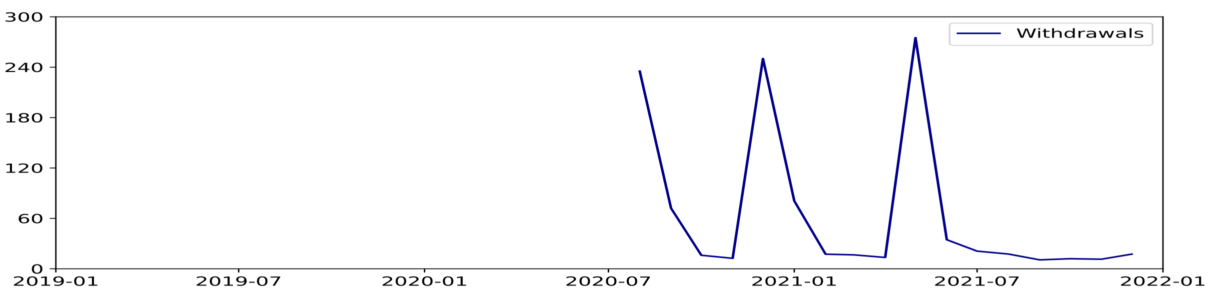
(a) Consumption and labor income



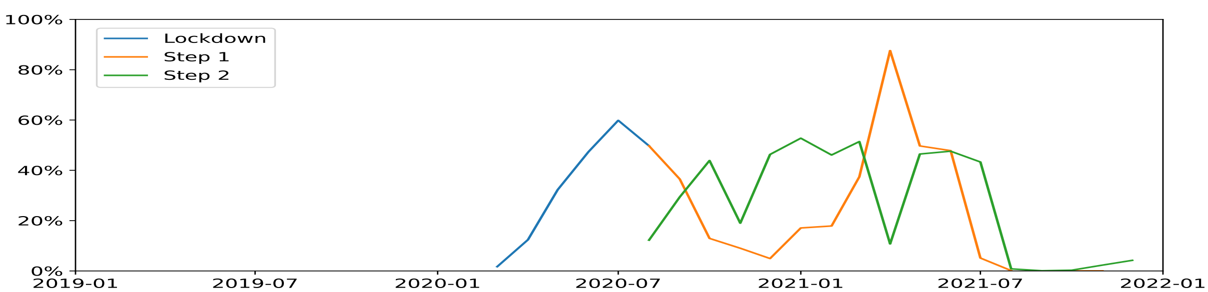
(b) Emergency Family Income



(c) Withdrawals



(d) Mobility constraints



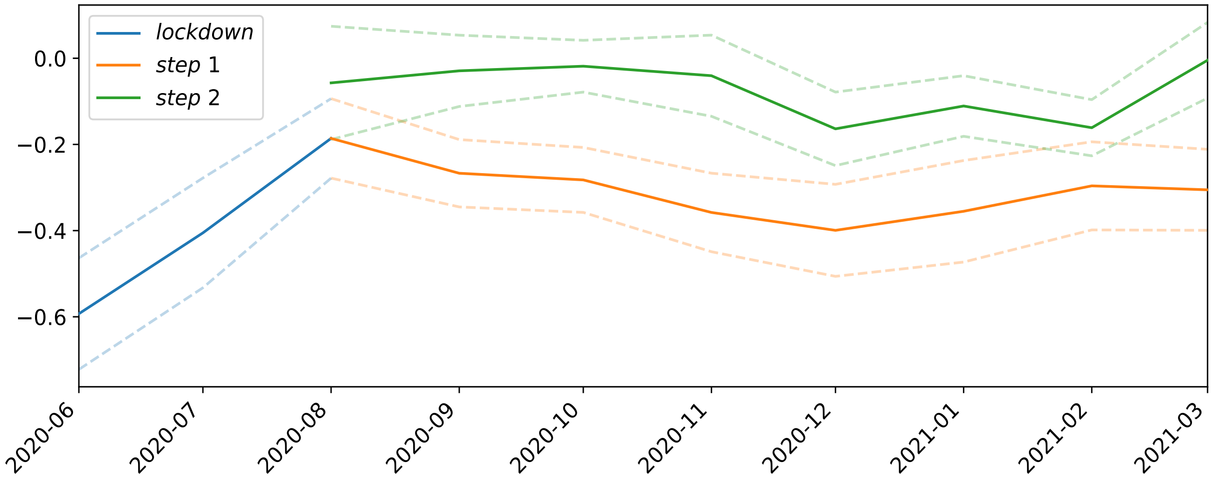
Notes: Figure 4a presents the evolution of the aggregate monthly labor income and consumption growth rates. Figures 4b and 4c presents the evolution of the monthly Emergency Family Income and withdrawals expressed in millions UF. Figure 4d presents the cross-municipality average of the percentage of days a municipality is under each mobility constraint is a month.

Figure 5: Consumption growth: cross-municipality dispersion over time

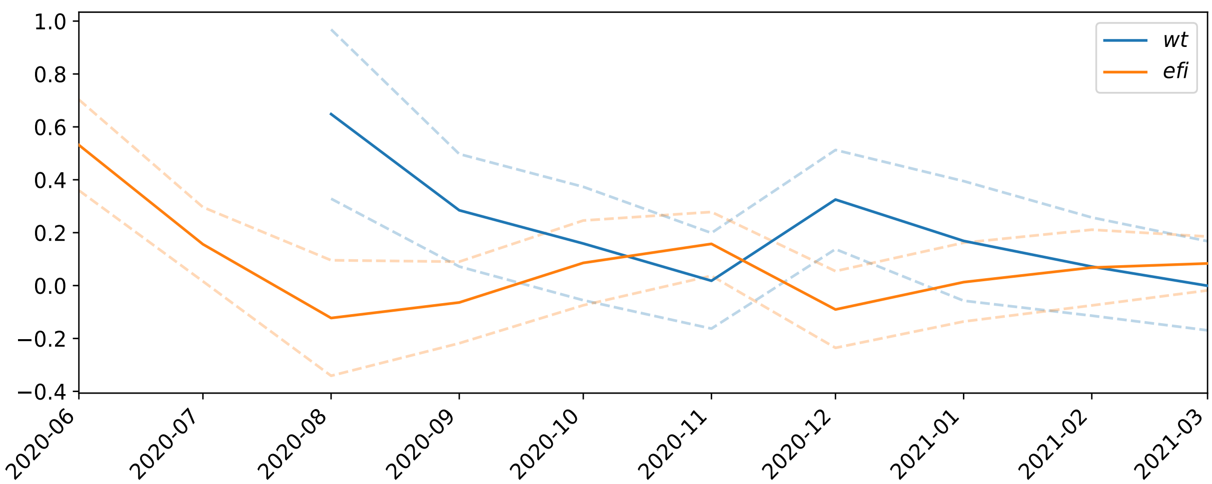
Notes: The figure presents the time-series evolution of the cross-municipality consumption growth rate. Each blue dot is the annual growth rate of consumption in a given municipality.

Figure 6: Impact of mobility constraints and income-support programs over time

(a) Mobility constraints



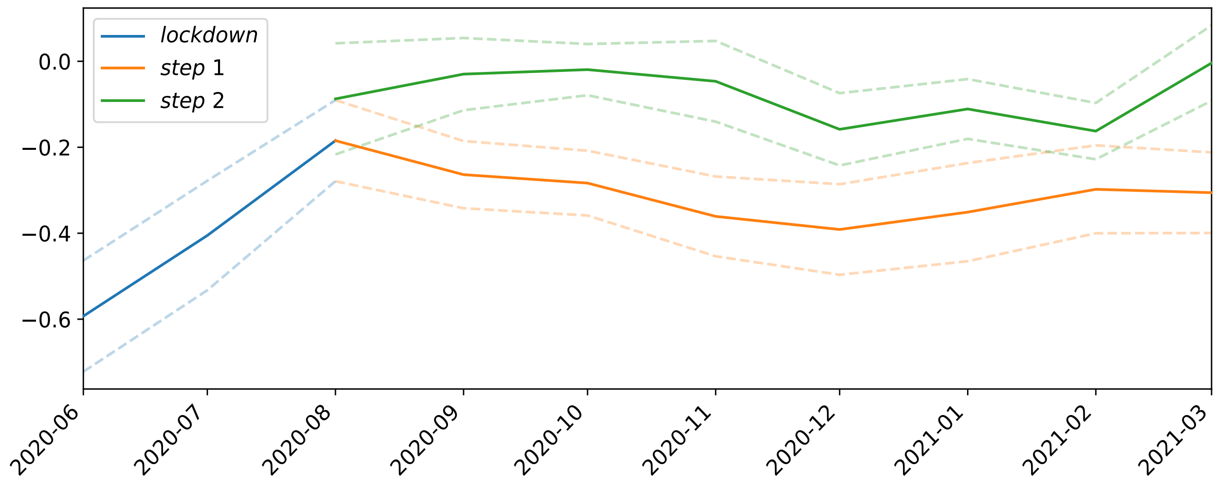
(b) Emergency Family Income and withdrawals



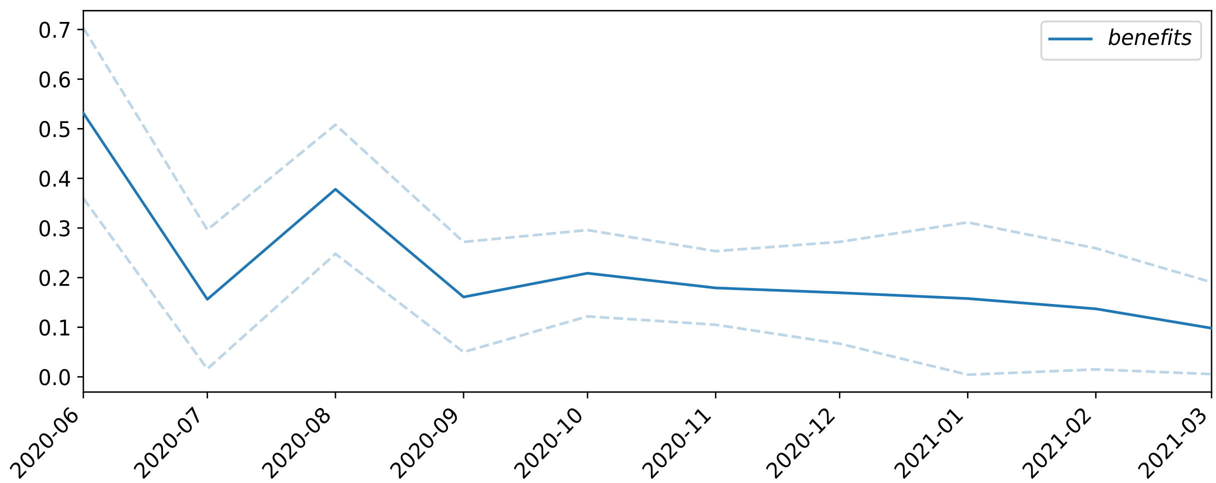
Notes: Figure 6a plot the coefficients $\beta'_{mob\,t}$ and Figure 6b plot $\beta_{efi\,t}$ and $\beta_{wt\,t}$ from estimating the regression $\Delta c_{r,m,t} = \beta_{inc\,t}\Delta income_{r,m,t} + \beta_{efi\,t} efi_{r,m,t} + \beta_{wt\,t} withdrawals_{r,m,t} + \beta'_{mob\,t} mobility_{r,m,t} + \mu_{r,t} + \epsilon_{r,m,t}$. $\Delta c_{r,m,t}$ is $\Delta \ln C_{r,m,t} - \overline{\Delta \ln C_{r,m}}$, where $C_{r,m,t}$ is consumption in region r, municipality m, month t, Δx_t is $x_t - x_{t-12}$, $\overline{\Delta \ln C_{r,m}}$ is the average growth rate in the pre-pandemic period. We perform the same demeaning procedure for labor income growth, $\Delta income_{r,m,t}$. $withdrawal_{r,m,t}$ is $\ln\left(1 + \frac{\text{Withdrawal}_{\text{r,m,t}}}{\text{INCOME}_{r,m,t-12}}\right)$; $efi_{r,m,t}$ is $\ln\left(1 + \frac{\text{EFI}_{\text{r,m,t}}}{\text{INCOME}_{r,m,t-12}}\right)$; $\text{WITHDRAWAL}_{r,m,t}$ and $\text{EFI}_{r,m,t}$ are cumulative withdrawals from pensions funds and Emergency Family Income receipts up-to period t. $lockdown$, $step\,1$, and $step\,2$ are the percentage of days the municipality is under each type of constraint policy in a period. The regression includes region-time-fixed effects, $\mu_{r,t}$.

Figure 7: Impact of mobility constraints and the sum of Emergency Family Income and withdrawals

(a) Mobility constraints

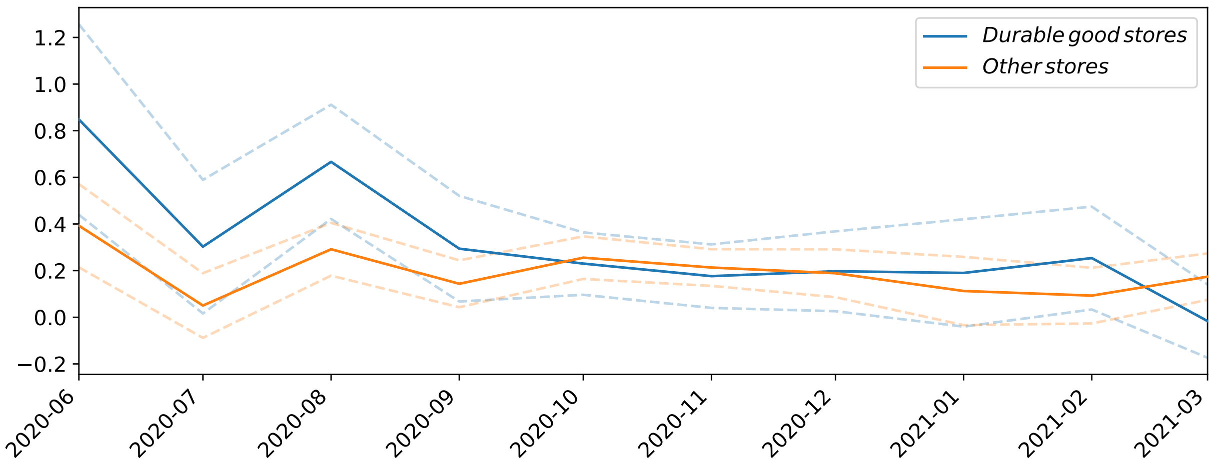


(b) Benefits



Notes: Figure 7a displays the coefficients $\beta'_{mob\,t}$ and Figure 7b presents the coefficients $\beta_{ben\,t}$ from estimating month over month the regression $\Delta c_{r,m,t} = \beta_{inc\,t} \Delta income_{r,m,t} + \beta_{ben\,t} benefits_{r,m,t} + \beta'_{mob\,t} mobility_{r,m,t} + \mu_{r,t} + \epsilon_{r,m,t}$. $\Delta c_{r,m,t}$ is $\Delta \ln C_{r,m,t} - \overline{\Delta \ln C_{r,m}}$, where $C_{r,m,t}$ is consumption in region r, municipality m, month t, Δx_t is $x_t - x_{t-12}$, $\overline{\Delta \ln C_{r,m}}$ is the average growth rate in the pre-pandemic period. We perform the same demeaning procedure for labor income growth, $\Delta income_{r,m,t}$. $benefits_{r,m,t}$ is $\ln\left(1 + \frac{\text{WITHDRAWAL}_{r,m,t} + \text{EFI}_{r,m,t}}{\text{INCOME}_{r,m,t-12}}\right)$; $\text{WITHDRAWAL}_{r,m,t}$ and $\text{EFI}_{r,m,t}$ are cumulative withdrawals from pensions funds and Emergency Family Income receipts up-to period t. $lockdown$, $step\,1$, and $step\,2$ are the percentage of days the municipality is under each type of constraint policy in a period.

Figure 8: Impact of heterogeneity across type of goods

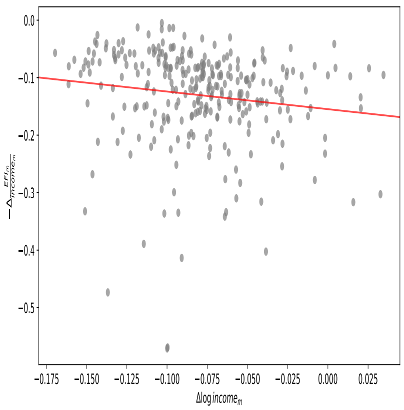


Notes: Figure 8 reports the coefficients β^{type}_{bent} from estimating the regressions $\Delta c^{type}_{r,m,t} = \beta^{type}_{inct}\Delta income_{r,m,t} + \beta^{type}_{bent} benefits_{r,m,t} + \beta^{type'}_{mobt} mobility_{r,m,t} + \mu^{type}_{r,t} + \epsilon^{type}_{r,m,t}$ for stores that sell durable or durable and non-durable goods, $type$, in region r, municipality m, month t, where $\Delta c^{type}_{r,m,t}$ is $\Delta \ln C^{type}_{r,m,t} - \overline{\Delta \ln C^{type}_{r,m}}$, $C^{type}_{r,m,t}$ is consumption, Δx_t is $x_t - x_{t-12}$, $\overline{\Delta \ln C^{type}_{r,m}}$ is the average growth rate in the pre-pandemic period. We perform the same demeaning procedure for labor income growth, $\Delta income_{r,m,t}$. $benefits_{r,m,t}$ is $\ln\left(1 + \frac{\text{WITHDRAWAL}_{r,m,t} + \text{EFI}_{r,m,t}}{\text{INCOME}_{r,m,t-12}}\right)$; $\text{WITHDRAWAL}_{r,m,t}$ and $\text{EFI}_{r,m,t}$ are cumulative withdrawals from pensions funds and Emergency Family Income receipts up-to period t. $lockdown$, $step\,1$, and $step\,2$ are the percentage of days the municipality is under each type of constraint policy in a period.

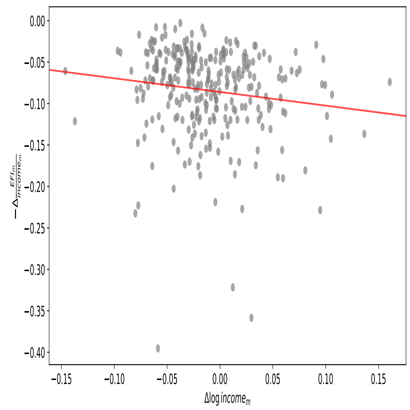
Figure 9: Income-support policies and income smoothing

Withdrawals (changed sign) v/s income

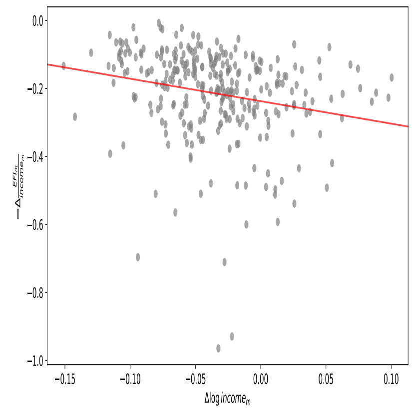
(a) 2020 vs. 2019



(b) 2021 vs. 2019

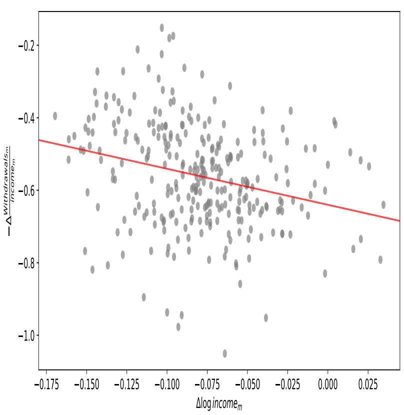


(c) Sum 2020-2021 vs. 2019

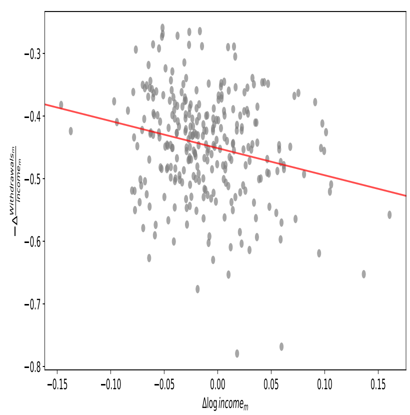


Emergency Family Income (changed sign) v/s income

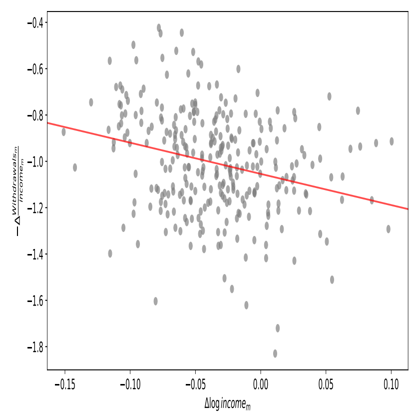
(d) 2020 vs. 2019



(e) 2021 vs. 2019



(f) Sum 2020-2021 vs. 2019



Notes: Figures 9a to 9c y-axis is the ratio of negative annual Emergency Family Income in 2020 (2021, and the sum of 2020 and 2021) to Labor income in 2019; Figures 9d to 9f y-axis is the ratio of negative annual Withdrawals in 2020 (2021, and the sum of 2020 and 2021) to Labor income in 2019; x-axis is growth rate of annual Labor income in 2020 (2021, and the sum of 2020 and 2021) with respect to 2019.

Appendices

A Data cleaning

We implement the following cleaning procedure to reduce unwanted noise that deteriorates the quality of the empirical analysis performed in this paper. The raw data considers information from 357 municipalities.

The procedure begins by manually removing eight municipalities because of their extreme geographical locations and one additional municipality from the wealth distribution standpoint.

After manually removing such municipalities, we control for missing values and outliers. We begin by calculating the demeaned year-over-year difference of $\log(sales_G)$ and $\log(income)$ with following expression

$$\Delta x_{c,ym} = \left(\log x_{c,ym} - \log x_{c,y-1m}\right) - \frac{1}{4}\sum_{y'=2016}^{2019}\left(\log x_{c,y'm} - \log x_{c,y'-1m}\right),$$

where x can take the values $sales_G$ or $income$, and the indices c, y, and m represent the municipality, year, and month respectively.

The data is split between the pre-pandemic period (between 2015 and 2020-03) and pandemic period (2020-04 onward), and we define an outlier as any value outside the bounds defined in table 11. It is important to remark that we remove the complete data from the municipality if a single value is missing or it is outside the defined bounds. The execution of the described procedure leaves a dataset with 290 municipalities.

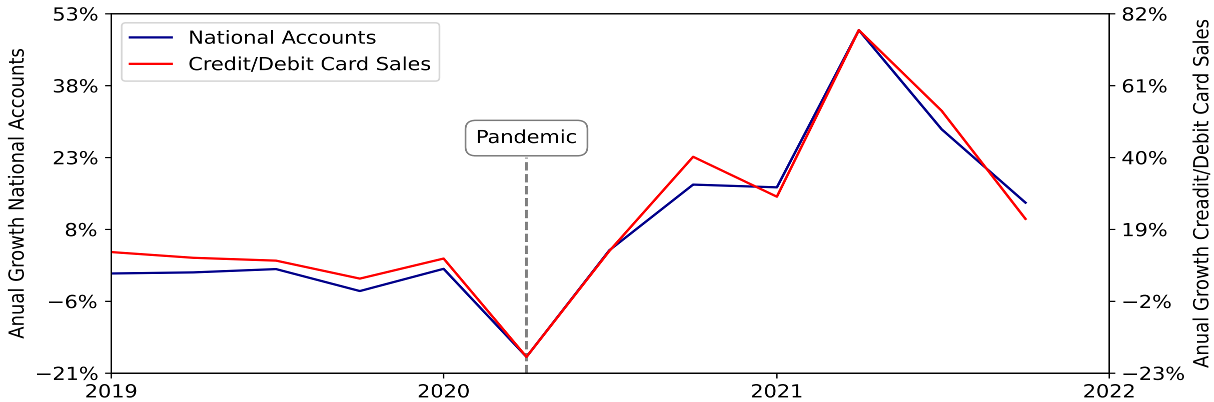
Table 11: Outliers bounds

	pre-pandemic	pandemic
sales	[-1.50, 1.50]	[-1.50, 1.50]
income	[-0.25, 0.25]	[-0.30, 0.30]

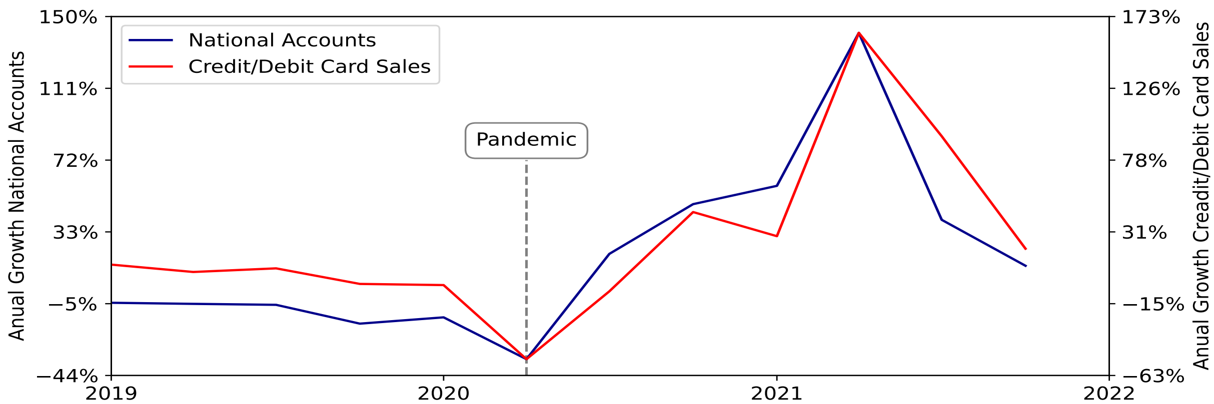
B National accounts comparison

Figure 10: Consumption national accounts and point of sales debit and credit cards

(a) Goods consumption



(b) Durable consumption



Notes: The blue line is the annual growth of quarterly goods and durable consumption, Figures 10a and 10b. The red line represent the same object for the quarterly total and durable retailers point of debit and credit card data.

Table 12: Comparison of point of sales debit and credit cards respect to national accounts consumption

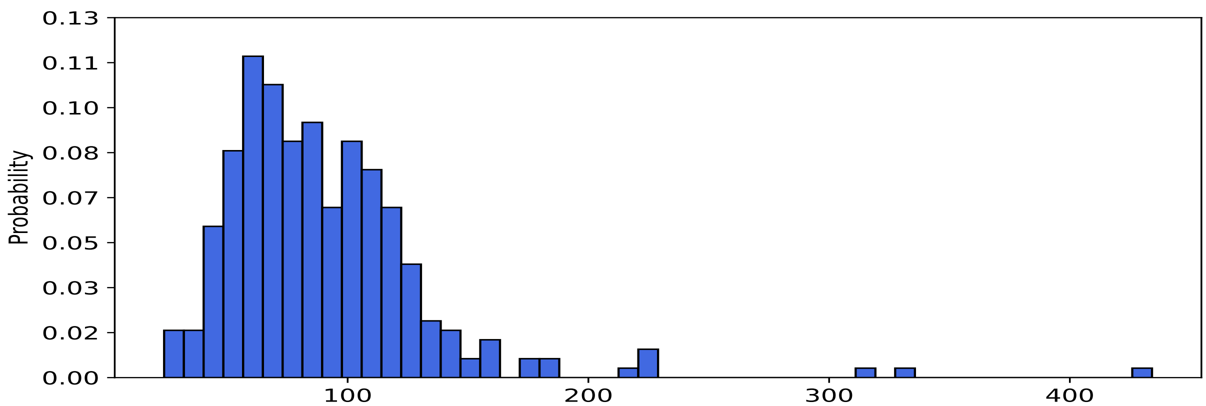
	Goods	Durable stores
Average share (2019-2021)	0.369	0.697
Correlation (2019-2021)	0.983	0.888

Notes: Time series average (first row) and correlation (second row) between the ratio and growth of point of sales debit and credit cards and Chilean national accounts goods and durable stores consumption.

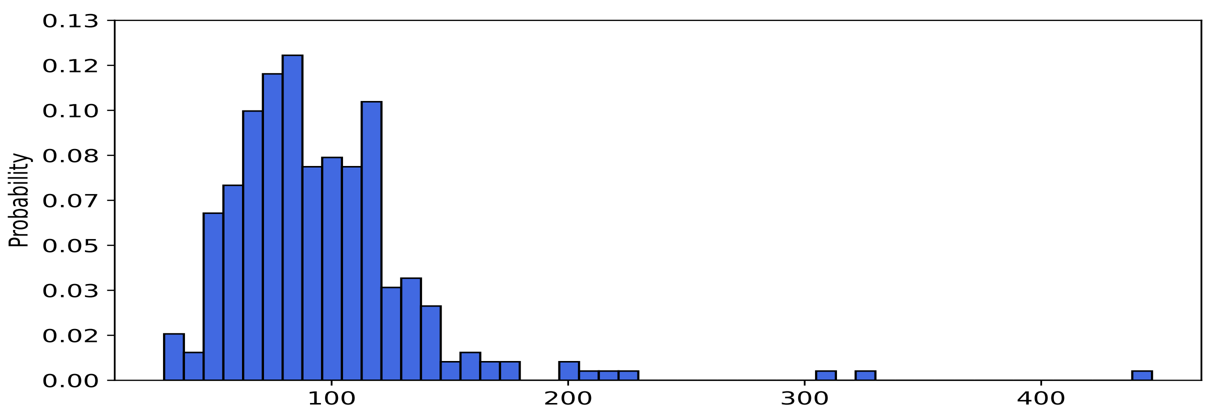
C Income distribution

Figure 11: Histogram: Labor income to working age population (2015-2019 vs 2020-2021)

(a) Labor income to working age population 2015-2019



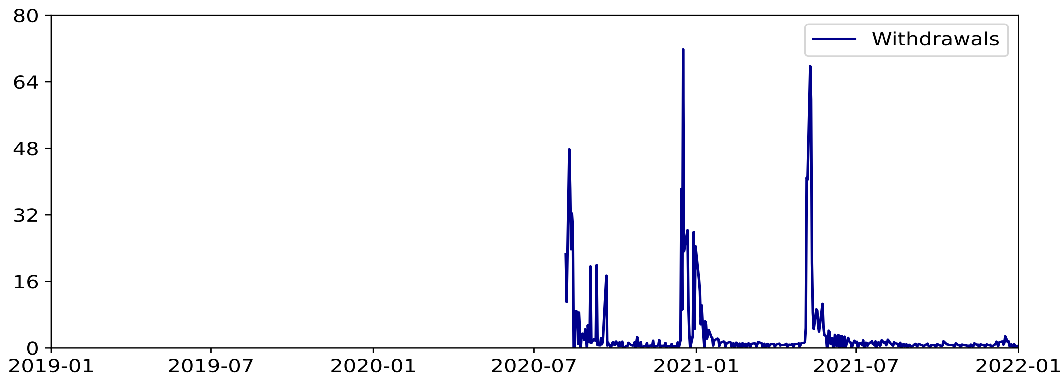
(b) Labor income to working age population 2020-2021



Notes: Histograms of labor earnings at the annual-municipality level expressed in real terms (Unidades de Fomento, an inflation adjusted index widely used in Chile to express nominal values in real terms) average 2015-2019, panel (a), and average 2020-2021, panel (b).

D Daily withdrawals

Figure 12: Withdrawals daily evolution



Notes: The figure reports the size of the daily withdrawal. Each spike is located at the beginning of the approval of new withdrawal law.

E Correlation matrix

Table 13: Correlation matrix main variables

	$\Delta sales$	$\Delta income$	$lockdown$	$step\ 1$	$step\ 2$	wt	efi	$benefits$
$\Delta sales$	1.000							
$\Delta income$	0.309	1.000						
$lockdown$	-0.442	-0.346	1.000					
$step\ 1$	-0.120	0.030	-0.113	1.000				
$step\ 2$	0.075	0.196	-0.161	0.038	1.000			
wt	0.444	0.541	-0.402	0.243	0.400	1.000		
efi	0.412	0.399	-0.304	0.158	0.196	0.749	1.000	
$benefits$	0.463	0.536	-0.411	0.233	0.376	0.985	0.837	1.000

Notes: The table shows how the variables entering the regressions in Table 4 correlate across 290 Chilean municipalities over the estimation period May 2020 - March 2021.

Table 14: Correlation matrix interaction terms

	$Income \times benefits$	$Schooling \times benefits$	$Leverage \times benefits$	$Age \times benefits$	$Sex \times benefits$
$Income \times benefits$	1.000				
$Schooling \times benefits$	0.719	1.000			
$Leverage \times benefits$	0.583	0.720	1.000		
$Age \times benefits$	0.461	0.449	0.278	1.000	
$Gender \times benefits$	-0.086	-0.392	-0.454	0.219	1.000

Notes: The table shows how the variables entering the regressions in Table 6 over the estimation sample.

F Emergency Family Income payments

Table 15: Emergency Family Income payments (Chilean pesos)

Household members	First	Second-sixth
1	65000	100000
2	130000	200000
3	195000	300000
4	260000	400000
5	304000	467000
6	345000	531000
7	385000	592000
8	422000	649000
9	459000	705000
10 or more	494000	759000

Notes: Emergency Family Income payment scheme according to the number of households members and round of payment. For further details, see Law 21,230.

Disclaimers:

The views expressed are those of the authors and do not necessarily represent the views of the Central Bank of Chile (CBC), International Monetary Fund, World Bank or their board members.
This study was developed within the scope of the research agenda conducted by the CBC in economic and financial affairs of its competence. The CBC has access to anonymized information from various public and private entities, by virtue of collaboration agreements signed with these institutions. The authors have a non-disclosure agreement with the CBC.
To secure the privacy of workers and firms, the CBC mandates that the development, extraction and publication of the results should not allow the identification, directly or indirectly, of natural or legal persons. Officials of the Central Bank of Chile processed the disaggregated data. All the analysis was implemented by the authors and did not involve nor compromise the IRS, Aduanas, and AFC.
The information contained in the databases of the Chilean IRS is of a tax nature originating in self-declarations of taxpayers presented to the Service; therefore, the veracity of the data is not the responsibility of the Service.
At the time of preparing this manuscript, Emiliano Luttini was employed by the CBC.