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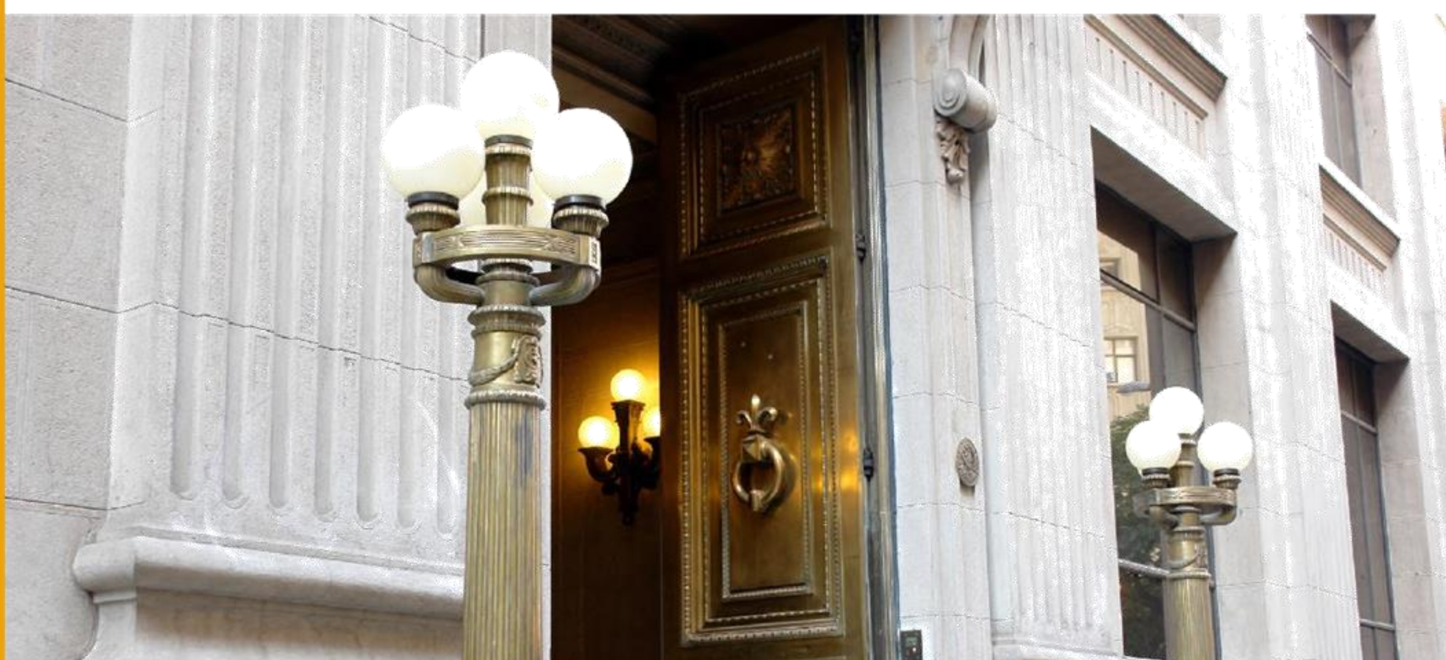

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Abstract

This work studies the impact of the Social Explosion and Covid crises on the household sector in Chile. The Social Explosion in October of 2019 represented a mass protest, much larger than similar events in other nations such as the Yellow Jackets. Using delinquency models calibrated with survey data, I show that household debt risk increased substantially after the Social Explosion across all income backgrounds, but fell slightly with the Covid pandemic due to the public policies implemented. The expansion of the public support policies in August of 2020 decreased the debt risk to levels similar to before the two crises.

Resumen

Este trabajo estudia el impacto del Estallido Social y de la pandemia Covid en los hogares en Chile. El Estallido Social de octubre de 2019 representó un protesto masivo, muy mayor que eventos similares en otros países como los Chalecos Amarillos. Utilizando modelos de morosidad de deuda calibrados con datos de encuestas, muestro que el riesgo de deuda de los hogares después del Estallido Social creció sustancialmente en todos los estratos de ingreso, pero bajó un poco con las políticas públicas implementadas después del inicio de la pandemia. La expansión de los mitigadores de políticas publicas en agosto de 2020 disminuyó el riesgo de la deuda de hogares a niveles similares al observado previamente a ambas las crisis.

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1 Introduction

Chile faced two significant macroeconomic shocks in the last quarter of 2019 and during 2020. The first event in October 18 of 2019 was the "Social Explosion", in which massive political protests motivated by social demands disrupted transportation in significant parts of the country and affected several businesses, particularly the retail sector and construction. The "Social Explosion" represented a shock entirely from a domestic origin and it had a large impact, with deseasonalized GDP volume falling -2.4% in the fourth quarter of 2019 relative to the same quarter in the previous year. Furthermore, after the "Social Explosion" the GDP growth forecasts for 2020 and 2021 were revised from a range of 2.75%-3.5% in 2020 and 3%-4% in 2021 to ranges of just 0.5%-1.5% and 2.5-3.5% (Central Bank of Chile 2020), respectively[1]. This domestic crisis was large relative to other social and political crises in other nations. For instance, the French yellow jackets movement in 2018 implied a loss of only 0.1% of GDP, while a study of 183 countries by Bernal-Verdugo, Furceri and Guillaume (2013) found that disruptions such as strikes and protests implied a fall between 0.3% to 0.6% of annual GDP in the short-run. The second shock was induced by the Covid-19 pandemic, which had both a global component (corresponding to the world-wide drop in demand) and a domestic component (with a National Emergency having been decreed on March 16 and several counties entering a forced lockdown on March 26 of 2020). By March of 2020 the GDP growth forecast for 2020 was revised downwards to a range of -1.5% to -2.5%, implying a loss of 2% to 3% in annual GDP growth relative to the forecasts in the previous quarter (Central Bank of Chile 2020). Relative to the same period in the previous year, GDP fell by 14% and 10.3% in the second and third quarters of 2020, with the annual GDP falling 5.8% in 2020.

This article provides an estimate of the impact of these twin shocks on the households' debt risk. Market perceptions from the Survey of Loan Officers in Chile after October of 2019 showed a much weaker outlook for household debt than for any industrial sector[2] (Central Bank of Chile 2020). As a developing economy, Chile has a significant amount of socioeconomic inequality (Madeira 2019a,

[1] These estimates imply that the "Social Explosion" in Chile represented a cost of 0.6% of annual GDP in 2019, plus a forecasted annual GDP cost around 2% in 2020 and 0.5% in 2021.

[2] In particular, more than 75% of the sample answered a "weaker" outlook for both consumer and mortgage loans demand. Also around 45% and 10% of the sample saw more "restrictive" conditions for consumer and mortgage loans supply, respectively (Central Bank of Chile 2020).

2019b) and a large fraction of informal workers with no access to official unemployment insurance benefits. For this reason, it is important to analyze the policy measures undertaken by the Chilean government and the heterogeneity of its impact across families.

To estimate the impact of the crises I use the Chilean Household Finance Survey (*Encuesta Financiera de Hogares*, in Spanish, from hence on, EFH). First, I estimate a delinquency model for whether loans of different types are in arrears for 3 months or more. The model is a partial equilibrium framework, which considers that the debts of households are already assigned and that labor market shocks impact the households, but the household delinquency does not feedback into the economy. The delinquency models account for several risk factors, including demographics (age, education, region and household size), unemployment risk, income, plus loan liquidity and financial solvency. A baseline scenario for the economic state on September of 2019 is specified, then updated according to the labor market statistics of similar worker types in the monthly Chilean Employment Survey to account for the heterogeneous unemployment flows, job quality loss and wage volatility that happened in the last quarter of 2019 and during 2020. Finally, I show the counterfactual stress test scenarios of debt risk with and without the government measures taken to support the households during the Covid crisis in Chile (Central Bank of Chile 2020), including a job retention program (OECD 2020), income bonus, a pension policy withdrawal, plus the deferral of taxes, loan payments and utilities. The results show that the Social Explosion increased household debt risk from 2.7% to 4.5%, while the Covid crisis and the associated policies actually decreased household debt risk slightly. The support policies were particularly effective after August, with the delinquency risk quickly dropping to 2.8% until the end of the year, a value similar to the ones before the crises.

This work is closest to microeconomic studies of household debt (Ampudia et al. 2016, Meriküll and Rõõm 2020) and policy studies of social reforms (Fonseca and Sopraseuth 2019). Fonseca and Sopraseuth (2019) use a structural model combined with wealth and employment surveys to estimate the impact of a social security reform in France and its implications for inequality. Similar to our study, Meriküll and Rõõm 2020 use a reduced-form model combined with administrative records and survey data on demographics, assets, income and consumption, to estimate the household debt risk. Our study makes a more granular estimate of the unemployment and income risks across a wide range of worker types using information from employment surveys, which is fundamental to evaluate the debt risk in an emerging economy like Chile where non-banking loans (Madeira

2018) and informal work (Madeira 2015a, Central Bank of Chile 2020) are prevalent among a significant share of the low income debtors. This granular measurement of unemployment risks is also particularly relevant in macroeconomic episodes with a strong reallocation component such as the Social Explosion and the Covid pandemic (Barrero et al. 2020). Furthermore, we also explicitly consider the heterogeneous propensity to default across distinct unsecured loan types. This study is also related to a growing literature on how surveys inform about the financial problems faced by families (Fortin 2019), especially in developing countries where non-bank lending is relevant and there is a significant share of informal employment. Household finance surveys, such as the Household Finance Consumption Survey in Europe or the Survey of Consumer Finances in the US, are increasingly used to study families' decisions on savings, investments and borrowing (Christelis et al. 2013, Christelis et al. 2017, Le Blanc et al. 2015, Bover et al. 2016). Finally, this study is also related to the recent studies of the effects of the Covid pandemic (Guerrieri et al. 2020). Our study adds to this literature by using detailed microeconomic data to show the heterogeneous impact of this crisis in Chile and how it interacted with an ongoing social-political crisis.

This work is organized as follows. Section 2 shows the indebtedness of the Chilean households and the delinquency models. Section 3 describes the two crises' impact on the economy and the different policy measures implement during the pandemic. Section 4 explains the stress test modelling approach. Section 5 summarizes the results, while section 6 concludes.

2 Data description and delinquency models

2.1 Income, debts and assets in the Chilean Household Finance Survey

The Chilean Household Finance Survey (EFH) is a cross-sectional survey that covered a total of 21,319 urban households over the period 2007 until 2017 (waves 2007, 2008, 2009, 2010, 2011, 2014 and 2017). This survey has detailed measures of the household members' demographics, income, assets (financial portfolio, vehicles and real estate) and debts, including mortgage, educational, auto, retail and banking consumer loans. In order to cover debts exhaustively, the survey elicits the loan terms (debt service, loan amount, maturity) for the 4 main loans in each category of debt. Households also report whether they applied for any loans in the previous year, whether any

Table 1: Income, demographics and loan motivations of the Chilean borrowers

Borrower type:	College ed. (% of households)[a]	Age[a] (years) Mean	$\ln(P_{i.t})$ P25	P50	P75	Households with consumer debt (%)	Motivated to "Pay other debts" (% of consumer debt)	Rejected loan applications (% of households)
Any debt	36.6	46.4	13.8	14.2	14.7	84.8	12.9	2.9
Consumer	35.6	45.9	13.7	14.2	14.7	100	12.9	3.1
Mortgage	44.1	47.1	14.0	14.5	15.0	68.5	8.6	2.8
Consumer and Mortgage	45.5	45.9	14.0	14.5	15.1	100	13.4	3.1
Borrowers By Income Strata:								
Strata 1 (pc 1-50)	14.6	49.5	13.4	13.6	13.8	86.4	9.5	2.8
Strata 2 (pc 51-80)	29.4	44.7	14.0	14.2	14.4	86.0	8.6	3.7
Strata 3 (pc 81-100)	65.2	44.5	14.7	15.0	15.5	81.2	13.6	2.1

All the values are in percentage points. except for the log permanent income (monthly): $\ln(P_{i.t})$.
a) College education and age correspond to the household head (the member of highest income).
EFH (2017). All values use household weights (not adjusted for the size of the household debt).

loan application was rejected, and the motives behind their consumer loan contracts. This section summarizes the borrower profiles in Chile using the 4,549 households in the 2017 EFH wave.

The EFH survey has limited data on income volatility and unemployment, because it is a cross-sectional survey and therefore it only measures self-reported unemployment at the month of the survey. For this reason I use the unemployment risks of the EFH workers based on the mean statistics for workers with similar characteristics from the Chilean Employment Survey (ENE), conditional on their education, age, industry, income quintile and region (Madeira 2018, 2019a). Each household i's permanent income is obtained as the sum of its non-labor income (a_i) plus the labor earnings of each labor force member k: $P_{i,t} = a_i + \sum_k P_{k(i),t}$. The permanent income of each household member is given by $P_{k(i),t} = (Y_{k,i}(1 - u_{k,i,t}) + Y_{k,i} rr_{k,i} u_{k,i,t})$, where $Y_{k,i}$ is worker k's earnings when in employment, $u_{k,i,t} = u(x_{k(i)}, t)$ is its probability of being in an unemployment spell, and $rr_{k,i}$ is its replacement ratio of income during unemployment relative to the earnings while working (Madeira 2018). Also, the unemployment risk of the household is estimated as a weighted average of the unemployment risk of its labor force members, using each member's permanent income as a weight: $u_{i,t} = \sum_k P_{k(i),t}/(P_{i,t} - a_i) u_{k(i),t}$.

Household debt in Chile reached a value close to 41% of the GDP in 2019, a high value for a developing economy, especially if one takes into account the high share of unsecured debt (Central Bank of Chile 2020). Using the last survey wave (the EFH 2017), Table 1 shows the fraction of

Table 2: Indebtedness ratios by borrower type

	Population[a]	Household	DSIR			CDPIR			DAR		
Borrower type:	(% of total)	debt[b](mean)	P25	P50	P75	P25	P50	P75	P25	P50	P75
Any debt	68.3	662.2	6.2	15.5	32.8	2.7	10.0	28.9	5.6	33.1	471.2
Consumer	54.8	578.2	7.9	17.7	35.3	2.6	9.9	28.1	4.6	30.2	390.6
Mortgage	32.9	1321.2	5.4	14.9	30.0	3.2	12.8	29.5	10.9	34.4	71.2
Consumer & Mortgage	21.1	1281.9	9.3	19.1	32.6	3.0	12.5	28.9	9.0	32.4	67.0
Borrowers By Income Strata:											
Strata 1 (pc 1-50)	25.8	158.3	9.1	20.9	48.1	2.4	7.4	26.1	2.9	21.6	80000
Strata 2 (pc 51-80)	23.4	452.4	6.5	14.8	31.4	3.0	12.1	34.7	6.0	30.2	144.0
Strata 3 (pc 81-100)	19.0	1581.6	3.9	10.9	23.3	3.3	11.8	26.6	11.8	40.4	195.3

EFH (2017). All the values are in percentage points. except *b*) which is in UF.
a) Population is given as a percentage of all the households in Chile.
All values use household weights (not adjusted for the size of the household debt).

college educated household heads and the mean age across different types of borrower: families with any debt, some consumer debt, some mortgage debt, and families with both consumer and mortgage debt. It also reports the percentiles 25, 50 and 75 of the permanent income (in log) across the borrower types. Table 1 also reports the fraction of households with some consumer debt, how much of that consumer debt is motivated for "Paying other debts" (see Madeira 2015b for a study of the consumer loan motivations in Chile, which shows that "pay other debts" is a strong motive among the Chilean families) and the fraction of families that had a rejected loan application in the last 12 months. The results show that households with mortgages report higher income (whether in percentile 25, 50 or 75) and are more likely to have a college education, but their age is similar to the households with consumer loans. Also, the mean household borrower has 12.9% of his consumer debt dedicated to pay previous loans. Around 2.9% of the borrowers report a rejected loan application in the last year. Households of higher income (strata 3) are more likely to be college educated, less likely to hold consumer debt, less likely to be rejected for a loan and dedicate a higher portion of their consumer debt to pay older loans.

Table 2 summarizes the indebtedness levels of the Chilean families, reporting the fraction of the population with different types of debt (any debt, consumer, mortgage, both consumer and mortgage), the household's total debt amount[3] and the population percentiles (25, 50, 75) of three

[3] The debt amount is reported in UF. UF is a real monetary unit in Chile, updated according to the consumer price inflation index, and is often used in long-term contracts such as mortgages, consumer loans and rents. 1 UF was roughly equivalent to 41 USD during 2017. In 2020, 1 UF was roughly equivalent to 36 USD.

different debt ratios: i) the debt service to monthly income ratio (DSIR), with the debt service including the loan amortization plus all the fees and interests to be paid in a given month; the consumer debt amount to the annual permanent income ratio (CDPIR); and the total debt amount to assets ratio (DAR). The debt service ratio (DSIR) has been shown to be a strong predictor of delinquency and liquidity constraints, whether in mortgages (Gerardi et al. 2018) or consumer loans (Johnson and Li 2010, Madeira 2019b). The consumer debt amount to the annual permanent income ratio (CDPIR) is a solvency measure, since some households can become stressed due to their total debt amount. It is especially focused on consumer debt because these loans are more likely to have higher interest rates and be an additional stress for households. The debt to asset ratio (DAR) is another solvency measure, which takes into account all debt (mortgage and consumer loans) relative to the assets of the household. This measure has been shown to be an important predictor of mortgage delinquency (Gerardi et al. 2018). Note that the DAR measure can take very high values in some poorer households if such households (for instance, non-home owners) have some debt but close to zero real and financial assets.

The results show that mortgage borrowers are more indebted in terms of the total household debt amount. However, consumer borrowers present both a higher debt service ratio (DSIR) and a higher debt asset ration (DAR) relative to mortgage borrowers, which makes sense since consumer loans are often used to pay for expenses and not for assets (such as houses) and also have higher fees and interest-rates. The consumer debt to permanent income ratio (CDPIR) is actually somewhat higher for mortgage borrowers. This can be explained because many households contract consumer loans to pay for expenses related to their homes, such as new furniture, home improvements or paying the real estate purchase fees.

In terms of borrowers of different income levels, it is clear that the poorest (strata 1) present the highest debt service ratio (DSIR), while the richest (strata 3) present the lowest debt service ratio (DSIR) but also show the highest debt to asset ratio (DAR), if one excludes the DAR statistic for the percentile 75 of the strata 1 (since the poorest households have very low assets). This makes sense since the rich benefit from longer maturities and lower interest rates (therefore the low DSIR levels), but also purchase more expensive homes (therefore the higher values of DAR).

The EFH survey also informs on the households' real assets (main home, other properties, and vehicles) and financial accounts. The financial assets include 9 distinct categories of assets, including stocks, mutual funds, bonds and savings accounts, voluntary pension funds, exotic instruments (such as derivatives, swaps or forward-future contracts), equity in non-public companies and funds[4], insurance contracts with savings components, and uncategorized financial contracts. Among the financial assets, the categories of stocks, mutual funds, bonds and savings accounts, plus voluntary pension funds, are considered to be liquid financial assets, since those accounts can be withdrawn with a small penalty. Table 3 summarizes the fraction of households with different categories of assets (real assets, financial assets, and financial liquid assets) and the ratio of asset value relative to debt (for the households with both positive assets and debts). As an emerging economy, the Chilean households have few financial assets (such as stocks, bonds or savings accounts) in comparison with developed countries (Le Blanc et al. 2015, Christelis et al. 2013). Almost 75% of the Chilean population have no financial assets at all and 83% of the households have no liquid financial assets. Among households with some debt, less than 19% of them have liquid financial assets, and even the median household that has some liquid assets can only cover 17% of its total debt amount by using such assets. For most households their only asset is their main home, with Chile having a high fraction of home-ownership due to state subsidized low cost housing. Around 76% of the households own real assets and most households are solvent if they can tap into their real wealth, with 75% of the real asset owners having real assets worth more than twice their liabilities.

Now I compare Chile with other countries with similar household finance surveys, using data from the Wealth Distribution Database of the OECD (based on surveys mostly from 2014), the USA's Survey of Consumer Finances (wave 2013), the ECB's Household Finance and Consumption Survey (using the wave 2, based on surveys implemented mostly in 2013 and 2014), and Uruguay's *Encuesta Financiera de Hogares Uruguayos* (EFHU, from 2014). The samples includes 31 countries, mostly developed economies from the OECD, although some variables are not available for all countries. Table 4 compares the Chilean household indebtedness in 2017 relative to the other countries, but the results are similar with the Chilean 2014 survey. Since most countries in the sample are richer than Chile, the last column includes the predictions made from an OLS and Quantile (QREG) linear regressions of each debt statistic and the GDP per capita (in PPP measured in USD) estimated from all countries in the sample, but with the outcome prediction for a country

[4] Here non-public equity is defined as equity in companies that are not tradeable in the stock market, for instance, ownership or participation of your family's company or participation in a society with other entrepreneurs.

Table 3: Real and Financial Assets by borrower type

	Fraction of households (in %) with no assets across asset classes				Ratios of Assets to Debt[a] (for households with assets)								
					Real assets to debt			Financial assets to debt			Liquid assets to debt		
Borrower type:	Any	Real	Financial	Liquid	P25	P50	P75	P25	P50	P75	P25	P50	P75
Non debtor	31.2	34.5	81.8	86.2		N/A			N/A			N/A	
Any debt	15.4	18.3	70.9	81.4	2.04	6.00	33.90	0.02	0.15	1.29	0.03	0.17	0.97
Consumer	16.5	19.6	71.6	82.0	2.04	6.73	40.48	0.02	0.16	1.51	0.03	0.19	1.25
Mortgage	3.4	4.3	60.9	77.1	1.70	2.69	5.31	0.00	0.05	0.26	0.01	0.06	0.25
Consumer & Mortg.	3.0	3.6	59.5	77.8	1.60	2.43	4.71	0.00	0.04	0.21	0.01	0.05	0.24
Borrowers By Income Strata:													
Strata 1 (pc 1-50)	26.3	30.1	82.0	86.8	2.77	13.50	63.32	0.03	0.22	1.92	0.04	0.23	1.56
Strata 2 (pc 51-80)	12.1	15.6	74.5	83.6	1.85	5.30	30.10	0.01	0.11	0.97	0.02	0.14	1.00
Strata 3 (pc 81-100)	4.9	6.0	51.8	71.3	1.86	3.59	13.83	0.02	0.17	0.98	0.03	0.16	0.67
All households:													
Strata 1 (pc 1-50)	32.7	36.5	85.3	88.6									
Strata 2 (pc 51-80)	14.3	17.7	74.5	82.9									
Strata 3 (pc 81-100)	7.6	8.9	54.7	72.6									
All households	21.1	24.2	74.9	83.1									

EFH (2017). *a*) Values are in number, meaning that 1 implies Assets equal Debts.
All values use household weights (not adjusted for the size of the household debt).

with the same GDP per capita as Chile. Therefore I compare the Chilean debt statistics with the range of countries in the sample (summarized by their minimum, median and maximum statistics) and with an hypothetical country similar to Chile obtained from the OLS and QREG predictions. The OLS gives a comparable prediction for a country similar to Chile, while the quantile 75 give a high indebtedness value for countries with similar GDP per capita as Chile.

Relative to a country of similar GDPpc, Chile has a large fraction of households with any debt, non-mortgage debt and debt in credit cards/lines, since these values are well above the quantile 75 of similar countries and also well above the median in the sample of all countries. The percentage of Chilean households with a mortgage is close to the quantile 75 of similar countries, while the share of households with "No access to credit" is slightly below its quantile 75. Also, the share of non-mortgage debt in terms of the aggregate household debt of 24.6% is slightly above the quantile 75 of similar countries, confirming that Chile is a country with a large use of non-mortgage (or consumer) debt. Chile is also below the median country in terms of the Debt to Income Ratio, whether one uses the median (p50) or the percentiles 75 and 90 of the population of borrowers. However, Chile is very close to the median country in terms of its population's Debt Service to

Table 4: **Comparison of household debt indicators in Chile versus other countries**

Indicators (in %)	Nr of countries	Chile (2017)	Min	Median	Max	OLS*	Q-75*
Households with:							
Any debt	31	66.4	21.2	47	84.9	42.2	46.2
Mortgages	30	21.2	6.5	25	47.6	17.4	18.9
Non-mortgage debt	30	60.9	10.3	33.2	68	33.8	37
Debt in credit cards and lines	23	44.1	3.8	13.2	81.6	19.2	22.6
No credit access	21	8.7	3.4	7.6	20.8	8.2	9
Non-Mortgage Debt / Household Debt:							
Aggregate Ratio	27	24.6	1.6	14.2	63.5	20.9	24.2
Debt to Income Ratio:							
p50 of country's debtors	22	24.8	11.5	63.4	242.8	57.2	54.3
p75 of country's debtors	21	88.6	54.7	188.2	611.7	164.4	173
p90 of country's debtors	21	191.7	149.6	343.2	1450.6	356.5	406.1
Debt Service Ratio (no credit cards and lines of credit):							
p50 of country's debtors	22	14.0	8.4	13.4	35.3	14.4	16.2
p75 of country's debtors	21	24.5	15.8	23	62.5	25.3	26.6
p90 of country's debtors	21	41.3	26.2	38.3	143	47.5	51.2
Debt motivations (as a % of the total consumer debt in the country):							
Residence and real estate	21	8.9	1.4	20.8	50.2	24.1	32.6
Vehicles	21	15.7	6.6	24.5	70.3	13.9	20.6
Entrepreneurship/Investment	21	5.6	0.2	2.7	16.4	5.6	5.6
Pay other debts	21	19.1	0	5.4	25.2	9.7	13.5
Education	21	21.7	0	7.2	38.3	8.4	13.8

Sources: EFH (Chile), EFHU (Uruguay), HFCS (Europe), Survey of Consumer Finances (USA), Wealth Distribution Database (OECD).
* The OLS and Quantile regression use a constant and $\ln(GDP_{c,t}^{PPP,pc})$ as controls. The models then provide a prediction for a generic country $\ln(GDP_{c,t}^{PPP,pc}) = GDP_{Chile,2017}^{PPP,pc}$.

Income Ratio[5]. Finally, in terms of the debt motives, relative to comparable countries, the Chilean borrowers are less likely to use consumer loans for expenses related to their home and real estate, but they are more likely to use debt for both "Pay other debts" and "Education" purposes.

In summary, Chile is a country with a large number of borrowers with non-mortgage and credit card debt, besides a robust fraction of mortgage borrowers. However, Chile has a normal debt amount and debt service (as measured by the DIR and DSR) relative to comparable countries.

[5] The DIR differs from the CDPIR, because the DIR includes all the household debt and uses the monthly income in the denominator (rather than the annual permanent income). The DSR differs from the DSIR defined before, because the DSR does not include credit cards and lines of credit to adopt a similar definition for all countries (since the European surveys do not include debt service for credit cards and lines).

2.2 The empirical delinquency models

I now estimate the delinquency model for each debt type L (L being total household debt, mortgages, consumer loans, bank credit cards, retail credit cards) using information of whether the household i at the time t of the survey is in arrears for 3 months or more ($Dr^L_{i,t} = 1$). For simplicity all the delinquency models are parameterized using the probit discrete choice model:

$$\Pr(Dr^L_{i,t} = 1 \mid \beta^L, X_i, Z^{ST}_{i,t}) = \Phi(\beta^L(X_i, Z^{ST}_{i,t})) \tag{1}$$

The model includes two vectors, one vector X_i related to demographic variables of the household that are fixed, plus a second vector $Z^{ST}_{i,t}$ with time-varying risk factors that are affected by the stress test scenarios (Madeira 2014). The vector X_i includes region, age, marriage status, education of the household head plus number of household members. Therefore X_i is fixed in the sense that its variables are not affected by the business cycle or the stress tests. The vector $Z^{ST}_{i,t}$ includes the household's current monthly income (the sum of both non-labor income and the observed labor income of each member k, $\ln(Y_{i,t}) = \ln(a_i + \sum_k Y_{k(i),t})$), unemployment risk ($u_{i,t}$, a weighted average of the unemployment probability of each member, Madeira, 2018), the consumer debt to annual permanent income ratio ($CDPIR_{i,t}$), the debt service to monthly current income ratio ($DSIR_{i,t}$), a dummy variable for whether the household has no liquid financial assets ($noLiqA_{i,t}$) and the ratio of liquid financial assets to total debt ($rLiqD_{i,t}$). For the mortgage loan model I add the Debt to Assets Ratio ($DAR_{i,t}$) as a control. These variables were described in Tables 1, 2 and 3.

Some of the variables in the vector $Z^{ST}_{i,t}$ - such as the unemployment risk ($u_{i,t}$) and the consumer debt to annual permanent income ratio[6] ($CDPIR_{i,t}$) - are generated regressors, which are estimated from similar worker types from another dataset, the Chilean Employment Survey (ENE). Given consistent estimates of the generated regressors from the ENE data (with the ENE sample being independent from the EFH survey), it is possible to obtain a consistent estimator for the β^L coefficients of the probit model (Wooldridge 2010), but the variance of those $Var(\beta^L)$ coefficients needs to account for the error component in the generated regressors. Since the probit model is an M-class model estimator, then consistent estimates for the β^L estimator and its

[6] $CDPIR_{i,t} = \frac{\text{ConsumerDebt}_{i,t}}{12 \times P_{i,t}}$ has a denominator of permanent income $P_{i,t} = a_i + \sum_k P_{k(i),t}$, with some generated components that depend on the unemployment risk and the replacement ratio of each working member.

variance-covariance matrix elements can be obtained by a simple bootstrap procedure (Wooldridge 2010). I obtain a number B of bootstrap replicas of the ENE data to create a distribution of all the labor market parameters $(u^{(b)}_{k,i,t}, rr^{(b)}_{k,i})$. Then for each bootstrap replica b, I create a different vector of generated regressors $Z^{ST(b)}_{i,t}$ in the EFH survey: $u^{(b)}_{i,t} = \sum_k u^{(b)}_{k(i),t} P^{(b)}_{k(i),t}/(P^{(b)}_{i,t} - a_i)$, $CDPIR^{(b)}_{i,t}$ =ConsumerDebt$_{i,t}/(12 \times P^{(b)}_{i,t})$, with $P^{(b)}_{k(i),t} = (Y_{k,i}(1 - u^{(b)}_{k,i,t}) + Y_{k,i} rr^{(b)}_{k,i} u^{(b)}_{k,i,t})$, $P^{(b)}_{i,t} = a_i + \sum_k P^{(b)}_{k(i),t}$, and $b = 1, ..., B$. Estimating the same probit model using the vectors $X_i, Z^{ST(b)}_{i,t}$, one obtains a set of B consistent estimates of the coefficients $\beta^{L(b)}$, which can be used to provide a consistent estimate for the coefficients $\hat{\beta}^L = \frac{1}{B}\sum_b \beta^{L(b)}$, its variance $Var(\hat{\beta}^L) = \frac{1}{B}\sum_b(\beta^{L(b)} - \hat{\beta}^L)^2$, and standard-error $Se(\hat{\beta}^L) = \sqrt{Var(\hat{\beta}^L)}$.

The delinquency risk models are estimated using the last 4 EFH waves (2010, 2011, 2014, 2017) in order to account for different shocks that affected household risk over the years and which may concern lenders. The results in Table 6, which use 1,000 bootstrap replicas of the ENE data to obtain the generated regressors $u_{i,t}$ and $CDPIR_{i,t}$, show two different model estimates for each loan type. The first model considers both the debt measures ($DAR_{i,t}$, $CDPIR_{i,t}$, $DSIR_{i,t}$) and the liquid financial assets of the household ($noLiqA_{i,t}$, $rLiqD_{i,t}$), while the second model only includes the debt measures as a risk factor. Both models have very similar results. The reason why I include the model with no asset measures as a robustness check is due to the fact that less than 20% of the borrowers have such assets (as seen in Table 3) and therefore those parameters may be less precisely estimated due to the small number of households in the EFH data with such assets.

The results in Table 5 show that delinquency risk is associated with a lack of financial liquid assets, unemployment risk (although it is not statistically significant for mortgages), low income, high consumer debt relative to annual permanent income (measured by $CDPIR_{i,t}$, although the coefficient is not statistically significant for mortgages), and high monthly debt service relative to current income (measured by $DSIR_{i,t}$, although the coefficient is not statistically significant for banking consumer loans), lower education and larger households. The results also show that a lack of financial assets is significantly associated with the delinquency for both mortgages and all the consumer debt types (although it is not statistically significant for consumer debt aggregated for all its categories). The ratio of the financial liquid assets to the total debt has the correct sign (being negative, therefore more financial assets implies lower delinquency), but is not statistically significant (except for the case of the retail cards). This result also makes sense, because less than

Table 5: Delinquency (arrears for 3 months or more) probit models

Mean coefficients and standard-errors from 1,000 bootstrap replicas of the ENE					
Controls	Consumer loan (any)	Banking consumer loan	Banking credit card	Retail credit card	Mortgage debt
	Model estimates with both debt measures and liquid asset variables				
$noLiqA_{i,t}$	0.125	0.280*	0.345***	0.123*	0.464*
	(0.0982)	(0.158)	(0.136)	(0.0717)	(0.246)
$rLiqD_{i,t}$	-0.0401	-0.0413	-0.0705	-0.0217*	-1.033
	(0.0262)	(0.0758)	(0.0610)	(0.0114)	(1.038)
$DAR_{i,t}$					-0.0162
					(0.173)
$u_{i,t}$	2.183***	1.321	2.719***	2.587***	0.803
	(0.872)	(1.187)	(1.030)	(0.557)	(1.216)
$\ln(Y_{i,t})$	-0.175**	-0.264**	-0.117**	-0.203***	-0.0997*
	(0.0571)	(0.0889)	(0.0466)	(0.0565)	(0.0587)
$CDPIR_{i,t}$	0.378***	0.439***	0.720***	0.307***	0.114
	(0.0989)	(0.155)	(0.120)	(0.0875)	(0.190)
$DSIR_{i,t}$	0.108	-0.0506	0.254***	0.658***	1.309***
	(0.137)	(0.212)	(0.109)	(0.103)	(0.191)
$members_i$	0.116***	0.0866***	0.0176	0.127***	0.146***
	(0.0202)	(0.0301)	(0.0242)	(0.0149)	(0.0370)
$College$	-0.320***	-0.573***	-0.160*	-0.522***	-0.497***
$education_i$	(0.0823)	(0.126)	(0.0944)	(0.0647)	(0.129)
N	4,808	2,327	4,796	7,592	3,074
Pseudo R2	0.071	0.109	0.097	0.122	0.118
	Model estimates without liquid asset variables for the households				
$DAR_{i,t}$					0.0482
					(0.172)
$u_{i,t}$	2.180***	1.312	2.670***	2.593***	0.958
	(0.779)	(1.197)	(1.032)	(0.561)	(1.214)
$\ln(Y_{i,t})$	-0.194***	-0.300***	-0.125***	-0.216***	-0.118*
	(0.056)	(0.0875)	(0.046)	(0.0583)	(0.0617)
$CDPIR_{i,t}$	0.359***	0.409**	0.734***	0.308***	0.133
	(0.118)	(0.182)	(0.117)	(0.0871)	(0.191)
$DSIR_{i,t}$	0.122	-0.108	0.247**	0.658***	1.281***
	(0.137)	(0.217)	(0.108)	(0.102)	(0.190)
$members_i$	0.118***	0.088***	0.0223	0.130***	0.148***
	(0.0201)	(0.030)	(0.0242)	(0.0150)	(0.0364)
$College$	-0.324***	-0.590***	-0.178**	-0.528***	-0.539***
$education_i$	(0.0830)	(0.127)	(0.094)	(0.0653)	(0.129)
N	4,808	2,327	4,796	7,592	3,074
Pseudo R2	0.07	0.108	0.096	0.122	0.118

Models estimated using the pooled EFH waves (2010, 2011, 2014, 2017).
Other Controls: Constant, age, technical education, residence in the Santiago capital area, gender and marriage status of the household head.

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

20% of the families have such assets in Chile (Table 3), therefore the empirical model may have difficulty separating between a low default rate for wealthy households with some financial assets and an even lower default rate for even richer borrowers. In the appendix, I show that very similar results are obtained if one estimates the probit model using bootstrap replicas for both the ENE and the EFH datasets.

3 Impact of the Covid 19 crisis on the Chilean economy

3.1 Evolution of firm equity, credit and labor markets

The costs of the pandemic are estimated to be around 1.3% to 2% of annual GDP for each month of strict lockdowns (Central Bank of Chile 2020). Figure 1 shows the evolution of economic activity using the Monthly Activity Index (IMACEC, for its abbreviation in Spanish) as a log index with the base level being September of 2019, which is an approximation of the Real GDP at a monthly frequency. The Monthly Activity Index shows a strong decline of -6.5% and -5.8% for the months of October and November relative to September of 2019, right after the Social Explosion. The log index shows again a drop of -5.8% in the month of March, a strong reaction to the Covid crisis, especially if one takes into account that the national emergency was only declared on March 16 and the fist urban areas in lockdown and quarantine only started on March 26. The Mining activity index dropped more at the end of 2019 than the Non-Mining activities, due to other macro shocks such as a lower economic expansion in China (the major importer of copper, Chile's major export), but Mining was less affected by the pandemic until June of 2020.

Figure 1 also shows a steep fall in consumer debt, which started after the Christmas of 2019 and then accelerated with the pandemic after March of 2020. However, except for consumer loans, the total credit remained stable and even growing for the entire period of 2019 and 2020, with robust growth in commercial debt and mortgages until June and December of 2020, respectively. Therefore the pandemic did not imply a shortage of credit for businesses and homeowners, partly due to the bank credit lines created by the Central Bank of Chile and other liquidity measures for bank and corporate debt implemented by the Financial Market Commission (García 2021).

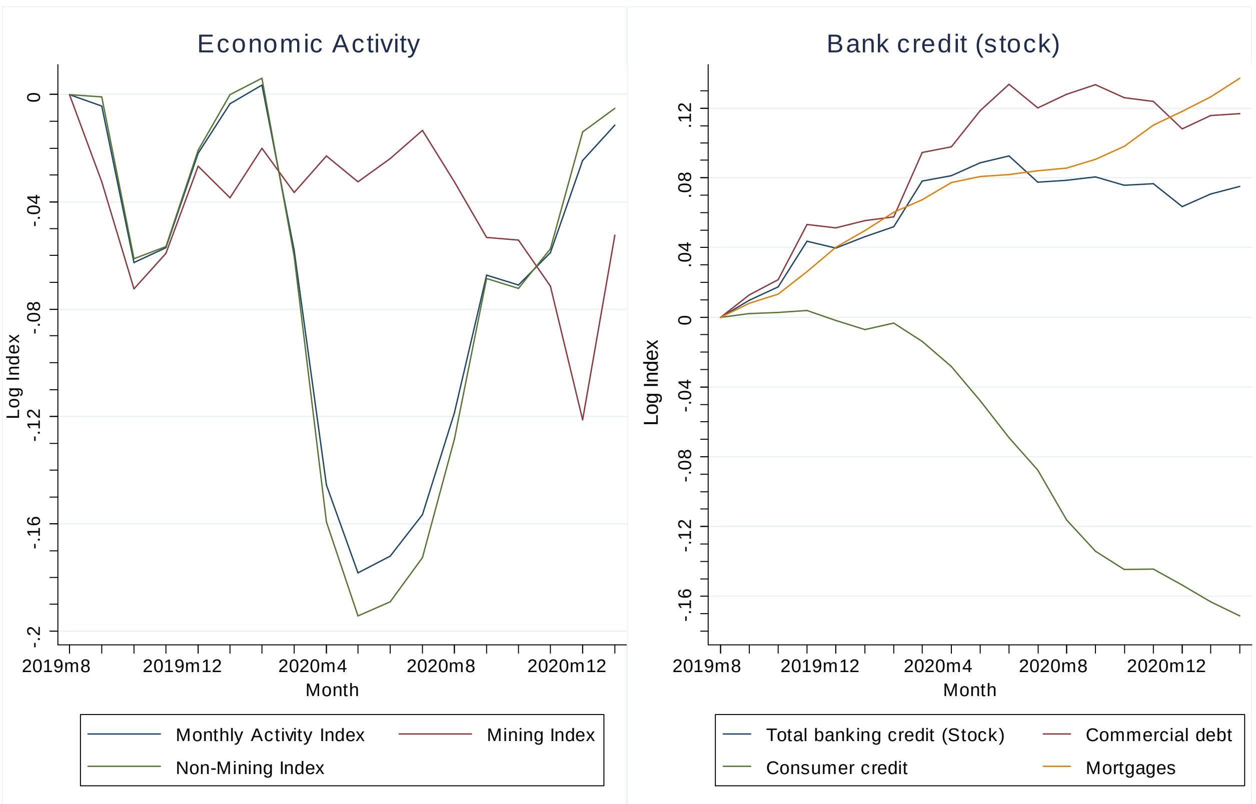

Figure 1: Economic Activity and Bank credit stock between August 2019 and February 2021

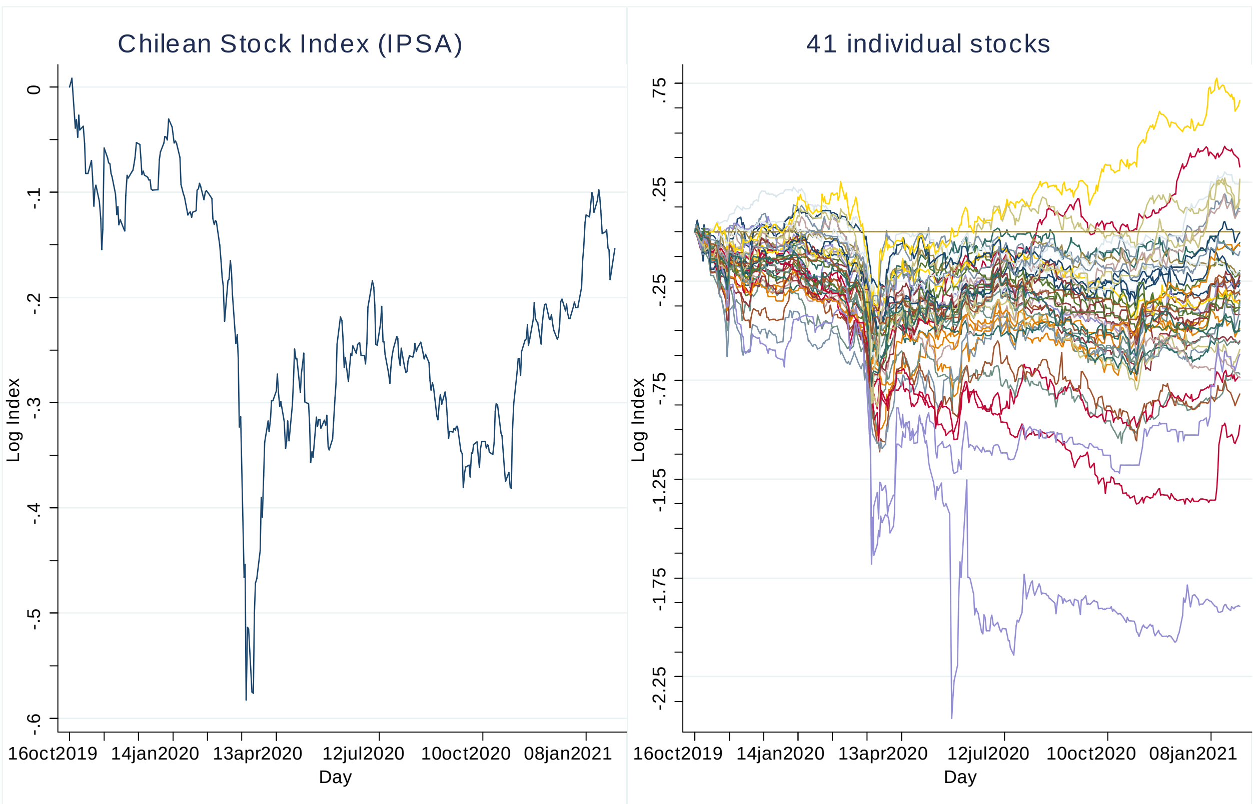

Figure 2: Evolution of the Chilean equities between October 16, 2019 and February 2, 2021

Table 6: Hours worked during the Social Explosion in % of the labor hours in September of 2019

Month (year 2019)	Oct	Nov	Dec	Oct	Nov	Dec	Oct	Nov	Dec	Oct	Nov	Dec
Sex / Education	Secondary or less			Technical educ.			College or more			All workers		
Men	94.8	97.0	100.8	103.0	106.9	109.8	91.5	101.9	102.4	95.1	99.3	102.2
Women	94.5	98.2	109.5	94.3	104.3	109.3	88.2	94.4	103.0	92.6	98.2	107.6
Both genders	94.7	97.4	103.7	98.7	105.6	109.5	90.0	98.4	102.7	94.1	98.9	104.3

Source: Estimates from the Chilean Employment Survey (ENE, 2019-2020).

Figure 2 represents the Chilean stocks in log relative to their value on October 16, 2019. The Chilean Stock Market Index (IPSA) dropped 15% in the month following the Social Explosion. It recovered a substantial part of its value by January of 2020 and then started falling with the international pandemic. The IPSA stock market and all its 41 stocks hit a bottom on March 16, 2020, as a national emergency was declared, before recovering somewhat after the government announced support measures for companies and households. Therefore the Covid crisis represented a much larger shock than the Social Explosion and one with higher comovement among firms.

Besides impacting the unemployment rate, both the Social Explosion and the Covid shocks caused a significant disruption for employed workers, therefore the best measure of their overall labor impact is the total number of hours worked. Using the Chilean Employment Survey (ENE), Figure 3 shows that during the Social Explosion there was a significant drop in the total hours worked for all the industries in Chile, except for Agriculture and Manufacturing. This makes sense because both Agriculture and Manufacturing businesses are far from the urban centers, which were the targets of the social and political marches. Furthermore, employment in Agriculture benefitted from the harvest season in the late Spring and early Summer months (October, November and December). The Social Explosion was especially disruptive for the Energy and Services sectors. Table 6 shows that the Social Explosion affected the labor hours of both men and women, but with a much stronger impact on women (whose labor hours fell 7.4% in October of 2019), due to concerns about urban safety[7] and also because female work intensive industries such as retail were more strongly hit by the crisis. With the exception of men with Technical education, all the education levels were negatively affected by the Social Explosion, with total hours falling for technical, secondary and college educated workers. However, by December of 2019 workers across all education levels had recovered their pre-Social Explosion labour hours.

[7] Several companies had to invest more in security and reduce work shifts (Central Bank of Chile 2019).

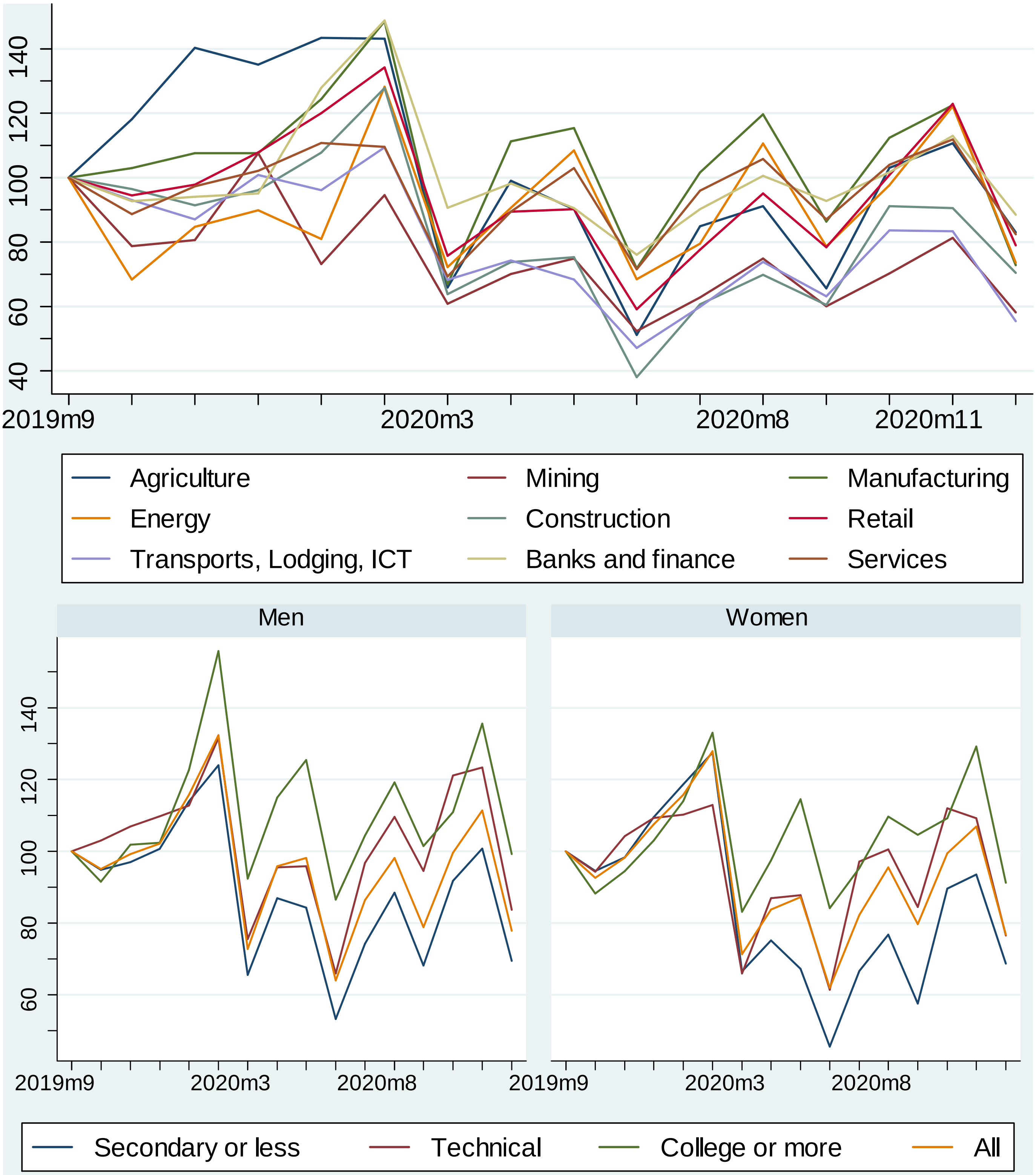

Figure 3: Work hours relative to September of 2019 (in %), by economic sector and gender-education

Curiously, the Covid pandemic affected all the industries with a similar timing (Figure 3), with stronger downturns during the months of March, June, September and December, which coincided with the imposal of quarantines in several parts of the country, especially in the Santiago capital area (which concentrates around 40% of the population and GDP of the country). There were therefore downturns of labor market activity during the quarantines, followed by brief recoveries during the months in which the lockdowns were eased. The pandemic was less harsh for the Manufacturing, Agriculture and Mining sectors, which experienced smaller downturns and stronger recoveries.

3.2 Policy measures taken in Chile to soften the Covid shock

Chile implemented a package of fiscal measures, a delaying by the Financial Market Commission of the Basel III standards for banks, plus a monetary policy rate cut, bank credit lines and liquidity measures of the Central Bank of Chile (Central Bank of Chile 2020). The household measures can be grouped in three categories: i) income, tax relief and expenses support, iii) debt deferral and lower interest rates, and iii) a pension account withdrawal.

The income and expenses support (with tax loans) announced in 2020 include:

i) a Covid voucher announced in March targeted at poor families with no formal income (50,000 pesos for each child, with a minimum of 50,000 pesos per family in case of no children)[8] and then substantially expanded in May, June and August. I denote this monthly income support

[8]By May the government announced a larger Family Emergency Income (*Ingreso Familiar de Emergencia*, IFE, in Spanish). The first payment of the IFE in May was targeted at families within the first three income quintiles and with an estimated value of more than half of their income coming from informal labor. For the two lower income quintiles, the program gave 65, 130, 195, 260, 304, 345, 385, 422, 459, 494 thousand monthly pesos for households with a respective size of 1, 2, 3, 4, 5, 6, 7, 8, 9 and 10 or more members. In the third income quintile the program gave 43, 86, 130, 173, 203, 230, 257, 281, 306, 330 thousand monthly pesos for households with a respective size of 1, 2, 3, 4, 5, 6, 7, 8, 9 and 10 or more members. After June, the IFE payments were expanded to the lowest 4 income quintiles, giving 100, 200, 300, 400, 467, 531, 592, 649, 705, 759 thousand monthly pesos for households with a respective size of 1, 2, 3, 4, 5, 6, 7, 8, 9 and 10 or more members.

A Middle Class bonus was announced in August with a single payment (not to be repeated) for workers that lost at least 30% of their income relative to the previous year, giving 500, 400, 300, 200 and 100 thousand pesos for workers with a prior monthly income, respectively, between 400 thousand and 1.5 million, 1.5 and 1.6 million, 1.6 and 1.7 million, 1.7 and 1.8 million, and between 1.8 and 2 million pesos.

(described exhaustively in the footnote 7) as $Voucher_{i,t}(x_i)$, which depends on the time period plus the household income quintile, whether the household had no formal income, the number of household members (in March and April it only depended on the number of children) and whether the household had a formal income loss above 30% (according to the August benefit);

ii) the Employment Protection Law, which allows companies to give workers access to income through the public unemployment insurance system while temporarily suspending their activity or retaining the workers on a 50% labor schedule;

iii) a deferral of the public utilities' payments;

iv) a deferral of the real estate tax for properties appraised below 133 million pesos (4,640 UF);

v) a deferral of the tax debts targeted at lower income citizens and small companies;

vi) in August of 2020 the tax administration sponsored a program of zero interest rate loans of up to 650,000 pesos[9], which was available for workers that had a monthly income above 400,000 pesos during 2019 but that experienced an income fall above 30% after the beginning of the pandemic in 2020; for the repayment of this zero interest rate loan, the government would make an amortization in the annual tax returns of each worker in 2022 for 10% of the loan amount, and a 30% amortization 2023, 2024 and 2025, and forgive the remainder of the loan if it was not fully repaid by 2024.

The debt relief measures include:

i) a reduction in the monetary policy rate of 125 basis points;

ii) a temporary reduction of the stamp tax on revolving debt and new loans with a maturity of 6 months or less to 0%;

iii) a deferral implemented voluntarily by commercial banks and credit unions allowing the next 3 installment payments (or 6 payments at some banks) on mortgages and commercial loans to be paid at the end of the credit maturity[10];

iv) a flexible payment scheme for credit cards and lines of credit, allowing one payment deferral.

Finally, on July 30th of 2020 the Congress implemented an exceptional measure that allowed all workers to withdraw a significant amount of up to 150 UF (around 5,500 USD) from their

[9] This corresponds roughly to 820 USD if one applies the 2020 average exchange rate of 792 pesos per USD.

[10] This debt deferral started in late March of 2020 as a special scheme from a few banks, but it was quickly copied by all the banks and major credit unions within a few weeks. Banks selected only customers that had no arrears prior to March. During the first 3 weeks of the program (April 1 to April 24) the banks had deferred payments for around 12% of their loan portfolio, according to data from the Chilean Banking Authority.

accumulated individual pension accounts[11]. This measure is possible because Chile has a social security mostly based on compulsory contributions (up to a maximum taxable wage) that workers make to pension funds in private companies.

The benefit value of these measures for each household is calibrated using their EFH information on income, children, real estate properties, county of residence, loans (mortgages, consumer loans, credit cards, lines of credit, and other debts) plus $Exp(x_i)$, a median estimate of the expenses in utilities from the Chilean Family Expenditure Survey of 2017, based on families with a similar income (in log), number of adults and children. To account for the time-variation of the programs I create dummy variables with the name of the month in capital letters denoting a benefit introduced that month and kept at least until the end of 2020, say: $MARCH_t \equiv 1(t \geq March - 2020)$.

The income and expenses support for each household i includes the time-changing $Voucher_{i,t}(x_i)$ plus a median estimate of the expenses in utilities $Exp(x_i)$ from the Chilean Family Expenditure Survey of 2017, based on families with similar characteristics (x_i includes income, number of members and children). Based on numbers from the Chilean Unemployment Insurance by June of 2020, for the Employment Protection Law I consider that 7% of the workers have their contract frozen and receive 40% of their income from unemployment benefits, while 3% are on reduced work hours and receive 30% of their income through unemployment benefits: $EmpProLaw_i = \sum_k 0.40 \times 1(\eta_{i,k} \leq 0.07) Y_{k,i} fe_{k,i} + 0.30 \times 1(\zeta_{i,k} \leq 0.03) Y_{k,i} fe_{k,i}$, with $\eta_{i,k}$ and $\zeta_{i,k}$ being pseudo-uniform random-numbers and $fe_{k,i}$ is a dummy denoting whether worker k has a formal employment contract. The real estate tax deferral for each household i is given as $RETD_i = (0.00025/3)(\sum_{v=0}^{3} V_{i,v} 1(V_{i,v} \leq 133,000,000))$, with $V_{i,v}$ denoting the survey reported property appraisal value and $v = 0, 1, 2, 3$ being the main family home and up to 3 other properties that may be owned by the family. The tax rate 0.025% is applied to properties every quarter, but it is divided by three to be measured monthly. The deferral of tax debts is taken to be the VAT rate (19%) for the monthly income reported by households from their micro businesses or self-employment: $TDD_i = 0.19 \sum_k Y_{k,i} se_{k,i}$, with $se_{k,i}$ being a dummy variable for whether worker k is a micro-entrepreneur or in formal self-employment. Finally, the government sponsored zero interest rate loan of up to 650,000 pesos (given in three monthly installments) for each worker with an above 30% income loss corresponds

[11] A similar Pension Withdrawal was legislated on the December 10th of 2020, but its effects only apply for 2021 and therefore are not modelled in the stress tests exercises in this article.

to a total household support of $PubLoan_i = \sum_k (650,000/3)1(Y_{i,k,t=2020} \leq 0.70 P_{i,k,t=2019})$, with $Y_{i,k,t}$ being the worker's simulated income in 2020 and $P_{k(i),t=2019} = (Y_{k,i}(1-u_{k,i,t}) + Y_{k,i} rr_{k,i} u_{k,i,t})$ being its permanent labor income evaluated at the unemployment risk ($u_{k,i,t=2019} = u(x_{k(i)}, t)$) that a worker of his characteristics faced in 2019. Since this public sponsored loan is only paid gradually over the tax returns between 2022 and 2025 (being forgiven later on), then it does not affect the current debt service of the household. The total income policy support $psY_{i,t}$ is therefore given by

$$psY_{i,t} = Voucher_{i,t}(x_i) + APRIL_t \times (Exp_i(x_i) + EmpProLaw_i + TDD_i + RETD_i) + \\ + AUGUST_t \times PubLoan_i \quad (2)$$

The benefit obtained from the lower stamp tax (a reduction from a monthly rate of 0.033% to 0%) and monetary policy rate is given as $B\_ST\_MPR_i = (0.00033 + 0.0125/12) \sum_{rt=1}^{3} \sum_{l=1}^{3} L_{i,rt,l}$, where rt denotes the debt type (1 bank credit card, 2 retail credit card, 3 bank credit line) and $l = 1, 2, 3$ denotes up to 3 loans reported by the household in each debt type, assuming that households keep similar amounts of revolving loans as in 2017. The Monetary Policy Rate reduction of 1.25% is divided by 12 to be measured in monthly terms. Other loan categories reported in the EFH, such as banking consumer installment loans, retail installment loans, educational, automobile and credit union debt, typically have maturities of 12 months or more and at a fixed interest rate, therefore these do not apply for lower stamp tax and interest rate. Also, since some households may become more indebted, while other households may lose access to debt during the pandemic, I do not include new loan creation to compute these benefits. Furthermore, as observed in Figure 1 the volume of consumer loans fell steeply throughout the crisis, therefore the take up of new consumer loans by households must have been low. The flexible credit card scheme and the debt deferral for non-defaulting customers ($Df_i = 0$) is measured as $DebtD_i = (1 - Df_i)(\frac{1}{3} \sum_{rt=1}^{2} \sum_{l=1}^{3} L_{i,rt,l} + \sum_{rt=4}^{5} \sum_{l=1}^{3} Ds_{i,rt,l} + \sum_{v=0}^{3} Mds_{i,v})$, being equivalent to one third of the monthly bank and retail credit card bills ($rt = 1, 2$) plus the debt service of banks and credit unions consumer installment loans ($Ds_{i,rt,l}$) and the mortgage debt service for the main home and up to three other properties ($Mds_{i,v}$). The total policy support that households received in terms of a lower debt service (due to a lower monetary policy rate, lower stamp tax, and the debt deferral scheme) sums up as

$$psDs_{i,t} = MARCH_t \times (B\_ST\_MPR_i + DebtD_i) \quad (3)$$

Finally I account for the pension withdrawal policy, which allowed each member of the pension system (anyone who has held a formal job in the past) to withdraw up to 100% of its funds for accounts with a value below 35 UF, up to 35 UF for accounts between 35 and 350 UF, up to 10% of the funds for accounts between 350 and 1,500 UF, and 150 UF for accounts above 1,500 UF. 97% of the workers requested their pension withdrawal within the first 2 months (Central Bank of Chile 2020). The value of each pension withdrawal for each k member is given by $pw_{k,i} = \min(PWI_{k,i}, 35UF)1(PWI_{k,i} \leq 35UF) + 35UF \times 1(35UF < PWI_{k,i} \leq 350UF) + 0.10 \times 1(350UF < PWI_{k,i} \leq 1500UF) + 150UF \times 1(PWI_{k,i} > 1500UF)$. The information on the balance of the pension account $PWI_{k,i}$ of the household respondent comes from self-reported survey answers, while for the other members it is imputed from a log-linear regression with their log-work income, gender, education level and a quadratic term of the age. The total policy support that households received in terms of access to their compulsory pension savings is therefore

$$psPension_{i,t} = AUGUST_t \times \textstyle\sum_k pw_{k,i} \quad (4)$$

Table 7 shows the mean plus the percentiles 25, 50 and 75 of these benefits across the households in each income strata, from the poorest (strata 1: the lowest 50 percentiles of household income, $Y_{i,t} = a_i + \sum_k Y_{k,i}$) to the richest (strata 3: the top 20 percentiles of household income). Since the Income and Expenses support changed over time, I summarize its impact both at the beginning (April) and at the end of the period (August). Results available in a web appendix show that the income and expenses support ($psY_{i,t}/P_{i,t}$) in May was only slightly higher than the April numbers. However, the income and expenses support in June and July was approximately half-way between the benefits of April and the August ones, with the ratio $psY_{i,t}/P_{i,t}$ reaching a mean value of 13.2%. The income and expenses support ($psY_{i,t}/P_{i,t}$) was quite significant, representing 9.1% and 20.0% of the average household's permanent income in April and August, respectively. These policies were quite progressive, with a much higher impact on the poor and the middle class, with the average household in strata 1 (the poorest), 2 (the middle class) and 3 (the richest) receiving a benefit of 13.6%, 6.8% and 3.3%, respectively, in terms of their permanent income.

The debt deferral was only a small amount relative to the overall households' permanent income,

Table 7 - Public policy benefits as a fraction of the household monthly permanent income or as fraction of the debt service or total debt (in %): Mean statistics and percentile distribution (25, median, 75) inside each group

EFH 2017	Income and expenses support							
	$psY_{i,t}/P_{i,t}$: April 2020				$psY_{i,t}/P_{i,t}$: August 2020			
	Pc25	Pc50	Pc75	Mean	Pc25	Pc50	Pc75	Mean
All households	3.8	6.5	11.7	9.1	9.4	17.3	28.6	20.0
Strata 1 (pc 1-50)	8.1	11.1	17.2	13.6	18.2	25.2	36.2	27.7
Strata 2 (pc 51-80)	4.0	5.0	6.8	6.8	10.7	15.8	24.9	18.3
Strata 3 (pc 81-100)	1.9	2.7	3.4	3.3	4.0	5.9	8.5	7.0
	Debt deferral and pension withdrawal							
	$psDs_{i,t}/P_{i,t}$: March 2020				$\frac{1}{6}psPension_{i,t}/P_{i,t}$: August 2020			
	Pc25	Pc50	Pc75	Mean	Pc25	Pc50	Pc75	Mean
All households	0.0	0.3	8.3	6.9	1.2	5.0	9.7	7.1
Strata 1 (pc 1-50)	0.0	0.0	2.4	4.1	0.2	3.5	9.0	6.5
Strata 2 (pc 51-80)	0.0	0.9	9.8	7.4	2.4	6.5	10.8	8.1
Strata 3 (pc 81-100)	0.0	7.2	16.2	11.9	2.8	5.2	8.8	6.8
	Debt deferral as a fraction of debt service and pension withdrawal as a fraction of total debt (for households with loans)							
	$psDs_{i,t}/Ds_{i,t}$				$psPension_{i,t}/D_{i,t}$			
	Pc25	Pc50	Pc75	Mean	Pc25	Pc50	Pc75	Mean
All borrowers	2.7	25.6	47.0	28.6	3.0	16.1	90.1	164.5
Strata 1 (pc 1-50)	0.9	6.3	27.2	15.4	3.7	28.2	134.8	207.9
Strata 2 (pc 51-80)	3.7	26.0	44.4	27.2	4.3	20.5	92.2	189.6
Strata 3 (pc 81-100)	32.3	48.2	66.8	48.0	2.2	6.3	33.3	75.4

especially because it provides no benefit for households without debts. However, it is possible to see that this measure did provide a strong relief for some households with large debts, especially the richer ones. In fact, the effect of this measure increases with the household income (since the richer households are more likely to have mortgages and mortgages of larger amounts), with its effect as a fraction of the debt service of borrowing households being 28.6% on average and 15.4%, 27.2% and 48.0% for the average borrowing households in the strata 1, 2 and 3, respectively.

The pension withdrawal was a huge policy that represented 7.1% in terms of the monthly income of the households (it is divided by 6 to account that the pension withdrawal happens only once and not as a recurring payment), but with an heterogeneous impact. The average borrower could count on a pension withdrawal of 164% of its total debt. However, the median and the percentile 25 of the borrowers can only pay 16.1% and 3.0%, respectively, of their debts by using the pension withdrawal.

Several other policy measures were targeted at firms and banks, with liquidity provisions for Small and Median Enterprises (SMEs), a revision of the timetable for the Basel III banking standards and credit facilities for banks (which are described in longer detail in García, 2021).

4 The Stress Test modelling approach

4.1 The Stress Test scenarios for the unemployment rate and other factors

This section summarizes the approach for using the EFH data to estimate different economic scenarios for the impact of the "Social explosion" and "Covid" shocks. First, since the EFH survey is from 2017, the dataset is updated until February of 2020 using administrative records of the formal employment that match the real IDs of the interviewed households with their social security administration records. For the informal workers (around 27% of the labor force) and for all workers after February of 2020, I simulate their employment transitions using statistics from workers with similar characteristics in the Chilean Employment Survey for the months in 2019 and 2020.

The Stress Test scenarios (in Table 8) follow the economic shocks observed for the entire period between September of 2019 and December of 2020. Each stress test scenario is associated with a sub-period of 2019 to 2020: September of 2019 (just before the October's Social Explosion),

Table 8: The Stress Test scenarios

	Scenarios						
Period: year	2019			2020			
Period: months	Sept	Feb	mid- -March	mid- -April	May-June- -July	August	Sep to Dec
Scenarios	Sept 2019	Feb 2020	Base Covid	I	II	III	IV
Economic shocks:							
i) Unemployment rate	6.9%	7.8%	8.3%	9.9%	13.1%	12.6%	10.4%
ii) Income and job quality	No	Yes			Yes		
iii) Covid support policies	No	No			Yes and No		
Covid job retention shock:							
		7% of labor force would lose employment and 3% would enter a half-time schedule with 30% less pay without the Employment Protection Program					

February of 2020 (the final month of the Social Explosion before the Covid pandemic arrived in Chile), mid-March of 2020 (which coincides with the first quarantines implemented in Chile on March 16), mid-April of 2020 (before households had access to major income support policies), May to July of 2020 (when the unemployment rate stabilized around 13.1%), August of 2020 (when the Chilean government implemented a major middle-class income support, a state subsidized loan, and allowed a significant pension fund withdrawal), and September to December of 2020 (when the unemployment rate lowered to 10.4%). The official unemployment rate in Chile corresponds to a 3 month moving-average around a central month (therefore the official rate on a given month, say March, corresponds to the average unemployment measured in February, March and April). For this reason I re-calculate the unemployment rate for each period using the date of the interviews available in the micro-data of the Chilean Employment Survey (in Spanish, *Encuesta Nacional de Empleo*, hence on ENE), which is the basis for the official employment statistics[12].

The Stress Test scenarios can be summarized in three components: i) the aggregate unemployment rate, ii) income volatility and job quality shocks which affect the income received by workers even if they remain employed, and iii) the government designed policies to support households and borrowers due to the Covid crisis. To measure the impact of the "Social explosion" and Covid

[12] Therefore for the periods of Sept 2019, Feb 2020, May-June-July 2020, August 2020, September to December of 2020, use the interviews collected in those periods only to calculate the unemployment flows and other labor market shocks. The periods of mid-March and mid-April of 2020 correspond to an average of 40% of the previous month and 60% of the current month to obtain a rough estimate of the mid-month labor market situation.

I estimate the reaction of households for different aggregate unemployment scenarios. Therefore the difference between September of 2019 and February of 2020 gives us the impact of the "Social explosion" shock. I then consider a Covid shock, which starts at 8.3% of aggregate unemployment in mid-March when the first quarantines were implemented in Chile. The unemployment rate then increased rapidly and stabilized around 13.1% during the period of May-June-July, before lowering until 10.4% in the last 4 months of the year.

Besides the unemployment rate estimated from the microdata of the ENE survey in 2019 and 2020, I consider that the Covid pandemic would have implied a job loss of 10% of the labor force in a scenario in which the government had not actively supported the job market. One specific feature of this pandemic is that several countries adopted job retention schemes, subsidizing wages of companies to keep their workers on the payroll while being in a state of furlough or reduced work hours (OECD 2020). In fact by May of 2020 around 50 million workers across the OECD were covered by such job retention schemes (OECD 2020). An Employment Protection Law in Chile was implemented in Chile in March of 2020, shortly after the first quarantines were announced. This employment scheme would cover 70% of the wages of workers on furlough and a complement of 25% of the wages of workers on a reduced hour schedule for the companies in the areas experiencing a lockdown imposed by the health authorities. Due to the speed with which the lockdowns were decreed during March and early April, the Employment Protection Program quickly covered more than 70,000 companies by April and almost 750 thousand workers. The number of workers covered by the job retention is therefore roughly similar to 10% of the labor force, which fluctuates between 7.5 and 7.9 million labor force members (including both formal and informal work) depending on the calendar month of the year (Madeira 2015a). The number of workers in furlough or reduced schedule under the Employment Protection Program remained at a high level before dropping in October. However, by December there were still around 100 thousand workers on furlough and more than 250 thousand workers receiving complementary subsidies during their employment. This employment protection measure was crucial in a labor market scenario where analysts forecasted unemployment rates could quickly reach 20% without state support (Central Bank of Chile 2020), therefore its impact is accounted for in the comparisons with and without policy support.

In each stress test scenario t, households receive both income shocks and some public policy support ($psY_{i,t}$, $psDs_{i,t}$, $psPension_{i,t}$). All the shocks are heterogeneous according to the characteristics of each worker k, $x_{k(i)}$, in all households. These shocks and public policy support then affect the vector of variables $Z_{i,t}^{ST} \equiv \{u_{i,t}, Y_{i,t}, DSIR_{i,t}, CDPIR_{i,t}, noLiqA_{i,t}, rLiqD_{i,t}\}$ which affects the household's delinquency rate of each debt type L, Dr_t^L. Each working member k is subject to both a job quality wage loss $jwl_{i,k,t} = jwl(x_{k(i)}, t)$ with a certain probability ($jq_{i,k,t} = jq(x_{k(i)}, t)$) plus a continuous log-normal wage shock with a standard-deviation of $\sigma_{y_{i,k,t}} = \sigma_y(x_{k(i)}, t)$. Therefore the worker's income at the time t of the stress test is given by $Y_{i,k,t}^{ST}$:

$$Y_{i,k,t}^{ST} = \exp(\varepsilon_{i,k,t}\sigma_{y_{i,k,t}})Y_{i,k,t0} \times (1 - jwl_{i,k,t}) \times 1(\eta_{i,k}^{jq} \leq jq_{i,k,t}) \times EPP \times 1(\eta_{i,k}^{CJR} < CovJobR_t) \quad (5)$$

with $Y_{i,k,t0}$ being the labor income reported by the worker k at the time of the survey $t0$, while $\eta_{i,k}^{CJR}$, $\eta_{i,k}^{jq}$ are iid pseudo-uniform numbers and $\varepsilon_{i,k,t}$ is a pseudo-standard normal random number. $EPP = 0.70$ is the income protection factor for workers that enter the Employment Protection Program, which covers up to 70% of their wages if they are in a frozen labor or reduced hours due to the lockdown (which happens with a probability of 10%, $CovJobR_t = 0.10$).

The households' current income $Y_{i,t}^{ST}$ and permanent income $P_{i,t}^{ST}$ for the stress test period t is given by its income and expenses policy support $psY_{i,t}$, its non-labor income a_i (such as asset income or government subsidies) plus the labor income of each household member k (which is $Y_{i,k,t}^{ST}$ if employed with probability $1 - u_{i,k,t}$ and $Y_{i,k,t}^{ST} rr_{k,i}$ if unemployed with probability $u_{i,k,t}$, with $\eta_{i,k}^{u}$ being a pseudo-uniform random number):

$$Y_{i,t}^{ST} = psY_{i,t} + a_i + \sum_k Y_{i,k,t}^{ST} rr_{k,i} 1(\eta_{i,k}^{u} \leq u_{i,k,t}) + Y_{i,k,t}^{ST} 1(\eta_{i,k}^{u} > u_{i,k,t}) \quad (6)$$

The permanent labor income is similar to the current income, but accounts for the duration of the unemployment spell as a fraction of a year's time (which corresponds to 4 quarters), $du_{i,k,t} = \frac{1}{4}\max_h h \times \prod_{l=1}^{h} 1(\eta_{i,k,t+l}^{jf} > JobFind_{i,k,t})$, with $\eta_{i,k,t+l}^{jf}$ being a pseudo-uniform random number.

$$P_{i,t}^{ST} = psY_{i,t} + a_i + \sum_k Y_{i,k,t}^{ST} rr_{k,i} du_{i,k,t} 1(\eta_{i,k}^{u} \leq u_{i,k,t}) + Y_{i,k,t}^{ST} 1(\eta_{i,k}^{u} > u_{i,k,t}) \quad (7)$$

I then update the liquid asset measures ($noLiqA_{i,t}^{ST}$, $rLiqD_{i,t}^{ST}$) which are influenced by the pension withdrawal transforming illiquid pension funds into a liquid asset:

$$noLiqA_{i,t}^{ST} = \min(noLiqA_{i,t0}, 1(psPension_{i,t} = 0)) \quad (8)$$

$$rLiqD_{i,t}^{ST} = rLiqD_{i,t0} + \frac{psPension_{i,t}}{D_{i,t0} + 3 \times psDs_{i,t}} \tag{9}$$

with the denominator of the ratio of liquid assets to debt taking into account that the public support in terms of the debt service reduction ($psDs_{i,t}$) is not a debt pardon and therefore the borrowers will have to repay the three monthly installments that are deferred as an additional debt at a later maturity. In the same way, I update the indebtedness ratios ($DSIR_{i,t}^{ST}$, $CDPIR_{i,t}^{ST}$, $DAR_{i,t}^{ST}$), which take into account the new income measures ($Y_{i,t}^{ST}$, $P_{i,t}^{ST}$) and that the monthly debt service is reduced by the deferral policy ($psDs_{i,t}$), but that the overall consumer debt and the total debt increase by the respective three installment payments of consumer debt and mortgages that are delayed until a later maturity:

$$DSIR_{i,t}^{ST} = \frac{Ds_{i,t0} - psDs_{i,t}}{Y_{i,t}^{ST}} \tag{10}$$

$$CDPIR_{i,t}^{ST} = \frac{ConsD_{i,t0} + 3 \times (DebtD_i - (1 - Df_i) \sum_{v=0}^{3} Mds_{i,v})}{12 \times P_{i,t}^{ST}} \tag{11}$$

$$DAR_{i,t}^{ST} = \frac{D_{i,t0} + 3 \times DebtD_i}{A_{i,t0}} \tag{12}$$

In each stress test scenario, I then sum the delinquency probabilities of each household ($\Pr(Dr_{i,t}^{L} = 1 \mid \beta^{L}, X_i, Z_{i,t}^{ST})$) according to their characteristics ($X_i, Z_{i,t}^{ST}$) and their weight (w_i^{L}, given by the loan amount of household i relative to the total debt of type L in the economy) to obtain the aggregate delinquency rate of each debt type (Dr_t^{L}) and the aggregate household debt delinquency rate (Dr_t, which is the weighted sum of the delinquency rates of each debt type, w^{L}, given by the ratio of the total debt amount L relative to the sum of the household debt of all types):

$$Dr_t^{L} = \sum\nolimits_{i=1}^{N} w_i^{L} \Pr(Dr_{i,t}^{L} = 1 \mid \beta^{L}, X_i, Z_{i,t}^{ST}) \tag{13}$$

$$Dr_t = \sum\nolimits_{l=1}^{L} w^{L} Dr_t^{L} \tag{14}$$

Notice that the stress tests are subject to both estimation error and simulation error. The estimation error comes from the β^{L} coefficients being imprecisely estimated (see Table 5). The simulation error comes from the idiosyncratic random shocks ($\eta^{u}_{i,k}$, $\eta^{CJR}_{i,k}$, $\eta^{jq}_{i,k}$, $\eta^{jf}_{i,k,t+l}$, $\varepsilon_{i,k,t}$). To reduce the simulation error, I expand the EFH 2017 sample with replacement 1,000 times. This reduces the simulation error to close to nothing, since the 4,549 households become 4.549 million households, which is very close to the almost 5 million households that exist in Chile. I then simulate this 4.5 million extended sample for each bootstrap replica of the $\beta^{L(b)}$ coefficients estimated in section 2, obtaining the stress test delinquency rates ($Dr^{L(b)}_t$, $Dr^{(b)}_t$) for each replica. The mean delinquency rates over all the bootstrap replicas are:

$$\hat{D}r_t = \frac{1}{B}\sum\nolimits_b Dr^{(b)}_t \text{ and } \hat{D}r^L_t = \frac{1}{B}\sum\nolimits_b Dr^{L(b)}_t \text{ for each } L \tag{15}$$

In an online appendix I show that the standard-error of the simulated stress-tests ($Se(\hat{D}r_t) = \sqrt{\frac{1}{B}\sum_b(\hat{D}r^{(b)}_t - \hat{D}r_t)^2}$) is negligible for reasonably-sized cell groups, such as for each of the three income strata or the entire population, although the uncertainty is more significant for some small cells such as households with a non-employed household head.

4.2 Stress tests with additional Credit market shocks

A credit crisis is difficult to model in the stress tests, because - although it is an hypothesis that could have happened - Chile has not faced a banking crisis since the 80s (García 2021). To model an hypothetical credit crisis, I consider that some households can pay the interests on their debt but can only pay part of the amortization component, then remaining solvent only with access to new loans (Gerardi et al. 2018, Madeira, 2018). For this reason I consider a stress test scenario with credit market shocks, although such scenario did not materialize due to the special policy credit lines and other measures applied to banks (García 2021). Households are credit constrained or not ($cc_{i,t} = 1$) if they fulfill two conditions: i) if their monthly debt service ($Ds_{i,t}$) plus their estimated non-durable median consumption needs (nd_i) is above their monthly income ($Y_{i,t}$); ii) if households are highly indebted already, presenting a consumer debt ($ConsD_{i,t}$) that is above the percentile 90 of debt for other households (cd^{P90}_i) with similar characteristics $x_{i,t}$:

$$cc_{i,t} = 1(Ds_{i,t} + nd_i > Y_{i,t}) \times 1(ConsD_{i,t0} > cd^{P90}_i) \tag{16}$$

To estimate cd_i^{P90} and nd_i, I use linear quantile regression with households of similar characteristics $x_{i,t}$, in terms of permanent household income (in log), number of adults aged 18-65, number of children, age and education of the household head, home ownership, and residence in the capital area. In the stress test exercise, I consider that households do not actively seek new loans (except for the additional debt implicit in the debt deferral, therefore $ConsD_{i,t0}$ is constant), therefore the only element changing the credit constrained status ($cc_{i,t}$) is $Y_{i,t}^{ST}$. The credit shock exercise considers that in a credit crisis, lenders could reduce credit and households already credit-constrained before the survey would increase their delinquency rate to 15% and could further increase their delinquency rate by 35% if they remain credit constrained during the stress test (although some households that receive income policy support may increase and actually become non credit constrained during the stress test):

$$Dr_{i,t}^{L}(credit\_shock) = \max(0.15 \times cc_{i,to} + 0.35 \times cc_{i,t}^{ST}, Dr_{i,t}^{L}) \text{ for each } L \tag{17}$$

Note that this calibration choice is based on rules of thumb[13], being a simple hypothetical example of how a credit crisis in which lenders become more averse to some borrowers could develop. An online appendix considers some robustness variations of this exercise.

4.3 Labor market variables used in the stress tests and delinquency models

The unemployment risk ($u_{k,t}$), job quality risk ($jq_{k,t}$) and replacement ratio ($rr_{k,t}$) of the EFH workers k are based on the mean statistics for 504 worker types (given by a vector x_k of their education, age, industry, income quintile and region) from the quarterly Chilean Employment Survey (ENE). The unemployment risk $u_{k,t}$ is defined as the probability that the worker is unemployed at a given period ($U_{k,t} = 1$) conditional on his characteristics x_k. The job quality risk is taken as the probability there is a job quality loss ($Jq_{k,t} = 1$) conditional on his characteristics x_k, meaning that at least one of 4 events is reported by the worker: i) if the worker changes from a formal job with contract to an informal job (no contract) or to self-employment; ii) if the worker changes from

[13] One analysis in the online appendix does show that 15% is a reasonable value for the delinquency rate of the credit constrained borrowers, since these borrowers have a 12% delinquency rate for mortgages and consumer loans.

a large company (with more than 50 workers) to a small or medium company; iii) if the worker is not satisfied with their current employment or is looking for more hours of work.

Conditional on the workers' characteristics $x_k = \{$Santiago Metropolitan area or not, Industry (primary, secondary, tertiary sectors), Gender, Age (≤ 35, $35-54$, ≥ 55), Education (secondary school or less, technical degree, college), and Household Income quintile$\}$, the empirical estimation of the probabilities $u_{k,t}$ and $jq_{k,t}$ is obtained as

$$\Pr(Y_{k,t} = 1 \mid x_{k,t}) = \frac{\sum_v 1(Y_{v,t} = 1, x_{v,t} = x_{k,t})}{\sum_v 1(x_{v,t} = x_{k,t})}, \text{ for } Y = U, Jq \tag{18}$$

The $JobFind_{k,t}$ is defined as the workers' probability of finding a job in the current quarter ($U_{k,t} = 0$) given that they were unemployed in the previous quarter ($U_{k,t-1} = 1$) conditional on their characteristics x_k:

$$\Pr(U_{k,t} = 0 \mid U_{k,t-1} = 1, x_{k,t}) = \frac{\sum_v 1(U_{k,t} = 0, U_{k,t-1} = 1, x_{v,t} = x_{k,t})}{\sum_v 1(U_{k,t-1} = 1, x_{v,t} = x_{k,t})} \tag{19}$$

Besides measuring labor participation, unemployment and formal work status in each quarter, the ENE also measures respondents' labor income $W_{k,t}$ in the fourth quarter of every year. The ENE dataset has a panel component, since each worker can be followed for 6 quarters and that implies one can measure the income loss between employment-unemployment status flows and from continuous wage shocks even if the worker remains employed. Using a pooled set of two-year panel data samples (see Madeira 2015a for more details), it is possible to estimate the income volatility as

$$\sigma_{k,t} = \sqrt{\frac{\sum_v 1(x_{v,t}=x_{k,t})(\ln(W_{v,t}/W_{v,t-1}))^2}{\sum_v 1(x_{v,t}=x_{k,t})}} \tag{20}$$

and the replacement ratio of income during unemployment as

$$rr_{k,t} = \frac{\sum_v W_{v,t} 1(x_{v,t}=x_{k,t}, U_{k,t}=1) / \sum_v 1(x_{v,t}=x_{k,t}, U_{v,t}=1)}{\sum_v W_{v,t} 1(x_{v,t}=x_{k,t}, U_{k,t}=0) / \sum_v 1(x_{v,t}=x_{k,t}, U_{v,t}=0)} \tag{21}$$

As explained in section 2, bootstrap replicas of these statistics are obtained for all the 504 worker types to compute the estimation error components of the generated regressors in the delinquency risk models and of the simulated stress test scenarios. The Chilean Employment Survey covers around 12,000 households (corresponding to around 25,000 workers) in each month (Madeira 2015a), therefore its statistics can be precisely estimated even with 504 worker types. All the labor market calibration of the stress tests are done with the ENE micro-data until the end of 2020.

5 Results

Table 9 summarizes the results of the stress tests for both the total debt and each individual debt type for the periods just before the Social Explosion (September of 2019), after the Social Explosion and before the pandemic (February of 2020) and at the beginning of the Covid pandemic in mid-March of 2020 (which considers the scenarios with and without policy support). All the results are weighted by the debt value of each household, therefore the numbers represent the delinquency risk (in percentage) for the debt aggregate of each group.

The impact of the "Social Explosion" period on households is estimated to be quite strong, with delinquency risk on total household debt increasing from 2.7% (Sep 2019) to 4.5% (Feb 2020). The results show that the Social Explosion increased the delinquency risk of all debt types, particularly consumer loans and credit cards, across all income strata, but with a more negative impact on the poor (strata 1) and the middle class (strata 2). This makes sense, because most of the businesses and jobs affected by the political disruption were in the inner city, in which the poorest and middle class neighborhoods reside. Overall, delinquency risk falls sharply with income and even before the Social Explosion the total debt delinquency risk of the strata 1 and 2 were 7.7% and 4.5%, respectively, which are almost 5 and 3 times the delinquency risk of the richest households.

At the beginning of the Covid pandemic in mid-March, Chile was facing a renewal of the social protests with the end of the summer season and the start of a new academic year. However, this renewal of political protests was interrupted on March 16 when the first general lockdowns and harsh quarantines were implemented across the country. Therefore the mid-March scenario mixes the early period of the pandemic with a brief renewal of the Social Explosion and it is not possible to separate both effects. The results show that without support policies the early period of the Covid pandemic would have presented very similar debt risks as at the end of the Social Explosion (February of 2020). However, due to the support policies the debt risks actually fell, with the total debt risk being reduced from 4.7% to 4.1%. This reduction was strong both for mortgages (which

Table 9: Household delinquency by debt type (% of the debt of each type)

Models using the Financial Liquid Asset measures						
EFH 2017	Total	Mortgage	Consumer Loans	Bank Consumer Loans	Bank credit cards	Retail credit cards
September 2019 (before the Social Explosion):						
All debtors	2.7	1.3	5.2	4.3	3.0	6.4
Strata 1	7.7	4.0	10.0	11.3	6.1	15.6
Strata 2	4.5	2.4	7.3	7.2	4.3	9.9
Strata 3	1.6	0.8	3.8	2.8	2.2	4.1
February 2020 (after the Social Explosion):						
All debtors	4.5	2.7	7.5	6.5	4.4	9.5
Strata 1	12.1	7.9	14.2	15.7	8.8	22.0
Strata 2	7.0	4.7	10.1	10.5	6.4	14.2
Strata 3	2.8	1.8	5.6	4.5	3.3	6.4
Base Covid scenario, Mid-March 2020 (with support policies):						
All debtors	4.1	2.3	6.8	5.8	4.1	8.8
Strata 1	11.5	7.3	13.6	14.4	8.5	21.3
Strata 2	6.5	4.1	9.5	9.5	6.0	13.4
Strata 3	2.4	1.5	5.0	3.9	3.0	5.7
Base Covid scenario, Mid-March 2020 (without support policies):						
All debtors	4.7	2.8	7.7	6.7	4.6	9.8
Strata 1	12.3	8.2	14.5	16.1	9.2	22.6
Strata 2	7.3	4.9	10.5	10.9	6.7	14.8
Strata 3	2.9	1.9	5.8	4.7	3.4	6.6

benefitted more from the debt deferral program) and consumer loans, with delinquency risk falling from 2.8% to 2.3% and from 7.7% to 6.8% for mortgages and consumer loans, respectively.

Table 10 shows the stress test results, according to the households' income strata and work industry. All income strata are adversely affected by both crises, with Agriculture and Construction being the industries more severely affected by the Social Explosion (with delinquency risks increasing to 4.2% and 5.5%, respectively). Considering the policy support, the Covid pandemic reached its peak of delinquency risk of 4.4% in scenario II, which corresponds to the May-June-July period with an aggregate unemployment rate of 13.1%. The delinquency risk then falls substantially to 2.8% in August of 2020 and to 2.7% during September to December of 2020, which is quite similar to the level observed in September of 2019 before the big shocks of the Social Explosion and Covid crisis, with this improvement being due to the policy support implemented in August. Without policy support the delinquency risk would have increased to 5.7% in May-June-July and remained at that level in August, while dropping only slightly during September to December when the unemployment rate

Table 10: Delinquency by income strata and economic activity of the household head
(% of the debt of each group)

Stress tests that use the models with the liquid financial assets measures							
EFH 2017	"Social Explosion" in October 2019		Covid Crisis simulation With the support policies				
Income Strata	Sept 2019	Feb 2020	Base	I	II	III	IV
1	7.7	12.0	11.5	11.1	11.4	8.2	8.0
2	4.5	7.1	6.5	6.5	6.8	4.3	4.1
3	1.6	2.8	2.4	2.5	2.7	1.6	1.6
All debtors	2.7	4.5	4.1	4.1	4.4	2.8	2.7
Economic Sector$^{a)}$	Sept 2019	Feb 2020	Base	I	II	III	IV
Agriculture, Silviculture, Fishing	1.6	4.2	3.1	3.0	3.2	2.0	1.9
Construction	2.9	5.5	5.0	5.1	5.4	3.5	3.4
Lodging, Restaurants, Retail	3.3	5.4	4.9	4.8	5.1	3.5	3.4
Manufacturing, Energy, Other Services	2.6	4.0	3.6	3.6	3.9	2.4	2.3
Public administration, Education	2.9	5.1	4.7	4.7	4.9	3.1	3.0
Retired and Non-employed	2.2	3.7	2.8	2.8	2.9	2.0	1.9
			Without the support policies				
Income Strata			Base	I	II	III	IV
1			12.3	13.2	14.1	14.0	13.6
2			7.4	8.1	9.0	8.9	8.4
3			2.9	3.3	3.7	3.7	3.4
All debtors			4.7	5.2	5.7	5.7	5.4
Economic Sector$^{a)}$			Base	I	II	III	IV
Agriculture, Silviculture, Fishing			4.6	5.1	6.3	6.1	5.5
Construction			5.8	6.4	7.1	6.9	6.6
Lodging, Restaurants, Retail			5.6	6.1	6.7	6.7	6.4
Manufacturing, Energy, Other Services			4.1	4.6	5.1	5.0	4.8
Public administration, Education			5.3	5.8	6.3	6.3	5.9
Retired and Non-employed			3.8	4.5	4.8	4.7	4.6

a) Economic sector is determined by the work industry of the household member of highest income.

fell a few points. This means that the policies implemented in August (which consisted of a pension withdrawal plus a middle class income bonus and a zero interest rate sponsored loan) were decisive in controlling the debt risks of the pandemic. In the online appendix, I report a similar table implemented with the delinquency models that ignore the financial liquid assets of the household. The results from those models are quite similar to Table 10, except for the scenarios III and IV in which a substantially higher debt risk of 4.2% and 4.0% is reported. Table 10 reports a lower debt delinquency of 2.8% and 2.7% for scenarios III (August) and IV (September to December) because it accounts for the pension withdrawal as new liquid assets and this effect would not be captured without the asset variables.

Table 11: Delinquency by income strata and economic activity
of the household head (% of the debt of each group)

Stress tests that use the models with the liquid financial assets measures							
With Credit shocks during the Social Explosion and Covid Crisis							
EFH 2017	"Social Explosion" in October 2019		Covid Crisis simulation With the support policies				
Income Strata	Sept 2019	Feb 2020	Base	I	II	III	IV
1	7.7	13.5	12.9	12.6	12.8	9.7	9.6
2	4.5	8.1	7.5	7.5	7.8	5.3	5.1
3	1.6	3.1	2.7	2.8	3.0	1.9	1.9
All debtors	2.7	5.1	4.6	4.6	4.9	3.3	3.2
			Without the support policies				
Income Strata			Base	I	II	III	IV
1			13.8	14.7	15.5	15.4	15.0
2			8.4	9.2	10.0	9.9	9.5
3			3.2	3.6	4.0	3.9	3.7
All debtors			5.3	5.7	6.3	6.2	5.9

Finally, Table 11 shows what could have happened if a credit market crisis was combined with the labor market deterioration implied by the Social and Covid crises. The effect of the credit market shock is very similar during both the Social Explosion and the Covid pandemic. The delinquency risk would increase from 4.5% to 5.1% in February of 2020 if a credit shock had impacted the economy. Similarly, all the Covid scenarios would also show an increase between 0.4% and 0.6% in terms of the delinquency risk, independently of whether the other policy support was implemented or not. This shows that the bank credit lines and other loan relaxation measures implemented by the public authorities may have been crucial to avoid a worse debt crisis.

An explicit comparison of these results with those of households in other countries during the pandemic is difficult. In developed economies so far the pandemic economic crisis has not resulted in bank insolvency, because the banking sector started 2020 with much higher capital ratios than in the previous Great Financial Crisis of 2008 (ECB 2020). In Australia, Canada, Finland, Germany, Italy, the United Kingdom and the United States, households in the bottom 20% of the wealth distribution could not cover more than three months of lost income by drawing down savings (Zabai 2020). However, bank profitability has deteriorated over the last year both in Chile and in developed economies (ECB 2020, Central Bank of Chile 2020). It is possible that government measures such as income subsidies (ECB 2020), tax relief or debt repayment moratoriums may temporarily mask the underlying debt risk factors until a recovery develops (Zabai 2020). For instance, in the case of the US the debt delinquency for household consumer loans, credit cards and student debt increased substantially during 2019, but remained stable during 2020 due to government support measures such as the Coronavirus Aid, Relief and Economic Security (CARES) Act and debt deferral provisions (Famiglietti and Garriga 2020). In Canada, a stress test exercise of household debt risk also shows that the government income support policies and the debt deferral were effective to avoid a strong increase in mortgage delinquency, but the results are very sensitive to the assumption of a quick labor market recovery in 2021 (Bilyk et al. 2020). Therefore it is still early to know which countries did best in terms of household delinquency in this last crisis and how the debt moratoria may turn into losses later on (ECB 2020, Zabai 2020).

6 Conclusions

This works provides an estimate of the impact of the twin shocks of the "Social Explosion" and the "Covid pandemic" on the Chilean households, with a focus on debt delinquency. Using calibrated stress tests based on the Chilean Household Finance Survey (EFH), I find that the Social Explosion had a strong impact on both mortgages and consumer loans, increasing the total household debt risk from 2.7% to 4.5%. Mortgage and consumer delinquency worsened from 1.3% to 2.7% and from 5.2% to 7.5%, respectively. The Social crisis was expected to persist with renewed vigor in March of 2020, but the political protests were interrupted by the pandemic and the successive lockdowns. With the policy measures implemented during the pandemic, the debt risk actually fell slightly to 4.1% during the early stages of the Covid crisis, but increased again to 4.4% by mid 2020 due to the weak labor market conditions and an unemployment rate that reached 13.1%.

The Covid economic policy measures were effective in reducing the delinquency risk, which could have reached 5.7% by mid 2020 in the absence of support policies that boosted household income, deferred debt payments and allowed access to liquid pension assets. The policy measures were so strong in boosting household income and liquidity that by August of 2020 the debt delinquency had declined to just 2.8%, a value quite similar to the 2019 numbers before the twin shocks hit. Furthermore, the delinquency risk of the Social Explosion and Covid pandemic could have been 0.4% to 0.6% worse if a credit crisis had happened, but this outcome may have been attenuated by the quick and decisive credit flow support from the public authorities.

I find that all the public policies - whether income support, debt deferral and the pension withdrawal - were important for the households' budgets, but with different degrees of heterogeneity. The income support measures were very progressive policies, with a much higher impact on the poor than on the middle class and the richer households. These policies represented 9% of the average household income early in the pandemic, but were expanded to 20% by August.

Finally, future research should study the significant general equilibrium effects of these two crises, which could potentially impact corporate and sovereign solvency (Farhi and Tirole 2018).

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The double impact of deep social unrest and a pandemic: Evidence from Chile

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Abstract

This appendix provides further information and robustness tests to the original article.

JEL Classification: D12; D21; E21; G20.

Keywords: Latin America; Credit; Pandemics; Inequality.

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1 Appendix: contents

Table A.1 adds labor market statistics for Men and Women of different education levels in each industry during the the Social Explosion. This info complements Table 6 in the article.

Table A.2 shows the estimated results from the delinquency model regressions of each debt type, which use bootstrap replica samples of both the ENE (Employment Survey used for the generated regressors) and the EFH (Household Finance Survey). The results are very similar to Table 5 in the original article, which applies bootstrap replicas just to the ENE data for generating the regressors in the EFH delinquency model. The results are also very similar to the delinquency model estimates for the CASEN survey in 2006 and the EFH waves of the years 2007, 2008-2009, 2010, 2011, in Madeira (2014), which account for the endogeneity of the debt amount by using the unemployment risk of the household at the time the loan decision was made as instruments.

Table A.3 shows the income and expenses policy support in May (which has similar amounts as April) and in June (which shows amounts that are roughly half-way between the months of April and August) of 2020. This complements Table 7 in the article.

Table A.4 shows that there are approximately 2.8% of credit constrained borrowers in the EFH survey dataset, which show a 12.0% delinquency rate for both mortgages and consumer loans. This shows that the 15% calibrated parameter in the article is a reasonable value.

Table A.5 shows the standard-errors of the Stress Test simulations in Table 10 (which also apply to the first column of Table 9), confirming that the resulting simulation exercise is accurate for broad groups of the population, although the uncertainty can be large for some scenarios of small groups such as the Non-Employed Household Heads.

Table A.6 shows a simulation of a less "harsh" credit market shock, in which the delinquency rate parameter of the credit-constrained households is at least 10% and can increase to 40% during the stress test. The results are broadly similar qualitatively to Table 11 in the article, although the delinquency numbers in this exercise are somewhat smaller.

Table A.7 shows the results of the stress tests using the models that do not include the financial liquid asset measures. These numbers are similar to Table 10 in the article, except for the scenarios of August (scenario III) and September to December (scenario IV). It is worth noting that the scenarios III and IV have the impact of the pension withdrawal which increased the liquid assets available to households substantially. Therefore for those scenarios the models used in Table 10 of the article are more appropriate and the results show a higher impact of the public policy.

Figure 1 plus the Tables B.1 and B.2 show the results of an earlier exercise implemented in April of 2020, when the pandemic and public policies associated with it were at an early stage. Table B.1 shows the stress tests according to the aggregate unemployment rate predicted for Chile in the models of the IMF (2020) and Central Bank of Chile (2020). The unemployment risk of the 504 worker types are then calibrated according to how their group unemployment rates behaved relative to the aggregate labor market in the past 20 years (Figure 1). Table B.2 then shows the results of the prospective exercise of Stress Test according to different risk scenarios. The results differ from the Tables 8, 9 and 10 in the article in 3 aspects: i) this calibration was limited to aggregate unemployment projections and did not use the micro-data for the employment available now for the period of October 2019 until December of 2020; ii) the results do not include the policy measures adopted in August of 2020, iii) the results apply the model without financial liquid assets (unlike Table 10), iv) these results use a sample that is 50 times the size of the EFH, therefore the results have more simulation error than the results based on 1,000 times of the EFH sample size which are reported in Tables 9, 10, 11 of the article and Tables A.6 and A.7 of this appendix.

Figure 2 at the end of the appendix shows the kernel distribution (with an Epanechnikov function and the Silverman's rule for the optimal bandwidth) of the current income and permanent income of the households in the Chilean Household Finance Survey (EFH) dataset in 2017. Both measures are similar and present a correlation of 85.5%. However, as shown in Figure 2, the Permanent Income has fewer observations with very low values of income. This is because it imputes an income for the unemployed members of the household based on their last labor earnings and the replacement ratio of income during unemployment for workers of their characteristics. The replacement ratio of income needs to be estimated from the data, because the benefits depend on how many months were discounted for the unemployment insurance fund.

The current income of the household i is obtained as the sum of both labor income of each of its members k ($Y_{k,i}$) and the non-labor income of the household (a_i): $Y_{i,t} = a_i + \sum_k Y_{k(i),t}$. The non-labor income includes alimony, child support and family allowances, intrafamily transfers and remittances, government subsidies, water and food allowances, donations, retired pension income, disability pensions, widow or orphan pension income, insurance payments and financial assets' income, income from real estate and vehicles (including rental and implicit income from livestock and agricultural products of the property), and income-dividends from personal businesses.

Each household i's permanent income is obtained as the sum of its non-labor income (a_i) plus the labor earnings of each labor force member k: $P_{i,t} = a_i + \sum_k P_{k(i),t}$. The permanent income of each household member is given by $P_{k(i),t} = (Y_{k,i}(1 - u_{k,i,t}) + Y_{k,i}rr_{k,i}u_{k,i,t})$, where $Y_{k,i}$ is worker k's earnings when in employment, $u_{k,i,t} = u(x_{k(i)}, t)$ is its probability of being in an unemployment spell, and $rr_{k,i}$ is its replacement ratio of income during unemployment relative to the earnings while working (Madeira 2018). $u_{k,i,t}$ and $rr_{k,i}$ are obtained from the Employment Survey, ENE, from the same year and quarter as the EFH survey interviews from workers with similar job characteristics $x_{k(i)}$, with $x_k = \{$Santiago Metropolitan area or not, Industry (primary, secondary, tertiary sectors), Gender, Age (≤ 35, $35 - 54$, ≥ 55), Education (secondary school or less, technical degree, college), and Household Income quintile$\}$.

Calibrating the household credit market shocks

Consumers can be subject to credit constraints (Attanasio and Weber 2010). Suppose households can pay the interests on their debt but can only pay part of the amortization component, then such households remain solvent only if they have access to new loans (Herkenhoff et al. 2016, Madeira, 2018). For this reason the harshest stress scenarios also include credit market shocks. Households are credit constrained or not ($cc_{i,t} = 1$) if they fulfill two conditions. The first condition is that households are "constrained by expenses" ($ExpensesC_{i,t} = 1$) and therefore have a requirement for more debt. This happens if their expenses ($NDDS_{i,t} = Ds_{i,t} + nd_i$), given by the sum of their monthly debt service ($Ds_{i,t}$) plus their estimated consumption needs (nd_i), are above their monthly income ($Y_{i,t}$): $ExpensesC_{i,t} = 1(NDDS_{i,t} > Y_{i,t})$. The consumption needs of each EFH household i are obtained from the median non-durable expenditures of households with similar characteristics $x_{i,t}$ in the Chilean Family Expenditure Survey of 2017 (Madeira 2018, 2019a). The second condition is that households must be highly indebted already ($DebtC_{i,t} = 1$), therefore lenders may refuse further loans to them. This condition is evaluated by measuring households with a consumer debt amount ($cd_{i,t}$) that is above the percentile 90 of debt for other households

Table A.1: Hours worked during the Social Explosion in % of the labor hours in September of 2019

	Secondary or less			Technical educ.			College or more			All workers		
Month (year 2019)	Oct	Nov	Dec	Oct	Nov	Dec	Oct	Nov	Dec	Oct	Nov	Dec
Men												
Agriculture, Fishing, Mining	106.5	115.2	111.6	77.5	108.9	128.9	85.5	104.6	138.4	101.3	113.3	116.4
Manufacturing and Energy	86.7	103.6	105.9	156.1	131.8	107.3	112.6	97.6	103.4	98.7	105.5	105.6
Construction	104.6	89.9	96.6	103.6	128.8	89.1	65.8	94.6	100.6	98.5	93.8	96.6
Retail	85.9	99.7	98.6	122.8	116.4	119.0	91.4	106.8	90.4	91.9	103.3	99.8
Transports, Lodging, ICT	86.5	75.9	93.0	96.3	114.6	132.0	99.2	96.6	117.9	88.8	83.5	99.7
Banks and finance	80.0	84.5	93.8	100.0	92.9	98.4	101.2	114.5	93.1	92.0	99.1	94.3
Public administration, Services	106.8	98.0	101.1	76.5	80.1	103.5	85.5	94.2	101.7	93.5	93.7	101.7
All sectors	94.8	97.0	100.8	103.0	106.9	109.8	91.5	101.9	102.4	95.1	99.3	102.2
Women												
Agriculture, Fishing, Mining	118.4	185.8	174.4	137.4	126.4	225.5	140.1	74.9	191.8	122.5	170.0	180.8
Manufacturing and Energy	83.0	101.6	106.4	124.2	86.4	93.7	112.3	111.7	103.1	95.8	101.0	103.6
Construction	94.1	132.9	100.9	56.3	36.6	95.9	65.5	32.0	81.5	76.1	67.3	92.4
Retail	94.1	84.0	114.2	97.1	128.2	129.7	117.2	88.1	123.9	97.9	91.2	117.9
Transports, Lodging, ICT	117.7	75.5	124.8	158.0	173.2	100.9	75.0	157.2	56.5	120.5	110.6	108.8
Banks and finance	100.6	95.3	96.5	106.8	91.0	110.5	78.4	78.5	88.5	93.5	88.3	96.1
Public administration, Services	89.5	96.3	100.9	80.9	101.7	101.7	84.8	101.7	104.8	86.1	99.4	102.5
All sectors	94.5	98.2	109.5	94.3	104.3	109.3	88.2	94.4	103.0	92.6	98.2	107.6
Both genders												
Agriculture, Fishing, Mining	108.2	125.2	120.5	85.7	114.3	142.1	92.7	100.7	145.5	104.3	121.3	125.4
Manufacturing and Energy	85.8	103.1	106.0	144.1	114.8	102.2	112.6	101.6	103.3	97.9	104.3	105.1
Construction	104.2	91.7	96.8	94.7	103.9	91.0	65.7	82.8	96.9	96.5	91.4	96.2
Retail	89.7	92.5	105.7	110.6	122.1	124.1	101.2	99.7	103.1	94.5	97.9	107.9
Transports, Lodging, ICT	89.8	76.1	96.4	113.3	130.7	123.4	94.8	107.5	108.4	93.0	87.1	100.9
Banks and finance	89.8	90.2	95.1	103.2	94.3	104.0	91.0	98.3	91.0	92.7	94.1	95.2
Public administration, Services	95.8	96.9	101.0	79.6	95.3	102.2	85.1	98.9	103.6	88.7	97.4	102.2
All sectors	94.7	97.4	103.7	98.7	105.6	109.5	90.0	98.4	102.7	94.1	98.9	104.3

ENE (2019-2020).

Table A.2: Delinquency (arrears for 3 months or more) probit models

Controls	Consumer loan (any)	Banking consumer loan	Banking credit card	Retail credit card	Mortgage debt
	Mean coefficients and standard-errors from B=1,000 bootstrap replicas of both the EFH and ENE survey datasets				
	Model estimates with both debt and liquid asset ownership measures				
$noLiqA_{i,t}$	0.127	0.284*	0.328**	0.121*	0.368
	(0.0996)	(0.167)	(0.144)	(0.0722)	(0.260)
$rLiqD_{i,t}$	-0.0601	-0.481	-4.139	-0.0261**	-8.151**
	(0.0393)	(0.325)	(1.321)	(0.0127)	(3.194)
$DAR_{i,t}$					-0.012
					(0.173)
$u_{i,t}$	2.194***	1.331	2.804***	2.582***	0.735
	(0.781)	(1.196)	(1.034)	(0.555)	(1.227)
$\ln(Y_{i,t})$	-0.176**	-0.278**	-0.122**	-0.214***	-0.135**
	(0.0568)	(0.0887)	(0.0519)	(0.0528)	(0.067)
$CDPIR_{i,t}$	0.350***	0.405**	0.758***	0.347***	0.143
	(0.119)	(0.183)	(0.148)	(0.111)	(0.256)
$DSR_{i,t}$	0.121	0.0445	0.301***	0.663***	1.306***
	(0.138)	(0.123)	(0.109)	(0.103)	(0.199)
$members_i$	0.114***	0.0860***	0.0169	0.128***	0.153***
	(0.0202)	(0.0302)	(0.0244)	(0.0147)	(0.0375)
$College$	-0.326***	-0.588***	-0.163*	-0.520***	-0.492***
$education_i$	(0.0824)	(0.127)	(0.0953)	(0.064)	(0.134)
	Model estimates without the liquid asset ownership measures				
$DAR_{i,t}$					0.051
					(0.172)
$u_{i,t}$	2.180***	1.312	2.776***	2.536***	0.730
	(0.871)	(1.197)	(1.039)	(0.558)	(1.230)
$\ln(Y_{i,t})$	-0.194***	-0.300***	-0.133**	-0.229***	-0.162**
	(0.0559)	(0.0875)	(0.0551)	(0.0541)	(0.0693)
$CDPIR_{i,t}$	0.359***	0.409**	0.780***	0.353***	0.167
	(0.118)	(0.182)	(0.145)	(0.111)	(0.254)
$DSR_{i,t}$	0.122	-0.0108	0.294***	0.669***	1.262***
	(0.137)	(0.217)	(0.108)	(0.102)	(0.197)
$members_i$	0.118***	0.0885***	0.0220	0.131***	0.155***
	(0.0201)	(0.0300)	(0.0244)	(0.0148)	(0.0370)
$College$	-0.325***	-0.590***	-0.180**	-0.527***	-0.536***
$education_i$	(0.0830)	(0.127)	(0.0952)	(0.0643)	(0.134)

Models estimated using the pooled EFH waves (2010, 2011, 2014, 2017).
Other Controls: Constant, age, technical education, residence in the capital area, gender and marriage status of the household head.

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

Table A.3: Public policy benefits as a fraction of the household monthly permanent income or as fraction of the debt service or total debt (in %)

EFH 2017	Income and expenses support							
	$psY_{i,t}/P_{i,t}$: May 2020				$psY_{i,t}/P_{i,t}$: June 2020			
	Pc25	Pc50	Pc75	Mean	Pc25	Pc50	Pc75	Mean
All households	3.7	5.9	14.4	11.2	4.1	8.9	20.8	13.2
Strata 1 (pc 1-50)	7.4	12.4	27.7	18.1	9.4	18.6	27.2	19.4
Strata 2 (pc 51-80)	4.0	4.9	6.3	7.1	4.8	6.8	18.4	11.6
Strata 3 (pc 81-100)	1.9	2.7	3.4	3.3	1.9	2.7	3.4	3.3

(cd_i^{P90}) with similar characteristics $x_{i,t}$ in the EFH survey. To estimate cd_i^{P90} and nd_i, I use estimates in a linear quantile regression with households of similar characteristics $x_{i,t}$, in terms of permanent household income (in log), number of adults aged 18-65, number of children, age and education of the household head, home ownership, and residence in the capital area.

Table A.4 reports the average amounts for the estimated non-durable expenditures, the sum of non-durables and monthly debt service, plus the fraction of households that are subject to a need for extra debt ($ExpensesC_{i,t}$), a condition of being already highly indebted ($DebtC_{i,t}$), and being Credit Constrained ($cc_{i,t}$, both conditions simultaneously). The results show that expenditures and the sum of expenditures plus debt service are increasing in income. However, the need for higher debt is decreasing in income level, although there is a higher fraction of upper income households with high values of indebtedness. The results for the credit constraint calibration also make sense. Although only 4.3% of the indebted households are credit constrained, note that the fraction of credit constrained households that are in delinquency for any loan is 12% and the fraction of households with a delayed payment in their bank credit card is 16.4%. This indicates that the credit constraint measure is highly correlated with household liquidity needs and loan problems.

Prospective exercise of labor market risk before the microdata in 2020 was available

While the pandemic was still starting, I performed the following stress tests in April of 2020, before there was any micro-data available to do a more precise exercise. These stress tests differ in relation to the article in the sense that: i) this calibration was limited to aggregate unemployment projections and did not use the micro-data for the employment available now for the period of

Table A.4: Average values from the EFH 2017 for the non-durable expenditures (monthly, in UF), non-durable expenditures plus debt service (UF, monthly) and fraction of households with debt requirements, high indebtedness and credit constrained (percentage of the group's households)

Household Type	Non-durable expenses (in UF)	Non-durable expenses plus debt service	$ExpensesC_{i,t} = 1(NDDS_{i,t} > Y_{i,t})$	$DebtC_{i,t} = 1(cd_{i,t} > cd_i^{P90})$	$cc_{i,t} = DebtC_{i,t} \times ExpensesC_{i,t}$
All	13.2	20.1	16.4	6.4	2.8
Income Strata:					
Strata 1: P1-P50 (poorest)	7.2	10.1	23.0	5.2	3.3
Strata 2: P51-P80	14.8	21.4	13.5	7.3	2.7
Strata 3: P81-P100	25.4	42.5	5.0	8.0	1.9
Any Debt	14.7	25.2	19.7	9.7	4.3
Mortgage Debtors	17.0	31.9	12.6	10.6	3.3
Consumer Debtors	14.7	26.1	20.9	10.5	4.7
Bank Credit Card Debtors	15.8	26.6	19.1	8.3	3.7
Retail Credit Card Debtors	14.0	22.7	19.0	7.7	3.7
No delinquency	15.8	28.4	18.8	12.3	5.1
Delinquency (3 months):					
Mortgage or Consumer loan	13.7	26.1	29.9	23.4	12.0
Consumer loans	14.3	28.0	33.1	26.6	14.4
Bank credit card delay	16.1	36.8	41.9	29.3	16.4
Retail credit card delay	11.2	21.4	39.7	12.8	8.8

October 2019 until December of 2020; ii) the results do not include the policy measures adopted in August of 2020, iii) the results apply the model without financial liquid assets (unlike Table 10), iv) these results use a sample that is 50 times the size of the EFH, therefore the results have more simulation error than the results based on 1,000 times of the EFH sample size which are reported in Tables 9, 10, 11 of the article and Tables A.6 and A.7 of this appendix.

he Stress Test scenarios (in Table 5) can be summarized in four components: i) the aggregate unemployment rate, ii) income volatility and job quality shocks which affect the income received by workers even if they remain employed, iii) frictions in renewing consumer loans, and iv) the government designed policies to support households and borrowers due to the Covid crisis. To measure the impact of the "Social explosion" and Covid I estimate the reaction of households for 6 aggregate unemployment scenarios, from 7.0% on September of 2019 (just before the "Social explosion") to the level of 7.8% observed in February 2020, just before the start of the Covid crisis.. Therefore the difference between September of 2019 and February of 2020 gives us the impact of the "Social explosion" shock. I then consider a Covid shock, which starts at 7.8% of aggregate

Table A.5: Standard errors of the estimated Delinquency rate (in %)
Model with Liquid assets measures

EFH 2017	"Social Explosion" in October 2019		Covid Crisis simulation With policy support				
Income Strata	Sept 2019	Feb 2020	Base	I	II	III	IV
1	0.0936	0.2175	0.1106	0.0222	0.0870	0.0519	0.0444
2	0.0783	0.1026	0.0110	0.1091	0.0662	0.0451	0.0294
3	0.0293	0.0086	0.0139	0.0260	0.0060	0.0035	0.0174
All debtors	0.0306	0.0277	0.0199	0.0296	0.0059	0.0048	0.0184
Economic Sector$^{a)}$	Sept 2019	Feb 2020	Base	I	II	III	IV
Agriculture, Silviculture, Fishing	0.0595	0.9575	0.4624	0.0019	0.0238	0.5377	0.0282
Construction	0.0019	0.3888	0.1642	0.0508	0.1184	0.1162	0.1662
Lodging, Restaurants, Retail	0.0148	0.0583	0.0657	0.0135	0.1082	0.0799	0.0830
Manufacturing, Energy, Other Services	0.0485	0.0759	0.0293	0.0739	0.0275	0.0387	0.0563
Public administration, Education	0.0024	0.1569	0.0147	0.0056	0.0047	0.0650	0.0725
Retired and Non-employed	0.0250	0.0857	0.1899	0.3288	0.0024	0.3770	0.7680
			Without the support policies				
Income Strata			Base	I	II	III	IV
1			0.0579	0.1051	0.0629	0.1189	0.0961
2			0.0402	0.0941	0.1227	0.0696	0.0858
3			0.0787	0.0341	0.0429	0.0499	0.0481
All debtors			0.0650	0.0129	0.0253	0.0276	0.0423
Economic Sector$^{a)}$			Base	I	II	III	IV
Agriculture, Silviculture, Fishing			0.3663	0.2573	0.7368	0.1879	0.0626
Construction			0.2488	0.1244	0.2423	0.3249	0.4603
Lodging, Restaurants, Retail			0.1622	0.3144	0.2269	0.2332	0.0778
Manufacturing, Energy, Other Services			0.1346	0.0763	0.0512	0.1226	0.0409
Public administration, Education			0.2159	0.0535	0.1470	0.2563	0.2367
Retired and Non-employed			1.8058	1.4359	1.2278	0.4093	1.2374

a) Economic sector is determined by the work industry of the household member of highest income.

Table A.6: Delinquency by income strata and economic activity
of the household head (% of the debt of each group)

Stress tests that use the models with the liquid financial assets measures
With Credit shocks during the Social Explosion and Covid Crisis

$$cc_{i,t} = 1(Ds_{i,t} + nd_i > Y_{i,t}) \times 1(ConsD_{i,t0} > cd_i^{P95})$$

$$Dr^L_{i,t}(credit\_shock) = \max(0.10 \times cc_{i,to} + 0.30 \times cc^{ST}_{i,t}, Dr^L_{i,t})$$

EFH 2017	"Social Explosion" in October 2019		Covid Crisis simulation With the support policies				
Income Strata	Sept 2019	Feb 2020	Base	I	II	III	IV
1	7.7	12.8	12.2	11.8	12.1	8.9	8.7
2	4.5	7.7	7.0	7.1	7.4	4.9	4.7
3	1.6	2.7	2.5	2.6	2.9	1.8	1.7
All debtors	2.7	4.8	4.3	4.4	4.6	3.1	3.0
			Without the support policies				
Income Strata			Base	I	II	III	IV
1			13.1	14.0	14.8	14.8	14.3
2			7.9	8.8	9.5	9.5	9.0
3			3.1	3.4	3.9	3.8	3.6
All debtors			5.0	5.5	6.0	6.0	5.7

unemployment, the same value as the last official unemployment measurement in February. The Covid shock is calibrated to affect 10% of the labor force members. In a hypothetical scenario where no policy measures are made, these labor force members would become unemployed, which is realistic given that some analysts forecast that countries with little capacity to support companies and employment could quickly reach unemployment rates around 20% (IMF 2020a). It is assumed that under the Covid support policies these workers benefit from an employment support mechanism and therefore will not be unemployed except for the scenarios without government support measures in place. Therefore the Base scenario for the Covid crisis considers a 7.8% unemployment rate plus a 10% labor force mass that keeps its employment based on government support policies. I then consider four scenarios with increasing degrees of the aggregate unemployment rate at 8.5%, 10%, 11% and 13%, which may materialize as the Covid crisis deepens during 2020 (IMF 2020a forecasts an average unemployment rate of 9.7% in Chile for the year 2020). The three scenarios with 2 digits of unemployment (10%, 11%, 13%) also have an additional version with a credit market shock in which new loans are harder to get and more expensive.

In each stress test scenario t each individual household i receives random shocks and its risk vector $X_{i,t}$ changes because shocks to unemployment, unemployment duration, income, and credit shocks affect the variables $u_{i,t}, \ln(Y_{i,t}), CDPIR_{i,t}, DSR_{i,t}, DAR_{i,t}$. The EFH sample is expanded

Table A.7: Delinquency by income strata and economic activity of the household head
(% of the debt of each group)

Model without Liquid assets measures							
	"Social Explosion"		Covid Crisis simulation				
EFH 2017	in October 2019		With policy support				
Income Strata	Sept 2019	Feb 2020	Base	I	II	III	IV
1	7.7	12.2	11.6	11.2	11.5	10.8	10.6
2	4.5	7.2	6.5	6.6	6.9	6.3	6.1
3	1.6	3.0	2.5	2.6	2.9	2.6	2.5
All debtors	2.8	4.7	4.2	4.2	4.5	4.2	4.0
Economic Sector[a)]	Sept 2019	Feb 2020	Base	I	II	III	IV
Agriculture, Silviculture, Fishing	1.6	4.5	3.3	3.1	3.4	3.2	3.1
Construction	3.0	5.9	5.4	5.4	5.8	5.2	5.0
Lodging, Restaurants, Retail	3.3	5.5	5.0	5.0	5.3	4.9	4.8
Manufacturing, Energy, Other Services	2.6	4.1	3.6	3.7	4.0	3.7	3.5
Public administration, Education	2.9	5.2	4.7	4.7	5.0	4.6	4.5
Retired and Non-employed	2.4	4.2	3.1	3.1	3.4	3.1	3.1
			Without the support policies				
Income Strata			Base	I	II	III	IV
1			12.5	13.5	14.4	14.2	13.7
2			7.4	8.3	9.2	9.0	8.6
3			3.1	3.5	4.0	3.9	3.7
All debtors			4.9	5.4	6.0	5.9	5.6
Economic Sector[a)]			Base	I	II	III	IV
Agriculture, Silviculture, Fishing			4.7	5.5	6.7	6.3	5.6
Construction			6.2	6.8	7.6	7.5	7.0
Lodging, Restaurants, Retail			5.7	6.5	7.1	7.0	6.6
Manufacturing, Energy, Other Services			4.2	4.7	5.3	5.3	4.9
Public administration, Education			5.4	6.0	6.6	6.5	6.2
Retired and Non-employed			4.5	4.7	5.7	5.4	5.4

a) Economic sector is determined by the work industry of the household member of highest income.

50 times with replacement to reduce the randomness of the simulation error (Madeira, 2018).

The aggregate unemployment shocks affects workers in a heterogeneous way according to their type, with the stress affecting both how many workers enter unemployment (given by the job separation rate) and also the duration of the unemployment spells (given by the job finding rate). Using the 504 different types of workers (given by $x_k = \{$gender, age, education, industry, residence in capital area from the quarterly Chilean Employment Survey (ENE, Madeira 2015) for the period 1990 until 2019, I estimate the sensitivity of variable $y_{k,t}$ (which denotes the unemployment, job separation and job finding rates for each group k at time t) relative to the aggregate unemployment rate u_t to obtain the heterogeneous worker employment flow rates for each aggregate stress test scenario:

$$y_{k,t} = \gamma x_k + \theta x_k u_t \tag{1}$$

Using two pseudo uniform numbers the EFH workers are assigned to unemployment and for a given duration conditional on the unemployment and job finding rates of type k. According to the duration of the unemployment spell, the workers lose 40%, 50, 57% and 62% of their labor income for, respectively, one, two, three and four or more quarters of unemployment duration (implicit income replacement rates of the Chilean welfare system, Madeira 2015).

Figure 1 represents the distribution of the heterogeneous unemployment risk ($u_{i,t} = \sum_k u_{k(i),t} P_{k(i),t}/(P_{i,t} - a_i)$) and the probability of finding a job within 3 months ($\lambda^{UE}_{i,t} = \sum_k \lambda^{UE}_{k(i),t} P_{k(i),t}/(P_{i,t} - a_i)$) faced by the households in the most recent EFH wave 2017 for each stress test scenario (7.4%, 8.4%, 10%, 11%, 13% aggregate unemployment). Since several households have more than one working member, the probabilities are weighted by the permanent income of each member. The unemployment risk among the Chilean households can go from very low (less than 2.5%) to very high levels (above 20%). In the same way the job finding probability among households can go from as low as 15% to as high as 55%. Notice that a deep recession is not just a period when unemployment is high, but also one in which finding a new job is hard once unemployed (Davis et al. 2006). When the aggregate unemployment rate is 13%, there are many households with a high unemployment risk (above 20%) and also many households with long unemployment spell duration, since most households in that scenario have a job finding probability below 30%.

Table B.1: The Stress Test scenarios

Type of shock	Scenarios						
	Sept 2019	Feb 2020	Base Covid	I	II	III	IV
Economic shocks:							
i) Unemployment rate	7.0%	7.8%	7.8%	8.5%	10%	11%	13%
ii) Income and job quality	No	Yes	Yes	Yes	Yes: worse scenario		
iii) Frictions in renewing loans	No	No	No	No	No		
iv) Covid support policies	No	No	Yes and No	Yes and No	Yes and No		
Covid shock:							
a)			5% of labor force would lose employment if there was no policy support				
b)			5% of labor force would enter a half-time and 30% less pay schedule if no policy support				

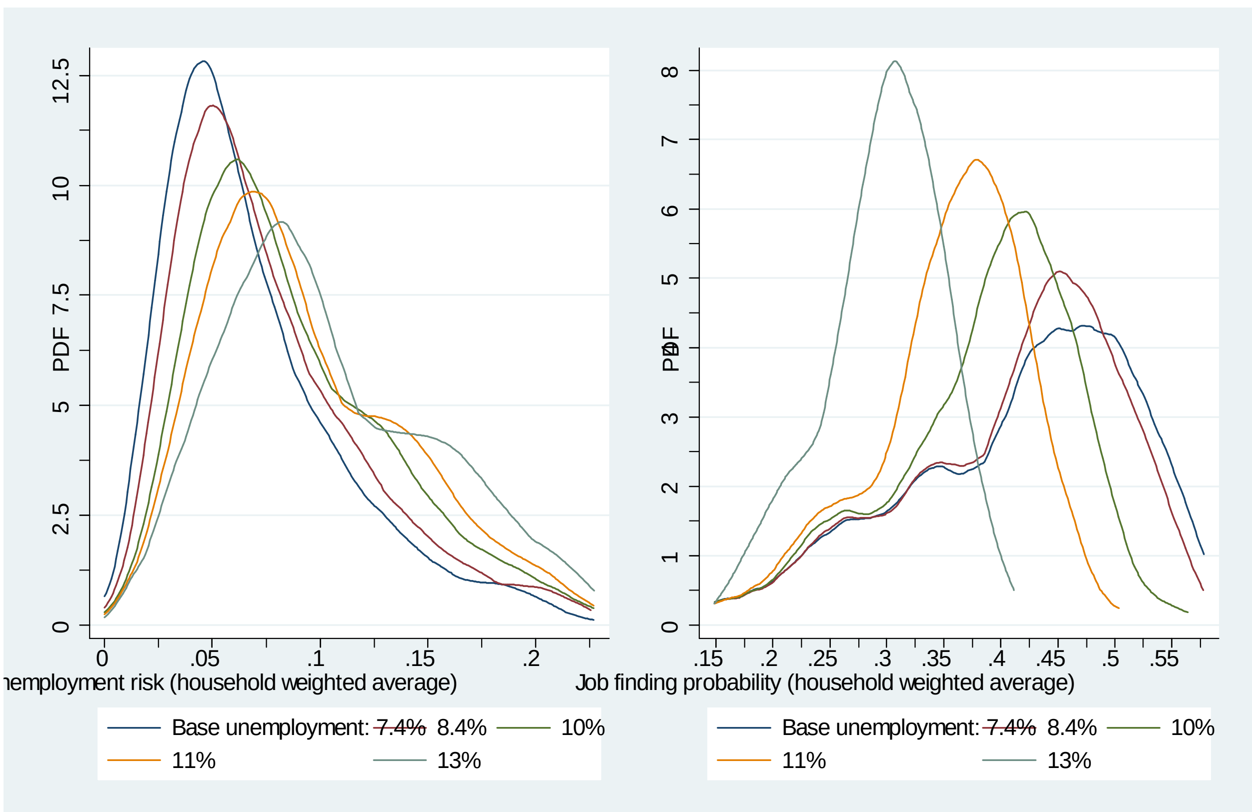

Figure 1: Impact of the stress scenarios on the household unemployment and job finding rates

Table B.2: Delinquency by income strata and economic activity of the household head
(% of the debt of each group)

Model without the financial liquid asset measures										
EFH 2017	"Social Explosion" in October 2019		Covid Crisis simulation (start in March 2020) With policy support							
			Without credit shocks					With credit shocks		
Income Strata	Sept 2019	Feb 2020	Base	I	II	III	IV	II	III	IV
1	9.0	10.6	10.2	10.9	11.9	12.4	13.3	14.9	15.4	16.2
2	5.1	6.1	5.8	6.4	7.0	7.4	8.2	9.8	10.1	10.9
3	1.9	2.7	2.1	2.5	3.2	3.3	4.0	4.2	4.3	5.1
All debtors	3.2	4.1	3.6	4.1	4.8	5.0	5.7	6.4	6.6	7.3
Economic Sector[a)]	Sept 2019	Feb 2020	Base	I	II	III	IV	II	III	IV
Agriculture, Silviculture, Fishing	3.9	5.5	5.3	9.0	14.2	16.7	19.1	17.2	18.8	20.3
Construction	3.4	5.1	4.7	5.6	7.3	7.9	10.1	8.5	9.2	11.4
Lodging, Restaurants, Retail	3.8	4.8	4.3	4.7	5.3	5.7	6.2	7.4	7.7	8.3
Public administration, Education	3.0	3.5	3.1	3.3	3.8	4.1	4.4	5.5	5.8	6.1
Manufacturing, Energy, Other Services	3.2	4.3	3.3	3.7	4.0	4.3	4.9	5.7	5.9	6.6
Retired and Non-employed	2.5	3.5	2.7	2.9	3.8	4.0	4.1	5.1	5.2	5.4
			Without the Covid support policies							
Income Strata			Base	I	II	III	IV	II	III	IV
1			10.9	11.6	12.6	13.3	14.2	15.9	16.5	17.3
2			6.3	6.7	7.4	7.8	8.4	10.2	10.6	11.1
3			3.0	3.2	3.4	3.6	3.8	4.5	4.7	4.8
All debtors			4.4	4.7	5.1	5.3	5.9	6.8	7.0	7.5
Economic Sector[a)]			Base	I	II	III	IV	II	III	IV
Agriculture, Silviculture, Fishing			5.5	9.2	14.4	16.9	19.2	17.3	18.9	20.3
Construction			5.2	5.7	7.3	7.9	10.1	8.5	9.2	11.4
Lodging, Restaurants, Retail			5.3	5.7	6.2	6.5	7.0	8.9	9.0	9.3
Public administration, Education			3.8	4.0	4.3	4.5	4.8	6.1	6.3	6.5
Manufacturing, Energy, Other Services			5.3	5.6	6.1	6.4	6.8	7.5	7.8	8.2
Retired and Non-employed			3.4	3.6	4.0	4.1	4.3	5.1	5.2	5.4

a) Economic sector is determined by the work industry of the household member of highest income.

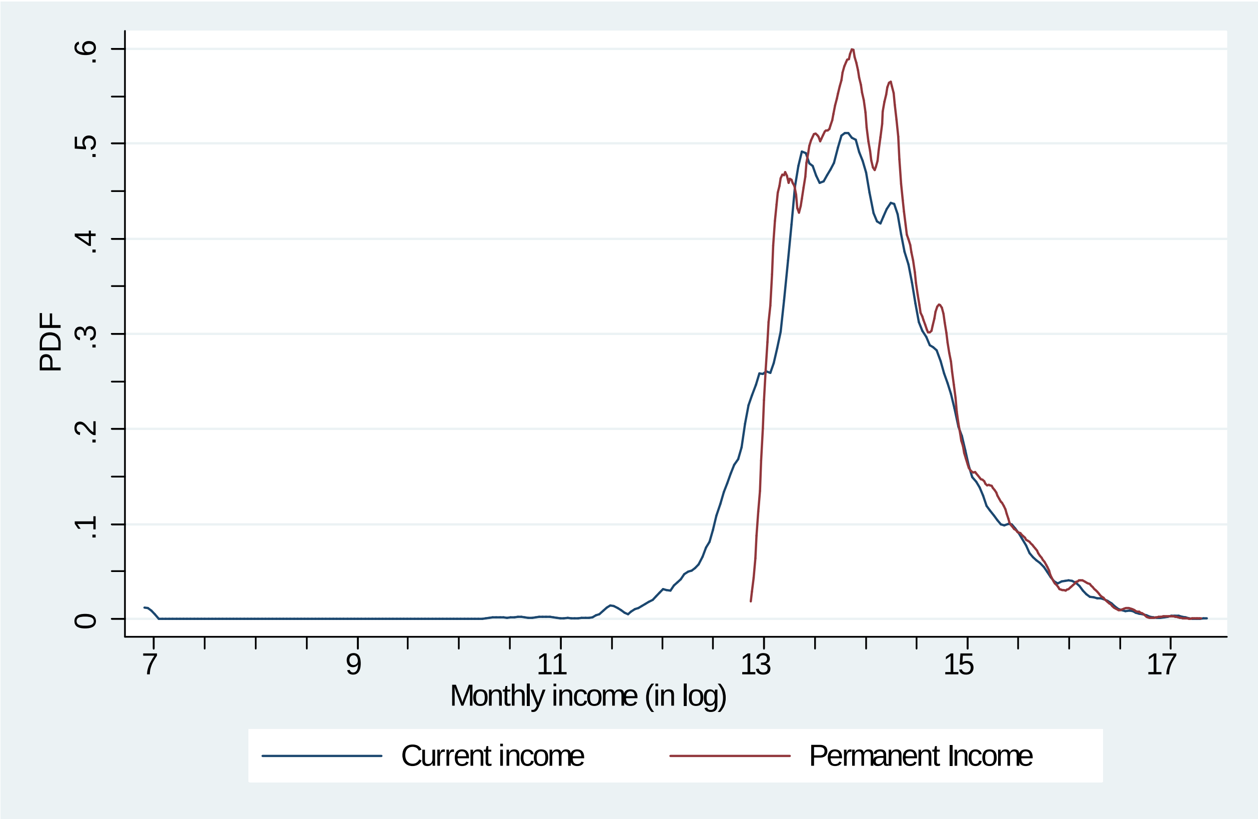

Figure 2: Kernel pdf distributions of the household current income and permanent income at the time of the EFH survey (wave 2017)

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