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“Propensity to consume over windfall liquidity shock: Evidence from quasi experimetal public policy in Chile”

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Windfall liquidity shock over Consumption and Debt: Evidence from quasi experimetal public policy in Chile

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Abstract

Leveraging detailed private banking data from Chile, this study examines the marginal propensity to consume over a liquidity shock ($MPC^{\Delta L}$) and marginal propensity to repay debt over a liquidity shock ($MPRD^{\Delta L}$) across diverse groups following an unexpected policy that allowed pension fund access during the COVID-19 crisis. Our findings highlight a pronounced $MPC^{\Delta L}$ among groups with lower levels of withdrawals, consumption, and cash reserves post-legislation, challenging the Permanent Income Hypothesis, Liquidity restriction models and suggesting a preference for a buffer-stock model. For $MPRD^{\Delta L}$, we observed an increased propensity to repay debt, notably in scenarios of high pre-existing debt, particulary in consumer debt, and among individuals with previously delinquency debt. This research provides key insights into the use of retirement savings for public policy during stressed economic scenarios.

Keywords: Consumption, Debt, MPC, PIH, Liquidity Constraints, Precautory saving, Behaviour

1 Introduction

Utilizing a comprehensive dataset from a leading Chilean bank, we compute $MPC^{\Delta L}$[1] and $MPRD_{\Delta L}$ in the context of massive and unprecedented liquidity shock stemming from a government policy during the pandemic crisis that allowed access to pension funds. Our methodology distinctively isolates variables including debts, assets, income, and liquidity constraints, alongside other financial and sociodemographic factors. While paralleling Aydin (2022) investigation into credit expansion, our study diverges by focusing on a novel, pension-driven liquidity shock. Additionally, we delve deeply into debt repayment behaviors, offering insights into the dynamics of financial decision-making during periods of enhanced liquidity.

Our study probes into classical consumption theories, including the Permanent Income Hypothesis (PIH), liquidity constraints, and buffer-stock models, testing their relative importance and applicability. Notably, our research enriches the consumption literature by offering rare insights into the response to liquidity shocks in Latin America, distinguished by its considerable magnitude and reliance on self-managed pension funds. Furthermore, we extend beyond traditional consumption analysis to examine the effects of such shocks on debt repayment across the entire population, providing a holistic view of the public policy's impact. Our robust dataset enables an in-depth understanding of consumption behavior, yielding critical insights for policymakers navigating the challenges of significant liquidity shocks.

While our analysis unveiled significant responses in both consumption and debt repayment, attributing these findings to a causal impact is challenging due to the absence of a perfect control group unaffected by simultaneous temporal influences. Nonetheless, our investigation, employing the controls available, offers valuable conclusions on the variations in impacts across different demographic segments. Regarding the $MPC^{\Delta L}$, our results seem to

[1]A key distinction in our study is between the classical Marginal Propensity to Consume (MPC) and the $MPC^{\Delta L}$ the latter represents a response to a non-wealth shock, crucially because the liquidity accessed by individuals derives from their own savings, not an external income shock. This insight is vital as it highlights the liquidity shock's unique nature, involving the reallocation of personal savings rather than an increase in wealth..

challenge the Permanent Income Hypothesis (PIH), which suggests that non-wealth shocks should not influence consumption. However, a closer examination, particularly when assessing heterogeneity based on liquidity constraint metrics, revealed a pronounced reaction among those not facing liquidity constraints. This observation prompted a further exploration into whether the buffer-stock model could better explain the significant and positive response observed across the populace. In the other hand, the $MPRD^{\Delta L}$ outcomes suggest a rational allocation of resources, evidenced by individuals prioritizing repayment of consumption debt—the category with the highest interest rates—and even more so for delinquent debt, which incurs the greatest costs in terms of interest and future access to credit due to reputational damage.

The findings from our study underscore the dual-edged implications for public policy: while the widespread increase in consumption validates the effectiveness of stimulus measures aimed at encouraging consumer spending, the indiscriminate nature of this boost highlights potential risks, such as depleted pension funds, consumption over a population that doesn't have problems of liquidity restriction and rising inflation. Conversely, the strategic repayment of high-interest and delinquent debts by individuals suggests a positive outcome, aligning with policy goals and indicating prudent financial management among the populace. In our view, this nuanced understanding presents a balanced view of immediate economic benefits against long-term fiscal sustainability.

The study is divided in 4 section. In the section 2, we explore the experimental enviroment and the academic framework. In the section 3, we explain the dataset that we used for the study, and also how is constructed the liquidity shock. In the section 4, we estimate the effect of the policy over the consumption, debt and various heterogeneities across them.

2 Framework

2.1 Experimental Environment

The Chilean pension system established in the 1980s, is a privately managed, individual capitalization scheme. Under this arrangement, formal workers are required to contribute 10% of their income to individual accounts administered by private companies, known as Pension Fund Administrators (AFPs in Spanish). These AFPs are responsible for investing these contributions. However, access to these funds is restricted until the owner reaches retirement age, set legally at 60 for women and 65 for men. The workers are free to choose which AFP will manage their accounts and to determine the risk/return profile of their specific fund[2].

This last rule was fulfilled for more than 40 years without hints of change until July of 2020. Amidst the financial turmoil triggered by the COVID-19 pandemic, the Chilean congress initiated a dialogue concerning a new law that would enable citizens to withdraw up to 10% of their pension savings from the AFPs for discretionary use. On the 30th of that month, an unprecedented piece of legislation was passed. It permitted Chileans to withdraw a fraction of their personal pension savings, subject to minimum and maximum withdrawal limits[3]. The funds could be accessed in two parts, free of charges, and were tax-exempt for individuals earning less than an equivanlent of $1,500 USD per month.

This legislation sparked controversy as it challenged the fundamental principle of myopia which is an implicit assumption underlying the mandatory savings mechanism for retirement. The law did not introduce or encourage any alternative measures for individuals to replenish the withdrawn amounts, stoking concerns that consumption of these funds would irreversibly deplete pension savings. Nonetheless, the law was viewed as a necessary short-term intervention to provide immediate financial relief for those negatively impacted by the

[2]Investment options are presented under a multi-fund scheme that offers five distinct types of pension funds. These funds, categorized from the least (E) to the most (A) risky, cater to a broad range of investment preferences and risk tolerances among the affiliates.

[3]See section 3.2 for the specifics details of the shock

pandemic. This rationale resonated with Congress and subsequently led to the successful approval of two additional withdrawals in December 2020 and April 2021[4]. Figure 1 illustrates the withdrawal amounts from the bank, while Figure 2 tracks the evolution of consumption, highlighting the dates of the withdrawals. A straightforward visual analysis reveals that the withdrawals occurred closely following the approval of the law. Furthermore, it's observable that each withdrawal is succeeded by an increase in consumption in the following month.

The law was widely embraced by the population in the immediate aftermath of its enactment. Millions of Chileans reportedly withdrew from their pension funds within weeks of the law's passage. According to the Superintendencia de Pensiones, the governmental body that supervises the pension system, 10.3 million individuals —representing 97.6% of the target population- had withdrawn their first 10% by the end of 2020. This involved a staggering sum of US$ 19.846 billion, with an average withdrawal amounting to $1,660 USD per person. Remarkably, this average withdrawal equated to 184% of the mean salary in Chile, indicating a significant cash influx to and from nearly the entire working population.

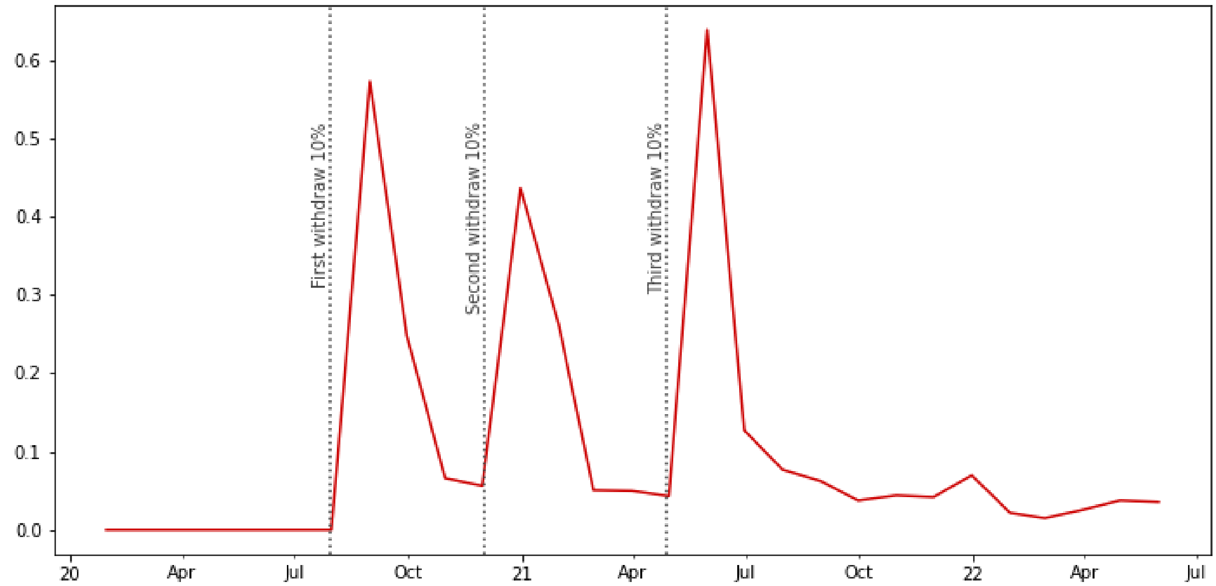
The unexpected nature of the first 10% pension withdrawal serves as a defining factor in its classification as a quasi-experimental liquidity shock. This unanticipated characteristic is supported by three main factors: the unprecedented and swift passage of the law within a month, limiting anticipatory behavior; the unexpected approval by a narrow margin given the composition of the congress, making it a risky prediction (95 congresist voted in favor and it was needed 93); and the possibility that the incumbent government, which was not in favor of the law, could have invoked a constitutional provision to prevent its enactment [6]. These collective circumstances highlight the policy's unexpectedness, instrumental in its identification as a quasi-experimental liquidity shock.

Adding to the unanticipated characteristic, the policy's exogenous nature further reinforces its status as a quasi-experimental liquidity shock. Triggered by the pandemic, rather

[4]The general terms of these withdrawals remained consistent, like the amounts of withdraws and limits

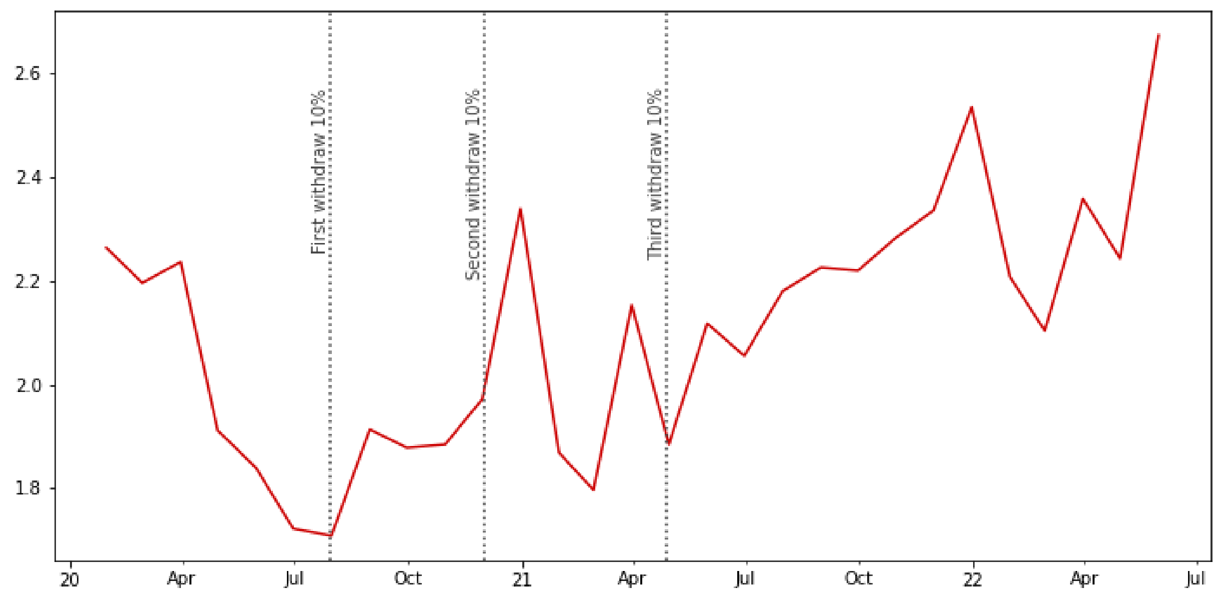
[6]There were politicians from the ruling party who publicly suggested this law be nullified using the constitutional decree that would prevent the law's promulgation.

Figure 1: Evolution of the withdraw deposits in the bank (Bn USD)



Note: Figures plot the aggregated amount retired to accounts of the bank. It can be seen that almost all the retire amount occurs just after the law of withdraws is approved.

Figure 2: Evolution of the bank consumption (Bn USD)



Note: Figure plot the aggregated consumption of the customers of the bank[5]. It could be seen that after every withdraw, the spending has a increasing amount.

than individual economic conditions, and impacting a broad spectrum of the population irrespective of socioeconomic status, it resulted in a widespread increase in liquidity. The treatment for this study is the shocks of liquidity, that means the access to an additional source of cash to consumption or saving.

This policy's aftermath provides a unique lens to analyze the impact of a liquidity shock on consumption patterns, savings decisions, and overall economic stability. The observations drawn from this context offer not only immediate insights into shock responses, but also valuable lessons for future economic policymaking amid crises.

2.2 Consumption literature

The theoretical foundation of this paper starts with the classical consumption literature, tracing back to Friedman's Permanent Income Hypothesis (PIH) Friedman (1957), postulating that the consumption decition of an agent is the result of an intertemporal maximization, smothing the consumption across their life. One implication of PIH and some of their popular variations as the well know sthocastic model of Certainly Equivalence of Hall (1978), is that consumption respond to racional expectations (RE) and are unaffected by non-wealth shocks, as liquidity shocks. However, the initial critiques to PIH rest in its inability to adequately explain the response to consumption made by predictable income changes and the existense to excessive consumption responses to non-permanent income shocks[7]. This has underscored the importance of liquidity access. Building upon the framework of an intertemporal consumption-maximizing agent, in Deaton (1991) posited that binding liquidity constraints could depress current consumption, thereby, triggering an exaggerated response for the binding agents to these non-permanent income shocks and to liquidity shocks.

[7]For the excesive response to consumption see Hall and Mishkin (1982) were they found a very large response to transitory income than can be valid with the PIH and RE using interest rate over 20%. Also, you can see a test of the perfect market assumption in Flavin (1981), where the autors found evidence that liquidity constraints, made by a macroeconomic proxy, has to be a relevant factor to explain the response to transitory income. Also in this last study, the autor found that there exist positive relationship between predictable income and Consumption. In this sence, a later study that is iluminating is Parker and Souleles (2004), where the agents reaction to a tax rebate is 2/3 done in the period of the receipt of the tax rebate, which was anunced months ago.

The literature has gone futher liquidity restrictions, arguin the importance of precautory motives. In Carroll. (1997), they argue that the optimal consumption involves the posibility of in future scenarios been with few cash on hand impliying non trivial response to consumption of income shocks. This could be an additional explanation of some pattern of consumption, specially arguin that not only liquidity restricted people had presented high MPC. One dificulty to distinct between these two theories is that the need of make a buffer is greater when there is low cash on hand, so that enconter with the liquidity restriction theory, predicting for both cases a high MPC for the people near the restriction.

Research on liquidity and buffer-stock models presents mixed findings. Studies like that Gross and Souleles (2002) using credit card data found evidence supporting the liquidity constraint model, particularly among those with lower liquidity, indicating a significant impact on consumption ($MPC^{\Delta L}$). However, they also observed effects among individuals not liquidity-constrained, aligning with buffer-stock models and challenging the notion of liquidity constraints. Olafsson and Pagel (2018), utilizing detailed Finnish financial data, found that consumption spikes on payday were independent of liquidity levels, contradicting both liquidity constraint and buffer-stock theories. Similarly, research by Aydin (2022) using banking data comparable to ours identified a positive $MPC^{\Delta L}$ effect mainly on those already having a financial buffer, suggesting the relevance of precautionary savings as per buffer-stock models. While these examples do not encompass the entire spectrum of consumption literature [8], they highlight the debate's significance in understanding economic stimulus' microfoundations.

Following that sence, the importance of $MPC^{\Delta L}$ goes beyond just to the impact of liquidity shocks. In fact, the economic literature has deepened in the relationship between the marginal propensity to consume out of liquidity, $MPC^{\Delta L}$, with the marginal propensity

[8] There are explanations to the excesive response of non permanent income including the more straight foward models in which the consumption response is due a rule of thumb in which individuals consume all their disposable resources Hall and Mishkin (1982) and Campbell and Mankiw (1990). Similar to that line, there exist framwork of behavorial economics that sustents, aparently non traditional maximization behaviour in the consumption decision as in Thaler and Shefrin (1981) or dinamically inconsisten patterns such as Laibson (1997).

to consume, MPC. The prevailing notion postulates that $MPC^{\Delta L}$ must serve as a lower bound for MPC. This is attributed to the fact that if a liquidity shock is consumed, the subsequent interest payments and repayment costs would inevitably deplete future resources. In fact, Aydin (2022) using the certainly equivalence of the permanent income model and doing a permutation to the optimal consume pattern we obtain the following formula:

$$\frac{\Delta C^{*}}{\Delta L} = \frac{\Delta C^{*}}{\Delta A} - \left(\frac{R}{1+R}\right)\frac{\Delta C^{*}}{\Delta Y^{P}}$$

one might interpret the resultant liquidity shock as analogous to a one-time income shock, adjusted for the long-term foregone consumption. Consequently, the marginal propensity to consume from this liquidity shock, denoted as $MPC^{\Delta L}$, serves as a lower bound for the overall marginal propensity to consume (MPC)[9]. Thus, examining $MPC^{\Delta L}$ could illuminate our understanding of income shocks, frequently invoked in public policy discourse during economic crises. An intriguing dimension of this investigation centers on the 10% withdrawal policy in Chile. It exhibits striking parallels with traditional liquidity shocks, notably in its augmentation of credit.[10] Moreover, its repayment is oriented towards the future, eliminating concerns about potential delinquency, making more clean the notion of liquidity shock. However, if individuals fail to recognize that the early withdrawals stem from their own savings, their response could be magnified, perceiving the liquidity surge as an unanticipated income boost.

Empirical research on the usage of withdrawals for consumption and debt repayment is significantly limited, especially in Chile. The study by Fuentes OM (2023.) is a rare instance, analyzing factors behind withdrawal decisions in Chile, yet lacking data on consumption and debt to draw conclusions about consumption models. Hamilton et al. (2023.) offers insights into spending patterns and credit card payments post-withdrawal, tracking expenditure categories through card transactions. However, their study, situated in Australia, captures only

[9]These two would equate in scenarios where the borrowed amount does not necessitate repayment

[10]Mathematically, it can be conceived as credit, where the cost of interest is the forgone returns from ceasing savings investments, and the repayment is future-oriented, devoid of possible delinquency.

a fraction of those eligible for withdrawals, highlighting a geographical disconnect with our Chilean context. Additionally, their inability to link withdrawal behavior with previous debt levels limits the assessment of $MPRD^{\Delta L}$, omitting variations in pre-withdrawal debt status.

Our study emerges from utilizing unique data from a leading Chilean bank to analyze Chile's unexpected liquidity shock, focusing on the marginal propensity to consume ($MPC^{\Delta L}$) and the marginal propensity to repay debt ($MPRD^{\Delta L}$). This unique analysis is made possible by our unique dataset, which allows for an in-depth examination of consumption models and economic behavior. Through regression discontinuity, we expect to find a significant positive effect on consumption, challenging the Permanent Income Hypothesis (PIH). However, establishing causality is problematic due to the absence of a perfect control group, as nearly all working-age individuals participated in the withdrawal. Assuming temporal effects impacted the population uniformly, as would a two-way fixed effect strategy, we explore heterogeneities in impact that offer quasi-causal interpretations.

Our findings reveal a declining $MPC^{\Delta L}$ with the amount withdrawn and across consumption levels, suggesting a diminishing marginal propensity to consume contrary to PIH predictions. Investigating whether liquidity constraint or buffer-stock models better explain consumption behavior, we find evidence supporting the buffer-stock model and countering liquidity constraints. Additionally, we observed a greater propensity to pay debt at higher debt levels, particularly among consumers and delinquent populations, which is more financially rational due the high cost of consumption debt and delinquency status.

This study enriches the literature by addressing the unique nature of the liquidity shock, its alignment with forward-looking agents and consumption smoothing, and by being one of the first to connect such massive shock in Latin America with consumption and debt payments. The richness of our data enables the testing of multiple theories and the quantification of their effects, offering a comprehensive view of consumption behavior. Moreover, our insights into debt payments shed light on policy implications, assisting policymakers in understanding consumer behavior during widespread liquidity shocks in times of crisis.

3 Data

3.1 Description of the data

The data used in this paper come from one of the two largest banks in Chile. We have administrative data about spending, liquidity (accesible resources of the client and flexible revolving debt), balance sheets (assets and liabilities) and the amount retired of their previtional savings. Also, there is a subset of 793.370 unique customers, above 942.172 analized, whose principal employees have a direct deposit of their remuneration into their bank[11]. In that sence, this information is very similar with Aydin (2022).

With the internal data we made a monthly panel with a mean of 860.643 clients per month, between Junary 2020 and May of 2022. This data could be divided in three groups. The first group are sociodemografic variables. The second group of information is the monthly balance sheet of every customer. That is the amount at the end of the month, an also the daily medium stock of every asset (Time deposits, demand deposits, investment products, cash in Saving Accounts and Others), debts (Consumption Credits, Credit Cards, Mortgage Credit and Others) and also liquidity access made by the liquid resources aviable and the amount of flexible credit aproved with the bank. The last group considers the daily inflows and outflows of all their accounts with the bank, being able to know the amount of this transactions and some categorical characteristics. These information is very usefull because we are able to separate inflows by regulars and the shocks of the previtional withdrawl. Even more, for the previtional withdrawl, the bank created an special account in order to be the first step of the withdraw. We tracked that a 26,1% of the amount withdrawed, went direct to accounts in other banks. Because of this, as is discused in the section 4, we believe that our estimation is a lower bound of the effectively short run effect of the withdraws. We suplement our database with an additional external source from regulatory agent, Comision

[11]Because this bank is the largest in number of accounts for companies, it has very rich data about the deposits of remuneration made by the companies. There are around 2 millions of deposits per month, so we can know not just if some customers has their deposits to our bank, but also if some of then have a deposit of they remuneration to another bank in case it isn't to our bank.

Table 1: Descriptive statistics from the Database

	Count (MM)	Mean	Std	P10	Median	P90
Demographics						
Male (%)	34.58	0.57	0.49	0.00	1.00	1.00
Age	34.58	39.55	13.48	25.00	37.00	59.00
Married (%)	34.58	0.36	0.48	0.00	0.00	1.00
Employement rate	34.58	0.46	0.50	0.00	0.00	1.00
Financial Flows						
Income	34.58	0.72	2.51	0.00	0.00	1.96
Income > 0	15.94	1.55	3.52	0.31	0.97	3.20
Consumption	34.58	1.29	93.78	0.00	0.16	2.81
Credit card	34.58	0.98	93.78	0.00	0.00	2.03
Debit card	34.58	0.31	0.59	0.00	0.04	0.90
Withdraws	34.58	0.06	0.39	0.00	0.00	0.00
Withdraws > 0	1.35	1.61	1.17	0.51	1.07	3.77
1st Withdraw > 0	0.45	1.51	0.94	0.61	1.12	2.25
2nd Withdraw > 0	0.42	1.45	0.93	0.61	1.03	2.21
3rd Withdraw > 0	0.48	1.84	1.47	0.20	1.10	4.43
Balance Sheet Bank						
Mortage loan	34.58	7.25	30.77	0.00	0.00	11.53
Consumption loan	34.56	2.00	15.67	0.00	0.00	3.87
Credit Card loan	34.56	0.74	2.68	0.00	0.00	1.87
Used credit line	34.56	0.09	0.51	0.00	0.00	0.06
Current account	34.56	2.85	29.76	0.00	0.24	5.93
Other demand deposits	34.56	0.51	2.33	0.00	0.00	1.04
Time deposits	34.56	1.16	19.83	0.00	0.00	0.00
Investment funds	34.58	1.80	29.20	0.00	0.00	0.00
Balance Sheet System						
Debt	34.58	25.68	69.47	0.00	1.39	77.47
Delinquent debt	34.58	0.02	0.63	0.00	0.00	0.00
Consumption debt	34.58	5.76	20.12	0.00	0.75	14.94
Limit consumption debt	34.58	7.97	22.22	0.00	0.94	24.03

para Mercados Financieros (CMF), which contains the monthly detailed loans that has every customer with all the bancarian system. This information could be decomposed in the between the different types of loans and the historical of delinquency of the client. These information is crucial to known a more integral view of the balance sheet of the customer.

Our dataset uniquely serves customers identified by the bank's loyalty and remuneration criteria, meaning their primary financial inflow is through the bank[12]. This rich data allows for an encompassing analysis of the marginal propensity to consume ($MPC^{\Delta L}$) and repay debt ($MPRD^{\Delta L}$) through both major consumption pathways: debit and credit. Unlike many well-known studies, such as Gross and Souleles (2002), which focused on credit card usage accounting for only 20% of consumption methods[13], our approach captures a broader spectrum of consumer behavior. The detailed debt variables within our dataset enable us to estimate $MPRD^{\Delta L}$ comprehensively and examine heterogeneities across the system. Moreover, the data's scope permits analysis of a vast array of clients under diverse financial conditions, including liquidity constraints, varying debt levels, and employment status proxies.

Although being the primary bank for our subjects does not ensure exclusive banking relationships over time—a concern also noted in Aydin (2022)—the breadth of our client base helps to reflect the broader population accurately. By comparing key variables from our dataset against national statistics in Exhibit A, we demonstrate our sample's effective representation of the general populace, thereby alleviating external validity concerns. To counter potential classification errors, we implement controls such as individual fixed effects. While achieving perfect external validity is challenging, the conservative nature of our estimations, underscored in our results, assures the reliability of our theoretical contributions.

[12]This involves tracking the complete transaction history of clients, regardless of their loyalty status throughout the period.

[13]Gross and Souleles (2002) limited their examination to credit card data, neglecting the significant portion of consumption that occurs through debit transactions.

3.2 Description of the liquidity shock

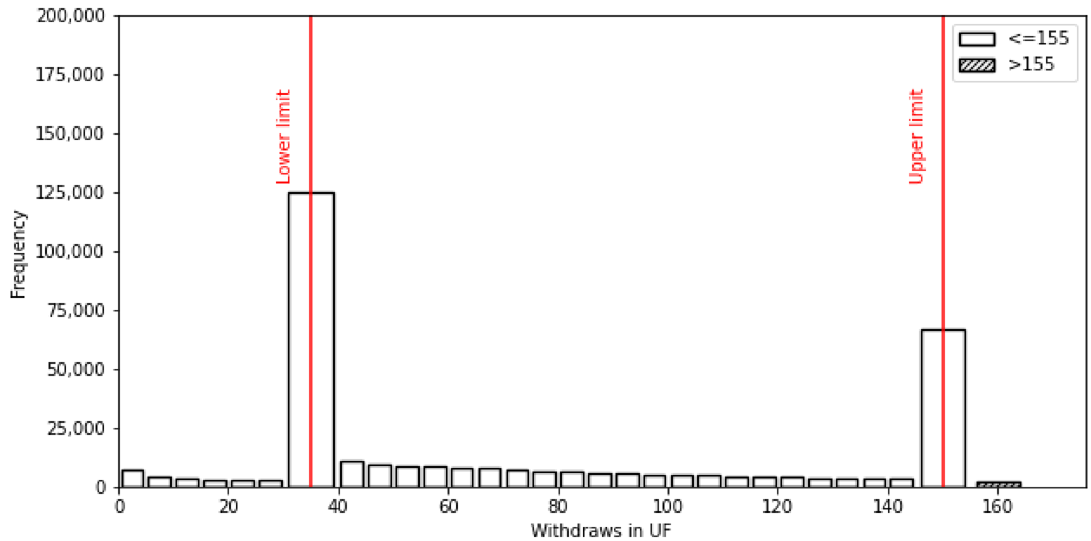
In this section, we will specifically focus on the information related to the liquidity shock, which allows access to pension funds and facilitates withdrawals without usage restrictions. The specifics of the law dictated a minimum withdrawal of 35 Unidades de Fomento (UF), an inflation-indexed unit of account used in Chile (approximately $1,200 USD as of 2021), and a maximum withdrawal of 150 UF (approximately $5,400 USD as of 2021). If the total savings did not meet the minimum withdrawal limit, individuals were permitted to withdraw all their savings.

Figure 3 displays the distribution of the initial liquidity shock. This shock was constructed based on withdrawals made by individuals from the bank, normalized by the UF (Unit of Account) value for each month. Given that the specific UF value for each withdrawal isn't delineated, there might be slight discrepancies between the anticipated UF amount individuals believed they withdrew and the actual amount credited to their bank accounts. During the period between August 2020 and November 2020, further withdrawals were not possible, and those who withdrew did so at the maximum limit[14]. Given these conditions, the distribution is accurately represented for all individuals who made withdrawals from the bank. Notably, the shock distribution is segmented into four relevant distinct groups. These groupings align coherently with previously discussed withdrawal minimums and maximums.

The first group, ranging from 0 UF to 35 UF, comprises individuals who, due to insufficient savings, must withdraw their 100% pension savings. The second group, clustered at the lower limit, consists of individuals whose 10% withdrawal equates to 35 UF or less, representing from their savings a range between [10%- 100%). Between the lower and upper limits, we find individuals who have effectively withdrawn 10% of their pension savings. In the fourth group, individuals are concentrated whose 10% equals or surpasses 150 UF, and thus, can withdraw a maximum of 150 UF, withdrawing from their savings a range that

[14] According to statistics from the Pension Superintendency as of July 2021, 99.64% of those who utilized the first withdrawal option did so by requesting 100% of their funds.

Figure 3: Withdraws distribution on the first period



Note: The figure shows the liquidity shock that every agent has been embraced in the first period of Withdraws until 30 November 2020. Because there wasn't any other withdraw until December 2020, we know that this shock has to correspond to the first withdraw.

is between (0% -10%). The individuals that are over the forth group represents a subset (0.6%) slightly above 150 UF with an avarage of withdraws about 166 and a median value of 156. We hypothesize that these discrepancies may arise from our lack of precise knowledge regarding the UF value referenced by the AFPs during withdrawal, potentially leading to values marginally higher than our estimates. These groups is omited in the analysis, because their lack of relevance and discrepance with the legal restriction.

In Exhibit A, we observe that nearly all shocks are confined within the bounds of the legal limits. However, contrasting with the previous graph, the average for those who acquired more than 155 UF here stands at 247 UF. Moreover, there are data points reporting observations nearing 300 UF, suggesting that some individuals executed their first two withdrawals in the second period. Upon analysis, we find that 6.1% of the individuals proceeded in this manner. For the third instance, the inference is analogous: the fifth group has an average of 270 UF, with observations nearing both 300 UF and even 450 UF. This would imply that these individuals made all three withdrawals within this period. Table №2 provides an overview of the withdrawal distribution based on these characteristics and offers insights into how many withdrawals occurred during each period.

In the bank's data, we do not have specific information on the magnitude of the liquidity shock experienced by each individual, but rather, how much of this shock they transferred to their bank current account. This presents three potential limitations. Firstly, for those who transferred their withdrawals to the bank, we lack knowledge of the effective magnitude of their shock, meaning the total they could have withdrawn. However, according to data from the pension oversight authority, we know that for the first withdrawal, 99.7% withdrew the maximum permissible amount. This implies that the sums transferred to the bank are representative of the liquidity shock in 99.7% of instances. The second limitation arises from a subgroup of individuals who did not transfer their money to our bank. Instead, they either moved it to other banks, placed it into voluntary savings accounts (APV), or chose not to withdraw it. Concerning the decision to make a withdrawal, data indicates that 97.5% utilized this option, suggesting that the non-withdrawal segment isn't a significant concern. Additionally, according to the pension oversight authority's July 2021 data, only 7.84% transferred their funds to voluntary pension savings accounts. If we assume that the effect across different banks was consistent - a reasonable assumption given the diversity and scale of segments catered to by the bank - this suggests that our results are representative of the remaining 92.26% of the population that transferred their funds to banking institutions. So this analysis just is conserned for the population that did their withdraws to a banks, which was the mainly motivation of the policy. Lastly for those who moved their money to other banks, this could pose an issue when utilizing individuals who didn't transfer funds to our bank as a control group. To address this potential bias in the estimated $MPC^{\Delta L}$ parameters, our empirical strategy, involving an event study and several controls, compares various withdrawal groups using placebo tests to ensure group comparability over time. Additionally, accounting for the transfer of funds from withdrawal accounts to other bank accounts, and the subsequent possible consumption, both our control and treatment groups could result in underestimated effects.

4 Results

4.1 Exploring the first withdraw over consumption

As a first step, we use the data from May of 2020 to October 2020 in order to test the first liquidity shock in an scenario of covid crisis, keeping advantage of it's unanticipability. In the Table 2 we can see the differences in mean of all the relevant variables:

Table 2: Descriptive statistics pre and post analysis

	May, Jun, July	Aug, Sept, Oct	Diff
Financial flows			
Consumption	2,027,772	2,170,740	142,968
Consumption (> 0)	2,140,143	2,245,784	105,640
Credit card	1,591,430	1,555,845	-35,585
Credit card (> 0)	2,725,016	2,691,805	-33,211
Debit card	436,343	614,895	178,553
Debit card (> 0)	499,982	674,821	174,840
Income	810,293	847,466	37,173
Income (> 0)	1,452,170	1,454,637	2,467
1st Withdraw	0	2,110,948	2,110,948
Employment rate	0.56	0.58	0.02
Balance Sheet			
Individual Resources	5,569,260	6,605,152	1,035,892
Time Deposits	1,011,568	989,588	-21,980
Current Account	3,128,387	3,978,755	850,368
Investment Funds	1,429,306	1,636,809	207,503
Debt (bank)	15,657,795	15,694,621	36,826
Mortgage debt (bank)	10,126,341	10,272,077	145,736
Consumption debt (bank)	3,194,414	3,143,397	-51,017
Credit card debt (bank)	944,554	908,324	-36,230
Debt (system)	32,738,761	32,282,699	-456,061
Consumption debt (system)	7,542,068	7,282,200	-259,868
Delinquent debt (system)	35,266	20,751	-14,515

Upon reviewing the compiled data, it's evident that from the 2,110,948 CLP withdrawn by individuals from the bank, monthly consumption saw an uptick of 142,968 CLP, personal resources increased by 1,035,892 CLP, and debt levels decreased by 456,061 CLP. Remarkably, this accounts for over 90% of the total withdrawn funds, highlighting the effective tracking of how these funds were utilized. The substantial match between the influx of extra funds and their application towards savings, debt repayment, and other expenditures reflects the thoroughness of our dataset in capturing individuals' complete financial landscape. Moreover, the analysis reveals that in the short term, individuals allocated their withdrawals towards a monthly marginal propensity to consume ($MPC^{\Delta L}$) of 6.72% (accumulating to 20.12% over three months), a marginal propensity to reduce debt ($MPRD^{\Delta L}$) of 7.22% monthly (accumulating to 21.61% over three months), and savings at 16.30% (accumulating to 49.05% over three months). These insights underscore the diverse financial decisions made post-withdrawal, offering a nuanced view of financial behavior during this period.

To investigate if financial behaviors hold after adjusting for variable movements and potential correlations with significant withdrawals, we employ a regression discontinuity approach. In an ideal scenario, the analysis would use the model:

$$C_{i,t} = \beta_0 + \beta_1 \cdot 1stWithd_{i,t} + u_{i,t} \tag{1}$$

Here $C_{i,t}$ represents the consumption for individual i in the month t, $1stWithd_{i,t}$ is the amount withdrawed by that individual in that timing. This equation faces three challenges in our context:

The primary concern of limited financial data not fully capturing an individual's economic behavior is mitigated by two compelling arguments. Firstly, July 2020 data shows only 9.6% of funds are transferred between banks by individuals, indicating that most funds deposited in a bank are likely to be utilized within that same institution. Secondly, behavioral tendencies—such as status quo bias, preference for simplicity, loyalty programs, and the costs associated with transferring funds—further discourage moving funds between banks. Together, empirical and behavioral evidence strongly suggests that inflows into a bank account reliably reflect an individual's consumption and savings patterns within that bank, validating our approach in measuring the impact of withdrawal policies on our bank's customers.

The second concern is regarding population bias. Wealth or consumption pattern differences, could potentially affect our coefficient of interest, β_1. However, our robust dataset significantly counters these concerns. It encompasses comprehensive individual tracking and a wide array of demographic and financial information, including age, marital status, sex, account balances, time deposits, investments, debt specifics, delinquency history, income, and, for certain subsets, proxies for employment. To further ensure data comparability and mitigate bias, we focus our analysis exclusively on participants who made withdrawals, applying the 'Effect of Treatment on the Treated' (ETT) principle. Despite excluding non-withdrawers, a notable 92.26% of our sample population underwent the treatment. Moreover, the implementation of individual fixed effects in our analysis serves to control for any intrinsic biases within this group, enhancing the reliability of our findings.

The third challenge involves general unobservable variables like seasonal changes, economic fluctuations, and COVID-19 impacts, which complicate month-to-month consumption pattern analysis. Our dataset attempts to overcome these issues by incorporating variables such as debt levels, income, and economic resources, thus capturing critical dimensions of economic activity and consumer behavior. To further address this, we employ a small temporal binning strategy, comparing July to August, under the assumption that the influence of unobserved variables is minimized during this period. This method enhances the robustness of our pre- and post-withdrawal analysis, aligning with our Equation (1). Additionally, we integrate timing fixed effects into our analysis to account for the close association between the timing of the treatment and its effects. By doing so, we ensure that β_1 reflects the impact of varying treatment levels, offering a nuanced understanding of the treatment's effect, distinct from the overall treatment impact.

In addressing the methodological challenges, we adopt a Fuzzy Regression Discontinuity

(FRD) design, with time serving as the running variable to differentiate between pre- and post-treatment observations. The uniform timing of the treatment for all participants eliminates concerns of manipulation in the running variable, ensuring a clear demarcation for our analysis. Our approach includes a monthly analysis to meticulously capture potential delayed effects on consumption following the withdrawal event. This temporal granularity allows for a more detailed examination of consumption patterns over time. Furthermore, we actively control for endogeneities by including variables for relevant economic factors and individual fixed effects in our model. This comprehensive approach aims to isolate the specific impact of withdrawals on consumption while accounting for other influencing economic variables. In order to include the last reasonament and to measure the posible effect, we estimate the following equations:

$$C_{i,t} = \beta_0 + \beta_1 \cdot 1stWithd_{it} + \zeta \cdot X_{i,t} + u_i \tag{2}$$

$$C_{i,t} = \beta_0 + \gamma_i + \beta_1 \cdot 1stWithd_{it} + \zeta \cdot X_{i,t} + u_i \tag{3}$$

$$C_{i,t} = \beta_0 + \gamma_t + \gamma_i + \beta_1 \cdot 1stWithd_{it} + \zeta \cdot X_{i,t} + u_i \tag{4}$$

In this equations, $1stWithd_{i,t}$ takes value of the liquidity shock exposed to the person i in the time t and $X_{i,t}$ are several sociodemograpics and financial controls for every i in t. In our analysis, we methodically adjust for a broad spectrum of factors. Initially, model (2) accounts for financial and sociodemographic variables to isolate the withdrawal effect. Then, model (3) introduces individual fixed effects, targeting unobservable personal attributes not covered previously. Finally, model (4) adds time fixed effects, essential for when the entire treated population received their treatment in August 2020. The last refines β_1 interpretation from a broad marginal propensity to consume over a liquidity shock to the propensity changes due to the liquidity shock, based on withdrawal amounts.

In the following table we can see the results of the four equations:

	Eq. 1		Eq. 2		Eq. 3		Eq. 4	
Feature	Coefficients	S.D.	Coefficients	S.D.	Coefficients	S.D.	Coefficients	S.D.
1stWith	0.183***	0.001	0.136***	0.001	0.059***	0.001	0.001***	0.001
Sociodemo	No		Yes		Yes		Yes	
Financials	No		Yes		Yes		Yes	
Individual effect	No		No		Yes		Yes	
Temporal effect	No		No		No		Yes	
N	1,763,592		1,763,592		1,763,592		1,763,592	
$TPost$	3		3		3		3	

p-values in parenthesis

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The initial equation results suggest a significant impact of withdrawals on consumption, with a monthly $MPC^{\Delta L}$ of 18.3%, implying a three-month impact of approximately 54.9%. However, as we introduce controls, the $MPC^{\Delta L}$ diminishes to 5.9% (accumulated 17.7%), indicating a substantial consumption impact that contradicts the Permanent Income Hypothesis (PIH), which would predict no effect. Although our control isn't perfect, the magnitude and significance of this impact provides strong evidence against the PIH.

Furthermore, the results from equation four, which includes time fixed effects to capture any consistent consumption effects in the following months, suggest that β_1 reflects changes in $MPC^{\Delta L}$ relative to withdrawal levels, evidenced by a 0.1% $MPC^{\Delta L}$ (accumulated 0.3%). This is because all the population is treated before August, which great part of the effect is captured by the fixed effect.

Given the significant consumption effect observed, even visually evident in Figure 2, we next explore which population segments are driving this consumption. In the following subsection, through heterogeneity analysis, we question whether it was individuals with higher or lower initial consumption levels who increased their spending more, and whether liquidity constraints or a buffer-stock model better explains this behavior.

4.2 Heterogeneities in the impact of the first withdraw over consumption

Despite not establishing a causal effect, our analysis reveals a pronounced impact of withdrawals on consumption. Moving beyond this overarching effect, our study delves into the nuances of how different segments—defined by demographics, income levels, and geographic locations—respond to liquidity shocks. To this end, we employ the same econometric model of (3) designed to uncover these heterogeneities but filtering for different quintiles.

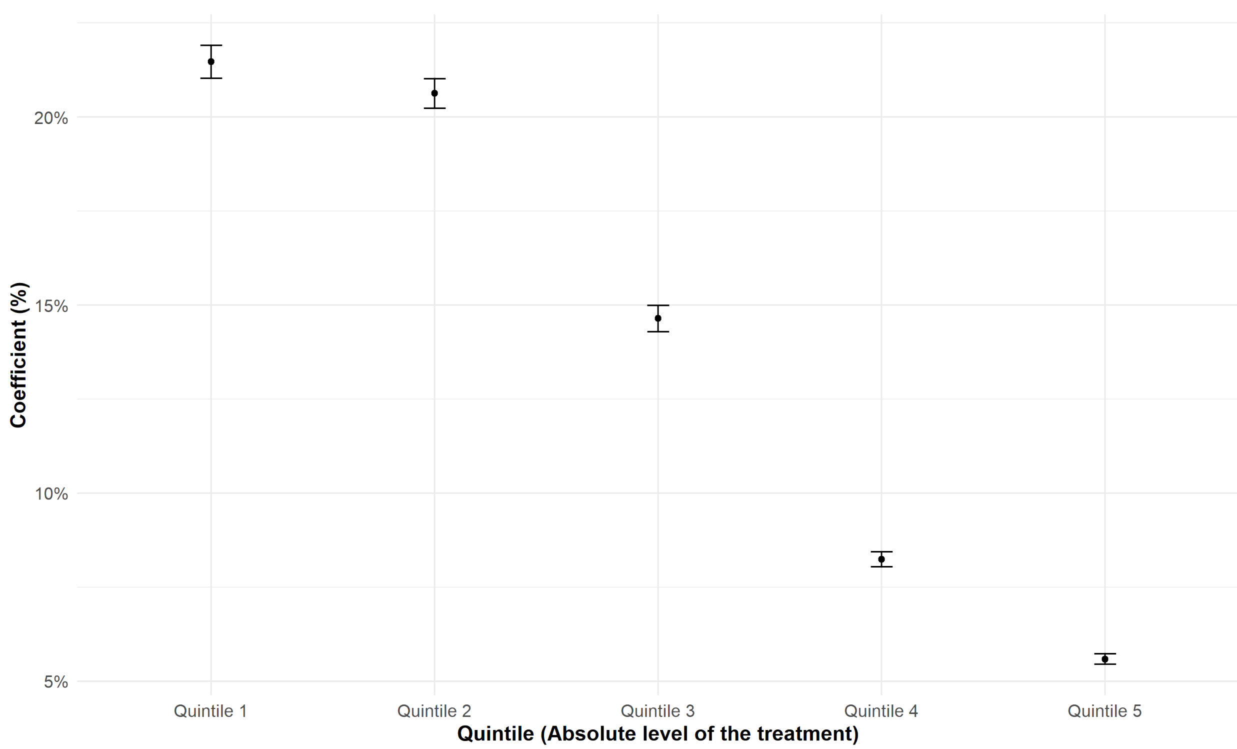
This methodological approach enhances our comprehension of the diverse responses to liquidity shocks across the population, even as we acknowledge the inherent challenges in directly measuring the overall treatment effect. Through this nuanced analysis, we gain deeper insights into the heterogeneity of the withdrawal effect, broadening our understanding of its implications on consumer behavior.

The fist quintile analysis that we do is dividing the population by quintiles of the shock. In the following table we can see how the consumption reacted by the diferences of amounts withdrawed. We don't see much diference in the absolute level of the consumption reaction across the quintiles, which would implied a decreasing $MPC^{\Delta L}$. The results of the econometric model is observed in the figure 4.

Withdraw and Consumption across quintiles of withdraw shock

	Withdraw		Consumption		
	Mean Value	Quintile Threshold	Mean May, Jun, July	Mean Aug, Sep, Oct	Difference
Quintile Groups					
1st Quintile Shock	769,973	1,012,029	805,001	946,656	141,655 ***
2nd Quintile Shock	1,020,871	1,039,998	983,768	1,153,017	169,249 ***
3rd Quintile Shock	1,479,012	2,066,844	1,306,820	1,461,235	154,414 ***
4th Quintile Shock	2,967,279	4,123,201	1,576,799	1,739,063	162,263 ***
5th Quintile Shock	4,353,385	4,543,201	1,952,002	2,102,494	150,491 ***

Figure 4: Coefficients of Impact of the treatment among Levels of Treatment (C.I. 95%)



Our findings reveal that the propensity to increase consumption following a liquidity shock was more pronounced in the lower shock quintiles, even after adjusting for factors such as liquidity, prior consumption levels, employment status, and individual fixed effect. This observation poses a challenge to traditional economic models like the Permanent Income Hypothesis (PIH) which typically predict a uniform and 0 response to liquidity shocks. Instead, our results suggest a more complex dynamic, with lower-shock segments demonstrating a stronger propensity to consume, highlighting the need for models that account for varying consumer behaviors across different income groups.

One hipotesis is that the population reacted at the shock as it were an income shock. A simplified prediction of an PIH it would capture a decreasing $MPC^{\Delta L}$ across the levels of consumption. So in the figure 5 we explore how the consumption reacted across the previous levels of consumptions. It's dificult to estimate de $MPC^{\Delta L}$ with the table, because the amount withdrawed is diferent across the quintiles of previous consumption. In the figure 6 we estimate including the controls.

Withdraw and Consumption across quintiles of relative withdraw shock

	Withdraw		Mean Consumption		
	Mean Value (%)	Relative to consumption (%)	May, Jun, Jul	Aug, Sep, Oct	Difference
Quintile Groups					
1st Quintile Shock	1,020,631	1020%	100,667	285,118	184,451***
2nd Quintile Shock	1,100,606	289%	381,813	617,572	235,759***
3rd Quintile Shock	1,413,568	197%	716,736	964,446	247,709***
4th Quintile Shock	1,484,764	109%	1,359,395	1,587,217	227,821***
5th Quintile Shock	2,338,554	57%	4,065,803	3,948,133	-117,669***

In our analysis, the $MPC^{\Delta L}$ for quintiles 1 to 4, based on prior consumption levels, remains relatively stable, contrasting with the highest quintile, which exhibits a negative reaction in consumption post-withdrawal. This observation does not align well with the Permanent Income Hypothesis (PIH), which would anticipate a uniform or decreasing marginal

Figure 5: Coefficients of Impact of the treatment among Levels of Consumption Treatment (C.I. 95%)

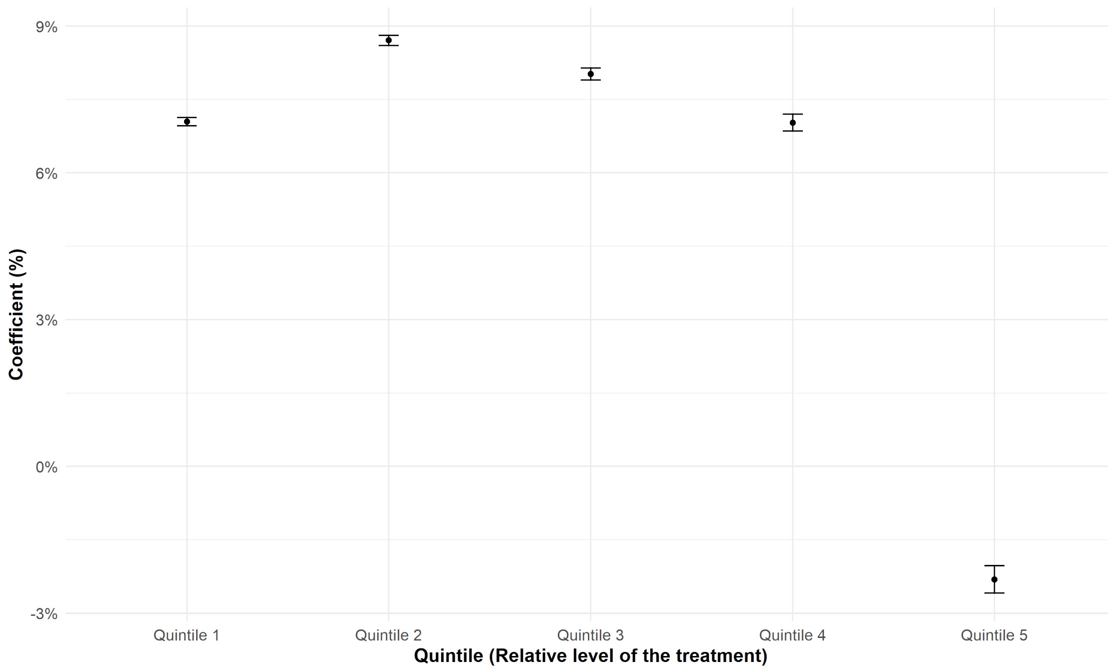


Figure 6

propensity to consume across all income levels. Instead, we observe an increasing consumption gap between the first and second quintiles, challenging the PIH and necessitating a reevaluation of existing consumption models. Specifically, the liquidity constraint model posits that consumption patterns are significantly dictated by liquidity levels. On the other hand, the buffer-stock model suggests that individuals with less financial cushioning (i.e., lower cash on hand) are likely to exhibit a stronger consumption response after a positive liquidity shock, highlighting a divergence in theoretical expectations and our observed data.

We will assess consumption responses at varying levels of cash on hand, incorporating all liquid assets and credit lines in alignment with standard literature practices. In the following figure we plot a theorical graph of how it would be excepted the $MPC^{\Delta L}$ across the differents levels of the cash on hand and how we could expect differences between these two models.

In the following figures we see how variates the consumption across diferent levels of cash on hand.

Figure 7: Coefficients of Impact of the treatment among Levels of Cash on hand (C.I. 95%)

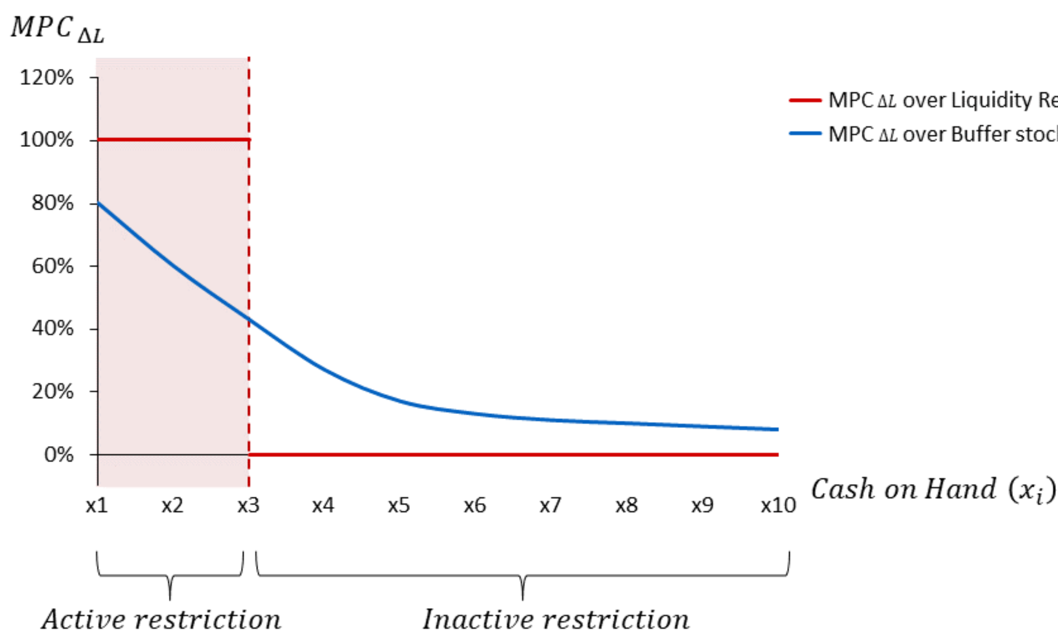


Figure 8: The graph illustrates a comparative analysis of the Marginal Propensity to Consume (MPC) curves within the liquidity constraint model and the buffer stock model in response to a liquidity shock. While the figures are indicative, it's evident that the liquidity constraint model forecasts a binary response—either a 100% or a 0% reaction—whereas the buffer stock model shows a progressive decline in MPC as Cash on Hand increases.

Consumption evolution across levels of Cash on Hand (C.H.)

	Cash on Hand		Consumption		
	Mean Value	Quintile Threshold	Mean July	Mean August	Difference
Quintile Groups					
1st Quintile (C.H.)	145,389	463,414	476,574	742,844	266,269***
2nd Quintile (C.H.)	1,113,557	2,007,080	803,471	1,066,099	262,627***
3rd Quintile (C.H.)	3,697,158	6,046,384	1,027,912	1,232,140	204,227***
4th Quintile (C.H.)	10,980,591	18,741,421	1,280,864	1,449,375	168,510***
5th Quintile (C.H.)	37,288,888	1,888,478,000	1,858,305	1,985,746	127,440***

Figure 9: Coefficients of Impact of the treatment among Levels of Cash on Hand (C.I. 95%)

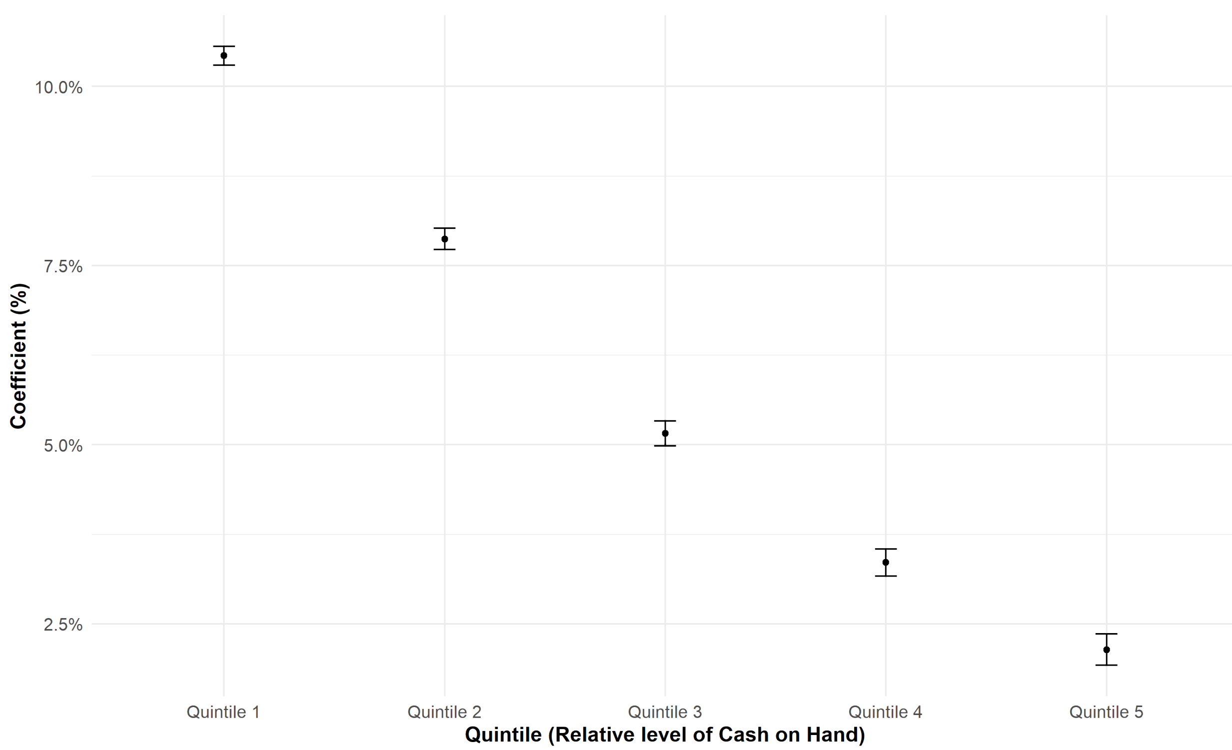


Figure 10

Assuming that the lowest possible Marginal Propensity to Consume from Liquidity

($MPC^{\Delta L}$) is zero, we find that the actual consumption response in the lower quintiles significantly diverges from the expected 100% in scenarios typically associated with liquidity constraints. This deviation indicates that the reality of consumer behavior is more complex than what liquidity-constrained models predict. On the other hand, the observed reduction in $MPC^{\Delta L}$ among individuals with increasing cash reserves supports the Buffer Stock model's premise. According to this model, while the consumption response to a liquidity shock remains positive across all levels of liquid assets, it progressively weakens as individuals' liquidity increases, suggesting a nuanced interplay between liquidity levels and consumption behaviors.

Following our analysis of consumption patterns, we turn our attention to debt management responses to the liquidity shock. This step broadens our evaluation of the public policy's impact, incorporating an analysis of debt repayment to offer a holistic view of its financial effects. This comprehensive approach enhances our understanding of the policy's influence on both spending behaviors and financial stability.

4.3 Impact of the first withdraw over debt and heterogeneities

This section transitions our focus from consumption to the impact of policy on debt, aiming to enhance financial health during economic stress by facilitating debt repayment. We will examine the Marginal Propensity to Repay Debt ($MPRD^{\Delta L}$) in the aftermath of a liquidity shock, analyzing how this propensity varies across different pre-withdrawal debt levels. The econometric aproach is the same, but using $Debt_{i,t}$ instead of consumption. In the first analysis we explore the diffents reactions across the levels of previously debt to the shock. In the following figures we can see the diferential in the impacts.

Transitioning from analyzing consumption, this section delves into the policy's effect on debt management, with the aim of bolstering financial health amid economic distress by promoting debt repayment. We'll scrutinize the Marginal Propensity to Repay Debt ($MPRD^{\Delta L}$) following a liquidity shock, specifically how this propensity shifts across various levels of debt held prior to the withdrawal. Employing a similar econometric approach, but substituting consumption with $Debt_{i,t}$, our initial investigation reveals diverse reactions to the shock based on previous debt levels. Subsequent figures will illustrate the varying impacts, highlighting the differential responses to the liquidity shock across the debt spectrum.

Withdraw and Debt across quintiles of Debt

	Withdraw	Mean Debt		
	Mean Value (%)	May, Jun, Jul	Aug, Sept, Oct	Difference
Quintile Groups				
1st Quintile Debt	1,533,692	50,994	151,875	100,881***
2nd Quintile Debt	1,580,168	589,962	1,029,220	439,257 ***
3rd Quintile Debt	1,946,845	4,065,150	3,653,623	-411,526 ***
4th Quintile Debt	2,559,904	17,868,779	15,078,243	-2,790,535 ***
5th Quintile Debt	2,969,890	92,505,725	91,839,845	-665,879 ***

The findings from our analysis reveal a trend for the higher levels of debt: individuals with larger pre-existing debts exhibit a higher propensity to repay debt, indicating that during times of economic stress, those more heavily indebted may prioritize repayment over those with lesser debt. Neverthless, for some quintiles it appears to be as the shock increase the levels of debt. One posible explanation is that for some group, the withdraw could have been used to pay the down payment of a mortgage. In order to see if this is posible, we go further dissect our analysis by distinguishing between consumption debt and household debt.

Figure 11: Coefficients of Impact of the treatment among Levels of Debt (C.I. 95%)

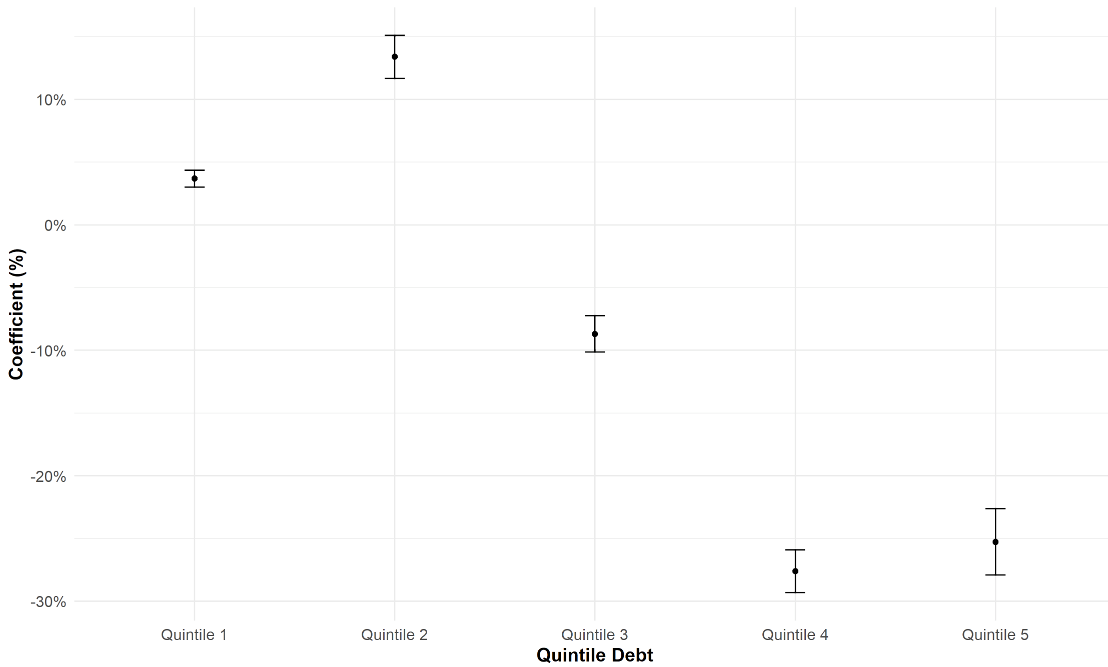


Figure 12

In the following figures we can see the diferential of the $MPRD^{\Delta L}$ by levels of debt and separated for the levels of debt in household and consumption.

Our analysis uncovers varied responses in debt repayment, influenced by both the magnitude and category of debt. Specifically, in the case of household debt, an uptick in repayment activity within the lower quintiles suggests that withdrawals might be channeling into real estate investments or mortgage repayments by homeowners. Also, for consumption debt, which typically carries higher interest rates, there's a noticeable decreasing trend, where individuals burdened with larger debts show a higher tendency towards repayment. This behavior could indicate an optimal approach to personal financial planning. Given this rationale, we further delineate between individuals based on delinquency status, as being delinquent is often associated with additional financial and reputational costs. These hipotesis is tested and showed by the results in the following graph.

The findings are definitive: individuals carrying pre-existing delinquent debt demonstrated a significantly higher propensity to repay compared to those without delinquent debt.

Figure 13: Coefficients of Impact of the treatment among Levels of Debt, consumption vs household (C.I. 95%)

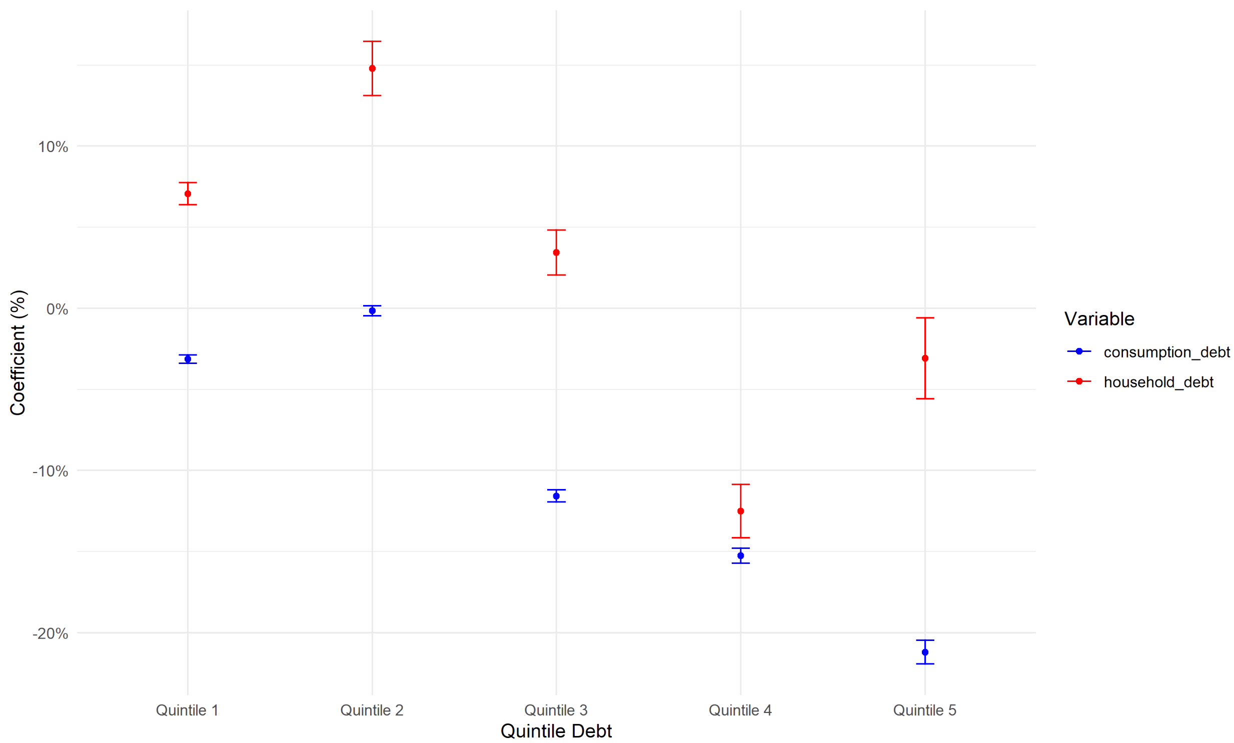


Figure 14

Figure 15: Coefficients of Impact of the treatment among Levels of Debt, delinquent vs non delinquent (C.I. 95%)

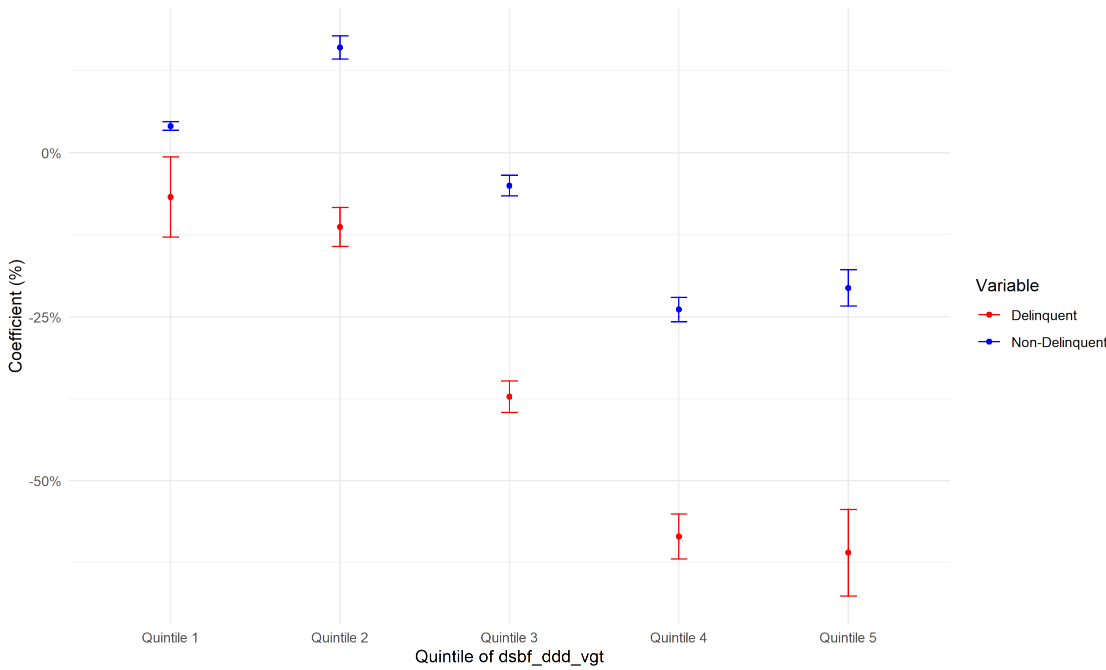


Figure 16

This behavior aligns with rational financial strategies, aiming to maximize the use of financial resources and enhance credit history. By prioritizing debt repayment, these individuals potentially position themselves more favorably for accessing future credit opportunities.

5 Conclusion

Our analysis provides significant insights, despite not establishing a causal relationship, suggesting withdrawals had a notable impact on consumption. We observed heterogeneity in the consumption response, with a declining Marginal Propensity to Consume from Liquidity ($MPC^{\Delta L}$) across withdrawal quintiles, challenging traditional economic models. Interestingly, smaller shocks led to higher consumption propensities post-withdrawal, indicating caution against larger withdrawals.

Additionally we didn't found a stricly decreasing $MPC^{\Delta L}$ across previous levels of consumptino, which would diverge from the Permanent Income Hypothesis (PIH) predictions, which anticipate a strictly decreasing $MPC^{\Delta L}$ if agents view the liquidity shock as an income shock.The analysis also shows that higher cash-on-hand levels correlate with decreased consumption, pointing towards precautionary motives driving post-withdrawal consumption behaviors over immediate liquidity needs.

Debt analysis revealed a direct correlation between debt levels and repayment propensity after withdrawals. Differentiating debt types, we found that increases in household debt were likely used for securing new mortgages or making repayments, while consumption debt repayments suggest an optimization of personal finances due to the higher costs associated with such debts.

Significantly, individuals with delinquent debt were more inclined to repay following a withdrawal than those without, reflecting rational financial behavior to minimize future costs and enhance creditworthiness. This deep dive into financial behavior post-liquidity shock reveals intricate consumption patterns and strategic debt management, underscoring the complexity of responses to such shocks.

This study, leveraging a nearly unique shock and dataset, sheds light on population reactions to a significant liquidity shock. These insights are invaluable for designing more effective public policies in the future.

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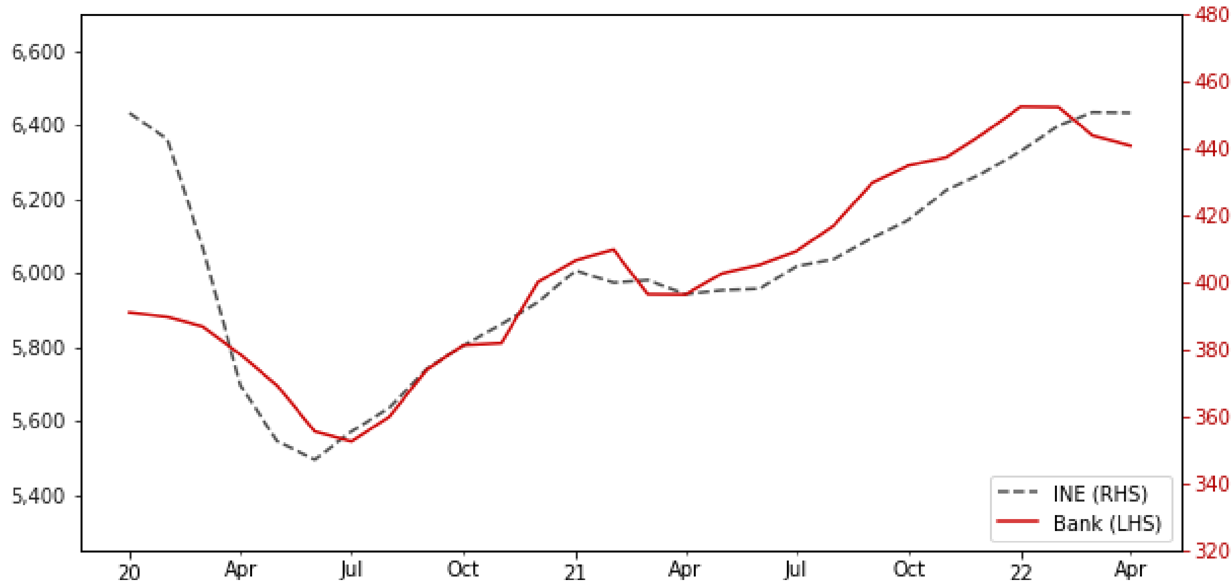
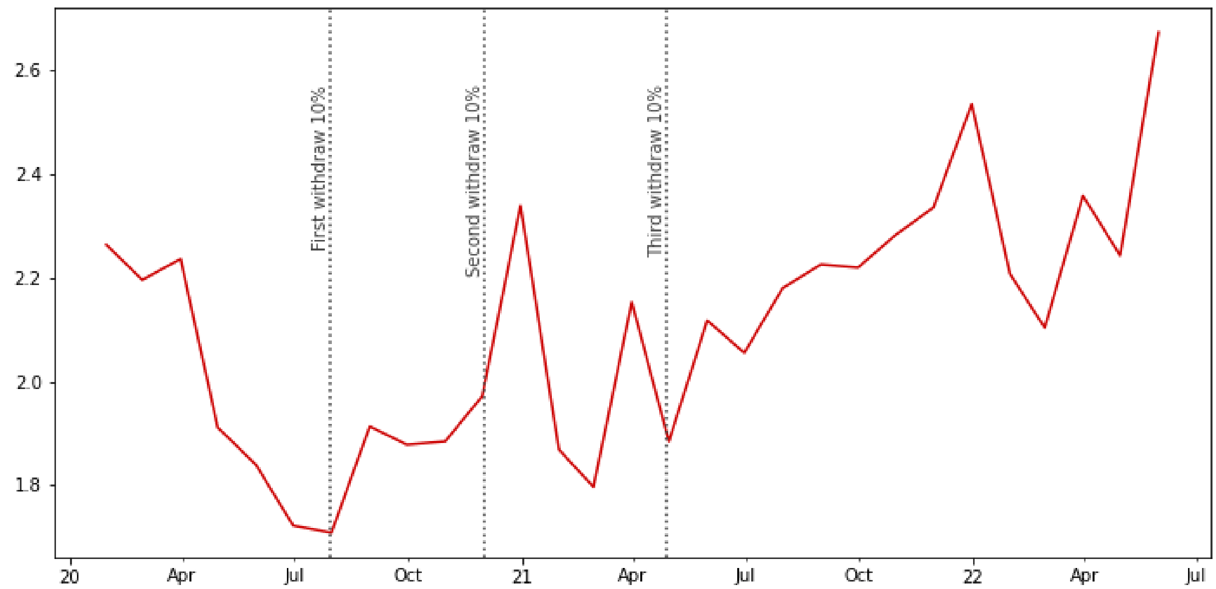
Appendix A: External validity of the bank variables

Figure 17: Comparative n° employees (thousands, $\rho_{x,y} = 0.822$)



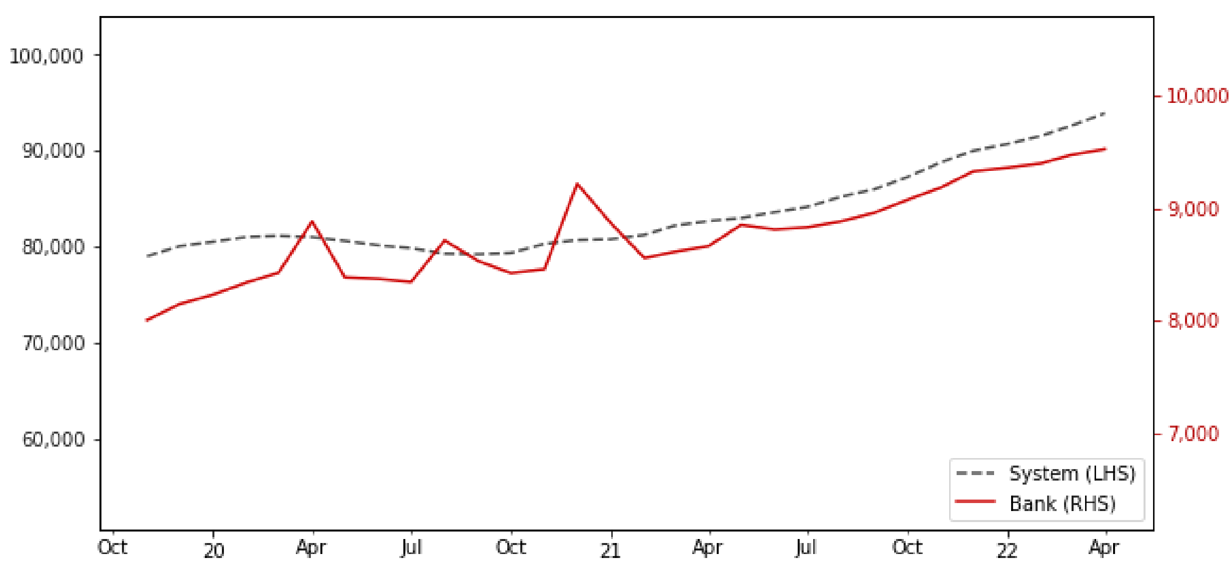
Note: Figures plot the proxy of labour status made by direct deposits from companies (mean rolling 3 months) compared to the 3 months labour index of INE. The Pearson coefficient ($\rho_{x,y}$) between this two series is 0.822.

Figure 18: Comparative consumption ($\rho_{x,y} = 0.763$)



Note: Figures plot the evolution of the agregated spending data of the bank (consumption) compared to the consumption index of minorist comerce sales of the central bank of Chile. The Pearson coefficient ($\rho_{x,y}$) between this two series is 0.763.

Figure 19: Comparative personal loans (Bn CLP, $\rho_{x,y} = 0.923$)



Note: Figures plot the evolution of personal loans (mean rolling 3 months) of the bank compared to the 3 months rolling system personal loans data of the CMF. The Pearson coefficient ($\rho_{x,y}$) between this two series is 0.914.