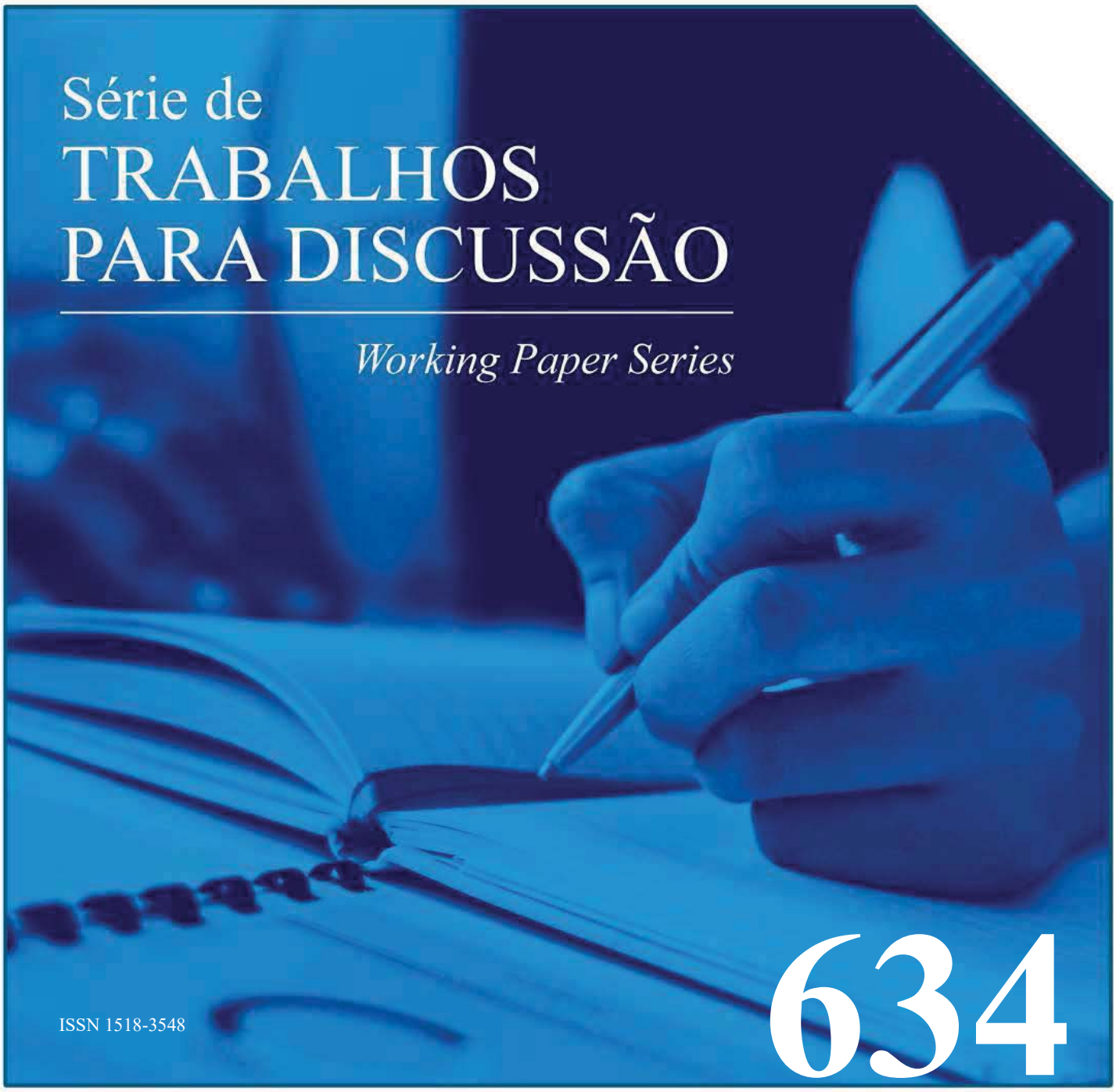

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Liquidity or Wealth? Consumption, Debt, and Financial Fragility After a Windfall

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Non-Technical Summary

In 2017 the Brazilian government allowed workers to withdraw resources from their inactive FGTS accounts, a compulsory severance fund that normally remained inaccessible except under very specific conditions such as retirement or the purchase of a home. These accounts had long yielded interest below market rates and were regarded as illiquid and financially unattractive. The reform unexpectedly released around 44 billion reais (US$13.6 billion) to around 26 million workers (30 percent of the labor force), equivalent to about 0.7 percent of GDP and 1.2 percent of national consumption. This sudden and unanticipated injection of funds provided a unique opportunity to study how households adjust consumption and borrowing when faced with a large financial windfall.

The paper analyzes how individuals used these withdrawals by distinguishing between two different channels. The first is a liquidity effect, which arises because previously inaccessible funds became available for immediate use. The second is a wealth effect, which reflects the present-value gain associated with replacing poorly remunerated FGTS balances with assets valued at market rates. To study these mechanisms, we combine rich administrative data from Brazil's labor registry (RAIS), the national credit information system (SCR) and withdrawals from this program at the individual level, covering over 11 million indebted workers. Using a difference-in-differences strategy that exploits the exogenous timing of withdrawals based on workers' birth months, we track how debt, repayment, defaults and credit card spending evolved after the policy.

The results show that workers facing tighter credit constraints mainly used the funds to reduce outstanding debt and lower default risk, reinforcing the view that liquidity windfalls are employed by cash-strapped households to repair their balance sheets. By contrast, workers in stronger financial positions expanded credit-financed consumption and took on new borrowing, treating the release more like a wealth gain than a liquidity injection. This behavior led to higher delinquency rates and greater volatility in credit card spending, indicating an increase in financial fragility. By decomposing the overall shock, we find that the liquidity component consistently promoted deleveraging and financial stability, while the wealth component encouraged durable consumption and risk-taking.

These findings carry important implications for both theory and policy. They provide rare empirical validation for modern heterogeneous-agent macroeconomic models, which predict that household responses to transfers depend not only on their balance sheet position but also on whether the transfer is perceived as spendable cash or a permanent addition to wealth. For policymakers, the results highlight that the structure of a transfer program is as important as its size. Policies that emphasize liquidity injections can stabilize household finances in times of stress, while those that act more like wealth transfers may stimulate demand but also raise vulnerability to debt and default. In the case of Brazil, a middle-income country with widespread indebtedness, the 2017 FGTS reform illustrates how the same policy can simultaneously reduce fragility for some groups while heightening it for others. More broadly, the study suggests that the design of fiscal interventions should carefully consider not only aggregate demand effects but also the distributional consequences for financial stability.

Sumário Não Técnico

Em 2017 o governo brasileiro permitiu que trabalhadores realizassem saques de suas contas inativas do FGTS, um fundo compulsório de indenização trabalhista que normalmente só podia ser acessado em condições muito específicas, como aposentadoria ou aquisição de imóvel. Essas contas, por muitos anos, renderam juros abaixo das taxas de mercado e eram vistas como ilíquidas e financeiramente pouco atrativas. A reforma liberou de forma inesperada cerca de 44 bilhões de reais (aproximadamente 13,6 bilhões de dólares) para cerca de 26 milhões de trabalhadores (aproximadamente de 30 por cento da força de trabalho), o que correspondia a cerca de 0,7 por cento do PIB e 1,2 por cento do consumo nacional. Esse choque súbito e não antecipado ofereceu uma oportunidade única para analisar como as famílias ajustam consumo e endividamento diante de uma transferência financeira de grande escala.

O estudo investiga como os indivíduos utilizaram esses recursos, diferenciando dois canais de impacto. O primeiro é o efeito de liquidez, decorrente do acesso imediato a fundos que antes eram inacessíveis. O segundo é o efeito riqueza, que reflete o ganho de valor presente associado à substituição de saldos do FGTS, mal remunerados, por ativos avaliados a taxas de mercado. Para analisar esses mecanismos, utilizamos dados administrativos detalhados provenientes de registro trabalhista do setor formal (RAIS), do sistema nacional de informações de crédito (SCR) e saques deste programa ao nível do indivíduo, abrangendo mais de 11 milhões de trabalhadores endividados. Com uma estratégia de diferenças-em-diferenças que explora a variação exógena do calendário de saques definido pelo mês de nascimento, acompanhamos a evolução do endividamento, da inadimplência e dos gastos com cartão de crédito após a política.

Os resultados mostram que trabalhadores mais endividados e com restrições de crédito usaram majoritariamente os recursos para reduzir dívidas e diminuir o risco de inadimplência, reforçando a ideia de que choques de liquidez são empregados por famílias financeiramente pressionadas para reparar seus balanços em vez de ampliar consumo. Em contraste, trabalhadores em situação financeira mais confortável expandiram o consumo financiado por crédito e assumiram novos empréstimos, tratando o saque menos como um reforço de liquidez e mais como um ganho de riqueza. Esse comportamento elevou as taxas de atraso e aumentou a volatilidade do gasto com cartão, sinalizando maior fragilidade financeira. A decomposição do choque mostra que a dimensão de liquidez promoveu de forma consistente o desalavancamento e a estabilidade, enquanto a dimensão de riqueza estimulou o consumo de bens duráveis e a assunção de riscos.

Essas evidências têm implicações relevantes tanto para a teoria quanto para a política econômica. Elas oferecem rara validação empírica para os modelos macroeconômicos de agentes heterogêneos, que preveem que as respostas das famílias dependem não apenas de sua posição financeira, mas também da forma como percebem a natureza da transferência, se como liquidez imediata ou como aumento permanente de riqueza. Para os formuladores de política, os resultados destacam que o desenho de um programa de transferências é tão importante quanto seu montante. Políticas que priorizam injeções de liquidez podem fortalecer as finanças familiares em períodos de estresse, enquanto aquelas que se assemelham a transferências de riqueza tendem a estimular a demanda, mas também a aumentar a vulnerabilidade ao endividamento e à inadimplência. No caso do Brasil, um país de renda média com endividamento disseminado, a reforma do FGTS em 2017 ilustra como a mesma medida pode, simultaneamente, reduzir a fragilidade de alguns grupos e ampliá-la para outros. De forma mais ampla, o estudo sugere que o desenho de políticas fiscais deve considerar não apenas os efeitos agregados sobre a demanda, mas também as consequências distributivas para a estabilidade financeira.

Liquidity or Wealth? Consumption, Debt, and Financial Fragility After a Windfall

Andre Brunelli*, Bruno Martins†, Carlos Carvalho‡

October 15, 2025

Abstract

This paper examines how individual consumers adjust consumption and debt in response to a large, exogenous financial windfall, using Brazil's 2017 FGTS reform, which allowed early access to previously illiquid severance fund balances. Leveraging rich administrative data linking credit registry and labor records, we use a difference-in-differences design exploiting quasi-exogenous eligibility timing based on birth month. We decompose the shock into liquidity and wealth components: the liquidity channel reflects early access to illiquid savings, while the wealth component arises from the present-value gain due to FGTS yields being persistently below market interest rates. Credit-constrained individuals primarily used the funds to reduce debt and lower default risk, while unconstrained consumers increased credit-financed spending, raising financial fragility. Liquidity components drove deleveraging and stability, whereas wealth components led to durable consumption and greater credit exposure. These results provide rare empirical validation of key Heterogeneous Agent New Keynesian (HANK) mechanisms and offer policy-relevant insights into how the composition of financial transfers influences consumer behavior and financial stability.

Keywords: Liquidity; Wealth; Consumption; Debt.
JEL Classification: D14; E21; G51; H31.

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Introduction

Understanding how consumers respond to liquidity and wealth shocks is central to macroeconomic theory and policy. Classical models such as the Permanent Income Hypothesis (Friedman, 1957) and the Life-Cycle Hypothesis (Modigliani Brumberg, 1954) predict that individuals smooth consumption in response to transitory income shocks by adjusting their savings and borrowing. More recent theoretical developments, particularly Heterogeneous Agent New Keynesian (HANK) models, emphasize that these responses depend critically on household characteristics, including constraints, wealth holdings, and access to credit (Kaplan Violante, 2014; Kaplan, Moll, Violante, 2018). While these models have improved our understanding of consumption dynamics, empirical validation remains challenging due to data limitations and the difficulty of disentangling income, liquidity, and wealth effects in real-world policy environments. This paper provides new empirical evidence on these mechanisms using a large-scale, quasi-natural experiment: the 2017 FGTS policy in Brazil, which released its previously inaccessible mandatory severance savings funds to workers in the formal sector.[1].

In that year, the Brazilian government implemented an unprecedented policy allowing workers to withdraw funds from inactive FGTS accounts, which are illiquid — except under specific conditions such as retirement or home purchase. The policy, motivated by macroeconomic stimulus goals, released a substantial volume of resources: approximately 44 billion reais (1.2% of national consumption and 0.7% of GDP) became accessible to roughly 26 million workers, representing around 30% of Brazil's labor force. Because these funds were previously inaccessible and yielded below-market returns, their sudden release constituted a hybrid financial shock — combining both liquidity (accessibility) and wealth (net worth) effects. This institutional setting provides an ideal laboratory to study how consumers react to financial windfalls of different types.

We use matched administrative records from the Central Bank of Brazil and the Ministry of Labor, covering over 11 million indebted workers, to examine changes in credit usage, default behavior, and repayment patterns in response to the FGTS release. Our empirical strategy relies on a difference-in-differences framework that exploits variation in eligibility and timing across individuals, as well as cross-sectional heterogeneity in financial constraints and prior characteristics of FGTS inactive accounts. A central contribution of this paper is the empirical disentanglement of the liquidity and wealth components of the shock. While most fiscal transfers — such as tax rebates or cash transfers — conflate liquidity and wealth effects, the FGTS program uniquely allows for the construction of individual-level measures that isolate these dimensions. Liquidity is measured as the accessible value of FGTS holdings, while the wealth effect is captured by the additional balance added to net worth without immediate liquidity value that stem from the interest rate differential between the FGTS funds' yield and the benchmark interest rate during the labor market lifecycle.

Our results reveal sharply heterogeneous responses along these two dimensions. Credit-constrained individuals — those with higher debt burdens, lower income, or limited credit access — respond to the shock primarily by reducing outstanding balances and avoiding defaults. This deleveraging behavior is consistent with models of precautionary savings and credit-constrained consumption smoothing, and reinforces the view that cash-strapped consumers use liquidity windfalls to repair balance sheets rather than increase consumption. In contrast, unconstrained consumers respond differently. Those with higher income or better credit access increase their use of non-revolving debt and credit card spending following the shock, suggesting that the perceived wealth increase relaxed borrowing constraints and induced new consumption. This behavior raises short-term financial fragility, as evidenced by increased delinquency rates and volatility in credit card usage.

By decomposing the shock into liquidity and wealth channels, we show that these responses

[1] *"Fundo de Garantia do Tempo de Serviço"* — in portuguese.

are not symmetric. The liquidity component of the shock — defined as the newly available cash — induces deleveraging across the distribution. However, the wealth component — capturing the broader perception of net worth change — drives credit-financed consumption and risk-taking among less constrained consumers. This distinction is crucial for macroeconomic modeling. HANK models predict that fiscal transfers have different effects depending on whether they operate as liquidity injections or permanent income shifts. Our empirical evidence supports this theoretical insight: the liquidity shock generates stabilizing effects by improving household balance sheets, while the wealth shock creates new consumption and vulnerabilities for some consumers.

These findings have important implications for both theory and policy. First, they provide rare empirical validation of a key mechanism in heterogeneous agent models: that the marginal propensity to consume and borrow depends not just on household characteristics but on the perceived nature of the financial shock. Second, they suggest that the macroeconomic impact of fiscal interventions depends crucially on whether consumers view them as spendable liquidity or changes in lifetime wealth. This distinction affects both the short-term aggregate demand response and the longer-term implications for financial stability. Finally, our findings caution against assuming that wealth transfers always lead to beneficial consumption increases; among unconstrained consumers, wealth effects may instead lead to excessive borrowing and greater default risk.

This paper contributes to a growing empirical literature on the effects of fiscal transfers, liquidity shocks, and wealth changes on household behavior. Studies such as Johnson, Parker, and Souleles (2006), Parker et al. (2013), and Baker (2018) document how consumers respond to income tax rebates and economic stimulus payments, with constrained households typically exhibiting higher marginal propensities to consume. Agarwal and Qian (2014) show that credit-constrained households in Singapore used liquidity windfalls to repay debt and reduce default risk. Mian and Sufi (2011) and Gennaioli, Shleifer, and Vishny (2012) emphasize the role of credit cycles and leverage in shaping financial fragility. Our findings also relate to recent work on the "wealthy hand-to-mouth" (Kaplan, Violante, and Weidner, 2014), where households with illiquid assets respond differently to shocks than those with liquid wealth.

While this paper contributes to a growing body of work on household responses to income shocks and financial fragility, it could be further situated within the literature on policy-induced liquidity versus asset windfalls in developing countries. Notably, Banerjee et al. (2017, 2020) evaluate the macroeconomic and microeconomic effects of unconditional basic income (UBI) pilots in India and Kenya, finding evidence that cash transfers stimulate consumption and reduce poverty without large inflationary effects. These studies underscore the importance of transfer design and targeting in shaping aggregate and distributional outcomes. In a related vein, Dupas and Robinson (2013) demonstrate how access to liquid savings accounts enables Kenyan small-scale entrepreneurs — especially women — to accumulate assets and maintain higher levels of consumption, showing that liquidity constraints play a major role in shaping long-run outcomes. Bachas et al. (2021) and Egger et al. (2019) also provide evidence from Latin America and sub-Saharan Africa on how cash transfers affect debt, investment, and consumption smoothing.

These studies emphasize that the distinction between temporary liquidity and permanent wealth is critical in interpreting behavioral responses, a point directly addressed by our decomposition approach. By leveraging a quasi-experimental liquidity windfall with high-frequency administrative credit data, our paper contributes new empirical evidence to this literature, particularly in the context of middle-income countries. Unlike most existing studies, we are able to directly distinguish between liquidity and wealth effects, allowing for a clearer mapping to theoretical predictions from HANK models. In doing so, we offer rare empirical validation of how the nature of a financial windfall — not just its size or timing — matters for consumer behavior and macroeconomic outcomes.

The rest of the paper is structured as follows. Section II provides institutional background on the FGTS program, describes the 2017 policy change and details the data. Section III outlines the empirical strategy, including identification assumptions and presents overall results. Section IV focuses on the results considering heterogeneity by consumer type and debt category. Section V presents the main results using the decomposition into liquidity and wealth effects. Section VI briefly discusses the results through th lens of HANK models discusses the implications for macroeconomic models and financial stability. Section VII reports robustness checks and Section VIII concludes with policy recommendations and directions for future research.

I. The Program of Funds Release from Inactive Accounts of the FGTS in Brazil in 2017

In the late 2016, Brazil was trying to resume growth following the worst recession in its documented history in 2015 and 2016, when real GDP per capita accumulated a 8.5 percent fall. On December 22, 2016, in a surprise pronouncement of the former President of Brazil, the government announced a Program that would release funds from inactive accounts of a government-controlled compulsory fund for workers - the FGTS[2] - whose employment contract terminated until 31 December 2015[3] as an attempt to reduce consumer financial fragility, since consumer debt stood at record levels, and to boost consumption.

Workers cannot freely access the funds from their inactive accounts. Withdrawals are permitted under specific conditions[4], which therefore means an inactive FGTS' account is an illiquid asset and we will argue that the funds release Program in 2017 represents a liquidity shock to workers who qualified to the Program. Nevertheless, it is an unusual illiquid asset since it is compulsory and yields low interest rates - lower than the base rate set by the Central Bank of Brazil, SELIC rate[5]. Therefore, the liquidity shock gives rise to a wealth effect associated to the interest rates differential between the one that yields an inactive FGTS' account and the SELIC rate. In fact, these accounts have accumulated real losses at least for the past two decades. Interestingly, although shocks to liquidity and wealth arrive together, we show that we can distinguish the spending and borrowing responses to a change in liquidity from the responses to a change in resources.

While the amount each beneficiary was allowed to withdraw was proportional to his or her life cycle wages, the average withdrawal was US$523[6]. The size of the shock was substantial considering a middle income economy. The average withdrawal accounts for 80 percent of the average monthly earnings of employed people in Brazil in 2017. As a matter of comparison, the growth dividend that a typical qualified Singaporean received in the growth dividend program

[2]FGTS is a compulsory fund created in 1966 imposed by the government to formal employment contracts so that employers deposit in banking accounts for an employee at *"Caixa Econômica Federal"* (CEF - a government-owned financial institution), at the beginning of each month, the amount corresponding to 8 percent of each employee's wage. An account becomes inactive when an employee either quits or is dismissed for just cause.

[3]As stipulated by provisional executive order n. 763/2016.

[4]The criteria to access an inactive account's funds are not in general a workers' choice and can be summarized as follows: i. dismissal without just cause; ii. termination of a fixed-term contract; iii. retirement; iv. death; v. permanence outside the FGTS regime for three years in a row; vi. purchase of housing, liquidation, amortization or mortgage payment; vii. serious illness; viii. company extinction, ix. termination of contract by mutual fault or force majeure, x. personal need in case of emergency or serious reasons linked to natural disaster and xi. suspension of casual job. The only criterion that represents a choice is vi. For this reason we excluded workers who had real estate debt before the program in our analysis. See Section II for more details.

[5]The FGTS accounts yield 3 percent per year plus the reference rate (TR). The TR was used as a reference for interest rates in Brazil and makes the monetary correction of various types of investment, such as savings accounts. The fund is used by the government in subsidized credit lines in the housing sector.

[6]The exchange rate applied is US$1=BRL$3.2591 as of December 2016 - Exchange rate - Free - United States dollar (sale) - end of period from the Central Bank of Brazil. All other amounts in BRL$ applies this exchange rate henceforth.

in Singapure in Agarwal and Qian (2014) accounted for 18 percent of monthly median income in Singapore in 2011. Approximately 25.99 million people benefited from the FGTS Program in Brazil in 2017 - around 30 percent of the labor force, which implies the program totaled US$13.6 billion. This amount accounted for approximately 1.2 percent of the aggregate household consumption expenditure[7] and 0.7 percent of the Brazilian GDP in 2017, which is comparable to the size of the 2001 and 2008 US tax rebates (Johnson et al, 2006; Johnson et al, 2013).

Withdrawals from inactive FGTS accounts were uncapped, allowing eligible workers to withdraw the full balance for any purpose. To qualify, individuals must have resigned or been dismissed for just cause on or before December 31, 2015. The timeline for accessing funds was exogenously determined based on the worker's birth month, introducing plausibly exogenous variation in withdrawal timing. Five groups were defined accordingly: (1) those born in January or February could withdraw starting by March 10, 2017; (2) March, April, or May, from April 10; (3) June, July, or August, from May 12; (4) September, October, or November, from June 16; and (5) December, from July 14. All withdrawals had to be completed by July 31, 2017. This setup allows us to separately examine the effects of the policy's announcement (unanticipated) and of the actual withdrawals (anticipated), consistent with theoretical predictions that distinguish between the two. It also provides rare causal evidence in a large, middle-income country during a period of economic recession.

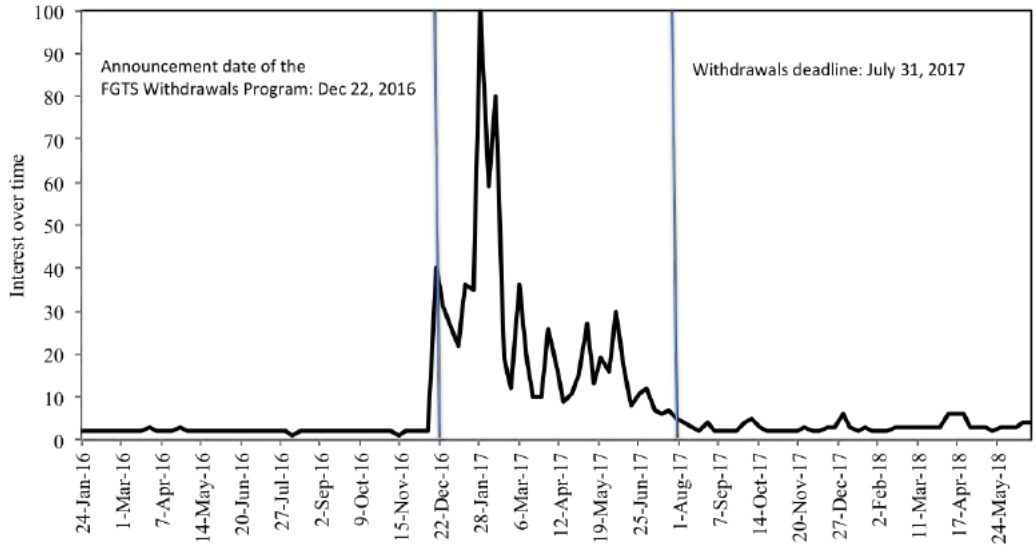

Figure 1: Web Searches for "FGTS Saque" on Google Trends.

Notes: This figure depicts a web search on Google Trends for "FGTS saque" ("FGTS withdrawal" in english) in all categories of websites in Brazil in a 30-month period between Jan 24, 2016 an Jun, 24 2018. As the website states, numbers represent search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. A score of 0 means there was not enough data for this term.

We found evidence supporting that the withdrawals release program of inactive accounts from the FGTS in Brazil was an unanticipated liquidity shock. We perform a thorough search on the web media related to the program and find no information one-year period before the announcement. We also perform a Google Trends search in a 30-month period comprising the

[7]According to the National Accounts System of the Brazilian Institute of Geography and Statistics (IBGE) - excluding imputed rent for dwelling services.

announcement and timeline of the program. We see in Figure 1 that before the announcement date virtually no search were done. On the other hand, searches for the program become more salient on the web from this date through the withdrawals deadline. All major newspapers media also start to cover the stimulus program, publicizing that the worker could: (i) consult the account balance on the CEF's website (the government-owned financial institution that manages the fund), (ii) on the website of the FGTS itself, (iii) or through an app for smartphones and tablets and (iv) it was also possible to make a registration to receive information from the FGTS by messages in the mobile or by e-mail. Moreover, workers could access the program's benefits by receiving a bank transfer, in case the worker was a CEF client and had previously authorized it online, and by going either to a bank ATM or to a bank branch.

II. Data and Identification

We merge three individual-level datasets with administrative records using the public individual registration number.[8] We begin by tracking all 44.92 million individuals with formal labor contracts between 1994 and 2016 who held at least one inactive FGTS account during this period, as identified in the RAIS administrative registry. From this population, we draw a 2 percent random sample in order to make the processing of the data and subsequent regressions computationally feasible. This sampled dataset is then merged with administrative records obtained from the government-owned bank Caixa Econômica Federal (CEF), the depository institution of FGTS resources. The CEF dataset identifies the 25.99 million workers who qualified for the 2017 program and performed withdrawals from their inactive accounts, providing the birth date of each worker along with the amount and date of withdrawals between March and July 2017. The resulting dataset is next merged with another dataset that has consumer credit transactions and belongs to the Credit Information System (SCR) from the Central Bank of Brazil (CBB) in a 29-month period range between January 2016 (2016:01) and May 2018 (2018:05)[9]. The SCR is a registration dataset managed by the CBB that is fed monthly by all financial institutions in Brazil, which documents all formal credit operations in the country[10]. The database contains transaction-level information on all debt modalities, credit scores, limits and demographic characteristics, including age, home address, zip code and county. We aggregate the data at individual-month level so as we have individual balances for all revolving and non-revolving debt modalities[11]. We also include balance of past due debt and default debt. Past due debt refers to 15 to 90 days past due loans and default debt refers to past due loans with more than 90 days. We apply these variables to emphasize the program responses in terms of individual debt deleveraging and use credit card spending representing one modality of consumption spending[12] - between July 2017 and July 2018, around 50% of Brazilian consumers had credit cards and credit card transactions accounted for approximately 30% of total household consumption

[8] Datasets are subject to individual confidenciality and were obtained for research purposes with a de-identified number associated to the public individual registration number.

[9] Another government-mandated program, "Abono Salarial", was announced in June 2018. It transferred one minimum wage to a subgroup of formal workers who qualified to it. Thus, we restricted the end of the sample to 2018:05 to avoid confounding results.

[10] More precisely, from July 2016 all credit operations in the banking system that sum up at least US$61.4 (BRL$200) and before July 2016 all credit operations in the banking system that sum up at least US$307 (BRL$1,000).

[11] In December 2016, when the program was announced, revolving debt, as overdraft and (overdue) credit card debt account for around 30 percent of total consumer debt. These modalities are the most expensive ones, accounting for notables 329 and 498 percent annual interest rates. Non-revolving modalities have lower interest rate levels. For example, payroll debt accounts for a 29 percent annual interest rate. As a reference, the SELIC rate stood at 13.65 percent annually.

[12] According to a household survey on household spending in Brazil - *POF-IBGE - "Pesquisa de Orçamentos Familiares - Instituto Brasileiro de Geografia e Estatísticas"*. It is the Brazilian analogue of the Survey of Consumer Finance in the US.

spending.. Moreover, heterogeneity of debt modalities and demographic information allow us to assess differences in responses to the program by modalities and across (constrained and unconstrained) workers. Then, we merge the resulting dataset with labor market records, more precisely the Annual Report of Social Information (RAIS), which is managed by the Ministry of Economy. The RAIS is a dataset in which all employers must feed with several features of the job title and demographic information of the employees in formal labor contracts, including earnings, age, date of birth, gender, race, schooling, occupation and information on the labor contracts, such as for example, when a employee starts to work, when either a employee quits or is dismissed and the reason why he or she is dismissed. Therefore our dataset focuses on indebted eligible workers, who have records both in the credit database and in the formal sector of the labor market. Our datasets merge resulted in a intermediary dataset from which we exclude treated workers with no record on either credit card spending or total debt in the SCR database during our sample period (i.e., 2016:01-2018:05). Moreover, to address the concern that outliers could obliterate overall responses, we also exclude workers in the bottom and top 1% of the distributions of credit card spending, total debt and program's withdrawals amount. Then, to account for the fact that withdrawals timing possibly endogenously reflect qualified workers' demographic characteristics or seasonal as well as the average of all other concurrent aggregate factors, we exclude beneficiaries who made delayed withdrawals with respect to the initial month when they were allowed to do withdrawals from the inactive FGTS' accounts. The number of beneficiaries who did withdrawals in months after the initial month of funds release accounts for around 13 percent of qualified workers in this database.[13] Finally, we exclude workers with positive real estate debt balances prior to the Program (until November 2016). A housing purchase, a liquidation, an amortization or a mortgage payment is the only criterion for a worker to normally access the funds from an inactive FGTS' account that represents a worker's choice.[14] It also reflects qualified workers' demographic characteristics and could be endogenously correlated with consumption and borrowing behavior. We were left with a final full dataset containing 164 thousand observations of treated workers. These people account for a BRL$2,284 (US$638) average withdrawal.[15]

By delimiting the scope of our analysis, it is worth mentioning that we focus on credit card spending and borrowing effects of the program in the Brazilian credit information system. Due to data limitations, we cannot track spending and debt outside the SCR. We also do not track portfolio investment, which may be another destination of part the withdrawals amounts, specially among richest workers. Furthermore, this study is based on individual information, hence it does not consider likely unfolded household effects.

Nevertheless, the richness of our debt transaction-level information as well as the individual demographics in our dataset allow us to better understand responses heterogeneity. For example, whether individuals spend and borrow differently, and when they do so following a positive financial shock. To this respect, these data overcome substantial obstacles in terms of accuracy, scope and frequency that usually limits to obtaining reliable answers to these important issues. Although we do not have a detailed data on credit card relative to studies that use micro-level credit card data (e.g., Gross and Souleles, 2002; Agarwal, Liu, and Souleles, 2007; Aaronson, Agarwal, and French, 2012) or jointly data on credit card, debit card, and checking accounts (Agarwal and Qian (2014), Gelman et al. (2014), Baker (2018)), we have a more complete information on each individual indebtedness in our sample. Rather than observing only aggregate debt or one specific debt modality, we have information on modalities available in all banking system in the country. Moreover, relative to traditional household spending and balance-sheet datasets in the US such as the Survey of Consumer Finance (SCF), our sample is larger, allows

[13] More precisely 87.2 percent of the eligible workers withdrawn their funds from inactive accounts on the initial month of the funds release.

[14] We argue that the other criteria are not a workers' choice. See footnote 4 for a description of the criteria that allow a worker to normally withdraw from an inactive FGTS' account.

[15] Workers outside SCR account for around half of our sample's average withdrawal (BRL$1,154 - US$354).

high frequency analysis and have negligible measurement error.

We use the first seven months in our data (2016:01-2016:07) to identify consumers' pretreatment demographics and job as well as inactive accounts' characteristics. We then remove this range period from our sample for a cleaner identification. As a result, the final range period in our study is from 2016:8-2018:05.

Similarly to the US tax rebates in 2001 and 2008, qualified workers do not access the stimulus money at the same time in our policy experiment. Meanwhile, unllike those programs, we cannot cleanly identify the stimulus effect from the random payout timing. In our case, it is the initial day of the withdrawal release that is exogenously defined according to the workers' month of birth. Qualified workers do not exclusively receive a pre-defined amount of stimulus money by electronic deposit in their checking account, as in the US stimulus policies. They also might go to an ATM or bank branch to voluntarily withdraw it. We see in data that around 90 percent of the withdrawals occurs in the first month of the funds release for each of the five groups of eligible workers. However, the exact total withdrawal amount and the day it occurs possibly endogenously reflect workers' demographic characteristics or seasonal as well as the average of all other concurrent aggregate factors.

Therefore, instead of exploring variation on withdrawal timing, we use a difference-in-differences approach and rely on the untreated workers to identify the spending and debt response. The untreated workers were raised as follows. In the RAIS database we have information on when a employee quits or is dismissed for just cause. Since these events define the deactivation of an FGTS' account, it implies that we know whether a worker had an inactive account. As mentioned previously, we tracked all 44.92 million individuals with formal labor contracts between 1994 to 2016 that had any inactive account in this period. Among these individuals, the ones who were eligible and did withdrawals, as indicated by the merge with the CEF's dataset, were assigned to the treatment group, while those individuals who did not qualify to the program due its eligibility criteria[16] were considered the control group.

	Treatment group		Control group			Matched Treatment group		Matched Control group		
	Mean (1)	SD (2)	Mean (3)	SD (4)	Diff.	Mean (5)	SD (6)	Mean (7)	SD (8)	Diff.
Panel A. Demographics of the treatment and control groups										
Age	36.63	9.82	37.75	10.80	1.11***	36.58	9.75	36.58	9.77	0.00
Monthly income in 2016	1,478	2,154	1,750	3,035	272***	1,450	2,014	1,452	2,033	1.80
Education Level										
Elementary School	0.13	0.33	0.12	0.33	-0.01***	0.13	0.33	0.13	0.33	0.00
High School	0.56	0.50	0.51	0.50	-0.05***	0.56	0.5	0.56	0.5	0.00
Higher Education	0.31	0.46	0.37	0.48	0.06***	0.31	0.46	0.31	0.46	0.00
Female	0.48	0.50	0.50	0.50	0.02***	0.48	0.5	0.48	0.5	0.00
Non-white	0.48	0.50	0.43	0.49	-0.05***	0.48	0.5	0.48	0.5	0.00
$Withdrawal	2,284	3,549				2,287	3,547			
Observations	164,157		7,430,162			163,994		162,345		

(*Continued*)

Table 1: Summary Statistics

[16]That is, individuals who have accounts created after December 31, 2015 or the ones who have accounts cleared by withdrawals made before the program announcement.

	Treatment group		Control group		Matched Treatment group		Matched Control group	
	Mean (1)	SD (2)	Mean (3)	SD (4)	Mean (5)	SD (6)	Mean (7)	SD (8)
Panel B. Spending and debt information of the treatment and control groups								
Credit card spending	2,075	3,032	2,153	3,514	2,075	3,032	2,153	3,514
Total debt	7,183	20,245	8,631	25,988	7,183	20,245	8,631	25,988
Revolving debt	949	2,373	994	2,643	949	2,373	994	2,643
Non-revolving debt	6,598	20,264	8,247	26,329	6,598	20,264	8,247	26,329
Default								
Total debt	1,116	3,535	1,176	3,968	1,116	3,535	1,176	3,968
Revolving debt	842	2,614	824	2,775	842	2,614	824	2,775
Credit card	761	2,329	743	2,451	761	2,329	743	2,451
Overdfraft	485	1,755	439	2,017	485	1,755	439	2,017
Non-Revolving	679	2,703	749	3,180	679	2,703	749	3,180
Real estate					0	0	117	438
Vehicles	330	1,074	404	1,149	330	1,074	404	1,149
Payroll	750	3,011	1,059	4,077	750	3,011	1,059	4,077
Installments	163	647	248	1,148	163	647	248	1,148
Personal	88	324	60	227	88	324	60	227
Other goods	217	740	295	847	217	740	295	847
Other	633	2,623	615	2,870	633	2,623	615	2,870
Past due								
Total debt	1,017	3,334	1,108	3,751	1,017	3,334	1,108	3,751
Revolving debt	700	2,313	733	2,526	700	2,313	733	2,526
Credit card	618	2,021	644	2,186	618	2,021	644	2,186
Overdfraft	393	1,555	388	1,804	393	1,555	388	1,804
Non-Revolving	625	2,557	701	2,959	625	2,557	701	2,959
Real estate					87	339	150	598
Vehicles	293	1,002	320	1,021	293	1,002	320	1,021
Payroll	610	2,723	732	3,240	610	2,723	732	3,240
Installments	122	572	199	948	122	572	199	948
Personal	55	262	44	197	55	262	44	197
Other goods	166	618	233	743	166	618	233	743
Other	578	2,461	586	2,696	578	2,461	586	2,696
Observations	164,157		7,430,162		163,994		162,345	

Table 1: Summary Statistics - *Continued.*

Notes: This table reports the summary of statistics of our treatment and control sample both before and after Coarsened Exact Matching (based on the k-to-k matching). The treatment sample consists of workers who qualify for the Withdrawal Program of the FGTS in 2017 (workers who had an inactive account of the FGTS until December, 31 2015) and the control sample consists of all workers who did not qualify for the program (individuals with FGTS accounts created after December 31, 2015 or with accounts cleared by withdrawals made before the program announcement). We exclude individuals: i.with no information in the SCR database in our period sample (2016:08-2018:05), ii. in the extreme percentiles of credit card spending, total debt and withdrawals, iii.with delayed withdrawals with respect to their initial release month, and iv. with mortgage balance prior to the Program. Panel A exhibits the comparison of demographics between the treatment and control groups, both before and after coarsened exact matching. Panel B shows the comparison of credit card spending, total debt, revolving and non-revolving debts, and information on debt default and past due debt for selected debt modalities between the treatment and control groups in the 25-month sample period (2016:05–2018:05), both before and after coarsened exact matching. See Appendix A.11 for definitions on debt modalities. All the amounts are in the local currency (BRL$), and US$1=BRL$3.2591 as of December 2016.

Table 1 exhibits summary statistics of demographics in Panel A, and credit card spending and debt variables for the treatment and control groups. We see that the control group is not directly comparable with the treatment group along key dimensions in the full (unmatched) sample. For example, on average the control group is richer and higher educated than the treatment group. The amount available in the withdrawals program depends on individual's life cycle income, for which we use monthly income (labor earnings) in 2016 as proxy. Moreover, the level of education is also proxy for financial literacy. This suggests that the treatment group may have spending and indebtedness patterns intrinsically different from that of the control group.

For a sound identification of the policy effect, workers in the treatment and control groups should also have comparable levels of income and education. Motivated by this evidence, we build a matched sample of workers in the treatment and control groups that are similar in observable characteristics. More precisely, we compute Coarsened Exact Matching (CEM) to coarsen the data using a rich set of income, as well as demographics information including age, schooling, gender and race, dummies on characteristics of inactive FGTS' accounts (reason for the last ending of job contract, year of the last inactive account and number of inactive accounts), occupation as well as dummies for each of the 27 states as fixed effects to control for regional differences in a continental country as Brazil. Then we take advantage of the size of our database to perform a k-to-k matching so that the same number of treated and control units are located within all strata for each covariate.[17]

We compute the CEM in the first seven months of our (pre-treatment) sample for each of the five groups of treated workers. We then stack all treated workers from each group in a vector with all treated workers from the matched sample.[18] In addition, we remove this range period for a cleaner identification. We see that differences in several characteristics either shrink significantly or become statistically insignificant in Table 1. In addition to the mean statistics, distributions of monthly income in 2016 and age of the treatment and control groups after matching are also similar and comparable (Figure 2). Notwithstanding, we acknowledge that the matched sample might not eliminate the unobservable differences between treated and untreated workers, which would affect their spending and debt behaviour.

Our database allows to explicitly test for any difference between the treatment and control groups in spending and debt trends during the pretreatment period. We also present several robustness checks to validate our matched sample approach. Moreover, we assess external validity of our results by carrying out the difference-in-differences regressions in the full (unmatched) sample.[19]

The difference-in-differences identification approach requires the control group to have the same spending and indebtedness patterns as the treatment group in the pretreatment period so that their behavior after the policy announcement constitutes a valid counterfactual. To illustrate it, we plot the unconditional means of treatment and control groups of workers in the matched sample from 2016:09-2018:05[20] for total debt and total debt default in Figure 2. We see, for example, that the difference in total debt default between the treatment group and the control group before the announcement of the FGTS' withdrawals program remains virtually

[17]We additionally compute propensity score matching (PSM) based on a logistic regression, using the same covariates on the baseline CEM methodology, and perform the nearest-neighbor matching based on the computed propensity scores on data. Moreover, we further consider all treated workers with some spending and debt information in the SCR database (unmatched database). We exploit the estimated propensity scores by including them as regression weights (CEM or PSM) in the full sample difference-in-differences analysis.

[18]We apply CEM in each group separately to control for seasonal consumption/savings behavior related to birth months.

[19]We also perform the regressions for each of the five groups separately and the responses are similar across groups, which further supports our approach to stack qualified workers from the five groups in one vector.

[20]We carried out the same analysis on different start periods from 2016:05 to 2016:11 by varying the matching period and the unconditional means and main results show similar figures. The unconditional means for total past due debt are similar to the total default debt ones.

constant, which confirms the underlying identifying assumption of parallel pre-trends. Note that the lines depicting treatment and control visibly diverge after the program announcement, which provides a suggestive evidence of the workers response to the shock.

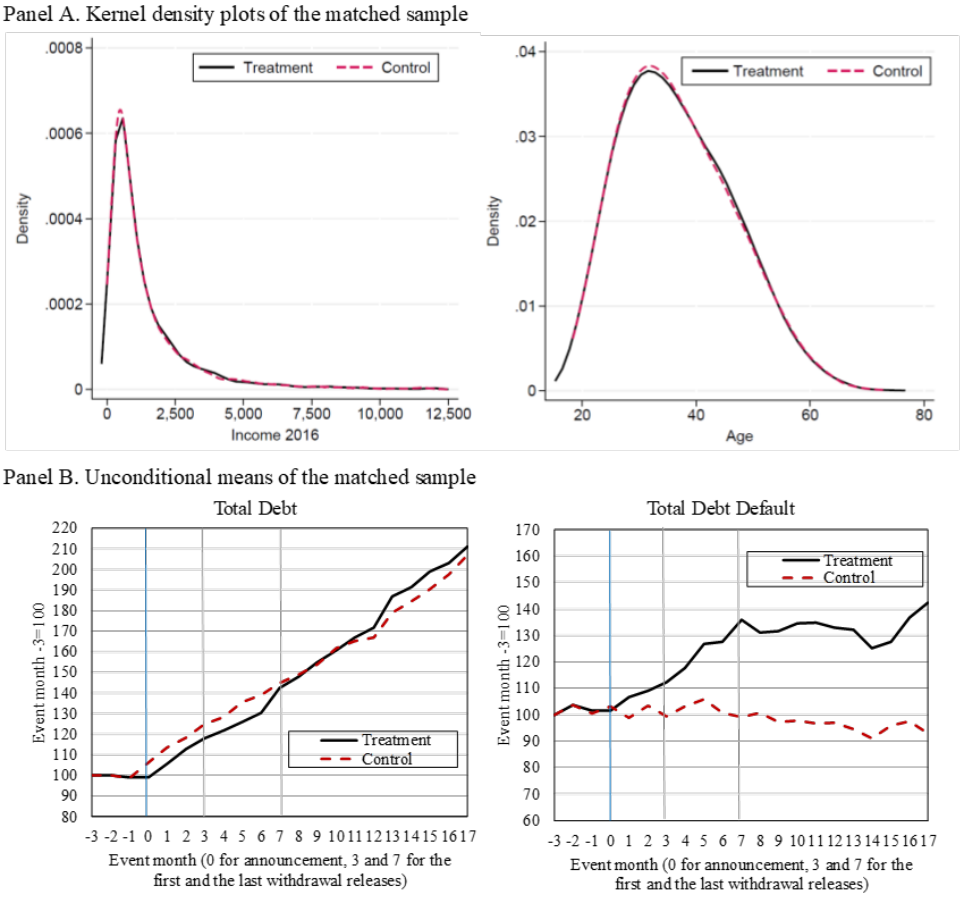

Figure 2: Summary Statistics of the Matched Sample.

Notes: Panel A shows the treatment group and the control group comparison of distributions of average monthly income in 2016 and age during the period 2016:01-2016:07, after the coarsened exact matching. Panel B shows the unconditional mean of total debt and total debt default of the treatment and control group during the period from 2016:09 to 2018:05.

III. Methodology and Overall Results

We now assess the responses using a difference-in-diferences regression approach. We first estimate the average response of total debt and credit card spending to the FGTS' withdrawals release program and the associated response in terms of financial fragility represented by total debt default, total past due debt and credit card spending volatility. Second, we split the after-policy period into the announcement and withdrawal periods. Lastly, We assess dynamics using a distributed lag model.

The overall effects of the FGTS shock on credit card spending, debt, and financial fragility will underscore the need to examine heterogeneity across workers — distinguishing responses by credit access, debt type, and perception of the shock. This motivates our subsequent decomposition into liquidity and wealth components, which reveals the mechanisms behind these diverse outcomes.

We present the overall results in the period range from four months before (pre-treatment: 2016:08-2016:11) to seventeen months after the announcement of the program (post-treatment:

2016:12-2018:05). Remind that the treatment group corresponds to workers who qualified to the program and performed withdrawals from their inactive accounts. The control group corresponds to workers that did not qualify to the program, that is, individuals whose accounts were created after December 31, 2015 or individuals who cleared up their inactive account before the program announcement.

A. The Average Response of total Debt, Credit Card Spending and Financial Fragility

Tables 2 and 3 show results following two types of model specification. The first type shows the average total debt and the average monthly credit card spending responses to the program. A similar specification presents the total debt default, total past due debt and credit card spending volatility responses to the program. The equation of the first type follows:

$$Y_{i,t} = \beta_{pre} \times \$W_i \times 1_{pre} + \beta_{post} \times \$W_i \times 1_{post} + \alpha_i + \delta_t + \epsilon_{i,t} \quad (1)$$

The dependent variable, $Y_{i,t}$, is either total debt stock (balance amount) or credit card spending for individual i at the end of month t. $\$W_i$ is the withdrawal amount of the FGTS Program that worker i did, and is equal to 0 for the control group. 1_{pre} is a dummy variable equal to 1 for the period before the announcement of the program (i.e, 2016:09-2016:11).[21] 1_{post} is another dummy variable equal to 1 for the months after announcement of the program (i.e, $\geq$ 2016:12). α_i is the individual dummy used to absorb differences in individual preferences. δ_t is the year-month dummy, included to absorb seasonal as well as the average of other concurrent aggregate factors. We clustered standard errors at the individual level. β_{pre} captures the difference of credit card spending (or total debt) trend between treatment and control groups in the pretreatment window, 2016:09-2016:11 (compared to the benchmark period, i.e, 2016:08). Note that β_{pre} must be statiscally and economically indistinguishable from zero for validity of the difference-in-difference design. On the other hand, β_{post} measures the average monthly post-policy response of credit card spending per $1 withdrawn by a treated worker (compared to the benchmark period) relative to the post-policy spending change of the control group. β_{post} has a different interpretation if $Y_{i,t}$ is total debt, since this dependent variable is a stock variable in levels, instead of a flow variable such as credit card spending.[22]. It then measures the average post-policy response (in the whole post-policy window) of total debt balance per $1 withdrawn by a treated worker (compared to the benchmark period) relative to the post-policy change of total debt of the control group.

Table 2 shows results on the average total debt and credit card spending responses by applying equation (1) in panel A and equation (2) in panel B. We present results applying the baseline matching approach (CEM) and additionally by propensity score matching (PSM)[23] for robustness. In panel A, the coefficients on $\$W_i \times 1_{pre}$ capture the difference in total debt or spending per $1 of the withdrawal amount between the treatment and control groups in the period before announcement (2016:09-2016:11) relative to the first month in our sample period (2016:08). Analogously, the coefficients on $\$W_i \times 1_{post}$ measure the responses after

[21] Period 2016:08 is absorbed to identify the benchmark credit card spending or debt stock patterns in the estimation. We varied the number of absorbed months (2016:05-2016:08) and accordingly the months before announcement (2016:06-2016:11) by computing the CEM in the first four months of our (pre-treatment) sample to balance treated and untreated observable characteristics. Overall results are similar.

[22] We could alternatively define $Y_{i,t}$ as total debt change $\triangle Y_{i,t} = Y_{i,t} - Y_{i,t-1}$. However, we apply total debt in stocks due to variable stability and easy of interpretation across model specifications. Note that either the monthly sum of total debt change or the average of total debt in stock levels in the post-policy windows are equivalent responses.

[23] The same covariates from the CEM approach are applied in the PSM which uses logistics regressions based on the nearest neighbor.

announcement (2016:12-2018:05) relative to the first month in our sample period. In Panel A, coefficient estimates on the pretreatment period variable, $\$W_i \times 1_{pre}$, are both economically small and statistically insignificant in the total debt and credit card spending in the first and third columns.

dependent variable:	Total Debt		Credit Card Spending	
matching type:	CEM	PSM	CEM	PSM
Panel A				
$\$W \times 1_{pre}$	0.01 (0.63)	0.01 (0.48)	0.00 (0.27)	0.00 (0.17)
$\$W \times 1_{post}$	0.07 (0.70)	0.10 (0.97)	0.01 (1.30)	0.02* (1.79)
Constant	8,341*** (88.13)	8,366*** (88.57)	2,156*** (200)	2,131*** (231)
Adjusted R^2	0.63	0.61	0.71	0.72
Panel B				
$\$W \times 1_{pre}$	0.01 (0.63)	0.01 (0.56)	0.00 (0.27)	0.00 (0.17)
$\$W \times 1_{announce}$	-0.07* (-1.68)	-0.05 (-1.13)	-0.00 (-0.39)	-0.00 (-0.03)
$\$W \times 1_{withdrawn}$	0.12 (0.91)	0.15 (1.11)	0.02* (1.65)	0.02** (2.14)
Constant	8,341*** (88.13)	8,366*** (88.13)	2,156*** (200)	2,131*** (196)
Adjusted R^2	0.63	0.61	0.71	0.72
Observations	225,989	240,660	225,989	240,660
Fixed Effects	Individual, Month-Year			

Table 2: The Average Debt and Spending Response to the FGTS Program

Notes: This table shows the monthly average spending response (equations (1) and (3)) in the period from 2016:08 to 2018:05 using the matched sample. Panel A presents the estimation results of equation (1), and panel B shows the estimation results of equation (3). $W is the amount withdrawn by the treatment group, and is equal to 0 for the control group. 1_{pre} is a binary variable equal to 1 for the months before the announcement (i.e., 2016:08-2016:11). 1_{post} is a binary variable equal to 1 for the months after the announcement of the Withdrawals Program (i.e., $\geq$ 2016:12). 1_{announce} is equal to 1 for each of the five groups following their release timing, respectively: 2016:12 to 2017:02, 2016:12 to 2017:03, 2016:12 to 2017:04, 2016:12 to 2017:05, 2016:12 to 2017:06. 1_{withdraw} is equal to 1 for each of the five groups in the following the following initial months: 2016:03, 2016:04, 2016:05, 2016:06, 2016:07, respectively, and end month 2018:05 for all groups. We stack all treatment groups in one vector of 1_{announce} and another vector of 1_{withdraw}. Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. *t*-statistics are reported in parentheses under the coefficient estimates. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Panel A of Table 2 also shows in the first column that for each \$1 withdrawn by the treatment group implies a \$0.01 rise on average in total debt for the treatment group relative to the control group (t-statistic=0.63) before the program announcement and a \$0.07 (t-statistic=0.70) increase after the announcement. The third column shows that the treatment group spend \$0.00 (\$0.002) more on monthly average using credit card relative to the control group before the program (t-statistic=0.27) and \$0.01 after the program announcement (t-statistic=1.30). Note that both the estimates for total debt and credit card spending after the program are not statistically significant. Interestingly, we show further in this analysis that it might reflect either opposite sign variation in the responses dynamics or heterogeneity of worker types and debt categories.

Panel A of table 3 shows the estimates related to financial fragility and are slightly different from equation (1):

$$Y_{i,t} = \beta_{pre} \times 1_{FGTS} \times 1_{pre} + \beta_{post} \times 1_{FGTS} \times 1_{post} + \alpha_i + \delta_t + \epsilon_{i,t} \tag{2}$$

The dependent variable, $Y_{i,t}$, is either total debt default or past due debt (in logs) and also credit card spending volatility, measured as the coefficient of variation, for individual i at the end of month t.[24] 1_{FGTS} is the a dummy variable equal to 1 (one) if the worker participates on the FGTS Program and 0 (zero), otherwise. Therefore, interpretation of β_{pre} and β_{post} refers to the average policy response in percentage terms of total debt default or past due debt by a treated worker, respectively before or after the program announcement (compared to the benchmark period) relative to responses of the control group during the same periods. Particularly for the coefficient of variation on credit card spending, this interpretations is related to the difference in standard deviations (in average terms) of credit card spending between workers in the treatment and control groups before or after the program announcement compared to the benchmark period.

Additionally, note that in order to compare workers with similar behavior in terms of paying back debt, we include in (2) a set o dummy variables defining nine different categories of credit scores in the month before program announcement.[25] In the equation applied to credit card spending volatility we include in (2) controls for both initial levels and volatility of credit card spending to assess whether spending became more volatile due to the program by comparing workers with similar levels and volatility of spending in 2016, before the program announcement.[26]

One can see from Panel A in Table 3 that the coefficient estimates on the pretreatment period variable, $1_{FGTS} \times 1_{pre}$, are both economically small and statistically insignificant in all columns. The first and the third columns show by fixing initial credit scores, that workers in the treatment group increased total debt default by 18 percent (t-statistic=2.69) and past due debt by 33 percent (t-statistic=3.86) after the program announcement. Furthermore, credit card spending became more volatile, fixing initial levels and volatility of spending, by 0.62 in terms of average spending (t-statistic=31.22).These results indicate that, prior to the stimulus program, there were no significant differences in indebtedness and spending patterns between

[24] We computed the coefficient of variation for each workers' relevant period, that is, the one before announcement, the period within announcements windows and during the withdrawal time slots.

[25] There are nine categories of credit scores: AA, A, B, C, D, E, F, G and H. we consider the scores in the month right before the program announcement, 2016:11. Thus, equation (2) becomes:
$Y_{i,t} = \beta_{pre} \times 1_{FGTS} \times 1_{pre} + \beta_{post} \times 1_{FGTS} \times 1_{post} + \sum_{k=1}^{K-1} \beta_{k,post} \times 1_{FGTS} \times 1_{post} \times 1_{Score\,k,2016} + \alpha_i + \delta_t + \epsilon_{i,t}$, such that k represents each of the nine (K) credit score categories. Thus, the term $1_{Score\,k,2016}$ is a dummy which distributes workers across credit score categories in November 2016.

[26] We compute average levels and volatility of credit card spending from January to November 2016, 2016:01-2016:11. Therefore, equation (2) becomes:
$Y_{i,t} = \beta_{pre} \times 1_{FGTS} \times 1_{pre} + \beta_{post} \times 1_{FGTS} \times 1_{post} + \beta_{1,post} \times 1_{FGTS} \times 1_{post} \times \text{Credit\_Volatility}_{i,2016}$
$+ \beta_{2,post} \times 1_{FGTS} \times 1_{post} \times \text{Credit\_Levels}_{i,2016} + \alpha_i + \delta_t + \epsilon_{i,t}$.

the matched groups of qualified and non-qualified workers. This strongly supports our research design, showing that the matched samples of qualified workers (treatment group) and non-qualified workers (control group) were balanced and similar in their indebtedness and spending trends. Therefore, the differences observed in these trends after the program's announcement accurately reflect the treatment group's response to the shock.

dependent variable:	Total Debt				Credit card spending	
	Default		Past Due		Volatility	
matching type:	CEM	PSM	CEM	PSM	CEM	PSM
Panel A						
$1_{FGTS} \times 1_{pre}$	-0.04	-0.02	-0.03	0.00	0.00	0.00
	(-1.61)	(-0.62)	(-0.80)	(0.06)	(1.01)	(1.50)
$1_{FGTS} \times 1_{post}$	0.18***	0.20***	0.33***	0.39***	0.62***	0.62***
	(2.69)	(3.73)	(3.86)	(5.73)	(31.22)	(30.97)
Constant	0.65***	1.76***	1.18***	2.60***	0.65***	2.11***
	(19.30)	(4.25)	(28.58)	(8.36)	(2.66)	(122)
Adjusted R^2	0.40	0.40	0.45	0.45	0.72	0.73
Panel B						
$1_{FGTS} \times 1_{pre}$	-0.04	-0.02	-0.03	0.00	0.00	0.00
	(-1.61)	(-0.62)	(-0.80)	(0.06)	(1.01)	(1.50)
$1_{FGTS} \times 1_{announce}$	0.01	0.05	0.12***	0.22***	0.63***	0.60***
	(0.21)	(1.15)	(2.56)	(4.17)	(33.86)	(33.03)
$1_{FGTS} \times 1_{withdrawn}$	0.25***	0.26***	0.41***	0.46***	0.64***	0.63***
	(2.82)	(4.09)	(3.77)	(5.63)	(28.24)	(28.19)
Constant	0.64***	1.76***	1.17***	2.60***	0.64***	2.10***
	(19.29)	(4.26)	(28.68)	(8.37)	(2.56)	(100)
Adjusted R^2	0.40	0.40	0.45	0.45	0.72	0.73
Observations	225,989	240,660	225,989	240,660	218,422	229,998
Fixed Effetcs	Individual, Month-Year					
Controls	Initial credit score	Initial credit score	Initial credit score	Initial credit score	Initial volatility, Initial level	Initial volatility, Initial level

Table 3: The Average Debt Default, Past Due Debt and Credit Card Spending Volatility Response to the FGTS Program

Notes: This table shows the monthly average spending response (equations (2) and (4)) in the period from 2016:08 to 2018:05 using the matched sample. Panel A presents the estimation results of equation (2), and panel B shows the estimation results of equation (4). 1_{FGTS} is a binary variable equal to 1 for the treatment group. 1_{pre} is a binary variable equal to 1 for the months before the announcement (i.e., 2016:08-2016:11). 1_{post} is a binary variable equal to 1 for the months after the announcement of the Withdrawals Program (i.e., $\geq$ 2016:12). 1_{announce} is equal to 1 for each of the five groups following their release timing, respectively: 2016:12 to 2017:02, 2016:12 to 2017:03, 2016:12 to 2017:04, 2016:12 to 2017:05, 2016:12 to 2017:06. 1_{withdraw} is equal to 1 for each of the five groups in the following initial months: 2016:03, 2016:04, 2016:05, 2016:06, 2016:07, respectively, and end month 2018:05 for all groups. We stack all treatment groups in one vector of 1_{announce} and another vector of 1_{withdraw}. Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. *t*-statistics are reported in parentheses under the coefficient estimates. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

B. Announcement versus Withdrawal Effect

The second specification type is similar to equations (1) and (2). The only difference is that it splits the 1_{post} dummy variable for the months after announcement of the program into two dummy variables. The first one is $1_{announce}$, which is equal to 1 for the months from announcement (inclusive) and the month immediately before the month of withdrawal releases for each of the five groups of qualified workers. The second dummy variable is $1_{withdrawn}$ and it is equal to 1 from the initial month of withdrawal releases for each of the five beneficiary groups and the last month of this sample (2018:05).[27] Therefore, $\beta_{announce}$ and $\beta_{withdrawn}$ in equations (3) and (4) have the same interpretation of β_{post} in equations (1) and (2), respectively, but the post announcement period is split into the announcement and withdrawal periods.

$$\begin{aligned} Y_{i,t} =& \beta_{pre} \times \$W_i \times 1_{pre} + \beta_{announce} \times \$W_i \times 1_{announce} + \beta_{withdrawn} \times \$W_i \times 1_{withdrawn} \\ &+ \alpha_i + \delta_t + \epsilon_{i,t} \end{aligned} \tag{3}$$

Panel B of Table 2 suggests that the statistical non-significance of the responses after program announcement, illustrated in Panel A, is partially due to the fact that there is response trends with opposite signs throughout this period. It shows in the first column that for each \$1 withdrawn by the treatment group implies a \$0.07 fall on average in total debt for the treatment group relative to the control group (t-statistic=-1.68) during the program announcement periods, before a \$0.12 rise (t-statistic=0.91) during the withdrawal periods. The third column shows that the treatment group does not significantly change its spending trend (\$-0.00 (\$-0.004)) on monthly average using credit card relative to the control group during the announcement periods (t-statistic=-0.39) and \$0.02 after the withdrawal release periods (t-statistic=1.65).

Estimates related to financial fragility are presented in Panel B of Table 3 and are slightly different from equation (2). Analogously, the same control variables are included in equation (2) applied either to total debt default and past due debt (in logs) or to credit card spending volatility in equation (3).[28]

$$\begin{aligned} Y_{i,t} =& \beta_{pre} \times 1_{FGTS} \times 1_{pre} + \beta_{announce} \times 1_{FGTS} \times 1_{announce} + \beta_{withdrawn} \times 1_{FGTS} \times 1_{withdrawn} \\ &+ \alpha_i + \delta_t + \epsilon_{i,t} \end{aligned} \tag{4}$$

Note again that interpretation of $\beta_{announce}$ and $\beta_{withdrawn}$ refers to the average policy responses in the announcement and withdrawal periods, respectively, in percentage terms if $Y_{i,t}$ is either total debt default or past due debt or the policy response in standard deviations (in average terms) of credit card spending if $Y_{i,t}$ is credit card spending volatility. The first column shows by fixing initial credit scores, that workers in the treatment group increased total debt default by 1 percent in the announcement period. However, it is not significant statistically (t-statistic=0.21). Debt default start to increase after the withdrawal releases, accounting for a 25 percent rise in this period. In the third column it is noticeable that financial fragility with respect to debt start before the withdrawal releases through rises in past due debt in the announcement periods (12 percent and t-statistic=2.56). The bulk of this policy response occurs in the withdrawal periods, at 41 percentage increase (t-statistic=3.77). Note, in addition, in the fifth column that by fixing initial levels and volatility of spending, there is no significant difference in the rise of credit card spending volatility in the announcement (0.63 and t-statistic=33.86) and withdrawal (0.64 and t-statistic=28.24) periods.

[27] One shall remind that we stack all treated workers from each group in a vector with all treated workers from the matched sample.

[28] See footnotes 25 and 26 for details.

Finally, it is worth mentioning that the estimates applying PSM to the matching data in Tables 2 and 3 are economically and statistically similar to our baseline estimates using CEM to the matched database.

In summary, our findings contribute two important insights to the literature on financial fragility to stimulus programs and liquidity/wealth shocks. First, consumers began delaying debt installments immediately after the program's announcement, even before the funds were released. Second, although we do not find evidence that credit card spending rose during the announcement period, it in fact become more volatile. This behavior does not align with workhorse life-cycle model's predictions for consumption and indebtedness in response to unexpected liquidity/wealth shocks. Previous studies on similar fiscal policies may have limited consumption and debt responses because they did not account for a effect in terms of financial fragility, especially during the announcement period. These results highlight the crucial role of indebtedness ability in enabling immediate delay on debt installments payment response to an unanticipated liquidity/wealth shock. Consumers essentially "borrowed" against the expected program funds and began delaying the payment of debt installments right after the program was announced.

C. The Dynamic Response of total Debt, Credit Card Spending and Financial Fragility

In addition to the average debt, spending and financial fragility effects, we gauge the dynamic patterns of these responses during the seventeen-month post-announcement period starting from three months before the program announcement, as equation (5) shows for debt and spending:

$$Y_{i,t} = \sum_{s=-3}^{17} \beta_s \times \$W_i \times 1_{month\,s} + \alpha_i + \delta_t + \epsilon_{i,t} \tag{5}$$

The coefficients β_{-3}, β_{-2} and β_{-1} capture the difference of trends in debt balance between the treatment and control groups in the pre-treatment months (2016:09,2016:10 and 2016:11), and we expect it to be economically and statistically insignificant. β_0 captures the immediate response during the announcement month (2016:12). The marginal coefficients β_1,..., β_{17} measure the average responses 1,..., 17 months after the announcement. Since, as we mentioned, spending is a flow variable, the graphs presents the cumulative response at each marginal monthly coefficient as follows: $b_s = \sum_{s=-3}^{s} \beta_t$ that describe the cumulative response in spending after s months, $s \leq 17$. The other variables since they are stock variables in levels, β_s states the response until month s. Again, these responses are represented per \$1 withdrawn by a treated worker (compared to the benchmark period) relative to the monthly response of the control group.

Panel A of Figure 3 displays the complete trajectories of the debt level and cumulative spending coefficients $s = -3, -2, \ldots, 16, 17$, with the dotted lines representing the corresponding 95% confidence intervals.[29] The standard errors for these cumulative effects are derived from the standard errors of the marginal coefficients in the regression, which are clustered at the individual level. This analysis can be interpreted as an event study, with month 0 marking the time of the announcement, and months 3 and 7 mark, respectively, the first and the last months of withdrawal releases.[30]

[29] Dotted lines in Graphs in all Figures henceforth also represents the corresponding 95% confidence intervals.

[30] Note that months 0, 1 and 2 capture exclusively the effects from the program announcement and months 3, 4 , 5 and 6 depict both announcement and withdrawal effects depending on each of the five groups of qualified workers. For example, for the group allowed to withdraw the funds from March, month 3 represents an withdrawal period, while for the groups whose worker were allowed to make withdrawals from April to July, month 3 marks an announcement response. Months from 7 to 17 mark exclusively withdrawal responses.

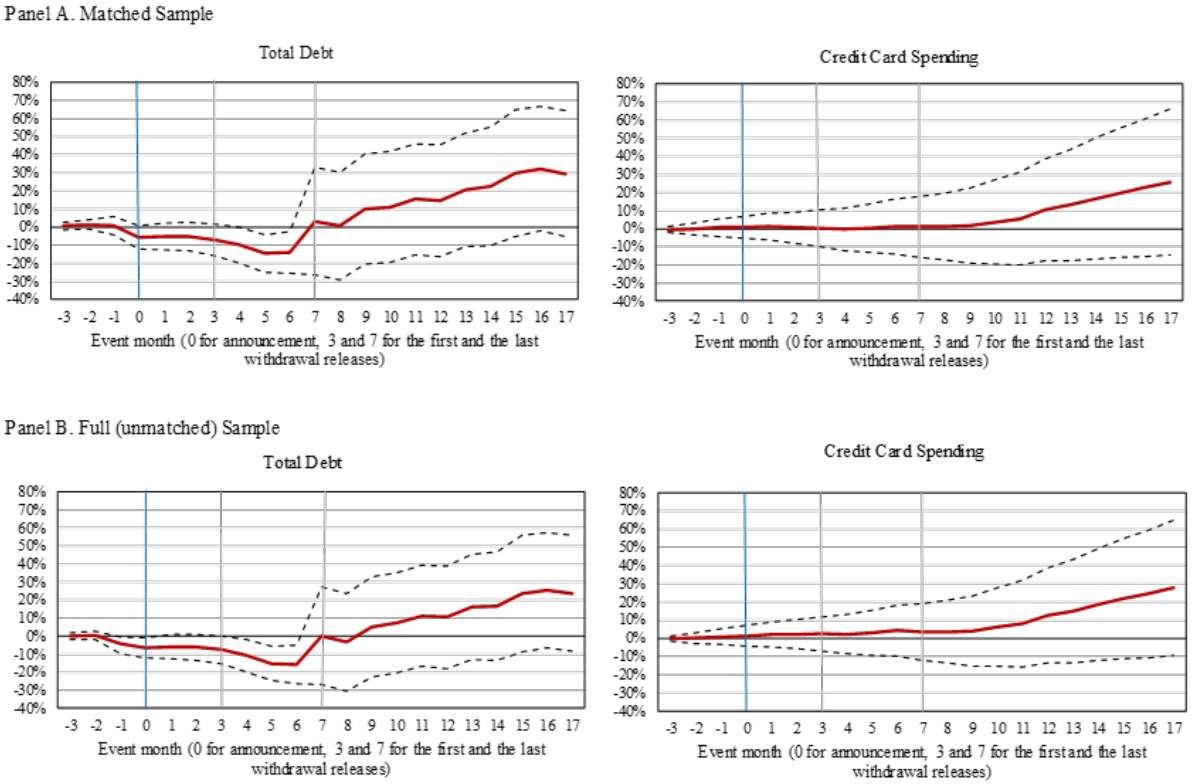

Figure 3: Estimated Debt and Spending Response Dynamics

Notes: This figure plots the entire paths of total debt response - coefficients β_s, $s = -3, -2, -1, \ldots, 16, 17$ - and cumulative credit card spending response - coefficients b_s, $s = -3, -2, -1, \ldots, 16, 17$, along with their corresponding 95 percent confidence intervals, as estimated from equation (5). The sample in panel A includes the matched treatment and control groups during the period of 2016:09-2018:05. Panel B reports results from the full unmatched sample in the same period. We estimate the full sample results with weighted least squares regressions, using the CEM weights as weights. The x-axis denotes the sth month after the announcement of the FGTS Program, and the y-axis shows the cash response (for every cash received).

Thus, Panel A of Figure 3 shows the differences in total debt and cumulative spending between the treatment group and the control group during the seventeen-month post-announcement period beginning from three months before the program announcement. In line with the regression results in Table 2, the three-month pre-announcement period is neither statistically nor economically significant. Workers reduce total debt gradually after the program announcement reaching a low at -\$0.14 per \$1 withdrawn (t-statistic=-2.76) on month 6 (June 2017), before starting to rise it continuously and then it reaches a plateau after month 15 (April 2018) at around \$0.30 (\$0.32 on month 16, t-statistic=1.84). Credit card spending exhibits a delayed and persistent response. Workers started to rise credit card spending after month 10 and it does not plateau at the maximum on month 17 with a cumulative rise of \$0.26 per \$1 withdrawn (t-statistic=1.66). Panel B of Figure 3 shows the same responses applied to the full (unmatched) sample in which the treatment and the control groups are not matched on demographic variables and the ones related to FGTS' inactive accounts. The main motivation for this is to assess whether the results can be generalized to the full sample. We exploit the estimated CEM weights by including them as regression weights in the full sample difference-in-differences analysis to address the challenge in statistical inference related to an unbalanced sample.[31] The

[31]The standard errors reported for the full sample analysis do not take into account the estimation error associated with estimating the propensity score, and the reported errors may thus be downward biased, making

intuition is to give a larger weight to those more similar workers in the control group (those with similar income, age, education, characteristics of the FGTS' inactive accounts). We overall see that the results exhibits similar levels and are more precisely estimated relative to results estimated on the matched sample.

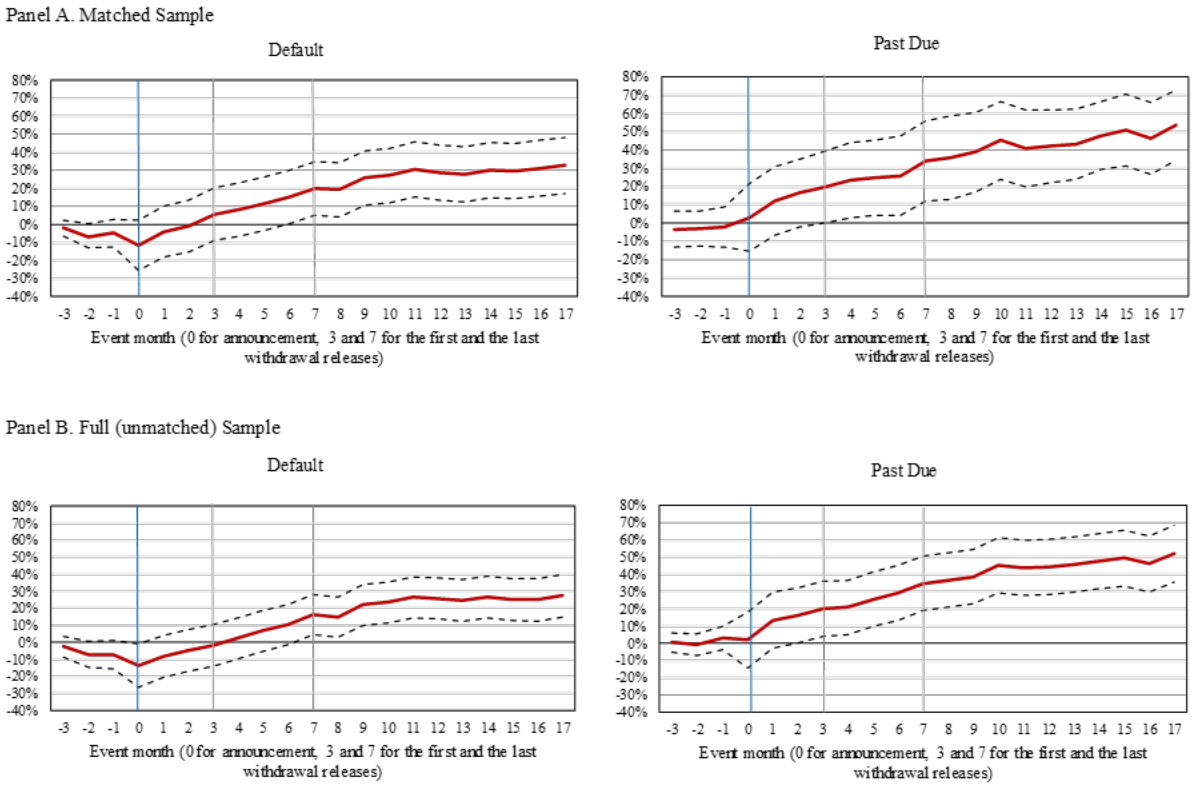

Figure 4: Estimated Default and Past Due Debt Response Dynamics

Notes: This figure plots the entire paths of total debt default and past due debt responses - coefficients β_s, $s = -3, -2, -1, \ldots, 16, 17$, along with their corresponding 95 percent confidence intervals, as estimated from equation (6). The sample in panel A includes the matched treatment and control groups during the period of 2016:09-2018:05. Panel B reports results from the full unmatched sample in the same period. We estimate the full sample results with weighted least squares regressions, using the CEM weights as weights. The x-axis denotes the sth month after the announcement of the FGTS Program, and the y-axis shows the cash response (for every cash received).

Equation (6) is similar to equation (5). However, note again that interpretation of β_s refers to the monthly average responses in percentage terms of the dependent variable. $Y_{i,t}$ is either total debt default or past due debt.[32]

$$Y_{i,t} = \sum_{s=-3}^{17} \beta_s \times 1_{FGTS} \times 1_{month\,s} + \alpha_i + \delta_t + \epsilon_{i,t} \tag{6}$$

Panel A of Figure 4 is aligned with the regression results presented in Table 3. It shows that the differences in total debt default and past due debt between the treatment group and the control group three-month before the program announcement and through the post-announcement period. Again, the three-month pre-announcement period is neither statistically nor economically significant. Workers gradually rise total debt default after the program announcement,

estimates appear more precise than they actually are. However, we believe that this issue is lessened by the size of our full sample.

[32]We do not exhibit the dynamic response of credit card spending volatility. By construction, it would depict virtually flat responses throughout the months.

before leveling off at around 30 percent on month 11 (33 percent at month 17, t-statistic=4.14). Total past due debt exhibits a rapid increasing response. Workers started to delay payment of debt installments from the announcement period. It then remains increasing indefinitely before reaching a maximum on month 17 at 54 percent (t-statistic=5.58). As in Figure 3, Panel B of Figure 4 shows the same responses applied to the full (unmatched) sample. Once again, the results show similar levels and are estimated with greater precision.

IV. Heterogeneity

A. Heterogeneity of total Debt, Credit Card Spending and Financial Fragility Responses Across Workers

We now examine the dynamics of heterogeneous responses across different types of eligible workers. Based on prior literature (e.g., Gross Souleles, 2002; Agarwal et al., 2007; Jappelli Pistaferri, 2010), we expect credit-constrained individuals to respond more strongly to the positive FGTS shock—showing greater increases in spending and/or reductions in debt—particularly when consumer debt interest rates exceed the basic policy rate. The same applies to financial fragility - decrease of default, past due debt and credit card spending volatility. Our rich array of demographics and credit information allows us to assess the full path of workers' heterogeneous responses in greater depth. In this subsection we estimate the heterogeneity in debt and spending responses to the shock across different groups of workers (constrained versus unconstrained consumers) using the following specification:

$$\begin{aligned} Y_{i,t} = \sum_{s=0}^{17} \beta_s \times \$W_i \times 1_{month\,s} + \sum_{s=0}^{17} \beta_{g_1,s} \times 1_{g1} \times \$W_i \times 1_{month\,s} + ... \\ + \sum_{s=0}^{17} \beta_{g_{(N-1)},s} \times 1_{g_{(N-1)}} \times \$W_i \times 1_{month\,s} + \alpha_i + \delta_t + \epsilon_{i,t} \end{aligned} \tag{7}$$

Equation (7) has a similar interpretation to equation (5). However, we assess heterogeneity across groups of workers by including additional terms in which $1_{g_{(N-1)}}$ is a dummy variable that selects the $(N-1)$ group of workers and $\beta_{g_{(N-1)},s}$ is the coefficient that captures this group response per \$1 withdrawn by a treated worker (compared to the benchmark period) relative to the monthly response of the control group (with one of the groups being absorbed). Moreover, since we have presented no pretreatment effect in previous equations, we absorb the pretreatment variables ($\sum_{s=-3}^{-1} \$W_i \times 1_{month\,s}$) to facilitate interpretation and increase power.[33]

We classify workers based on the level of credit constraint. We benefit from our rich array of demographics and credit information to define a measure of debt-to-limit as proxy of credit constraint. The credit-to-limit measure is calculated as the log ratio of total debt to the credit limit granted by the banking sector to each individual. [34] A consumer is considered to have low debt-to-limit if his average debt-to-limit in the year before the Program announcement is below the twenty-fifth percentile of the distribution in the cross section of workers in that period. Consumers have high debt-to-limit if their average debt-to-limit in that period is above the seventy-fifth percentile of the distribution. Consumers with high checking debt-to-limit

[33]We have performed and confirmed that our findings remain qualitatively consistent by including the pretreatment months in the analysis. Notably, the treatment and control groups show parallel trends during the pretreatment period across all subgroups in the heterogeneity analysis.

[34]We calculated total debt in 2016 from January to November - one month before the Program announcement. Credit limit is calculated as the average credit limit in the same period by adding up (total) credit limits for credit maturities smaller than 360 days and credit maturities greater than 360 days. We also applied debt-to-income in as an alternative proxy and the results are quantitatively similar - see the robustness section.

are likely to be more credit constrained, making it difficult for them to borrow to smooth consumption in response to negative shocks.[35]

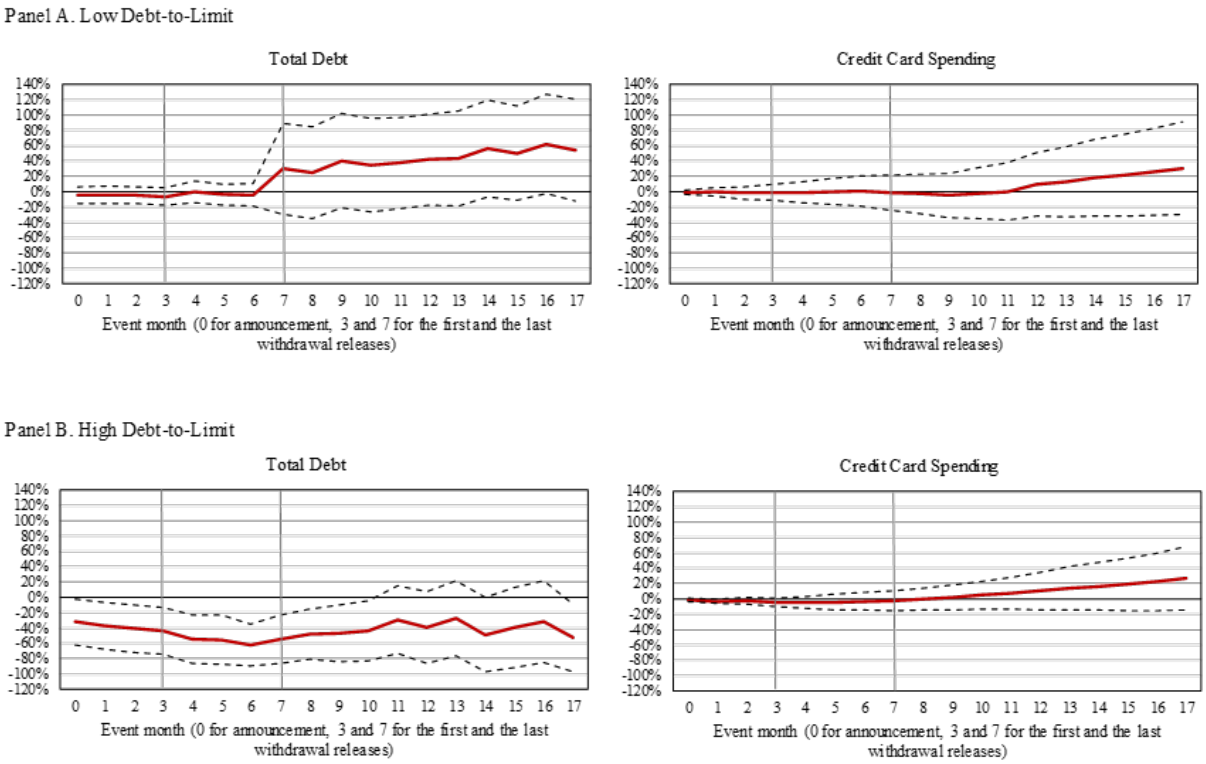

Figure 5: Heterogeneity in Debt and Credit Card Spending Response Across Workers

Notes: This figure plots the entire paths of total debt response - coefficients β_s, $s = -3, -2, -1, \ldots, 16, 17$ - and cumulative credit card spending response - coefficients b_s, $s = -3, -2, -1, \ldots, 16, 17$, along with their corresponding 95 percent confidence intervals, as estimated from equation (7). The sample includes the matched treatment and control groups during the period of 2016:12-2018:05. For each comparison panel, column 1 shows the total debit response and column 2 shows the cumulative credit card spending response.Panel A compares consumers with low debt-to-limit (i.e., average debt-to-limit between 2016:01 and 2016:11 ≤ 0.21, or twenty-fifth of sample). Panel B compares consumers with high debt-to-limit (i.e., average debt-to-limit between 2016:01 and 2016:11 ≥ 9.35, or seventy-fifth of the sample). The x-axis denotes the sth month after the announcement of the FGTS Program, and the y-axis shows the cash response (for every cash received).

Figure 5 shows the comparison across these two groups of workers in Panel A (low debt-to-limit - 'unconstrained') and Panel B (high debt-to-limit - 'constrained') on total debt stocks and cumulative credit card spending responses following equation (7). It is noted that there is virtually no heterogeneity on cumulative credit card spending across low and high debt-to-limit workers, whereas total debt the responses are generally distinct both economically and statistically across these two groups.

Credit card spending exhibits a delayed and persistent response, which similar to the aggregate response in Figure 3. Workers started to rise credit card spending around months 10 to 12 and it does not plateau at the maximum on month 17 with cumulative rises of \$0.30 per \$1 withdrawn (t-statistic=0.99) and \$0.27 per \$1 withdrawn (t-statistic=1.28), respectively by low

[35] Alternatively, low debt-to-limit consumers are often linked to precautionary saving motives. According to buffer stock models, when consumers face income uncertainty and lack full insurance, they tend to delay consumption and save as a safeguard against potential negative income shocks, especially in an incomplete market. In the event of an unexpected positive wealth shock, these consumers are likely to increase spending as the shock reduces their income uncertainty.

debt-to-limit and high debt-to-limit workers. Regarding total debt response, low debt-to-income workers show a delayed response and start to increase debt gradually from month 7 reaching by month 17 a \$0.55 rise per \$1 withdrawn (t-statistic=1.61). In contrast, high debt-to-income workers present an immediate deleverage response from the Program announcement (month 0 - zero) declining the debt stock by -\$0.32 rise per \$1 withdrawn (t-statistic=-2.41), before reaching a low by month 6 at -\$0.62 rise per \$1 withdrawn (t-statistic=-4.47). Then debt stocks starts to increase slightly up to month 11, before plateauing at around -\$0.40 per \$1 withdrawn without statistical significance.

$$\begin{aligned} Y_{i,t} = \sum_{s=0}^{17} \beta_s \times 1_{FGTS} \times 1_{month\,s} + \sum_{s=0}^{17} \beta_{g_1,s} \times 1_{g_1} \times 1_{FGTS} \times 1_{month\,s} + ... \\ + \sum_{s=0}^{17} \beta_{g_{(N-1)},s} \times 1_{g_{(N-1)}} \times 1_{FGTS} \times 1_{month\,s} + \alpha_i + \delta_t + \epsilon_{i,t} \end{aligned} \tag{8}$$

Equation (8) has an analogous interpretation to equation (6) and estimate the heterogeneity in debt default and past due debt. Unlike equation (7), interpretation of $\beta_{g_{(N-1)},s}$ refers to the monthly average responses of the $(N-1)$ group in percentage terms of the dependent variable by a treated worker (compared to the benchmark period) relative to the monthly response of the control group (with the second group being absorbed). $Y_{i,t}$ is either total debt default or past due debt.[36]

Figure 6 illustrates the comparison across these two groups of workers in Panel A and Panel B in responses on total debt default and past due debt following equation (8). The responses heterogeneity is striking and in accordance with total debt responses across the two groups of workers. That is, while credit 'unconstrained' workers leveraged themselves by rising total debt and also by increasing financial fragility following the FGTS' shock, 'constrained' workers benefited from this shock to deleverage and decline financial fragility. Panel A shows that low debt-to-limit workers start to increase default and past due debt from around month 3, when the withdrawals release started, and it remains increasing continuously until month 17, when it reaches a 0.48 percent rise (t-statistic=6.07) in total debt default and a 0.74 percent increase (t-statistic=7.24) in total past due debt, respectively. On the other hand, in Panel B we note that high debt-to-limit workers use the FGTS' shock to decrease financial fragility through debt slowly from around month 3 and then both total debt default and past due debt plateaued from month 13 at approximately -12 percent and -20 percent, respectively, although it is not statistically significant at 95 percent confidence interval. As we mentioned previously, we do not report heterogeneity across workers on credit card spending volatility dynamics by construction. However, Table A.12 in the Appendix shows that spending volatility rises across all workers, in special among high debt-to-limit workers.

[36] We include in (8) the same set of dummy variables defining nine different categories of credit scores in the year before program announcement as the ones included in equations (2), (4) and (6).

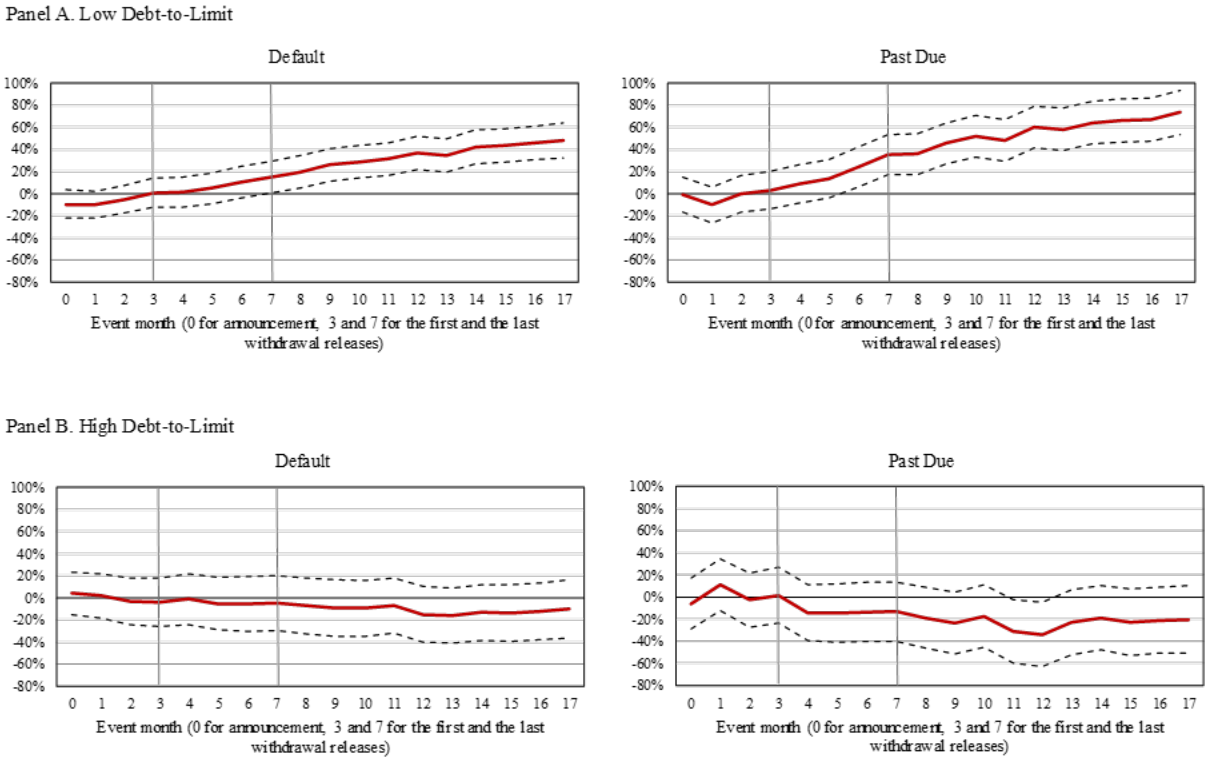

Figure 6: Heterogeneity in Default and Past Due Debt Responses Across Workers

Notes: This figure plots the entire paths of total debt default and past due debt responses - coefficients β_s, $s = -3, -2, -1, \ldots, 16, 17$ along with their corresponding 95 percent confidence intervals, as estimated from equation (7). The sample includes the matched treatment and control groups during the period of 2016:12-2018:05. For each comparison panel, column 1 shows the total debit default response and column 2 shows total past due debt response. Panel A compares consumers with low debt-to-limit (i.e., average debt-to-limit between 2016:01 and 2016:11 ≤ 0.21, or twenty-fifth of sample). Panel B compares consumers with high debt-to-limit (i.e., average debt-to-limit between 2016:01 and 2016:11 ≥ 9.35, or seventy-fifth of the sample). The x-axis denotes the sth month after the announcement of the FGTS Program, and the y-axis shows the cash response (for every cash received).

B. Heterogeneity of Debt Response and Financial Fragility by Debt Category

Heterogeneity in the type of spending response to positive income shocks is documented by extant literature (e.g., Parker et al,. 2013; Agarwal and Qian, 2014). However, little is know about consumer debt response heterogeneity. In our data, detailed information of debt categories is provided by the SCR database. We group them into two groups of debt: revolving and non-revolving. The former is comprised by (overdue) credit card debt and overdraft, while the latter contains real estate, vehicles, payroll, installments, personal, other goods, and others (remaining categories).[37]

Figure 7 results follow equation (5) so that $Y_{i,t}$ is either revolving debt, non-revolving debt or non-revolving debt excluding real estate (mortgages) and vehicles debt categories. Overall, it suggests that first, total debt response follows non-revolving debt response by visually comparing the graph in the right hand side with graphs on total debt in Figure 3. Second, revolving debt response is temporary. It starts to fall from the period workers get access to inactive accounts funds, by month 3, and reaches a low just after the month the withdrawal releases finishes, by month 8, at -\$0.12 rise per \$1 withdrawn (t-statistic=-2.82), before it increases rapidly towards zero. Third, by excluding real estate and vehicles debt categories from non-revolving

[37]See Appendix A.11 for definitions of debt categories.

debt (graph in the second row in the left hand side), non-revolving debt response is similar to the revolving debt response. Thus, it shows that the delayed increase in total debt arises from debt categories associated to big-ticket durable consumption goods, which is consistent with the wealth part of the FGTS' shock, as we will show in the next section.

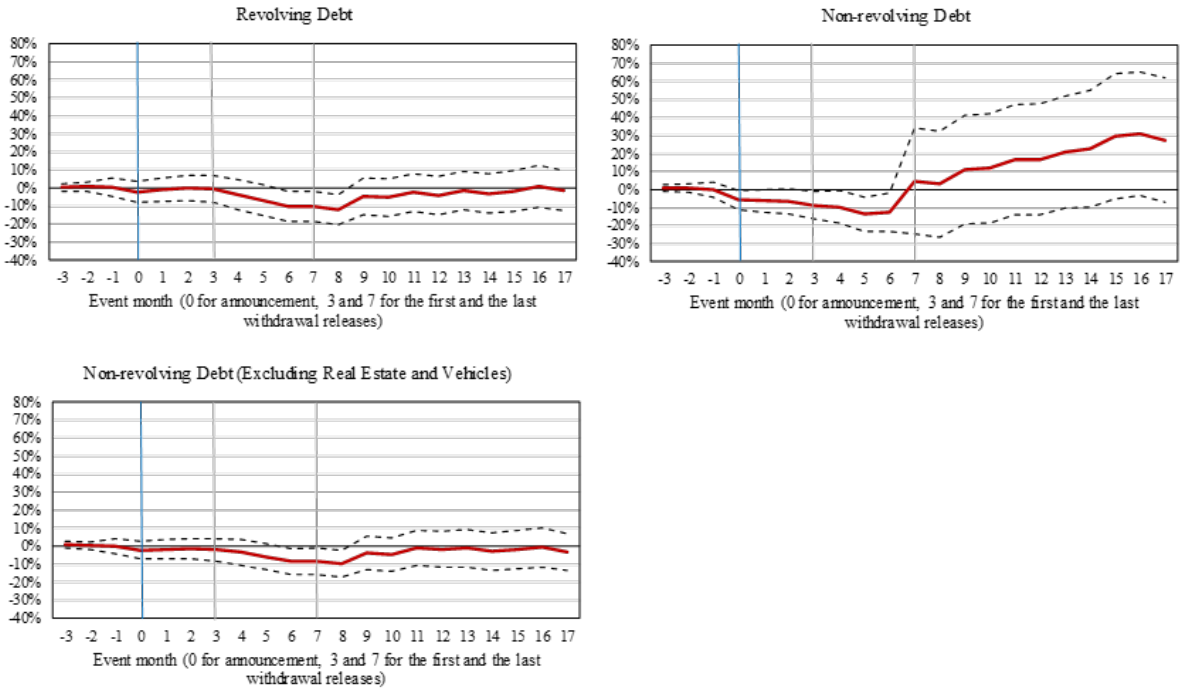

Figure 7: Estimated Revolving and Non-revolving Response Dynamics

Notes: This figure plots the entire paths of total revolving and non-revolving debt responses in the first row and in the second row total non-revolving debt excluding real estate and vehicles debt categories - coefficients β_s, $s = -3, -2, -1, \ldots, 16, 17$, along with their corresponding 95 percent confidence intervals, as estimated from equation (5). The sample includes the matched treatment and control groups during the period of 2016:09-2018:05. The x-axis denotes the sth month after the announcement of the FGTS Program, and the y-axis shows the cash response (for every cash received).

Table 4 shows the average responses across all debt categories on stock levels (Panel A), default (Panel B) and past due debt (Panel C) and across low debt-to-limit ($g_1 \equiv i \leq 25th$ - below the twenty-fifth percentile of the distribution in the cross section of workers prior to the program announcement) and high debt-to-limit ($g_2 \equiv i \geq 75th$ - above the seventy-fifth percentile of the distribution in the cross section of workers prior to the program announcement) workers.[38] Overall, it is noticeable that heterogeneity responses on total debt stocks, default and past due debt across low debt-to-limit and high debt-to-limit workers applies on revolving debt and non-revolving debt categories. That is, low debt-to-limit workers tend to increase debt, default and past due debt, whereas high debt-to-limit workers reduce it. Moreover, responses are more precisely estimated on revolving debt categories, since transactions are more frequent.

Results in Panel A show that low debt-to-limit workers increase both non-revolving and

[38] Panel A results follow an extension of equation (2) that includes heterogeneity so that $Y_{i,t}$ can be either total debt or any of the debt categories:
$Y_{i,t} = \beta_{post} \times \$W_i \times 1_{post} + \beta_{g_1} \times 1_{g1} \times \$W_i \times 1_{post} + ... + \beta_{g_{(N-1)}} \times 1_{g_{(N-1)}} \times \$W_i \times 1_{post} + \alpha_i + \delta_t + \epsilon_{i,t}$. Similarly, Panels B and C results follow an extension of equation (3):
$Y_{i,t} = \beta_{post} \times 1_{FGTS} \times 1_{post} + \beta_{g_1} \times 1_{g1} \times 1_{FGTS} \times 1_{post} + ... + \beta_{g_{(N-1)}} \times 1_{g_{(N-1)}} \times 1_{FGTS} \times 1_{post} + \sum_{k=1}^{K-1} \beta_{k,post} \times 1_{FGTS} \times 1_{post} \times 1_{Score\,k,2016} + \alpha_i + \delta_t + \epsilon_{i,t}$. Since we have presented no pretreatment effect in previous equations, we absorb the pretreatment variables to facilitate interpretation and increase power.

revolving types of debt, in which (overdue) credit card debt stands out.[39] Regarding non-revolving types of debt, real estate and vehicles debts account for the largest rise among low debt-to-income workers, although the low frequency of these transactions makes the estimate less precise. Therefore, unconstrained workers took benefit from the FGTS' shock to increase debt related to big-ticket durable consumption, but also to rise revolving debt. In contrast, high debt-to-income workers overall decreased debt categories to open room in terms of their ability to access the credit market to smooth consumption.

		Debt Categories										
	Total	Revolving Debt			Non-Revolving Debt							
dependent variable:		Credit Card	Overdraft	Total	Real Estate	Vehicles	Payroll	Installments	Personal	Other Goods	Others	Total
Panel A. Stock level												
$W \times 1_{i \leq 25th} \times 1_{post}$	0.29	0.02***	0.01***	0.03***	0.17	0.04	0.04	-0.00	0.00	-0.00	0.02	0.26
	(1.47)	(5.20)	(3.01)	(5.27)	(0.88)	(1.36)	(1.01)	(-0.23)	(0.55)	(-0.14)	(1.42)	(1.30)
$W \times 1_{i \geq 75th} \times 1_{post}$	-0.50***	-0.09***	-0.03**	-0.12***	-0.10	-0.03	0.06	0.00	-0.00	-0.02*	-0.29***	-0.38**
	(-2.64)	(-2.72)	(-2.34)	(-2.78)	(-1.20)	(-0.95)	(1.30)	(1.07)	(-0.95)	(-1.86)	(-2.77)	(-2.33)
Constant	8,335***	653.73***	337.91***	991.64***	1,330***	827***	2,733***	302***	3.03***	111***	2,037***	7,343***
	(96.52)	(89.58)	(76.41)	(98.76)	(17.94)	(57.87)	(129)	(67.83)	(20.95)	(16.26)	(75.75)	(87.44)
Adjusted R^2	0.63	0.51	0.50	0.52	0.55	0.46	0.87	0.49	0.32	0.66	0.72	0.63
Panel B. Default												
$1_{FGTS} \times 1_{i \leq 25th} \times 1_{post}$	0.18***	0.13***	0.01	0.14***	-0.00	-0.00**	-0.01	-0.02***	0.00	0.04***	0.09*	0.09*
	(2.98)	(3.17)	(0.91)	(3.36)	(-1.00)	(-3.30)	(-1.05)	(-6.62)	(0.36)	(4.39)	(1.94)	(1.89)
$1_{FGTS} \times 1_{i \geq 75th} \times 1_{post}$	-0.22**	-0.20**	-0.13***	-0.25**	-0.00	-0.00*	0.08***	-0.00	-0.02	0.02	-0.07	0.00
	(-1.97)	(-2.19)	(-3.25)	(-2.62)	(-1.00)	(-1.66)	(3.33)	(-0.80)	(-1.56)	(0.70)	(-0.89)	(0.02)
Constant	1.46***	-0.94***	-1.00***	-0.88***	0.00***	0.01***	2.53***	0.03***	0.01***	0.07***	0.55***	3.14***
	(5.82)	(-7.24)	(-13.80)	(-6.69)	(3.18)	(3.24)	(9.19)	(4.98)	(4.46)	(8.40)	(21.54)	(11.30)
Controls							Initial credit score					
Adjusted R^2	0.40	0.36	0.35	0.37	0.50	0.22	0.37	0.23	0.33	0.32	0.38	0.39
Panel C. Past Due												
$1_{FGTS} \times 1_{i \leq 25th} \times 1_{post}$	0.33***	0.28***	0.04**	0.30***	-0.00***	-0.02***	-0.01	-0.03***	-0.00	0.06***	0.14**	0.14**
	(4.31)	(4.98)	(2.32)	(5.22)	(-2.65)	(-6.01)	(-0.64)	(-8.05)	(-0.47)	(5.95)	(2.53)	(2.37)
$1_{FGTS} \times 1_{i \geq 75th} \times 1_{post}$	-0.38***	-0.31***	-0.15***	-0.35***	-0.00	-0.01***	0.09***	-0.00	-0.03**	-0.01	-0.06	-0.03
	(-2.86)	(-2.89)	(-3.15)	(-3.20)	(-0.19)	(-1.75)	(2.70)	(-0.47)	(-2.33)	(-0.30)	(-0.70)	(-0.32)
Constant	1.97***	-0.47***	-0.88***	-0.38***	0.00	0.03***	1.08***	0.04***	0.03***	0.07***	0.84***	1.99***
	(8.01)	(-3.48)	(-11.89)	(-2.79)	(1.53)	(4.15)	(4.34)	(6.00)	(7.43)	(5.17)	(25.89)	(7.82)
Controls							Initial credit score					
Adjusted R^2	0.45	0.39	0.38	0.40	0.26	0.28	0.48	0.26	0.33	0.39	0.44	0.45
Fixed Effects							Individual, Year-month					

Table 4: Heterogeneity in Debt Stocks, Default and Past Due Responses Across Debt Categories

Notes: This table shows the average responses across all debt categories on stock levels (Panel A), default (Panel B) and past due debt (Panel C) and across low debt-to-limit ($g_1 \equiv i \leq 25th$ - below the twenty-fifth percentile of the distribution in the cross section of workers prior to the program announcement) and high debt-to-limit ($g_4 \equiv i \geq 75th$ - above the seventy-fifth percentile of the distribution in the cross section of workers prior to the program announcement) workers in the period from 2016:08 to 2018:05 using the matched sample. Panel A presents the estimation results of an extension equation (1), and panel B shows the estimation results of an extension of equation (3) to include heterogeneity across quartiles of debt-to-limit. See footnote 37. Observations are the same from Tables 2 and 3. Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. t-statistics are reported in parentheses under the coefficient estimates. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Results show a similar pattern in Panels B and C relative to results in Panel A. That is, unconstrained workers increased financial fragility by rising both default and past due debt in most debt categories, while constrained workers tend to decrease default and past due debt. Interestingly, it is noticeable that constrained workers switched from the most expensive revolving

[39] As we mentioned, (overdue) credit card debt is the most expensive type of debt.

debt categories (a fall in debt stock, default and past due debt) to the cheapest non-revolving category - payroll debt, by increasing debt stocks and financial fragility through increased default and past due debt in this debt category. It seems to be a rational response and reinforces the idea that high debt-to-limit workers serve as a reliable proxy for constrained consumers, as it aligns with their efforts to alleviate credit limitations.

V. Decomposing the shock of the FGTS Program: Liquidity and Wealth Components

The FGTS shock would merely represent a liquidity shock, without its wealth part, as the Brazilian government unexpectedly released funds from previously illiquid assets—inactive FGTS accounts. However, since the yield on this asset has consistently been lower than the SELIC rate, the base interest rate set by the Central Bank of Brazil, the shock also reflects a wealth component tied to the difference between the SELIC rate and the returns on inactive accounts. Thus, we benefit from the distinct nature of this liquidity shock and the typical restrictions on accessing assets from inactive FGTS accounts to disentangle the liquidity component of the shock from the wealth component.

As mentioned in Section II, withdrawals from FGTS' inactive accounts are permitted in restricted situations. We claim that the criteria to access an inactive account's funds are not in genera a workers' choice. It can be summarized as follows: i. dismissal without just cause; ii. termination of a fixed-term contract; iii. retirement; iv. death; v. permanence outside the FGTS regime for three years in a row; vi. purchase of a property, liquidation, amortization or mortgage payment; vii. serious illness; viii. company extinction, ix. termination of contract by mutual fault or force majeure, x. personal need in case of emergency or serious reasons linked to natural disaster and xi. suspension of casual job. The only criterion that represents a choice is vi. For this reason we excluded workers who had real estate debt before the program in our analysis. By doing so, the remaining criteria are either beyond the workers' control or pertain to deterministic, long-term factors, as death and retirement. It then implies that owners of inactive accounts in this case do not take this asset into their information set to make consumption and debt short-run decisions.

We define the underlying wealth component of the FGTS shock using the minimum retirement age of 65 as a proxy for the primary long-term criterion workers consider in their consumption and debt decisions. Based on this, the wealth component of the shock is the present value calculated by the interest rate differential between the SELIC rate and the yield on inactive account funds, as stated in equation (9). By construction, the liquidity component of the shock is the difference between the total size of the shock and its wealth component, as defined by equation (10). Note that r_i^b denotes long-term real interest curves for fixed-rate bonds.[40] This rate is indexed for each worker i by following the time left to each worker to retire. That is, the time difference between their age at retirement, T, and their age at the end of the month when they were allowed to do withdrawals - any month from March to July 2017, t_i. r^f is the yield on inactive account funds. Using these rates ensures that the long-term interest rate (r_i^b) reflects current market expectations for the risk-free rate over each worker's remaining horizon until retirement. This allows for a realistic and forward-looking present value calculation when splitting the FGTS shock into wealth (future returns foregone) and liquidity (immediate cash) components. To calculate the wealth and liquidity components of the FGTS shock, we define the yield on inactive account funds as the average real return over the 2002–2016 period. This choice is motivated by the stability and policy-determined nature of the FGTS yield formula, which combines the TR benchmark rate with a fixed 3 percent annual premium. Given

[40]We apply the ANBIMA (the Brazilian Financial and Capital Markets Association) long-term interest rate curves - ETTJ (*text*"Estrutura a Termo da Taxa de Juros" - in portuguese).

the highly persistent and regulated nature of this return, and the fact that only two years in our sample exhibited positive real returns, using the historical average provides a realistic and policy-consistent estimate of the opportunity cost of holding funds in FGTS accounts. Over the 15-year period, the average real return was -2.0 percent with a standard deviation of 2.2 percentage points, suggesting a persistent and predictably low return profile that justifies using a long-term average for modeling forward-looking consumer behavior.

$$\$W_{i,wealth} = \{\$W_i[(1+r_i^b)^{(T-t_i)} - (1+r^f)^{(T-t_i)}]\}/[(1+r_i^b)^{(T-t_i)}] \tag{9}$$

$$\$W_{i,liquidity} = [\$W_i(1+r^f)^{(T-t_i)}]/[(1+r_i^b)^{(T-t_i)}] \equiv \$W_i - \$W_{i,wealth} \tag{10}$$

Figure 8 exhibits the distribution of the liquidity and wealth components of the FGTS shock, along with the treated workers, over time (years) leading up to retirement. By design, the FGTS shock equals its liquidity component at retirement (0 years remaining until 65). As we move further from retirement, the wealth component of the FGTS shock becomes increasingly dominant. This is because younger workers have more time for compound interest differentials (between FGTS and market rates) to accumulate, increasing the present value loss from early withdrawal—i.e., a larger wealth effect. The largest group of treated workers is concentrated around 30 to 35 years from retirement, which coincides with peak earning years. At this stage, both the FGTS balances and the time horizon are high, pushing the wealth component to its peak. However, for the youngest workers, despite their long time to retirement, the size of their FGTS balances is typically low, which limits the total shock value and explains the decline in the wealth component at the far right of the figure.

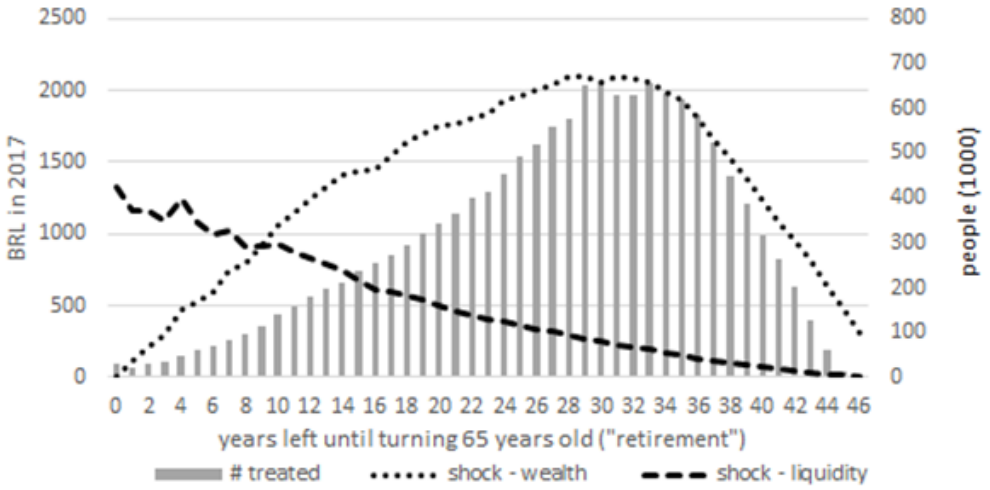

Figure 8: Distribution of the Liquidity and Wealth Components of the FGTS Shock and Treated Workers Across Years up to Retirement

Notes: This figure plots the distribution of the FGTS shock components and the number of treated workers by years remaining until age 65 (retirement threshold). The vertical bars represent the number of treated workers (in thousands, right y-axis) for each year-to-retirement group. The dotted line shows the average wealth component of the FGTS shock in BRL (left y-axis), and the dashed line shows the average liquidity component of the shock in BRL (also left y-axis). See definitions of the liquidity and wealth parts of the shock in equations (9) and (10). The x-axis indicates the number of years remaining until retirement.

A visual inspection of Figure 8 suggests that the wealth component makes up the majority of the shock, representing around 80 percent of its total size on average. Notably, the relative

size of the shock's components does not vary significantly across income, debt-to-limit ratios, or other demographic characteristics, apart from age by definition[41].

Table 5 presents the debt and credit card spending responses to the liquidity and wealth components of the FGTS shock. While the responses out of the liquidity component are larger, the debt and spending responses are overall more strongly driven by the wealth component, since it makes up approximately 4/5 of the total shock.

Panel A exhibits the response estimates following equation (11), which is similar to equation (1), but separates the withdrawal ($\$W$) into its liquidity ($\$W_{liquidity}$) and wealth ($\$W_{wealth}$) components. First, we note a substantial deleveraging effect out of the liquidity shock on total debt (-$0.61 per $1 from the liquidity component of the FGTS' shock on average after the program announcement - t-statistic=-2.63), mostly stemming from non-revolving debt, and credit card spending (-$0.10 per $1 from the liquidity component of the FGTS' shock on monthly average after the program announcement - t-statistic=-2.20).

$$\begin{aligned} Y_{i,t} =& \beta_{liquidity,post} \times \$W_{liquidity,i} \times 1_{post} + \beta_{wealth,post} \times \$W_{wealth,i} \times 1_{post} \\ &+ \alpha_i + \delta_t + \epsilon_{i,t} \end{aligned} \tag{11}$$

The rationale behind workers' responses to the shock, which in turn provides an assessment of the reliability of the measurement of its wealth and liquidity components, can be evaluated through the following thought experiment: how would workers have responded if they had experienced a pure liquidity shock? According to existing literature, when faced with costly debt, where interest rates for borrowing are sufficiently higher than bond rates, the optimal strategy would be to enhance access to the credit market by paying off expensive debt. This would help smooth consumption while reducing their reliance on credit cards for liquidity, thereby likely increasing cash-based spending.

And how would workers have responded if they had experienced a pure wealth shock? While it is optimal to increase credit card spending (an average of $0.04 per $1 from the wealth component of the FGTS shock after the program announcement, t-statistic = 2.48), as a proxy for consumption, from a sudden increase in net worth, the bulk of debt rise is accounted by non-revolving debt ($0.22 on average per $1 from the wealth component of the FGTS shock, t-statistic = 1.41). Unlike a liquidity shock, where debt repayment is prioritized, a wealth shock is less likely to trigger immediate debt reduction. The reasoning is that consumers may prefer to maintain or increase their debt levels, given the improved ability to repay over time due to the increase in net wealth. Non-revolving debt (such as mortgages or auto loans) might rise as consumers take on more debt for investments or large purchases, leveraging their increased wealth.

Results in Panel C, based on equation (13), reinforce the findings from Panel A by demonstrating that the majority of the debt and spending responses to the liquidity and wealth components of the shock take place after the withdrawal releases.

$$\begin{aligned} Y_{i,t} =& \beta_{liquidity,post} \times \$W_{liquidity,i} \times 1_{post} + \beta_{liquidity,g_1,post} \times 1_{g_1} \times \$W_{liquidity,i} \times 1_{post} + ... \\ &+ \beta_{liquidity,g_{(N-1)},post} \times 1_{g_{(N-1)}} \times \$W_{liquidity,i} \times 1_{post} \\ &+ \beta_{wealth,post} \times \$W_{wealth,i} \times 1_{post} + \beta_{wealth,g_1,post} \times 1_{g_1} \times \$W_{wealth,i} \times 1_{post} + ... \\ &+ \beta_{wealth,g_{(N-1)},post} \times 1_{g_{(N-1)}} \times \$W_{wealth,i} \times 1_{post} + \alpha_i + \delta_t + \epsilon_{i,t} \end{aligned} \tag{12}$$

$$\begin{aligned} Y_{i,t} =& \beta_{liquidity,announce} \times \$W_{liquidity,i} \times 1_{announce} + \beta_{liquidity,post} \times \$W_{liquidity,i} \times 1_{post} \\ &+ \beta_{wealth,announce} \times \$W_{wealth,i} \times 1_{announce} + \beta_{wealth,post} \times \$W_{wealth,i} \times 1_{post} \\ &+ \alpha_i + \delta_t + \epsilon_{i,t} \end{aligned} \tag{13}$$

[41] See Appendix A.9 for descriptive statistics considering the wealth and liquidity components of the shock across workers

Panel B is based on equation (12). We report results applied to low debt-to-limit, our proxy for unconstrained workers ($g_1 \equiv i \leq 25th$ - below the twenty-fifth percentile of the distribution in the cross section of workers prior to the Program announcement) to contrast with high debt-to-limit, or constrained workers ($g_2 \equiv i \geq 75th$ - above the seventy-fifth percentile of the distribution in the cross section of workers prior to the Program announcement).

First, unconstrained workers used the liquidity shock to deleverage, reducing both expensive debt and credit card spending as a financially optimal choice. The decline in reliance on credit cards for liquidity, as suggested by the aggregate data in Panel A, is driven by unconstrained workers (-\$0.10 per \$1 from the liquidity component of the FGTS' shock on monthly average after the program announcement - t-statistic=-1.17). On average, total debt decreased by \$0.82 per \$1 from the liquidity component of the FGTS shock (t-statistic = -2.14), particularly in non-revolving debt, as this represents the largest share of their debt. In contrast, constrained workers did not significantly use the liquidity resources to reduce debt or credit card spending. This is consistent with the fact that the increase in liquidity from the shock did not substantially improve their ability to smooth consumption through debt or credit cards, which may also explain a temporary increase in cash-based spending.

Second, the majority of the aggregate positive spending response from the wealth component is driven by unconstrained workers, who increased spending by \$0.05 per \$1 from the wealth component of the FGTS shock on monthly average after the program announcement (t-statistic=1.83). The lack of statistical significance in the aggregate debt responses from the wealth component in Panel A is due to contrasting behaviors between constrained and unconstrained workers. Unconstrained workers significantly increased their total debt by \$0.55 per \$1 from the wealth component (t-statistic = 1.79), particularly non-revolving debt, which is often linked to large durable goods purchases like homes and cars. Interestingly, they also increased revolving (high-interest) debt in response to the wealth component, which, rather than representing an optimal debt strategy, appears to indicate a rise in financial fragility. In contrast, constrained workers used the wealth shock primarily to reduce expensive total debt, with a reduction of \$0.66 on average per \$1 from the wealth component (t-statistic = -2.23). Since constrained workers have limited access to credit, reducing their debt burden frees up future resources and improves their ability to smooth consumption.

Table 6 shows that the wealth component of the shock contributes to both an increase in credit card spending volatility and a reduction in defaults and past due debt, particularly among constrained workers.[42] Notably, the wealth component also drives increased financial fragility among unconstrained workers. In contrast, the liquidity component of the shock helps mitigate financial fragility across all workers.

[42]Panels A, B and C follows similar equations to equations (11),(12) and (13), respectively, so as $Y_{i,t}$ is either total debt default, past due debt or credit card spending volatility. It also includes the same controls applied in previous equations associated to each of these dependent variables.

dependent variable:	Debt			Credit Card Spending
	Total	Revolving Debt	Non-revolving Debt	
Panel A				
$\$W_{liquidity} \times 1_{post}$	-0.61***	-0.03	-0.58***	-0.10**
	(-2.63)	(-0.78)	(-2.61)	(-2.20)
$\$W_{wealth} \times 1_{post}$	0.22	0.00	0.22	0.04**
	(1.38)	(0.03)	(1.41)	(2.48)
Constant	8,340***	986***	7,354***	2,156***
	(85.82)	(106)	(77.14)	(234)
Adjusted R^2	0.63	0.53	0.63	0.71
Panel B				
$\$W_{liquidity} \times 1_{i\leq 25th} \times 1_{post}$	-0.82**	-0.04*	-0.78**	-0.10
	(-2.14)	(-1.78)	(-2.05)	(-1.17)
$\$W_{wealth} \times 1_{i\leq 25th} \times 1_{post}$	0.55*	0.05***	0.50*	0.05*
	(1.79)	(5.67)	(1.64)	(1.83)
$\$W_{liquidity} \times 1_{i\geq 75th} \times 1_{post}$	0.28	0.16	0.12	0.02
	(0.45)	(1.13)	(0.22)	(0.25)
$\$W_{wealth} \times 1_{i\geq 75th} \times 1_{post}$	-0.66**	-0.18**	-0.48**	0.02
	(-2.23)	(-2.42)	(1.97)	(0.71)
Constant	8,324***	992***	7,332***	2,154***
	(93.54)	(99.40)	(84.49)	(251)
Adjusted R^2	0.63	0.52	0.63	0.71
Panel C				
$\$W_{liquidity} \times 1_{announce}$	0.05	-0.01	0.06	-0.03
	(0.36)	(-0.44)	(-0.52)	(-0.75)
$\$W_{wealth} \times 1_{announce}$	-0.11	0.02	-0.12**	-0.00
	(-1.58)	(0.94)	(-2.17)	(-0.04)
$\$W_{liquidity} \times 1_{withdrawn}$	-0.87***	-0.03	-0.84***	-0.13**
	(-2.82)	(-0.77)	(-2.80)	(2.32)
$\$W_{wealth} \times 1_{withdrawn}$	0.34	-0.01	0.35*	0.05***
	(-1.59)	(-0.37)	(-1.64)	(2.89)
Constant	8,340***	986***	7,354***	2,156***
	(85.50)	(106)	(76.83)	(234)
Adjusted R^2	0.63	0.53	0.63	0.71
Fixed Effects	Individual, Month-Year			

Table 5: Estimated Average Debt and Credit Card Spending Responses to Liquidity and Wealth Components of the FGTS' Shock

Notes: This table shows the average responses across total debt, revolving debt, non-revolving debt and credit card spending out of the liquidity and wealth parts of the FGTS shock following definitions in (9) and (10) in the period from 2016:08 to 2018:05 using the matched sample. Panel A shows estimates of the liquidity and wealth responses after the announcement of the program according to equation (11). Panel B presents estimations across low debt-to-limit ($g_1 \equiv i \leq 25th$ - below the twenty-fifth percentile of the distribution in the cross section of workers prior to the program announcement) and high debt-to-limit ($g_4 \equiv i \geq 75th$ - above the seventy-fifth percentile of the distribution in the cross section of workers prior to the program announcement) workers following equation (12). Panel C presents the estimation results from equation (13), which splits the post program period into the announcement and withdrawal periods. Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. t-statistics are reported in parentheses under the coefficient estimates. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

dependent variable:	Total Debt		Credit Card Spending Volatilty
	Default	Past Due	
Panel A			
$\$W_{liquidity} \times 1_{post}$	0.00002 (0.75)	0.00004 (1.37)	-0.00004 (-0.39)
$\$W_{wealth} \times 1_{post}$	-0.000004 (-0.37)	-0.000009 (-0.62)	0.00001*** (4.97)
Constant	1.05*** (161)	1.67*** (235)	0.50*** (4.46)
Adjusted R^2	0.40	0.45	0.71
Panel B			
$\$W_{liquidity} \times 1_{i \leq 25th} \times 1_{post}$	-0.00002** (-1.99)	-0.00002* (-1.84)	-0.00002 (-1.40)
$\$W_{wealth} \times 1_{i \leq 25th} \times 1_{post}$	-0.00002*** (-3.32)	-0.000009 (-1.19)	-0.000001 (-0.34)
$\$W_{liquidity} \times 1_{i \geq 75th} \times 1_{post}$	0.00002 (0.13)	0.00006 (0.45)	-0.00001 (-0.21)
$\$W_{wealth} \times 1_{i \geq 75th} \times 1_{post}$	-0.0001*** (-2.62)	-0.0001*** (-3.33)	0.0001*** (3.61)
Constant	0.96*** (13.38)	1.58*** (20.93)	0.53*** (24.65)
Adjusted R^2	0.40	0.45	0.71
Panel C			
$\$W_{liquidity} \times 1_{announce}$	0.00001 (0.47)	0.00004 (1.28)	0.000006 (0.47)
$\$W_{wealth} \times 1_{announce}$	-0.000009 (-0.73)	-0.00001 (-0.86)	0.00001*** (4.31)
$\$W_{liquidity} \times 1_{withdrawn}$	0.00002 (0.78)	0.00004 (1.21)	-0.000009 (-0.83)
$\$W_{wealth} \times 1_{withdrawn}$	-0.000002 (-0.19)	-0.000008 (-0.48)	0.00001*** (4.92)
Constant	1.05*** (161)	1.67*** (235)	0.50*** (4.51)
Adjusted R^2	0.40	0.45	0.71
Controls	Initial credit score	Initial credit score	Initial volatility, Initial level
Fixed Effects	Individual, Month-Year		

Table 6: Estimated Average Default Debt, Past Due Debt and Credit Card Volatility Responses to Liquidity and Wealth Components of the FGTS' Shock

Notes: This table shows the average responses across total debt default, total past due debt, credit card spending volatility out of the liquidity and wealth parts of the FGTS shock following definitions in (9) and (10) in the period from 2016:08 to 2018:05 using the matched sample. Panel A shows estimates of the liquidity and wealth responses after the announcement of the program according to equation (11). Panel B presents estimations across low debt-to-limit ($g_1 \equiv i \leq 25th$ - below the twenty-fifth percentile of the distribution in the cross section of workers prior to the program announcement) and high debt-to-limit ($g_4 \equiv i \geq 75th$ - above the seventy-fifth percentile of the distribution in the cross section of workers prior to the program announcement) workers following equation (12). Panel C presents the estimation results from equation (13), which splits the post program period into the announcement and withdrawal periods. Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. t-statistics are reported in parentheses under the coefficient estimates. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

In summary, the debt and spending responses to the FGTS shock display distinct patterns across its liquidity and wealth components. The liquidity shock prompted strong deleveraging, especially among unconstrained workers, who reduced both total debt and credit card use. Constrained workers, however, did not significantly cut debt, suggesting the liquidity infusion did not meaningfully enhance their consumption smoothing. The wealth component—accounting for a larger share of the shock—primarily drove spending increases among unconstrained workers, particularly on durables via non-revolving credit, while constrained workers used it to reduce costly debt, improving financial resilience. Regarding financial fragility, the wealth component raised credit card spending volatility and financial vulnerability, especially among unconstrained workers who accumulated revolving debt. In contrast, constrained workers saw declines in defaults and past due debt, likely due to deleveraging. The liquidity component reduced fragility across all groups, underscoring its stabilizing role. Overall, the findings show that liquidity shocks foster deleveraging and caution, while wealth shocks trigger more complex responses, potentially increasing risk among unconstrained workers.

VI. Interpreting the Results Through the Lens of HANK Models

Our empirical findings lend themselves to interpretation through the lens of modern macroeconomic theory, particularly Heterogeneous Agent New Keynesian (HANK) models. These models have reshaped our understanding of consumption and policy transmission by incorporating individual-level frictions such as liquidity constraints, borrowing limits, and heterogeneous income and wealth profiles. A central feature of HANK frameworks is that the effects of fiscal or monetary policy depend critically on the distribution of resources across households and on whether those resources are perceived as liquid or as changes in net wealth.

Our data show that credit-constrained consumers - typically lower-income, more indebted individuals - used the FGTS shock predominantly to reduce debt and avoid default. This behavior is consistent with high marginal propensities to consume out of liquidity, as predicted by HANK models. It aligns with the notion of "wealthy hand-to-mouth" (Kaplan et al., 2014) consumers who, even when they hold some illiquid wealth, exhibit strong responses to liquidity shocks but are limited in their ability to respond to changes in long-term wealth.

In contrast, unconstrained workers, who had greater access to credit and more stable income, responded differently: they increased spending and accumulated new debt, particularly in the form of non-revolving credit. The wealth component of the FGTS shock appears to have relaxed perceived credit constraints among these individuals, encouraging more consumption and, consequently, greater financial fragility. These patterns support model extensions that include endogenous borrowing constraints and wealth-based borrowing behavior, as in Guerrieri and Lorenzoni (2017), where perceived increases in net worth trigger risk-taking and future vulnerability.

An important contribution of our study is the clear empirical separation of liquidity and wealth channels, which is often challenging in applied settings. This separation directly relates to theoretical efforts in HANK models to disentangle how different types of transfers - temporary vs. permanent, liquid vs. illiquid - affect consumption dynamics and aggregate demand. Our findings show that the liquidity shock had stabilizing effects across the board, prompting deleveraging and reducing default risk. The wealth shock, by contrast, amplified financial risk and credit-financed consumption, especially among unconstrained consumers, while it induced debt deleveraging by constrained consumers. These asymmetric responses validate the emphasis in HANK models on the composition of household balance sheets and the role of liquidity in determining policy effectiveness.

To illustrate this interpretation, we develop a simple two-period consumption model with endogenous constraints under FGTS shocks and disaggregated cash and credit card consumption in line with the consumption model in Kaplan et al. (2014) (in the Appendix). The model illus-

trates how unconstrained agents, governed by intertemporal Euler equations, shift allocations in response to liquidity and wealth shocks, while constrained agents adjust primarily through credit behavior. By additionally imposing a low discount factor (present bias) to a benchmark model and assuming a high borrowing rate relative to asset returns ($r_b \gg r_a$), it replicates our main empirical findings: liquidity shocks induce deleveraging without increasing current consumption for constrained agents, while wealth shocks raise future consumption and credit use among the unconstrained. This microfounded framework helps rationalize the asymmetric debt and spending dynamics observed in the data and captures the qualitative logic of HANK mechanisms—like high marginal propensities to consume for constrained agents and different responses to liquid vs. wealth shocks.

These insights have broader implications. They suggest that aggregate responses to fiscal or monetary interventions cannot be fully understood without accounting for the type of shock delivered and the heterogeneity of consumers receiving it. For policy design, this underscores the importance of targeting credit-constrained consumers when the objective is to stimulate demand, while also exercising caution around wealth-style transfers that may fuel debt and fragility among less constrained individuals. In this way, our results provide both microeconomic validation of HANK predictions and macroeconomic relevance for designing more effective and equitable stabilization tools.

VII. Robustness

This section provides a set of robustness exercises designed to strengthen the empirical credibility of the main findings. We focus first on testing for potential endogeneity of the FGTS shock components using an instrumental variables approach. Then we test for behavioral validation of the wealth and liquidity measures of the shock using event study by distance to retirement. We also verify the stability of our baseline results to alternative definitions of constrained and unconstrained consumers, heterogeneity analysis beyond constrained vs. unconstrained, and alternative specifications that include additional fixed effects and other standard errors clusters. Finally, we briefly explore possible general equilibrium spillovers.

First, we address potential endogeneity concerns in the construction of the liquidity and wealth components of the FGTS shock by applying a two-stage least squares (2SLS) strategy. Specifically, we use the share of FGTS-eligible workers in the total workforce at the ZIP2 level as an instrument for the wealth component and the same share computed at the ZIP3[43] level as an instrument for the liquidity component. These instruments capture exogenous variation in FGTS exposure stemming from regional labor market composition and are plausibly unrelated to unobserved individual credit or consumption decisions. They reflect pre-existing labor market composition unrelated to individual-level preferences, behaviors, or outcomes, and they shift the magnitude of the shock components through program eligibility rather than through individual characteristics. The wealth component might be endogenous due to reverse causality, where individuals expecting higher future consumption or indebtedness may accumulate FGTS balances strategically. Similarly, the liquidity component could be endogenous if unobserved shocks (e.g., job separations or informal borrowing constraints) simultaneously influence early withdrawal eligibility and financial behavior. Furthermore, measurement errors in the decomposition of the total FGTS shock into liquidity and wealth components may introduce bias. The first-stage F-statistics on the first-stage regressions are large and above conventional thresholds, confirming the strength of the instruments. Second-stage regressions yield estimates that are consistent in sign and significance with the OLS baseline results reported in Panel A of Tables

[43] In Brazil, the postal code (CEP – *Código de Endereçamento Postal - in Portuguese*) is an eight-digit code used to designate geographic locations. We define ZIP2 and ZIP3 regions using the first two and first three digits of the CEP, respectively. ZIP2 divides the country into 91 broader geographic regions, while ZIP3 provides finer granularity with 848 distinct areas.

5 and 6. Moreover, Durbin-Wu-Hausman tests generally fail to reject the null hypothesis of exogeneity of the shock, further supporting our baseline identification strategy - See Tables A.1 and A.2 in the Appendix.

Second, to further validate our decomposition of the FGTS shock into liquidity and wealth components, we estimate event-study regressions by age group, splitting the sample into individuals below 50 years old (farther from retirement) and those 50 years old and above (closer to retirement)[44]. This split approximates the relative size of the wealth versus liquidity components (see Figure 8), given the longer horizon for compounding interest differentials among younger workers. We find that younger individuals initially reduce debt but subsequently increase both total and non-revolving debt. In contrast, older individuals consistently reduce debt, especially non-revolving liabilities, across all months - See Figure A.1 in the Appendix. These dynamics are sharper when isolating the wealth component, as reports Figure A.2 in the Appendix, where younger workers borrow more and older workers deleverage more aggressively. The liquidity component is associated with deleveraging across the board. These findings reinforce the behavioral interpretation of our decomposition: workers' responses vary meaningfully by their distance to retirement and the nature of the shock, supporting the view that the FGTS policy had heterogeneous effects on consumer behavior through distinct liquidity and wealth channels.

In an additional robustness exercise, we replicate our baseline analysis using alternative definitions of financial constraints and consumer heterogeneity. In Table A.3 in the Appendix, we replace the debt-to-limit ratio with debt-to-income (Panel A) and credit scores (Panel B) to rank individuals. In Table A.4 in the Appendix, we apply the same ranking strategies to study credit default, past due debt, and credit card spending volatility. Across all specifications, the key findings hold: constrained individuals reduce debt and exhibit fewer signs of financial fragility after the FGTS wealth shock, while unconstrained individuals increase consumption and leverage.

Further robustness is provided in Table A.5 and A.6 in the Appendix by replacing the debt-to-limit ranking with income (Panel A) and income growth (Panel B), and by restricting the sample to prime-age (from 25 to 54 years old) workers - Tables A.7 and A.8 in the Appendix. The results remain consistent, indicating that neither income levels nor growth prior to the program; or the youngest nor the oldest consumers drive our baseline effects. We also test whether our findings are sensitive to fixed effects and clustering choices. Estimates remain stable when including ZIP3-(month-year) and demographic-time (age groups-(month-year) and income growth quartiles-(month-year)) fixed effects. The ZIP3 $\times$ month-year fixed effects control for time-varying local economic conditions at a fine geographic level, capturing neighborhood-specific shocks and trends. The age groups $\times$ month-year fixed effects account for age-specific macroeconomic shocks and evolving life-cycle patterns, such as retirement, youth employment dynamics, or demographic-specific policy impacts. Lastly, the income growth quartile $\times$ month-year fixed effects capture heterogeneity in how recent macroeconomic changes affect individuals with different income trajectories, controlling for differential exposure to credit conditions, wage volatility, or inflation. We also double cluster standard errors at broader geographic levels (ZIP2 and year-month), which are more conservative than individual-level clustering and because consumption and debt patterns are likely correlated cross-sectionally and over time within nearby locations (see Tables A.9 and A.10 in the Appendix).

Overall, these robustness checks confirm that our results are not driven by a particular specification, omitted variables, spatial correlation, or the specific construction of constraint metrics. They provide additional confidence that our empirical strategy successfully isolates the causal effects of liquidity and wealth shocks from the FGTS policy change.

One last concern in estimating the causal impact of liquidity shocks is the potential for gen-

[44]We also split the sample using different age groups, for example, at 40, 45 and 55 years old and the results are similar.

eral equilibrium effects. To explore it, we estimated whether untreated individuals in areas with higher FGTS withdrawal intensity experienced greater changes in debt or credit card spending. We partition ZIP2 regions into quartiles based on their share of national FGTS withdrawals and interact treatment status with indicators for these quartiles in our regression framework. we expect that the coefficient from the fourth quartile to be closer to zero suggesting the response of untreated tends to be similar to the treated response due to general equilibrium spillovers. Although the coefficients from the fourth quartile are considerably smaller than the ones from first quartile, we mostly failed to reject the null that states the coefficients of the interaction terms representing the first and fourth quartiles are statistically equal (see Table A.11 in the Appendix). This indicates substantial estimation uncertainty and prevents a definitive conclusion about regional general equilibrium effects. Nevertheless, these findings provide suggestive evidence that general equilibrium spillovers, if present, are modest and unlikely to overturn our main consumer-level results.

In our setting, several features limit the relevance of such effects. First, although the FGTS program reached millions of workers, the total injection accounted for 0.7 percent of GDP. Second, implementation was staggered over time and across individuals, enabling identification using within-period variation that is unlikely to induce simultaneous price changes. Third, Brazil's labor market during the relevant period exhibited high unemployment and limited wage flexibility, reducing the potential for wage or employment feedback. Lastly, if the program had any general effect on aggregate credit conditions, this would likely attenuate differences between treated and untreated individuals, biasing our results toward zero. These factors suggest that our estimates are unlikely to be confounded by general equilibrium effects.

VIII. Conclusion

This paper provides new empirical evidence on how consumers adjust consumption and debt in response to a financial windfall from Brazil's 2017 FGTS withdrawal program. Using rich administrative data and quasi-random variation in timing and size, we disentangle the effects of liquidity and wealth shocks—a distinction central to macroeconomic modeling, particularly in Heterogeneous Agent New Keynesian (HANK) frameworks, which emphasize whether resources are perceived as spendable cash or permanent wealth.

Credit-constrained consumers used the windfall primarily to reduce debt, improving short-term financial stability. In contrast, unconstrained consumers expanded credit use — especially non-revolving debt—raising both consumption volatility and default risk. These heterogeneous responses reveal how the nature of a financial shock influences consumers decision-making. Liquidity shocks encourage deleveraging and stabilization, while perceived wealth gains may prompt riskier financial behavior and greater fragility.

Our findings validate key predictions in the household finance and HANK literature, showing that marginal propensities to consume and borrow vary systematically by consumer type and by how the shock is perceived. This underscores the need for macro models to incorporate liquidity constraints, credit access, and wealth heterogeneity when evaluating fiscal interventions.

While the identification is credible, it rests on observational data and cannot fully rule out all indirect channels. The liquidity–wealth decomposition, though carefully constructed, may not perfectly capture how households interpret these dimensions in practice. Moreover, our focus on short-run outcomes leaves open the question of long-term effects.

Future work could enhance policy relevance through formal welfare analysis using consumption-equivalent variation or fragility-adjusted utility, further behavioral tests of the liquidity–wealth distinction (e.g., alternative retirement cutoffs or durable purchases), numerical exercises with calibrated versions of HANK models, and exploration of optimal policy design—such as whether early FGTS withdrawals should be targeted or countercyclical.

In sum, this paper offers a rare empirical test of a core macroeconomic distinction. It

demonstrates how liquidity and wealth channels operate across heterogeneous consumers and delivers important insights for the design of more effective and targeted economic policy.

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Appendix

A.1 - Robustness: Instrumental Variables Approach

To address potential endogeneity in the FGTS shock estimates, we implement a two-stage least squares (2SLS) strategy leveraging exogenous regional variation in FGTS exposure. Specifically, we use the share of FGTS-eligible workers in the local workforce (includes treated and untreated workers) at the ZIP2 level as an instrument for the wealth component — capturing long-term exposure — and at the ZIP3 level for the liquidity component — capturing short-term access to funds. These instruments, based on pre-determined labor market composition, are plausibly exogenous to individual consumption and debt outcomes. First-stage F-statistics confirm instrument strength. The Durbin-Wu-Hausman tests suggest that any bias from endogeneity is limited. The 2SLS estimates mirror our baseline findings: liquidity shocks lead to deleveraging, while wealth shocks increase credit-financed spending and financial fragility.

dependent variable:	Total Debt	Credit card spending
$\$\widehat{W}_{liquidity} \times 1_{post}$	-53.76	-44.00*
	(-0.27)	(-1.76)
$\$\widehat{W}_{wealth} \times 1_{post}$	10.53	8.42*
	(0.28)	(1.76)
Constant	8,994***	2,804***
	(2.83)	(7.53)
Adjusted R^2	0.63	0.71
Fixed Effects	Individual, Month-Year	
F-statistic (1^{st} Stage)		
$\$W_{wealth} \times 1_{post}$	76.17***	76.17***
$\$W_{liquidity} \times 1_{post}$	44.24***	44.24***
Durbin-Wu-Hausman	0.12	1.57

Table A.1: Estimated Average Responses of Debt and Credit Card Spending to Liquidity and Wealth Components of the FGTS Shock: IV Estimates

Notes: This table presents the robustness results from Section VII using two-stage least squares (2SLS) regressions to estimate the causal effects of the FGTS shock. The second-stage estimations follow equation (11) on total debt and credit card spending, where the liquidity and wealth components of the shock are instrumented using their projected values from the first stage. Specifically, the share of FGTS-eligible workers at the ZIP3 level is used to instrument the liquidity component, and the share at the ZIP2 level is used for the wealth component. The analysis is based on the matched sample over the period from 2016:08 to 2018:05. Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. t-statistics are reported in parentheses beneath the coefficient estimates. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

dependent variable:	Total Debt		Credit card spending
	Default	Past Due	Volatility
$\widehat{\$W}_{liquidity} \times 1_{post}$	0.01 (1.09)	0.005 (0.79)	-0.10 (1.16)
$\widehat{\$W}_{wealth} \times 1_{post}$	0.001 (0.35)	-0.003 (-0.78)	0.002* (1.76)
Constant	0.75 (0.41)	3.62* (1.89)	1.08* (1.92)
Adjusted R^2	0.41	0.45	0.85
Controls	Initial credit score	Initial credit score	Initial volatility, Initial level
Fixed Effects	Individual, Month-Year		
F-statistic (1st Stage)			
$\$W_{wealth} \times 1_{post}$	2,878,745***	2,878,745***	216***
$\$W_{liquidity} \times 1_{post}$	427,269***	427,269***	90.99***
Durbin-Wu-Hausman	0.63	1.27	17.42***

Table A.2: Estimated Average Responses of Total Debt Default, Past Due Debt and Credit Card Spending volatility to Liquidity and Wealth Components of the FGTS Shock: IV Estimates

Notes: This table presents the robustness results from Section VII using two-stage least squares (2SLS) regressions to estimate the causal effects of the FGTS shock. The second-stage estimations follow equation (11) on total debt default, past due debt and credit card spending volatility, where the liquidity and wealth components of the shock are instrumented using their projected values from the first stage. Specifically, the share of FGTS-eligible workers at the ZIP3 level is used to instrument the liquidity component, and the share at the ZIP2 level is used for the wealth component. The analysis is based on the matched sample over the period from 2016:08 to 2018:05. Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. t-statistics are reported in parentheses beneath the coefficient estimates. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

A.2 - Robustness: Behavioral Validation of the Shock's Components - Event Study by Distance to Retirement

To empirically validate the interpretation of the FGTS shock as a mix of liquidity and wealth components that varies by distance to retirement, we estimate event-study regressions on monthly debt outcomes for two age groups: younger than 50 (far from retirement, larger wealth component); 50 and older (closer to retirement, larger liquidity component).

We apply this split across three versions of the shock: the total FGTS shock, the wealth component (based on interest rate differential and time to maturity), the liquidity component (immediate cash inflow minus present value). In this regard, Figure A.2 estimates rely on the

following specification of the shock parts' dynamics:

$$
\begin{aligned}
Y_{i,t} = & \sum_{s=0}^{17} \beta_s \times \$W_{liquidity,i} \times 1_{month\,s} + \sum_{s=0}^{17} \beta_{g_1,s} \times 1_{g1} \times \$W_{liquidity,i} \times 1_{month\,s} + ... \\
& + \sum_{s=0}^{17} \beta_{g_{(N-1)},s} \times 1_{g_{(N-1)}} \times \$W_{liquidity,i} \times 1_{month\,s} + \\
& + \sum_{s=0}^{17} \beta_s \times \$W_{wealth,i} \times 1_{month\,s} + \sum_{s=0}^{17} \beta_{g_1,s} \times 1_{g1} \times \$W_{wealth,i} \times 1_{month\,s} + ... \\
& + \sum_{s=0}^{17} \beta_{g_{(N-1)},s} \times 1_{g_{(N-1)}} \times \$W_{wealth,i} \times 1_{month\,s} + \alpha_i + \delta_t + \epsilon_{i,t}
\end{aligned}
\tag{A.1}
$$

We estimate separate monthly treatment effects and compare trajectories for: total debt, Non-revolving debt (e.g., auto loans and mortgages) and credit card spending.

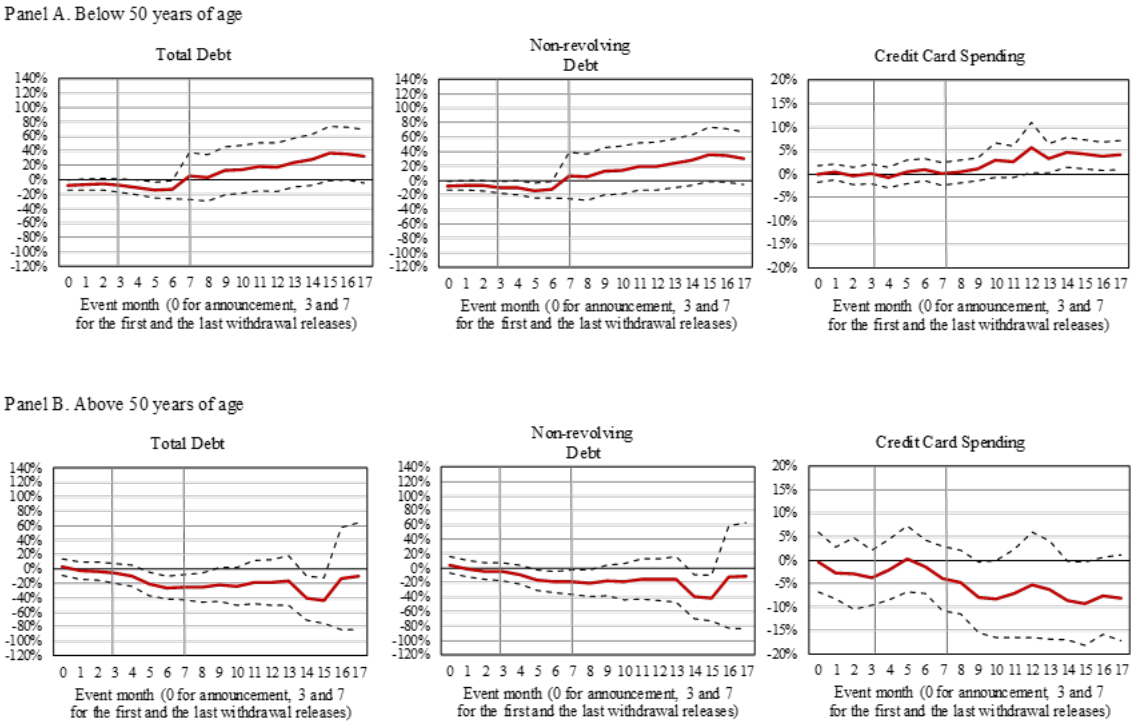

Figure A.1: Heterogeneity in Total Debt, Non-revolving Debt and Credit Card Spending Responses Across Workers - Younger and Older than 50 Years of Age

Notes: This figure plots the paths of total debt, non-revolving debt and credit card spending responses - coefficients β_s, $s = 0, 1, 2, 3, \ldots, 16, 17$ -, along with their corresponding 95 percent confidence intervals, as estimated from equation (7). The sample includes the matched treatment and control groups during the period of 2016:12-2018:05. For each comparison panel, column 1 shows the total debit response, column 2 shows the non-revolving response and column 3 shows the credit card spending response. Panel A compares consumers below 50 years of age (i.e., age $\leq$ 50 in 2016:11, right before the Program announcement). Panel B compares consumers above 50 years of age (i.e., age $\geq$ 50 in 2016:11, right before the Program announcement). The x-axis denotes the sth month after the announcement of the FGTS Program, and the y-axis shows the cash response (for every cash received).

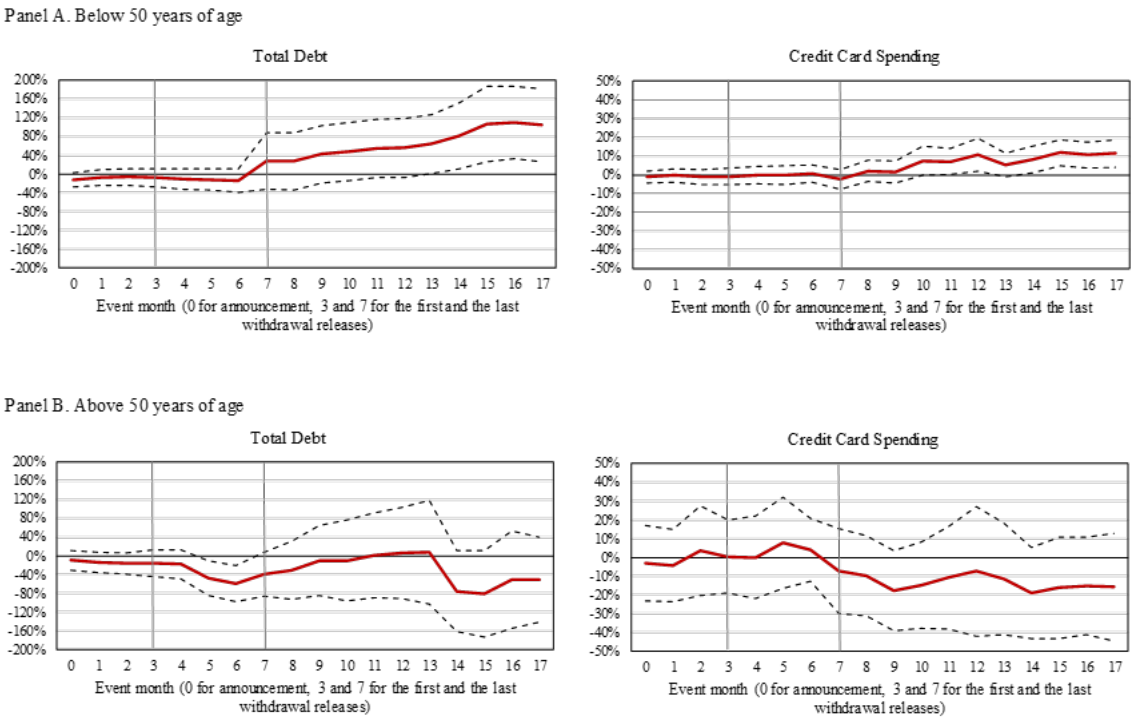

Figure A.2: Heterogeneity in Total Debt and Credit Card Spending Responses out of the Wealth Component of the Shock Across Workers - Younger and Older than 50 Years of Age

Notes: This figure plots the paths of total debt and credit card spending responses - coefficients β_s, $s = 0, 1, 2, 3, \ldots, 16, 17$ -, along with their corresponding 95 percent confidence intervals, as estimated from equation (14). The sample includes the matched treatment and control groups during the period of 2016:12-2018:05. For each comparison panel, column 1 shows the total debit response out of the wealth component of the shock, column 2 shows the credit card spending response out of the wealth component of the shock. Panel A compares consumers below 50 years of age (i.e., age ≤ 50 in 2016:11, right before the Program announcement). Panel B compares consumers above 50 years of age (i.e., age ≥ 50 in 2016:11, right before the Program announcement). The x-axis denotes the sth month after the announcement of the FGTS Program, and the y-axis shows the cash response (for every cash received).

This analysis provides strong visual and statistical support for your interpretation of the FGTS withdrawal as a composite of wealth and liquidity shocks, with responses varying by retirement proximity: younger individuals appear to interpret the wealth component as a permanent income gain, increasing credit card spending and long-term borrowing and financial commitments — especially in non-revolving debt. Older individuals, especially those nearing retirement, treat the shock primarily as liquidity and use it to deleverage.The smooth transition in behavior across age groups (as proxied by a 50-year threshold) supports the continuous decomposition logic already used in the baseline model.

A.3 - Robustness: Heterogeneity Across Workers by Alternative financial constraints

dependent variable:	Debt			Credit Card Spending
	Total	Revolving Debt	Non-revolving Debt	
Panel A (Across Debt-to-Income)				
$\$W_{liquidity} \times 1_{i \leq 25th} \times 1_{post}$	-1.13**	0.01	-1.14**	-0.11
	(-2.09)	(0.39)	(-2.12)	(-1.08)
$\$W_{wealth} \times 1_{i \leq 25th} \times 1_{post}$	0.73**	0.04***	0.69*	0.05*
	(2.03)	(4.73)	(1.92)	(1.73)
$\$W_{liquidity} \times 1_{i \geq 75th} \times 1_{post}$	-0.05	0.07	-0.12	-0.03
	(-0.08)	(0.41)	(0.25)	(-0.36)
$\$W_{wealth} \times 1_{i \geq 75th} \times 1_{post}$	-0.81***	-0.11*	-0.69***	0.03
	(-3.37)	(-1.65)	(3.66)	(0.90)
Constant	8,297***	983***	7,315***	2,158***
	(89.23)	(106)	(79.95)	(254)
Adjusted R^2	0.63	0.52	0.62	0.71
Panel B (Across Credit Scores)				
$\$W_{liquidity} \times 1_{i \leq 25th} \times 1_{post}$	-1.07***	0.00	-1.07***	-0.10
	(-2.74)	(0.03)	(-2.67)	(-1.17)
$\$W_{wealth} \times 1_{i \leq 25th} \times 1_{post}$	0.53**	0.02	0.52**	0.08***
	(2.23)	(1.18)	(2.16)	(2.93)
$\$W_{liquidity} \times 1_{i \geq 75th} \times 1_{post}$	-0.05	0.00	0.04	-0.07*
	(-0.13)	(0.03)	(0.14)	(-1.65)
$\$W_{wealth} \times 1_{i \geq 75th} \times 1_{post}$	-0.73***	-0.12*	-0.61***	0.02
	(-3.11)	(-1.67)	(3.47)	(1.02)
Constant	8,297***	991***	7,350***	2,155***
	(89.23)	(96.31)	(79.33)	(253)
Adjusted R^2	0.63	0.52	0.62	0.71
Fixed Effects	Individual, Month-Year			

Table A.3: Estimated Average Responses of total Debt, Non-revolving Debt, Revolving Debt and Credit Card Spending to Liquidity and Wealth Components of the FGTS Shock: Alternative Financial Constraints

Notes: This table shows the average responses across total debt, revolving debt, non-revolving debt and credit card spending out of the liquidity and wealth parts of the FGTS shock following definitions in (9) and (10) in the period from 2016:08 to 2018:05 using the matched sample. Panel A presents estimations across low debt-to-income (i.e., average debt-to-income between 2016:01 and 2016:11 ≤ 0.10, or twenty-fifth of sample) and high debt-to-income (i.e., average debt-to-income between 2016:01 and 2016:11 ≥ 1.29, or seventy-fifth of sample) workers following equation (12). Panel B presents estimations across first quartile of workers according to their credit scores ($g_1 \equiv i \leq 25th$ - below the twenty-fifth percentile of the distribution in the cross section of workers prior to the program announcement and fourth quartile of workers according to their credit scores ($g_4 \equiv i \geq 75th$ - above the seventy-fifth percentile of the distribution in the cross section of workers prior to the program announcement) following equation (12). There are nine categories of credit scores: AA, A, B, C, D, E, F, G and H. We consider the scores in the month right before the program announcement, 2016:11. Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. t-statistics are reported in parentheses under the coefficient estimates. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

dependent variable:	Total Debt		Credit Card Spending Volatilty
	Default	Past Due	
Panel A (Across Debt-to-Income)			
$\$W_{liquidity} \times 1_{i \leq 25th} \times 1_{post}$	0.00001 (0.67)	0.00003 (0.87)	-0.00002** (-2.10)
$\$W_{wealth} \times 1_{i \leq 25th} \times 1_{post}$	0.000001 (0.79)	-0.000005 (-0.61)	0.0000003 (0.11)
$\$W_{liquidity} \times 1_{i \geq 75th} \times 1_{post}$	-0.00002 (-0.18)	0.00006 (0.45)	0.000001 (0.01)
$\$W_{wealth} \times 1_{i \geq 75th} \times 1_{post}$	-0.0001* (-1.70)	-0.0001** (-2.41)	0.00002** (2.33)
Constant	1.01*** (14.18)	1.63*** (22.04)	0.69*** (11.19)
Controls	Initial credit score	Initial credit score	Initial volatility, Initial level
Adjusted R^2	0.40	0.45	0.84
Panel B (Across Credit Scores)			
$\$W_{liquidity} \times 1_{i \leq 25th} \times 1_{post}$	-0.00002 (-1.19)	-0.00002 (-1.40)	-0.00002 (-1.12)
$\$W_{wealth} \times 1_{i \leq 25th} \times 1_{post}$	-0.000001 (-0.82)	-0.00003 (-1.35)	0.000001 (1.32)
$\$W_{liquidity} \times 1_{i \geq 75th} \times 1_{post}$	0.0001 (1.13)	0.0001* (1.68)	0.00002 (0.55)
$\$W_{wealth} \times 1_{i \geq 75th} \times 1_{post}$	-0.0001** (-2.23)	-0.0001 (-1.29)	0.00002* (1.68)
Constant	0.96*** (12.18)	1.65*** (20.01)	0.63*** (9.94)
Controls	Initial credit score	Initial credit score	Initial volatility, Initial level
Adjusted R^2	0.40	0.45	0.84
Fixed Effects	Individual, Month-Year		

Table A.4: Estimated Average Responses of total Debt Default, Past Due Debt and Credit Card Spending Volatility to Liquidity and Wealth Components of the FGTS Shock: Alternative Financial Constraints

Notes: This table shows the average responses across total debt default, past due debt and credit card spending volatility out of the liquidity and wealth parts of the FGTS shock following definitions in (9) and (10) in the period from 2016:08 to 2018:05 using the matched sample. Panel A presents estimations across low debt-to-income (i.e., average debt-to-income between 2016:01 and 2016:11 $\leq$ 0.10, or twenty-fifth of sample) and high debt-to-income (i.e., average debt-to-income between 2016:01 and 2016:11 $\geq$ 1.29, or seventy-fifth of sample) workers following equation (12). Panel B presents estimations across first quartile of workers according to their credit scores ($g_1 \equiv i \leq 25th$ - below the twenty-fifth percentile of the distribution in the cross section of workers prior to the program announcement and fourth quartile of workers according to their credit scores ($g_4 \equiv i \geq 75th$ - above the seventy-fifth percentile of the distribution in the cross section of workers prior to the program announcement) following equation (12). There are nine categories of credit scores: AA, A, B, C, D, E, F, G and H. We consider the scores in the month right before the program announcement, 2016:11. Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. t-statistics are reported in parentheses under the coefficient estimates. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

To test the robustness of our findings to alternative measures of financial constraints, Tables A.3 and A.4 present estimates using different variables to rank worker constraint status. While the main analysis uses the debt-to-limit ratio as our benchmark indicator of financial constraint, we explore two complementary approaches. Panel A redefines constraint status using the debt-to-income ratio, classifying workers based on their debt burden relative to earnings. Panel B, in turn, uses quartiles of initial credit scores to contrast responses between the most and least creditworthy individuals (first vs. fourth quartiles). These alternative definitions offer distinct perspectives on financial vulnerability—one rooted in income flows and another in predicted access to credit. Across both specifications, we find broadly consistent patterns with our main results: constrained individuals deleverage in response to the FGTS shock, while unconstrained workers exhibit increased credit-financed spending and heightened financial fragility. These findings strengthen confidence that the heterogeneous responses documented in the paper are not sensitive to the specific constraint measure employed.

A.4 - Robustness: Heterogeneity Across Workers by Income and Income Growth

To further test the robustness of our results, Tables A.5 and A.6 investigate heterogeneity in the response to the FGTS shock based on workers' income level and recent income dynamics. In Panel A, we split workers by their initial average monthly income, measured between January and November 2016, comparing responses across the bottom and top quartiles. In Panel B, we distinguish workers based on real income growth by comparing average income in 2016 (January–November) to 2017 (January–November), identifying those with positive versus negative income trajectories. These additional exercises allow us to examine whether the financial response to the FGTS windfall differs by income position and recent earnings trends. In both cases, the results remain consistent with our baseline: lower-income or declining-income workers exhibit stronger deleveraging and stabilization behavior, while higher-income or growing-income workers are more likely to increase credit-financed spending, especially in response to the wealth component of the shock.

dependent variable:	Debt			Credit Card Spending
	Total	Revolving Debt	Non-revolving Debt	
Panel A (Across Income)				
$\$W_{liquidity} \times 1_{i\leq 25th} \times 1_{post}$	-1.34 (-1.41)	-0.04 (-0.36)	-1.12*** (-2.66)	-0.09 (-0.79)
$\$W_{wealth} \times 1_{i\leq 25th} \times 1_{post}$	0.62* (1.95)	0.09 (1.32)	0.51** (2.12)	0.02 (0.51)
$\$W_{liquidity} \times 1_{i\geq 75th} \times 1_{post}$	0.42 (0.36)	0.06 (0.85)	3.76 (1.33)	-0.01 (-0.29)
$\$W_{wealth} \times 1_{i\geq 75th} \times 1_{post}$	-0.32 (-1.35)	0.05 (0.29)	-0.68 (1.30)	0.03 (1.05)
Constant	3,495*** (78.68)	525*** (73.74)	2,951*** (63.10)	1,063*** (156)
Adjusted R^2	0.52	0.48	0.51	0.69
Panel B (Across Income Growth)				
$\$W_{liquidity} \times 1_{i\leq 25th} \times 1_{post}$	-0.95* (-1.67)	0.02 (0.57)	-0.91** (-2.10)	-0.15 (-1.29)
$\$W_{wealth} \times 1_{i\leq 25th} \times 1_{post}$	0.50 (0.96)	0.02 (1.04)	0.14 (0.57)	0.04 (1.05)
$\$W_{liquidity} \times 1_{i\geq 75th} \times 1_{post}$	0.48 (0.35)	0.12 (1.03)	-0.30 (-1.35)	0.02 (0.16)
$\$W_{wealth} \times 1_{i\geq 75th} \times 1_{post}$	-1.16** (-2.08)	-0.27** (-2.13)	-1.22*** (-4.27)	0.01 (0.23)
Constant	17,279*** (71.67)	1,703*** (60.75)	15,612*** (64.77)	3,898*** (178)
Adjusted R^2	0.61	0.50	0.61	0.68
Fixed Effects	Individual, Month-Year			

Table A.5: Estimated Average Responses of total Debt, Non-revolving Debt, Revolving Debt and Credit Card Spending to Liquidity and Wealth Components of the FGTS Shock: Income and Income Growth

Notes: This table shows the average responses across total debt, revolving debt, non-revolving debt and credit card spending out of the liquidity and wealth parts of the FGTS shock following definitions in (9) and (10) in the period from 2016:08 to 2018:05 using the matched sample. Panel A presents estimations across low income (i.e., average monthly income between 2016:01 and 2016:11 - twenty-fifth of sample) and high income (i.e., average monthly income between 2016:01 and 2016:11 - seventy-fifth of sample) workers following equation (12). Panel B presents estimations across low income growth (i.e., income growth between 2016:01-2016:11 and 2017:01-2017:11 - twenty-fifth of sample) and across high income growth (i.e., income growth between 2016:01-2016:11 and 2017:01-2017:11 - seventy-fifth of sample) following equation (12). Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. t-statistics are reported in parentheses under the coefficient estimates. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

dependent variable:	Total Debt		Credit Card Spending Volatilty
	Default	Past Due	
Panel A (Across Income)			
$\$W_{liquidity} \times 1_{i \leq 25th} \times 1_{post}$	0.00001 (0.67)	0.00003 (0.87)	-0.00002** (-2.10)
$\$W_{wealth} \times 1_{i \leq 25th} \times 1_{post}$	0.000001 (0.79)	-0.000005 (-0.61)	0.0000003 (0.11)
$\$W_{liquidity} \times 1_{i \geq 75th} \times 1_{post}$	-0.00002 (-0.18)	0.00006 (0.45)	0.000001 (0.01)
$\$W_{wealth} \times 1_{i \geq 75th} \times 1_{post}$	-0.0001* (-1.70)	-0.0001** (-2.41)	0.00002** (2.33)
Constant	1.01*** (14.18)	1.63*** (22.04)	0.69*** (11.19)
Controls	Initial credit score	Initial credit score	Initial volatility, Initial level
Adjusted R^2	0.40	0.45	0.84
Panel B (Across Income Growth)			
$\$W_{liquidity} \times 1_{i \leq 25th} \times 1_{post}$	-0.00002 (-1.19)	-0.00002 (-1.40)	-0.00002 (-1.12)
$\$W_{wealth} \times 1_{i \leq 25th} \times 1_{post}$	-0.000001 (-0.82)	-0.00003 (-1.35)	0.000001 (1.32)
$\$W_{liquidity} \times 1_{i \geq 75th} \times 1_{post}$	0.0001 (1.13)	0.0001* (1.68)	0.00002 (0.55)
$\$W_{wealth} \times 1_{i \geq 75th} \times 1_{post}$	-0.0001** (-2.23)	-0.0001 (-1.29)	0.00002* (1.68)
Constant	0.96*** (12.18)	1.65*** (20.01)	0.63*** (9.94)
Controls	Initial credit score	Initial credit score	Initial volatility, Initial level
Adjusted R^2	0.40	0.45	0.84
Fixed Effects	Individual, Month-Year		

Table A.6: Estimated Average Responses of total Debt Default, Past Due Debt and Credit Card Spending Volatility to Liquidity and Wealth Components of the FGTS Shock:Income and Income Growth

Notes: This table shows the average responses across total debt default, past due debt and credit card spending volatitly out of the liquidity and wealth parts of the FGTS shock following definitions in (9) and (10) in the period from 2016:08 to 2018:05 using the matched sample. Panel A presents estimations across low income (i.e., average monthly income between 2016:01 and 2016:11 - twenty-fifth of sample) and high income (i.e., average monthly income between 2016:01 and 2016:11 - seventy-fifth of sample) workers following equation (12). Panel B presents estimations across low income growth (i.e., income growth between 2016:01-2016:11 and 2017:01-2017:11 - twenty-fifth of sample) and across high income growth (i.e., income growth between 2016:01-2016:11 and 2017:01-2017:11 - seventy-fifth of sample) following equation (12). Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. t-statistics are reported in parentheses under the coefficient estimates. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

A.5 - Robustness: Prime-Age Sample Restriction

As an additional robustness check, we restrict the sample to prime-age adults (25–54 years old) to ensure that the main results are not disproportionately driven by the behavior of younger or older individuals, who may differ systematically in credit access, income stability, or retirement expectations. The findings remain consistent with those from the full sample, confirming that the observed heterogeneity in responses to liquidity and wealth components of the FGTS shock holds within this more demographically stable subgroup.

dependent variable:	Debt			Credit Card Spending
	Total	Revolving Debt	Non-revolving Debt	
Panel A				
$\$W_{liquidity} \times 1_{i\leq 25th} \times 1_{post}$	-1.91***	-0.04	-1.87***	-0.24
	(-2.82)	(-0.95)	(-2.77)	(-1.57)
$\$W_{wealth} \times 1_{i\leq 25th} \times 1_{post}$	0.75*	0.05***	0.71*	0.08**
	(1.93)	(4.19)	(1.81)	(2.07)
$\$W_{liquidity} \times 1_{i\geq 75th} \times 1_{post}$	0.78	0.43	0.35	-0.00
	(0.98)	(1.52)	(0.36)	(-0.02)
$\$W_{wealth} \times 1_{i\geq 75th} \times 1_{post}$	-0.73*	-0.23**	-0.50*	0.06
	(-1.94)	(-2.36)	(1.65)	(0.48)
Constant	8,738***	1,019***	7,719***	2,277***
	(83.21)	(92.97)	(75.11)	(248)
Adjusted R^2	0.63	0.52	0.62	0.71
Fixed Effects	Individual, Month-Year			

Table A.7: Estimated Average Responses of total Debt, Non-revolving Debt, Revolving Debt and Credit Card Spending to Liquidity and Wealth Components of the FGTS Shock: Prime-age sample Restriction

Notes: This table shows the average responses across total debt, revolving debt, non-revolving debt and credit card spending out of the liquidity and wealth parts of the FGTS shock following definitions in (9) and (10) in the period from 2016:08 to 2018:05 using the matched sample. It compares consumers with low debt-to-limit (i.e., average debt-to-limit between 2016:01 and 2016:11 ≤ 0.21, or twenty-fifth of sample) and consumers with high debt-to-limit (i.e., average debt-to-limit between 2016:01 and 2016:11 ≥ 9.35, or seventy-fifth of the sample) workers following equation (12). Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. *t*-statistics are reported in parentheses under the coefficient estimates. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

dependent variable:	Total Debt		Credit Card Spending Volatilty
	Default	Past Due	
$\$W_{liquidity} \times 1_{i \leq 25th} \times 1_{post}$	-0.00002 (-1.04)	-0.00001 (-0.60)	-0.000004*** (-3.49)
$\$W_{wealth} \times 1_{i \leq 25th} \times 1_{post}$	0.00002 (0.83)	-0.00001 (-1.43)	0.000004 (1.17)
$\$W_{liquidity} \times 1_{i \geq 75th} \times 1_{post}$	0.0002 (0.85)	0.00005 (0.22)	-0.0001* (-1.91)
$\$W_{wealth} \times 1_{i \geq 75th} \times 1_{post}$	-0.0001** (-2.52)	-0.0001** (-2.59)	0.0001*** (4.06)
Constant	0.94*** (17.19)	1.65*** (28.34)	0.40*** (6.87)
Adjusted R^2	0.40	0.45	0.84
Controls	Initial credit score	Initial credit score	Initial volatility, Initial level
Fixed Effects	Individual, Month-Year		

Table A.8: Estimated Average Responses of total Debt Default, Past Due Debt and Credit Card Spending Volatility to Liquidity and Wealth Components of the FGTS Shoc: Prime-age sample Restriction

Notes: This table shows the average responses across total debt default, past due debt and credit card spending volatitly out of the liquidity and wealth parts of the FGTS shock following definitions in (9) and (10) in the period from 2016:08 to 2018:05 using the matched sample.It compares consumers with low debt-to-limit (i.e., average debt-to-limit between 2016:01 and 2016:11 ≤ 0.21, or twenty-fifth of sample) and consumers with high debt-to-limit (i.e., average debt-to-limit between 2016:01 and 2016:11 ≥ 9.35, or seventy-fifth of the sample) workers following equation (12). Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. *t*-statistics are reported in parentheses under the coefficient estimates. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

A.6 - Robustness: Alternative Fixed Effects and Standard Error Clusters

As an additional robustness exercise, we test the sensitivity of our results to alternative fixed effects and clustering specifications. We re-estimate the main regressions including ZIP3-by-month-year fixed effects, as well as demographic-by-time interactions, defined by age group-by-month-year and income growth quartile-by-month-year. Age groups are categorized as younger than 25, prime-age (25–54), and 55 or older. Income growth is measured as the change in average monthly income between the pre-announcement period (2016.01–2016.11) and the post-announcement period (2017.01–2017.11). We also apply double clustering of standard errors by ZIP2 and year-month. Specifications (1) and (2) in Tables A.9 and A.10 follow equations (A.2)

and (A.3), respectively. Across all specifications, results remain robust and closely aligned with the baseline estimates, confirming the stability of our findings.

dependent variable:	Total Debt		Credit card spending	
model specification:	(1)	(2)	(1)	(2)
$\$W_{liquidity} \times 1_{i\leq 25th} \times 1_{post}$	-0.91**	-0.82**	-0.10	-0.09
	(-2.67)	(-2.35)	(1.47)	(1.31)
$\$W_{wealth} \times 1_{i\leq 25th} \times 1_{post}$	0.56*	0.54*	0.04*	0.04
	(1.89)	(1.79)	(1.73)	(1.53)
$\$W_{liquidity} \times 1_{i\geq 75th} \times 1_{post}$	0.23	0.14	0.02	0.04
	(0.38)	(0.25)	(0.28)	(0.75)
$\$W_{wealth} \times 1_{i\geq 75th} \times 1_{post}$	-0.71***	-0.76***	0.01	0.01
	(3.18)	(3.02)	(0.64)	(0.37)
Constant	8,383***	8,364***	2,153***	2,158***
	(114)	(111)	(289)	(297)
Adjusted R^2	0.63	0.63	0.71	0.71
Individual FE	X	X	X	X
ZIP3-(year-month) FE	X	X	X	X
Age groups-(year-month) FE		X		X
Income growth quartile-(year-month) FE		X		X
Standard Error Clusters:				
Year-month	22	22	22	22
ZIP2	90	90	90	90

Table A.9: Estimated Average Responses of total Debt, Non-revolving Debt, Revolving Debt and Credit Card Spending to Liquidity and Wealth Components of the FGTS Shock: Alternative Fixed Effects and Standard Errors Clusters

Notes: This table shows the average responses across total debt, revolving debt, non-revolving debt and credit card spending out of the liquidity and wealth parts of the FGTS shock following definitions in (9) and (10) in the period from 2016:08 to 2018:05 using the matched sample. It compares consumers with low debt-to-limit (i.e., average debt-to-limit between 2016:01 and 2016:11 ≤ 0.21, or twenty-fifth of sample) and consumers with high debt-to-limit (i.e., average debt-to-limit between 2016:01 and 2016:11 ≥ 9.35, or seventy-fifth of the sample) workers. Specifications (1) and (2) follow equations (A.2) and (A.3), respectively. Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. t-statistics are reported in parentheses under the coefficient estimates. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

dependent variable:	Total Debt				Credit card spending	
	Default		Past Due		Volatility	
model specification:	(1)	(2)	(1)	(2)	(1)	(2)
$\$W_{liquidity} \times 1_{i\leq 25th} \times 1_{post}$	-0.00003 (-1.17)	-0.00003 (-1.26)	-0.00001 (-1.04)	-0.00002 (-0.96)	-0.00002 (-1.27)	-0.00002 (-121)
$\$W_{wealth} \times 1_{i\leq 25th} \times 1_{post}$	0.00002 (0.27)	0.00002 (0.35)	-0.00001 (-1.51)	-0.00001 (-0.79)	0.000001 (0.15)	0.000001 (0.02)
$\$W_{liquidity} \times 1_{i\geq 75th} \times 1_{post}$	0.00004 (0.35)	0.00001 (0.09)	0.00001 (0.49)	0.00001 (0.10)	-0.00001 (-0.14)	-0.00003 (-0.59)
$\$W_{wealth} \times 1_{i\geq 75th} \times 1_{post}$	-0.0001*** (-2.91)	-0.0001*** (-2.87)	-0.0002*** (-3.04)	-0.0001** (-2.77)	0.0001*** (3.20)	0.00004*** (3.09)
Constant	0.62*** (5.06)	0.82*** (7.69)	1.19*** (7.95)	1.44*** (12.84)	0.33*** (28.66)	0.53*** (25.77)
Adjusted R^2	0.41	0.41	0.45	0.45	0.84	0.84
Controls	Initial credit score	Initial credit score	Initial credit score	Initial credit score	Initial volatility, Initial level	Initial volatility, Initial level
Individual FE	X	X	X	X	X	X
ZIP3-(year-month) FE	X	X	X	X	X	X
Age groups-(year-month) FE		X		X		X
Income growth quartile-(year-month) FE		X		X		X
Standard Error Clusters:						
Year-month	22	22	22	22	22	22
ZIP2	90	90	90	90	90	90

Table A.10: Estimated Average Responses of total Debt Default, Past Due Debt and Credit Card Spending Volatility to Liquidity and Wealth Components of the FGTS Shoc: Alternative Fixed Effects and Standard Errors Clusters

Notes: This table shows the average responses across total debt default, past due debt and credit card spending volatitly out of the liquidity and wealth parts of the FGTS shock following definitions in (9) and (10) in the period from 2016:08 to 2018:05 using the matched sample.It compares consumers with low debt-to-limit (i.e., average debt-to-limit between 2016:01 and 2016:11 ≤ 0.21, or twenty-fifth of sample) and consumers with high debt-to-limit (i.e., average debt-to-limit between 2016:01 and 2016:11 ≥ 9.35, or seventy-fifth of the sample) workers. Specifications (1) and (2) follow equations (A.2) and (A.3), respectively. If $Y_{i,t} = \{$total debt default, total past due debt$\}$, it includes initial credit scores as controls - a term $\sum_{k=1}^{K-1} \beta_{k,post} \times 1_{FGTS} \times 1_{post} \times 1_{Score\,k,2016}$ in (A.2) and (A.3.). If $Y_{i,t} = \{$credit card spending volatility$\}$, it includes initial spending volatility and initial spending level as controls - a term $\beta_{1,post} \times 1_{FGTS} \times 1_{post} \times \text{Credit\_Volatility}_{i,2016} + \beta_{2,post} \times 1_{FGTS} \times 1_{post} \times \text{Credit\_Levels}_{i,2016}$ in (A.2) and (A.3). Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. t-statistics are reported in parentheses under the coefficient estimates. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

$$
\begin{aligned}
Y_{i,t} =& \beta_{liquidity,post} \times \$W_{liquidity,i} \times 1_{post} + \beta_{liquidity,g_1,post} \times 1_{g_1} \times \$W_{liquidity,i} \times 1_{post} + ... \\
&+ \beta_{liquidity,g_{(N-1)},post} \times 1_{g_{(N-1)}} \times \$W_{liquidity,i} \times 1_{post} \\
&+ \beta_{wealth,post} \times \$W_{wealth,i} \times 1_{post} + \beta_{wealth,g_1,post} \times 1_{g_1} \times \$W_{wealth,i} \times 1_{post} + ... \\
&+ \beta_{wealth,g_{(N-1)},post} \times 1_{g_{(N-1)}} \times \$W_{wealth,i} \times 1_{post} + \alpha_i + ZIP3 \times \delta_t + \epsilon_{i,t}
\end{aligned}
\tag{A.2}
$$

$$
\begin{aligned}
Y_{i,t} =& \beta_{liquidity,post} \times \$W_{liquidity,i} \times 1_{post} + \beta_{liquidity,g_1,post} \times 1_{g_1} \times \$W_{liquidity,i} \times 1_{post} + ... \\
&+ \beta_{liquidity,g_{(N-1)},post} \times 1_{g_{(N-1)}} \times \$W_{liquidity,i} \times 1_{post} \\
&+ \beta_{wealth,post} \times \$W_{wealth,i} \times 1_{post} + \beta_{wealth,g_1,post} \times 1_{g_1} \times \$W_{wealth,i} \times 1_{post} + ... \\
&+ \beta_{wealth,g_{(N-1)},post} \times 1_{g_{(N-1)}} \times \$W_{wealth,i} \times 1_{post} + \alpha_i + ZIP3 \times \delta_t \\
&+ \sum_{s=1}^{3} Age\_Group_s \times \delta_t + \sum_{k=1}^{4} Income\_Growth\_Quartile_k \times \delta_t + \epsilon_{i,t}
\end{aligned}
\tag{A.3}
$$

A.7 - Robustness: General Equilibrium Spillovers

We further assess whether general equilibrium spillovers could bias our main results by exploring heterogeneity in treatment effects across regions with different aggregate FGTS exposure. Specifically, we rank workers based on the quartiles of the share of national FGTS withdrawals in their ZIP2 area. While point estimates for the fourth quartile (regions with the highest aggregate exposure) are generally smaller than those for the first quartile, we mostly fail to reject the null hypothesis that the coefficients of the interaction terms for the first and fourth quartiles are statistically equal (F-tests). This suggests that our results are not primarily driven by local general equilibrium spillovers.

dependent variable:	Debt			Credit Card Spending
	Total	Revolving Debt	Non-revolving Debt	
$\$W \times 1_{i \leq 25th} \times 1_{post}$	0.49 (1.18)	0.04** (2.30)	0.45 (1.08)	0.03* (1.81)
$\$W \times 1_{i \geq 75th} \times 1_{post}$	0.01 (0.05)	-0.03 (1.06)	0.03 (0.23)	0.01 (1.05)
Constant	8,325*** (79.13)	984*** (110)	7,341*** (70.61)	2,156*** (229)
Adjusted R^2	0.63	0.53	0.63	0.71
F-test $\$W \times 1_{i \leq 25th} \times 1_{post}$ = $\$W \times 1_{i \geq 75th} \times 1_{post}$	1.26	5.43**	0.94	0.63
Fixed Effects	Individual, Month-Year			

Table A.11: Estimated Average Responses of total Debt, Non-revolving Debt, Revolving Debt and Credit Card Spending to Liquidity and Wealth Components of the FGTS Shock: General Equilibrium Spillovers

Notes: This table shows the average responses across total debt, revolving debt, non-revolving debt and credit card spending out of the liquidity and wealth parts of the FGTS shock following definitions in (9) and (10) in the period from 2016:08 to 2018:05 using the matched sample. It compares consumers with low share of national FGTS withdrawals by ZIP2 areas (or twenty-fifth of sample) and consumers with high share of national FGTS withdrawals by ZIP2 areas (or seventy-fifth of the sample) following equation (12). Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. *t*-statistics are reported in parentheses under the coefficient estimates. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

A.8 - Heterogeneity of Credit Card Spending Volatility

dependent variable:	Credit card spending Volatility
$1_{FGTS} \times 1_{i \leq 25th} \times 1_{post}$	0.50*** (25.67)
$1_{FGTS} \times 1_{i \geq 75th} \times 1_{post}$	0.90*** (29.24)
Constant	0.96*** (31.24)
Adjusted R^2	0.72
Fixed Effetcs	Individual, Month-Year
Controls	Initial volatility, Initial level

Table A.12: Estimated Credit Card Spending Volatility Across Workers

Notes: This table presents the Credit Card Spending Volatility across low debt-to-limit ($g_1 \equiv i \leq 25th$ - below the twenty-fifth percentile of the distribution in the cross section of workers prior to the program announcement) and high debt-to-limit ($g_4 \equiv i \geq 75th$ - above the seventy-fifth percentile of the distribution in the cross section of workers prior to the program announcement) workers. The estimations follow an extension of equation (3): $Y_{i,t} = \beta_{post} \times 1_{FGTS} \times 1_{post} + \beta_{g_1} \times 1_{g1} \times 1_{FGTS} \times 1_{post} + ... + \beta_{g_{(N-1)}} \times 1_{g_{(N-1)}} \times 1_{FGTS} \times 1_{post} + \beta_{1,post} \times 1_{FGTS} \times 1_{post} \times \text{Credit\_Volatility}_{i,2016} + \beta_{2,post} \times 1_{FGTS} \times 1_{post} \times \text{Credit\_Levels}_{i,2016} + \alpha_i + \delta_t + \epsilon_{i,t}$. The analysis is based on the matched sample over the period from 2016:08 to 2018:05. Individual and year-month fixed effects are included, and standard errors are clustered at the individual level. t-statistics are reported in parentheses beneath the coefficient estimates. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.12 examines how the overall FGTS shock influenced credit card spending volatility across workers with different levels of financial constraints, ranked by their debt-to-limit ratio. Workers in the 25th percentile of the debt-to-limit distribution (relatively unconstrained) experienced an estimated 0.50-point increase in credit card spending volatility following the shock. In contrast, workers in the 75th percentile (highly constrained) saw a larger increase of 0.90 points. These results suggest that, while both groups became more volatile in their spending after the FGTS withdrawals, the effect was stronger for financially constrained individuals. This pattern indicates that constrained workers may have increased their reliance on revolving credit in a less stable way, possibly due to liquidity needs or limited access to cheaper borrowing alternatives, whereas unconstrained workers displayed a more moderate rise in volatility.

A.9 - Descriptive Statistics of Wealth and Liquidity Components of the FGTS Shock Across Workers

	Mean	Standard Deviation	Min	Max
Panel A - Quartile 1				
$\$W_{liquidity}$	511	1,154	0.76	18,696
$\$W_{wealth}$	2,331	3,542	0	23,184
Monthly Income 2016	1,481	2,240	0	32,459
Age 2016	37.02	9.47	19.37	64.41
Observations (Individuals)		1,421		
Panel B - Quartile 2				
$\$W_{liquidity}$	427	1,001	0.75	18,201
$\$W_{wealth}$	1,899	2,890	0	23,817
Monthly Income 2016	1,568	2,130	0	31,515
Age 2016	36.90	9.83	18.57	73.70
Observations (Individuals)		1,403		
Panel C - Quartile 3				
$\$W_{liquidity}$	328	592	0.49	6,080
$\$W_{wealth}$	1,742	2,765	0	24,310
Monthly Income 2016	1,462	1,876	0	21,832
Age 2016	35.93	9.62	18.25	68.08
Observations (Individuals)		1,417		
Panel D - Quartile 4				
$\$W_{liquidity}$	320	661	0.69	7,658
$\$W_{wealth}$	1,574	2,41	0	22,418
Monthly Income 2016	1,344	1,798	0	15,169
Age 2016	36.66	10.01	18.87	71.92
Observations (Individuals)		1,407		

Table A.13: Descriptive Statistics of Wealth and Liquidity Components of the FGTS Shock Across Workers.

Notes: This table shows descriptive statistics on the wealth and liquidity components of the FGTS shock across workers by quartiles of debt-to-limit (Quartiles 1-4). Monthly income 2016 is the monthly average of the labor income from 2016:01 to 2016.11. Age 2016 denotes the average age in 2016.11. Figures of the wealth and liquidity components of the shock and monthly income 2016 are in in BRL$. As a reference, the exchange rate applied is US$1=BRL$3.2591 as of December 2016 - Exchange rate - Free - United States dollar (sale) - end of period from the Central Bank of Brazil.

A.10 - A simple two-period consumption model with endogenous constraints under FGTS shocks

To build intuition for the empirical findings, we develop a simple two-period consumption model with endogenous borrowing constraints and exogenous shocks to illiquid assets, inspired by the approach in Kaplan et al. (2014). Much like their three-period framework used to characterize hand-to-mouth (HtM) behavior, our model serves as a stylized tool to illustrate how liquidity and wealth shocks can generate heterogeneous consumption and debt responses depending on agents' access to credit. While lacking ex-ante heterogeneity, the model helps classify constrained and unconstrained agents ex post, clarifying the mechanisms through which different types of FGTS-induced shocks propagate across the population. This minimalist setup mirrors the analytical spirit of Kaplan et al.'s model, which offers conceptual clarity and guidance for interpreting consumption behavior in the presence of illiquid assets and borrowing frictions.

Benchmark Model with Cash and Credit Card Consumption: No Shock vs FGTS Shocks

We next present a benchmark two-period consumption model with standard assumptions to explore how workers allocate spending across cash and credit card channels in response to FGTS shocks. The model incorporates basic intertemporal preferences, borrowing constraints, and a distinction between immediate (cash) and deferred (credit card) consumption. By comparing outcomes under no shock, a liquidity shock, and a wealth shock, the model helps clarify the timing and direction of consumption and debt adjustments. This setup provides a foundational framework to interpret the role of FGTS access in shaping household behavior through distinct liquidity and wealth effects.

Model Setup

- Two periods: $t = 0, 1$
- Utility: $U = \log(c_0) + \beta \log(c_1)$ where $c_0 = c_0^{\text{cash}} + c_0^{\text{cc}}$
- c_0^{cash}: paid at $t = 0$ with liquid resources (income and borrowing)
- c_0^{cc}: paid at $t = 1$ with no interest cost (credit card)
- Budget constraint: agents can borrow at r_b, save at r_a, with $r_b \gg r_a$
- Constrained agents face: $b_0 \geq -\bar{b}$
- Income: y_0, y_1; FGTS shocks (when present): $f_0 > 0$

Case 1: No Shock

Period 0 constraint:

$$c_0^{\text{cash}} \leq y_0 + b_0 \Rightarrow c_0 = c_0^{\text{cash}} + c_0^{\text{cc}}$$

Period 1 constraint:

$$c_1 = y_1 - (1 + r_b)b_0 - c_0^{\text{cc}}$$

Euler equation:

$$\frac{1}{c_0} = \beta \cdot \frac{1}{c_1} \Rightarrow c_1 = \beta c_0$$

Closed-form allocations (unconstrained):

$$\begin{aligned} c_1 &= \beta c_0 \\ b_0 &= c_0 - c_0^{\text{cc}} - y_0 \\ c_0^{\text{cc}} &= y_1 - (1 + r_b)b_0 - \beta c_0 \end{aligned}$$

Constrained agent:

$$b_0 = -\bar{b}, \quad c_0^{\text{cash}} = y_0 - \bar{b}, \quad c_1 = y_1 + (1 + r_b)\bar{b} - c_0^{\text{cc}}$$

Case 2: FGTS Liquidity Shock Only

Adjustment:

$$c_0^{\text{cash}} \leq y_0 + f_0 + b_0$$

Implications:

- Unconstrained: increase c_0, reduce b_0 (avoid costly borrowing), shift away from c_0^{cc} (due to intertemporal smoothing)
- Constrained: cannot increase c_0, but uses f_0 to reduce debt and interest payments

Case 3: FGTS Wealth Shock Only

Adjustment:

$$c_1 = y_1 + f_0(1 + r_a) - (1 + r_b)b_0 - c_0^{\text{cc}}$$

Implications:

- Unconstrained: forward-looking agent increases c_0 and b_0 to bring utility forward, especially if β is high, and may rely more on c_0^{cc}
- Constrained: cannot adjust b_0 or c_0^{cash}, but may increase c_0^{cc} anticipating future repayment capacity

Comparison Matrix: Liquidity vs Wealth Shock Relative to No Shock (with $r_b \gg r_a$)

Agent Type	Δc_0	Δc_1	Δb_0	Δc_0^{cash}	Δc_0^{cc}	**Notes**
Constrained (Liquidity)	$\leftrightarrow$	$\leftrightarrow$	$\downarrow$	$\leftrightarrow$	$\leftrightarrow$	Reduces credit card use to avoid costly borrowing, with no change in total consumption.
Constrained (Wealth)	$\leftrightarrow$	$\uparrow$	$\leftrightarrow$	$\leftrightarrow$	$\uparrow$	Cannot change present consumption but reallocates to increase c_1 via future income.
Unconstrained (Liquidity)	$\uparrow$	$\uparrow$	$\downarrow$	$\uparrow$	$\downarrow$	Shifts from credit card to liquid consumption due to liquidity relief and deleveraging.
Unconstrained (Wealth)	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	Borrows more today to smooth consumption in anticipation of future wealth.

Assuming $r_b \gg r_a$ accentuates the asymmetric role of liquidity vs wealth shocks. Liquidity shocks relax contemporaneous liquidity constraints, especially for constrained agents, allowing them to avoid high borrowing costs. In contrast, wealth shocks operate through expectations and affect behavior only among unconstrained or forward-looking agents who are willing to borrow at expensive rates to smooth consumption.

Extended Model with Parameter Conditions to Match Empirical Results

We then extend the benchmark model by introducing parameter restrictions that align the theoretical predictions with our empirical findings. This simple model imposes plausible constraints—such as a low intertemporal discount factor and large borrowing costs—to replicate the observed heterogeneity in responses across constrained and unconstrained individuals. It mirrors the logic of Kaplan et al. (2014), where simplified setups are used to clarify the mechanisms behind hand-to-mouth behavior. Our version captures key features such as debt deleveraging following liquidity shocks and increased consumption and debt after wealth shocks, thereby offering a basic and tractable framework to interpret the asymmetric effects found in the data.

Model Setup

- Two periods: $t = 0, 1$
- Utility: $U = \log(c_0) + \beta \log(c_1)$, with $c_0 = c_0^{\text{cash}} + c_0^{\text{cc}}$
- Credit card consumption c_0^{cc} is paid in $t = 1$ with no interest
- Borrowing at interest rate r_b, saving at r_a, with $r_b \gg r_a$ and $r_b > 1$
- Constrained agents: $b_0 = -\bar{b}$
- Income: y_0, y_1, shocks f_0 (liquidity) and f_1 (wealth via future return)

Case 1: No Shock

Constraints:

$$c_0^{\text{cash}} \leq y_0 + b_0 \qquad c_1 = y_1 - (1 + r_b)b_0 - c_0^{\text{cc}}$$

Euler: $\frac{1}{c_0} = \beta \cdot \frac{1}{c_1}$ implies $c_1 = \beta c_0$

Case 2: Liquidity Shock Only

Unconstrained:

- Increased liquidity allows c_0 to rise, b_0 to fall
- Euler implies $\beta < 1$ ensures lower b_0 and not higher c_0

Constrained:

- $b_0 = -\bar{b}$ fixed, $c_0^{\text{cash}} = y_0 - \bar{b} + f_0$ allows lower c_0^{cc} and thus lower c_1
- Total c_0 unchanged, b_0 unchanged, satisfying no increase in consumption and debt

Case 3: Wealth Shock Only

Unconstrained:

- Future wealth increases c_1 and encourages borrowing: $c_0 \uparrow$, $b_0 \uparrow$
- Standard Euler condition confirms allocations always hold

Constrained:

- c_0 fixed, $c_1 = y_1 + f_1(1 + r_a) + (1 + r_b)\bar{b} - c_0^{\text{cc}}$
- To have $c_1 \uparrow$, agents may cut c_0^{cc} and reduce debt default
- Requires low β to prevent overconsumption today

Matrix: Allocations and Conditions

Agent Type	Δc_0	Δc_1	Δb_0	Δc_0^{cc}	Condition	**Notes**
Constrained (Liquidity)	$\leftrightarrow$	$\leftrightarrow$	$\leftrightarrow$	$\downarrow$	Always	Uses f_0 to reduce credit card use only, consistent with debt reduction and unchanged consumption.
Constrained (Wealth)	$\leftrightarrow$	$\uparrow$	$\leftrightarrow$	$\downarrow$	β low, $r_b \gg r_a$	Cuts credit card spending to raise future consumption c_1, preventing overconsumption today.
Unconstrained (Liquidity)	$\leftrightarrow$	$\uparrow$	$\downarrow$	$\downarrow$	$\beta < 1$	Shifts from credit card to cash consumption, deleverages due to liquidity relief.
Unconstrained (Wealth)	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	Always	Borrows more in anticipation of future wealth, increasing both present and future consumption.

The matrix shows how specific parameter conditions replicate the empirical findings. Constrained agents maintain current consumption, using liquidity to reduce debt only if β is sufficiently low—reflecting present bias that discourages shifting resources to the future. Unconstrained agents behave as predicted by standard intertemporal optimization: they reduce debt under liquidity shocks and increase both consumption and debt under wealth shocks. Matching these patterns requires $\beta < 1$ and $r_b \gg r_a$, which limit consumption smoothing and make borrowing attractive only with future wealth gains.

A.11 - Concepts of Debt Categories Following the SCR from the Central Bank of Brazil.

- Debt Balance: corresponds to the sum of the outstanding balance of credit agreements at the end of the month. Includes new loans granted in the reference month and the appropriation of pro-rata interest on loans and financing.
- Overdue Credit Card (Credit card – revolving): financing operations for the remaining balance after the invoice is due and withdrawal operations with cash payment made using the credit function.
- Overdraft: Revolving credit linked to a checking account, in which a certain limit of funds is made available for use by the customer in unscheduled and short-term situations, through withdrawals, checks, payments, or bank transfers. Transactions classified under this category must include automatic amortization of the outstanding balance when deposits are made into the borrower's checking account. Advance transactions to depositors or retailers, which involve use in excess of the credit limit established in the contract, are considered under this category.
- Real Estate (mortgages): Includes housing finance operations related to the requirement for direction referred to in art. 1, item I, item "a" of the regulation attached to Resolution No. 3,932 of 2010, as well as those related to resources of budgetary origin or government funds and/or programs. It also includes real estate financing transactions related to the requirement for direction referred to in Article 1, item I, item "b" of the regulation attached to Resolution No. 3,932 of 2010, as well as transactions related to other sources of resources raised on the market.
- Vehicles: Financing for the purchase of vehicles intended for consumption by the contracting individuals. The contract must contain a fiduciary transfer clause, with the financed asset serving as collateral for the transaction.

- Payroll: Credit operations for retirees and pensioners of the National Institute of Social Security (INSS) and formal workers in the private and public sectors, with retention of part of the benefit of the contractor by the INSS, the private sector business or the public body to which the server is linked, for the payment of the loan installments - payroll deduction.
- Installments (Credit Card): Includes installment payments for purchases made with a credit card or for the amounts related to the card bill, with interest charged. Includes cash withdrawals with installment payments using the credit card function.
- Personal: Line of credit to individuals not linked to the acquisition of goods or services, and without withholding part of the contractor's salary or benefit for the payment of loan installments (payroll deduction).
- Other Goods: Financing for the purchase of other goods (excluding vehicles) intended for consumption by the contracting individuals.
- Other: Refers to credit operations with earmarked and non-earmarked credit outstanding that were not classified in the previous modalities for individuals.