Identifying Demand-Driven Inflation: Evidence from Pension Withdrawals in Chile*

Borağan Aruoba[†]
University of Maryland and NBER

Gonzalo García-Trujillo[‡]
Central Bank of Chile

Daniel Guzmán [§]
University of British Columbia

Felipe Saffie [¶]
University of Virginia and NBER

July 18, 2025

Very Preliminary and Incomplete — Please Do Not Cite

Abstract

We study the inflationary consequences of large, localized liquidity shocks using a quasi-experiment from Chile's COVID-19 response. Between July 2020 and April 2021, households were allowed to withdraw up to 30% of their pension savings, injecting the equivalent of 15% of GDP into the economy. Withdrawal intensity varied sharply across municipalities due to pre-existing pension balances, generating plausibly exogenous spatial variation in liquidity exposure. Linking administrative withdrawal records with high-frequency supermarket transaction data, we construct municipality-level price indexes for over 70 food products. We find that areas with larger withdrawals experienced significantly greater and more persistent food price inflation. Input costs rose more slowly and were only weakly correlated with withdrawal intensity, consistent with a demand-driven mechanism and limited pass-through. The inflationary effect persists after controlling for household debt and supplier costs. Our findings demonstrate how institutional variation and granular administrative data can uncover the demand-side origins of post-COVID inflation and inform the design of liquidity policies.

*The views expressed are those of the author and do not necessarily represent the views of the Central Bank of Chile or its board members. This study was developed within the scope of the research agenda conducted by the Central Bank of Chile (CBC) in economic and financial affairs of its competence. The CBC has access to anonymized information from various public and private entities, by virtue of collaboration agreements signed with these institutions. We thank Maria Antonia Yung for excellent research assistance.

[†]aruoba@umd.edu
[‡]ggarciat@bcentral.cl
[§]guzmangirondaniel@gmail.com
[¶]saffief@darden.virginia.edu

1 Introduction

The global inflation surge that followed the COVID-19 pandemic has renewed fundamental questions about the drivers of price dynamics and the appropriate policy response to macroeconomic shocks. While early price increases were widely attributed to supply-side disruptions—such as bottlenecks in global logistics, commodity spikes, and labor shortages—many countries also implemented aggressive fiscal and liquidity support programs. These included large-scale stimulus transfers, unemployment benefit expansions, tax deferrals, and—in some cases—early access to retirement savings. Understanding whether and how such demand-side interventions contributed to inflation is critical for the design of monetary and fiscal frameworks, especially in emerging markets where macroprudential and liquidity policies increasingly intersect.

In this paper, we provide new evidence that large, localized liquidity shocks can generate persistent, geographically concentrated inflation. We study a rare quasi-experiment from Chile's COVID-19 policy response, which authorized three rounds of early pension withdrawals between July 2020 and April 2021. Eligible individuals could withdraw up to 10% of their retirement savings in each round, with total disbursements equivalent to roughly 15% of GDP. Critically, the intensity of withdrawals varied sharply across municipalities due to pre-existing differences in pension balances. This variation was not targeted by design and was largely unanticipated, generating plausibly exogenous spatial heterogeneity in household liquidity.

We use this institutional variation to study how localized liquidity shocks affect consumer prices, input costs, and household balance sheets. Our empirical strategy combines three sources of administrative microdata: (i) individual-level withdrawal records from the pension system; (ii) daily transaction-level supermarket data, including shelf and wholesale prices; and (iii) anonymized credit registry data on household debt. The merged dataset yields a municipality-level panel covering 345 locations, more than 280,000 products, and 73 food categories from January 2018 through December 2022. The use of transaction-level prices and cost data—rather than aggregate inflation series—allows us to precisely track how prices respond to localized variation in liquidity.

We find that areas with greater withdrawal intensity experienced significantly more food price inflation. A 1% increase in cumulative withdrawals is associated with a 3% increase in local food prices over the next two years. These effects emerge quickly after the first withdrawal round and persist long after the last. Our estimates are robust to alternative treatment definitions, weighting methods, and balanced panel restrictions. In contrast, wholesale input costs arise more slowly, show weaker correlation with withdrawal intensity, and are unlikely to explain the observed price dynamics. We also document a significant decline in household debt in high-withdrawal municipalities, consistent with deleveraging. Further, price responses were attenuated in areas with higher pre-existing debt levels, suggesting that credit constraints shaped the marginal propensity to spend.

To assess whether these price responses reflect demand, we estimate a decomposition specification that includes both supplier costs and household debt as controls. The effect of withdrawals on prices remains large and statistically significant, pointing to a pure, residual demand

channel. Taken together, the results provide microeconomic evidence that localized liquidity injections—arising from household access to illiquid savings—can produce persistent inflation, even in the absence of traditional fiscal stimulus.

We interpret these findings using a simple two-period model with behavioral heterogeneity and a mandatory savings institution. In the model, rational households treat withdrawals as intertemporally neutral, while constrained agents behave as if the liquidity were windfall income. Consumption responses differ across types, and—under sticky prices—generate inflation via a standard New Keynesian Phillips Curve. The model predicts stronger inflation in municipalities with higher withdrawal intensity and lower baseline debt—precisely the patterns we observe in the data. While intentionally stylized, the framework provides a disciplined lens for interpreting the data and complements recent structural models of demand-side inflation.

Literature Review. This paper contributes to four intersecting literatures. First, it adds to recent efforts to decompose inflation into supply- and demand-driven components, as in Shapiro (2020), di Giovanni et al. (2023), Acemoglu and Farhi (2020), Baqaee and Farhi (2022), and Cesa-Bianchi and Ferrero (2021). Second, it speaks to empirical work on fiscal stimulus and liquidity shocks during COVID. Hamilton et al. (2023) document the effects of pension withdrawals in Australia; Miranda-Pinto et al. (2023) analyze heterogeneity in withdrawal effects in Chile; and Weinberg (2023), Pecher (2021), and Elgin et al. (2023) examine other forms of pandemic stimulus. Third, it connects to research on behavioral responses to savings access, including Gelber et al. (2019), Beshears et al. (2021), and Ganong et al. (2021), who emphasize the liquidity-sensitivity of household behavior. Finally, our empirical facts and model are consistent with structural frameworks that use microdata to study inflation heterogeneity and demand amplification, including MacKay and Miller (2021) and Cerrato and Gitti (2022). While our theoretical approach is deliberately minimal, it offers an internally consistent account of the mechanisms at play and complements these broader modeling efforts.

Outline. Section 2 describes the institutional setting and data sources. Section 3 presents our empirical strategy and core findings. Section 4 introduces the theoretical framework. Section 5 concludes and outlines directions for further quantitative analysis and policy interpretation.

2 Data and Context

We study how consumer prices evolved differentially across Chilean municipalities following large, heterogeneous withdrawals from pension savings accounts. To do so, we combine multiple administrative and transactional data sources that allow us to link the amount of pension savings withdrawn by residents in each municipality to the prices of food products sold by local supermarkets. All administrative data used in this analysis were accessed through the Central Bank of Chile (CBC).[1]

[1]To ensure the privacy of workers and firms, the CBC requires that the extraction, development, and publication of results prevent the identification—direct or indirect—of any natural or legal persons. Disaggregated data were processed by CBC officials. All analysis was conducted by the authors and did not involve, nor compromise, the Superintendency of Pensions or the Chilean Internal Revenue Service.

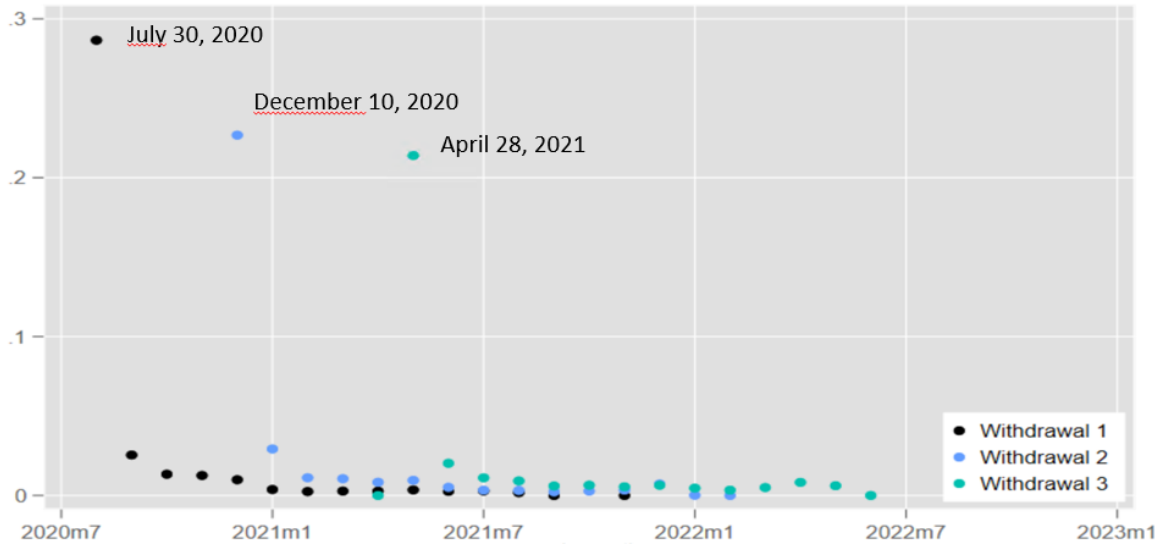


Figure 1: Timing and Intensity of Pension Withdrawals

Note: Each dot represents the fraction withdrawn each month from the total withdrawal amount.

2.1 Pension Withdrawals as a Policy Shock

In response to the economic crisis caused by COVID-19, Chile implemented a series of exceptional measures to support household liquidity. Most notably, Congress passed three separate laws in 2020 and 2021 allowing individuals to withdraw up to 10% of their accumulated savings in the privately managed pension system. Since 1981, Chile's pension system has been based on individual capitalization, with workers contributing to personal accounts managed by private Pension Fund Administrators (AFPs). Upon retirement, these funds are used to finance annuities or programmed withdrawals. Appendix A.1 provides further details on the institutional setup of the Chilean pension system.

The three rounds of pension withdrawals were approved in July 2020, December 2020, and April 2021. Figure 1 shows the timing and intensity of the withdrawals, measured in monthly flows. Disbursements were heavily front-loaded, with most funds withdrawn in the first month following each law's approval. The first round in July 2020 came as a political surprise. In total, the three rounds injected approximately $48 billion USD into the economy—equivalent to 15.3% of Chilean GDP.

To construct municipality-level withdrawal data, we use anonymized administrative microdata from the Superintendency of Pensions, which records the amount each individual withdrew in each of the three rounds. To assign each withdrawal to a municipality of residence, we use a unique anonymized identifier provided by CBC officials. This identifier allows us to merge the pension withdrawal records with the Chilean Unemployment Insurance (UI) dataset, which includes age, gender, education level, municipality of residence, and taxable income for the universe of formal workers. This linkage enables us to construct a high-resolution panel of total withdrawal amounts by municipality over time. Appendix A.2 describes the construction of this

panel in greater detail.

2.2 Supermarket Transaction Data and Price Index Construction

To measure local price dynamics, we use B2B electronic invoice data (Factura Electrónica) from the Chilean tax authority (SII), accessed via the Central Bank of Chile.[2] These data cover the universe of firm-to-firm transactions and include detailed information on product descriptions, quantities, transaction dates, buyer and seller IDs, and prices. Although these invoices do not capture final consumer purchases, Chilean supermarkets charge identical prices to both firms and households, allowing us to infer shelf prices with high accuracy. We follow closely the approach developed by Aruoba et al. (2024) to construct price series using this firm-to-firm transaction data.

We focus on food products, which are widely consumed, transacted at high frequency, and constitute a major share of supermarket sales. We restrict the analysis to food categories that overlap with the official national food CPI basket. Prices are constructed at the daily level using the modal transaction price for each product–municipality–supermarket combination. These are then aggregated into monthly product-level price indexes for each municipality.

The resulting dataset is an unbalanced panel covering 73 food categories (out of 76), 345 municipalities (out of 365), and more than 280,000 distinct products between January 2018 and December 2022. Appendix B.1 provides additional details on the invoice data, and Appendix B.2 outlines the filtering and construction procedures used to build the price index.

To validate our measure, we compare the constructed national food price index to the official CPI food index. Our price index tracks well the official CPI index over time, particularly around the pension withdrawal episodes. Figure B.1 in Appendix B.2 presents this comparison.

2.3 Local Cost Index Construction

In addition to shelf prices, the Factura data allow us to observe the purchase prices that supermarkets pay their suppliers. For each product–supermarket combination, we first identify the relevant set of suppliers and construct a national-level cost index using a weighted average of supplier prices. We then build a product–municipality cost index by aggregating these national supplier prices, weighting by each supermarket's share of sales within the municipality. The cleaning and filtering procedures used mirror those applied in the construction of the price index. Appendix B.3 provides a detailed description of this methodology and compares the resulting index to the official food CPI.

The final cost index is an unbalanced panel covering 73 food categories (out of 76), 345 municipalities (out of 365), and over 140,000 products. We construct a weighted national cost index by aggregating product-level indexes using the official food CPI category weights. As shown in Figure B.2 (Appendix B.3), this index closely tracks the official food CPI over time.

[2]The information contained in the SII database originates from self-declared taxpayer filings; the veracity of the data is therefore not the responsibility of the tax authority.

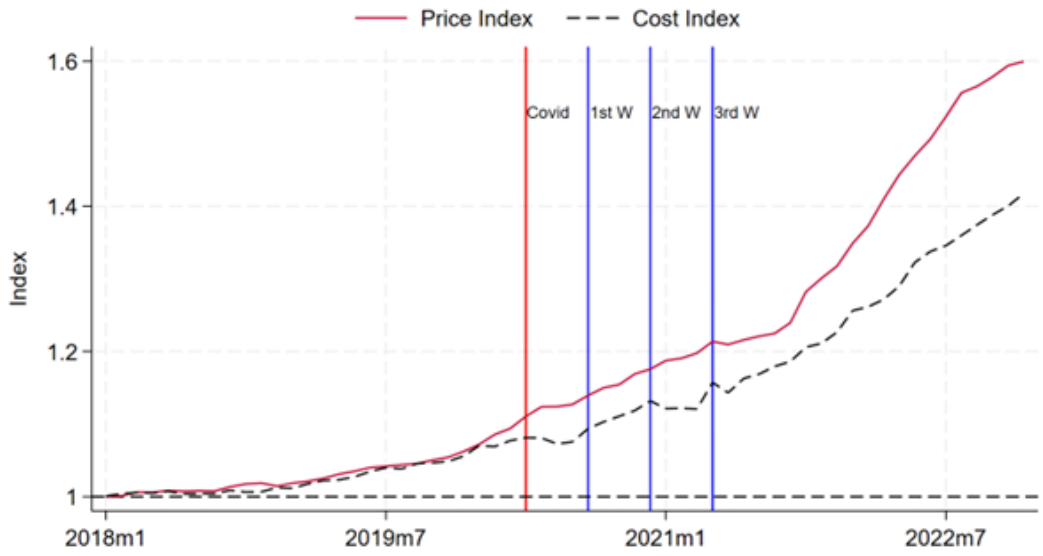


Figure 2: Evolution of Food Prices and Costs, 2018–2022

Appendix B.4 presents an alternative approach in which we construct the cost index by matching each product–municipality–supermarket observation to its closest supplier based on geographic proximity.

2.4 Joint Evolution of Prices and Costs

Figure 2 plots the national average food price index (constructed from supermarket sales) alongside the corresponding cost index (based on supplier purchase prices). The red line marks the onset of the COVID-19 pandemic in Chile (March 2020), and the three vertical lines indicate the timing of the pension withdrawal rounds.

Two patterns stand out. First, we observe distinct episodes of accelerated price increases: one emerging before the pandemic, and a second, more sustained acceleration beginning in the second half of 2021—after the third withdrawal round. Second, and more strikingly, a persistent gap opens between the price and cost indexes following the withdrawals. While costs rose moderately, final prices began rising faster and remained elevated relative to underlying input costs.

This divergence is visible in the raw data and offers early, suggestive evidence that post-COVID inflation in Chile was not driven solely by supply-side pressures. The timing aligns closely with the disbursement of pension withdrawals, pointing to a potentially powerful demand-side effect: liquidity injections into household balance sheets may have fueled localized consumption booms and upward price pressures.

While this visual pattern is promising, it is not yet conclusive. What follows is a formal empirical strategy that leverages a unique quasi-experiment—three surprise, spatially heterogeneous pension withdrawals—to isolate demand-driven inflation effects. The sharp geographic variation in withdrawal intensity, combined with high-frequency, local price data, offers an opportunity to identify causal demand effects with exceptional precision—something few settings

in the literature can match.

2.5 Debt, Liquidity Constraints, and the Nature of the Shock

Unlike traditional fiscal stimulus—such as direct transfers funded by the treasury—the pension withdrawals in Chile represented the early liquidation of households' own retirement savings. This distinction has critical implications for household behavior. If savings were optimal and agents were unconstrained, the withdrawals would not materially alter lifetime resources and should have been mostly saved or used to pay down debt. But if households were liquidity constrained, the withdrawals would behave like windfall income, fueling immediate consumption and inflationary pressure. In this context, existing debt burdens become a key mediator of spending responses: more indebted households may be more likely to use the funds to repay liabilities rather than to increase consumption.

Debt may also play a more subtle role. For constrained households facing delinquency or limited access to credit, the withdrawals could facilitate a return to credit markets—allowing agents to exit morosity, re-establish borrowing capacity, and smooth consumption over time. As such, debt is relevant both as an outcome variable (to detect repayment) and as a conditioning variable for heterogeneity in inflation responses.

We exploit a uniquely comprehensive dataset on household liabilities from the Report of Consolidated Debt, maintained by the Financial Market Commission (CMF) of Chile. This dataset contains the universe of individual and firm-level debts—including mortgage, consumer, and commercial loans—and differentiates between current and delinquent balances. The CMF compiles this data monthly using mandatory reports submitted by all supervised institutions, including banks, cooperatives, and money transfer subsidiaries.[3]

To study how debt evolved around the pension withdrawals, we construct a municipality-level index of household debt stocks between January 2019 and December 2022. Using anonymized credit registry microdata accessed via the Central Bank, we compute total consumer debt at the individual level. We then merge this with the Unemployment Insurance dataset using a common anonymized identifier to recover each individual's municipality of residence. This enables us to aggregate debt balances to the municipality-month level.

Figure 3 plots the evolution of total household debt alongside the timing of the withdrawal episodes (indicated by vertical lines). We observe a sharp reduction in aggregate debt immediately following the first round in August 2020, with the stock falling by approximately 1.4%. The number of individuals with recorded liabilities also declined—from 5.9 million to 5.5 million—before gradually recovering over the subsequent year. Appendix C.1 presents the detailed evolution. This pattern suggests that a sizable share of households used the withdrawals to reduce debt burdens, particularly in the immediate aftermath of the first withdrawal.

[3]Article 14 of the General Banking Law obliges the CMF to maintain permanent, consolidated records of all debtors in the financial system. This supervisory function ensures oversight over prudential soundness and depositor protection.



Figure 3: Evolution of Aggregate Household Debt, 2019–2022

This final dataset completes the construction of a high-resolution panel that forms the empirical foundation of our analysis. At the municipality level, we observe the intensity of pension withdrawals, based on administrative microdata from individual pension accounts. We match this to retail price indexes built from supermarket-level sales records, and to cost indexes constructed from supplier-level purchase prices for the same set of products. Finally, we incorporate detailed information on household debt stocks, using anonymized credit registry microdata linked to place of residence. The resulting dataset allows us to study the joint evolution of liquidity, spending, prices, and liabilities across space and time, in a setting where the policy shock varies exogenously across locations. This unique combination of institutional variation and administrative granularity enables a sharp empirical design—one that can disentangle demand-driven inflation from other sources of price pressure and assess the role of debt as both a constraint and an outcome.

3 Empirical Analysis

3.1 Identification Strategy

We investigate whether municipalities that experienced larger pension withdrawals also experienced greater local inflation in the months that followed. Our identification strategy relies on the fact that all regions in Chile were exposed to a common macroeconomic environment during this period—including global supply chain disruptions, national fiscal and monetary policy, and central bank communications—yet faced markedly different magnitudes of liquidity injection due to heterogeneity in pre-existing pension balances.

Because prices in our dataset are measured at the municipality level, we can exploit this cross-sectional variation to test whether areas with larger withdrawals experienced systematically higher price increases. If households in those municipalities increased their spending more—due to the additional liquidity—then prices for identical goods should have risen more rapidly in those areas. This provides a direct test of localized demand-driven inflation.

Crucially, the strategy compares otherwise similar municipalities that differed only in the intensity of the policy shock. The main threat to identification would be the presence of local supply shocks that are correlated with withdrawal intensity. However, we find no evidence of such a correlation. Moreover, any national or sectoral supply pressures—such as import costs, exchange rate fluctuations, or aggregate supply bottlenecks—are absorbed by our time-by-product fixed effects. These controls flexibly capture all common shocks at the product-month level and ensure that the residual variation in inflation is driven by differential exposure to pension withdrawals.

3.2 Empirical Specification

To estimate the effect of pension withdrawals on local inflation dynamics, we implement an event study specification at the product–municipality level:

$$P_{i,j,t} = \alpha + \left(\sum_{m=-G}^{M} \beta_m \cdot D_{t-m} \cdot \log W_i \right) + X_{i,t} + \gamma_{j,t} + \epsilon_{i,j,t} \tag{1}$$

Here, $P_{i,j,t}$ denotes the log price index of product j in municipality i at time t. The variable W_i is the logarithm of the total cumulative amount withdrawn in municipality i across all three rounds of pension withdrawals. The dummies D_{t-m} indicate event time m relative to the treatment date t_0, which we define as August 2020—the start of the first withdrawal round. The interaction $D_{t-m} \cdot \log W_i$ captures variation in exposure to the policy over time, across municipalities with different withdrawal intensities.

The coefficients β_m trace the dynamic effect of the liquidity shock. Because both the dependent variable and the treatment intensity are in logs, these coefficients can be interpreted as elasticities: β_m measures the percent change in prices associated with a 1% increase in cumulative pension withdrawals, m months relative to the treatment. We normalize these effects relative to the period immediately before treatment, setting $\beta_{-1} = 0$, so that all estimates are interpreted as deviations from the month prior to the first withdrawal.

The vector $X_{i,t}$ includes municipality-level controls such as population and average income, which account for differences in underlying demand capacity. We also include product-by-time fixed effects $\gamma_{j,t}$, which absorb any shocks common to all municipalities for a given product in a given month. These fixed effects flexibly control for national inflation trends, sector-specific supply shocks, changes in import prices, and monetary or fiscal policy shifts that affect all regions simultaneously.

Specification choices. The set $\{D_{t-m}\}_{m=-G}^{M}$ defines the window of event time dummies centered around t_0 (August 2020), which is the same for all municipalities. Each β_m thus estimates the differential effect of withdrawal intensity on prices, m months before or after the initial shock. As noted above, the pre-treatment period ($m = -1$) serves as the reference category.

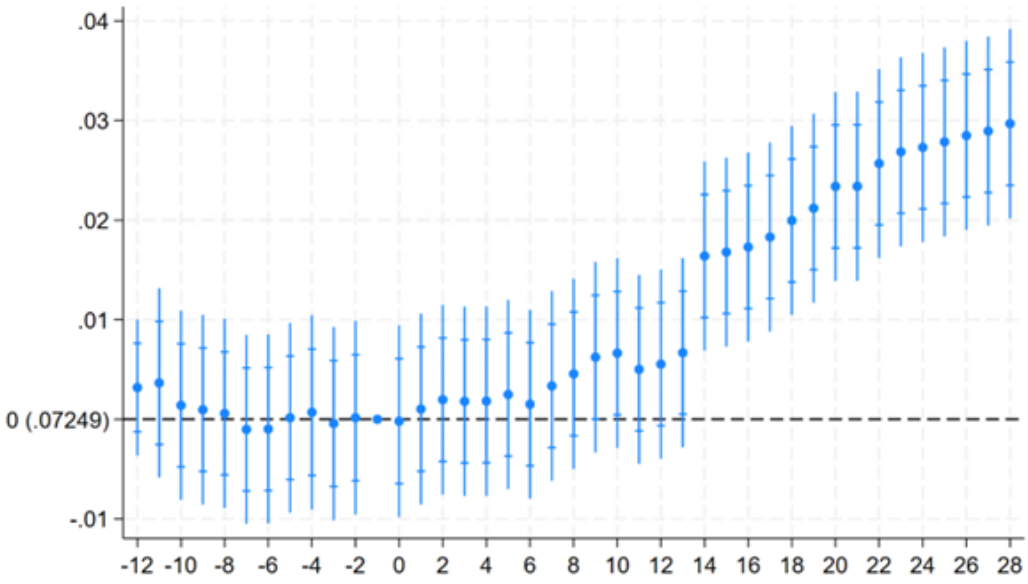


Figure 4: Event Study: Price Index Response by Withdrawal Intensity

Note: Figure reports the resulting β_m coefficients from equation 1, with 95% confidence intervals. The dependent variable is the log of the product-level price index at the municipality level. β_m coefficients represent the elasticity of prices with respect to a 1% increase in cumulative withdrawals, at each month m relative to the August 2020 treatment date. Product-by-time fixed effects are included.

Source of identification. Unlike a typical event study, where units are treated at different times, all municipalities in our setting experience the policy shock at the same time. Identification comes instead from variation in treatment intensity: the amount withdrawn varies across locations due to differences in pension balances, income levels, and withdrawal behavior. This variation is plausibly exogenous to short-run inflationary dynamics and provides the basis for our causal estimates.

3.3 Main Result: Price Inflation and Withdrawals

We begin the analysis by estimating equation 1. Our results show that municipalities with higher withdrawal exposure experienced significantly greater increases after the withdrawal events in local food prices.

Figure 4 displays the dynamic response of food prices to withdrawal intensity. The horizontal axis reflects time relative to the initial withdrawal round (August 2020), and the vertical axis reports the estimated elasticity for each month. Shortly after the first withdrawal, prices begin to diverge across municipalities, with high-withdrawal areas experiencing faster price growth. This gap grows steadily over time and remains persistent throughout the two-year post-treatment window. By December 2022, a 1% increase in cumulative withdrawals is associated with nearly a 3% increase in food prices.

Because the coefficients β_m can be interpreted as elasticities, these results quantify the

marginal inflationary effect of additional liquidity: even small differences in withdrawal intensity translate into meaningful price variation across space.

Importantly, these estimates are identified conditional on a rich set of controls and fixed effects. We control for observable differences across municipalities—including population size and average labor income—to account for differences in baseline demand capacity. In addition, the inclusion of product-by-time fixed effects $\gamma_{j,t}$ absorbs all common shocks at the product-month level, including changes in global food prices, national monetary or fiscal policy, and supply chain disruptions. For any alternative explanation to confound these results, it would have to be correlated with withdrawal intensity across municipalities, while being orthogonal to both our control variables and product-level inflation trends.

Taken together, these findings provide strong evidence of localized demand-driven inflation in the aftermath of the pension withdrawals. The persistence of the effect—extending well beyond the initial disbursement period—suggests that the liquidity shock had a lasting impact on consumer behavior and pricing dynamics. This serves as direct microeconomic evidence for a demand-based inflation channel operating during Chile's post-COVID recovery.

3.4 Result 2: Cost Index Inflation

Next, we examine whether the pension withdrawals had any effect on the local cost index, constructed from supermarkets' purchase prices. The idea is that if supermarket prices rose due to local demand pressures, these changes may have been passed upstream to suppliers—particularly if supermarkets increased their orders or faced tightening wholesale margins. To investigate this, we estimate the same specification as in equation 1, but replace the dependent variable with the log of the cost index for each product category j in municipality i at time t.

Figure 5 shows the estimated response of local cost indices to withdrawal intensity. While aggregate costs did rise during the post-COVID period (as shown previously in Figure 2), the event study reveals that this increase is not systematically related to variation in local withdrawals. The coefficients are generally small and statistically insignificant across most of the post-treatment period. This suggests that input costs did not respond meaningfully to localized demand shocks at the municipality level.

A plausible explanation for this result lies in the structure of the supply chain. Many suppliers serve multiple supermarket locations across different municipalities. As a result, their pricing behavior is more likely influenced by national or average demand conditions, rather than by localized liquidity surges. In this sense, the geographic granularity of the cost index may be less informative about local demand pressures, even if total national costs are rising.

Nonetheless, this variable remains an important input for the broader analysis. In principle, changes in supplier costs could affect consumer prices through a pass-through mechanism, and cost dynamics could differ across space depending on supply frictions or contract structures. While we find limited evidence that withdrawal intensity affected costs directly, we will include the cost index as a control in later regressions to ensure that our main price results are not confounded by omitted variation in input costs.

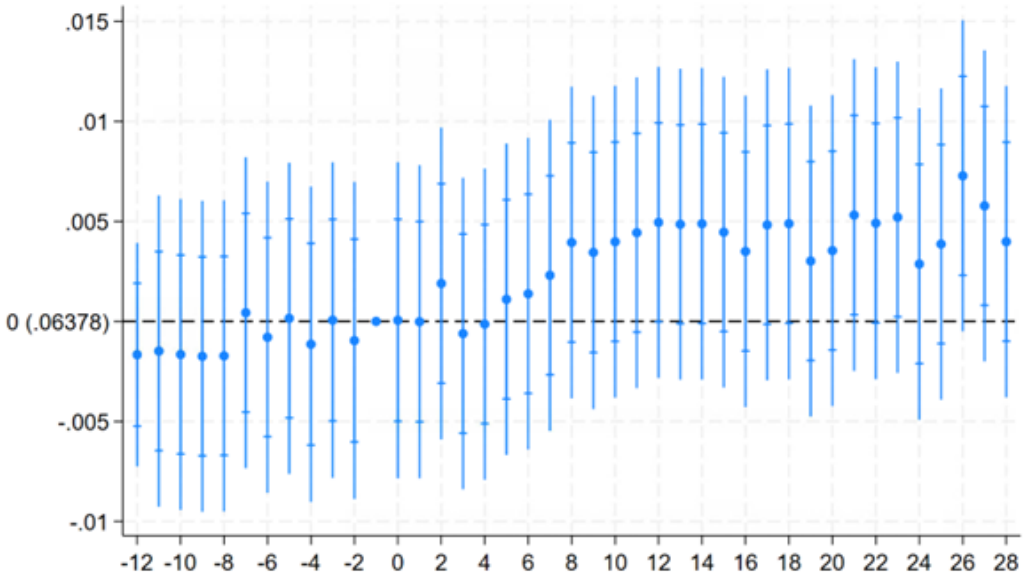


Figure 5: Event Study: Cost Index Response by Withdrawal Intensity

Note: Figure reports the resulting β_m coefficients with 95% confidence intervals. The dependent variable is the log of the product-level cost index at the municipality level. Time-by-product fixed effects are included. Coefficients represent the elasticity of costs with respect to a 1% increase in cumulative pension withdrawals.

3.5 Result 3: Withdrawals and Debt Repayment

In addition to prices and costs, household debt is a key outcome for understanding how pension withdrawals affected consumption and inflation. Because the policy involved the early liquidation of individual retirement savings rather than new fiscal transfers, its effect on spending behavior depends critically on whether households were liquidity-constrained. In unconstrained households, one would expect little or no consumption response to such a withdrawal; in contrast, constrained households might use the liquidity to repay existing debts, restore credit access, or smooth consumption.

To assess whether households responded to the withdrawals by deleveraging, we estimate the effect of withdrawal intensity on the evolution of consumer debt across municipalities. Specifically, we re-estimate equation 1, using the log of the municipality-level debt stock as the dependent variable. The debt measure is constructed from the credit registry microdata described in Section 2, aggregated monthly at the municipality level.

Figure 6 shows the dynamic response of debt stocks to the withdrawal shock. We observe a statistically significant decline in aggregate debt in municipalities with higher withdrawal intensity, beginning immediately after the first withdrawal round. This suggests that households used a meaningful portion of the liquidity to repay existing liabilities, particularly in the early post-withdrawal period.

The debt response is relevant not only as a behavioral outcome in its own right, but also for interpreting the inflation results in Section 3. If a substantial share of the liquidity was directed toward debt repayment—especially in more indebted areas—then the marginal propensity to

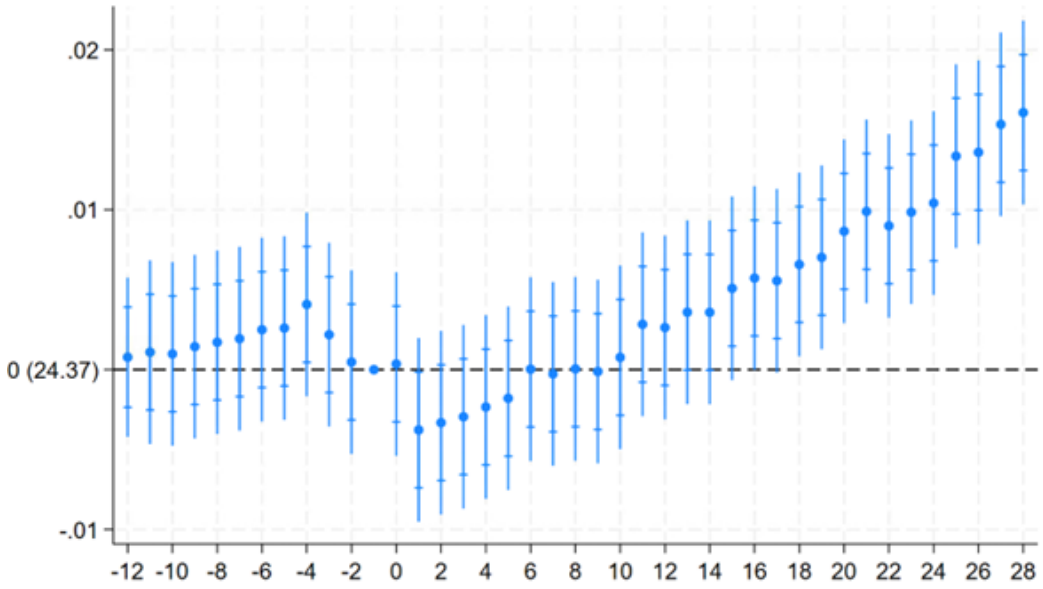


Figure 6: Event Study: Debt Response by Withdrawal Intensity

Note: Figure reports the resulting β_m coefficients from estimating equation 1, with debt stock as the dependent variable. Coefficients represent the elasticity of municipal debt levels with respect to a 1% increase in cumulative pension withdrawals.

consume out of withdrawals would vary systematically across space. This introduces an important channel of heterogeneity: the inflationary impact of the withdrawals may have been muted in municipalities with higher baseline debt. We explore this interaction explicitly in the next subsection.

More broadly, debt may also mediate access to future credit, particularly for households that used the withdrawal to exit delinquency. To account for these effects, we will include pre-existing debt as a control in subsequent regressions. This helps ensure that our inflation estimates are not confounded by local differences in credit constraints or consumption-smoothing behavior.

3.6 Result 4: Decomposing Demand and Cost Effects

Finally, we estimate an augmented version of our baseline specification to isolate the portion of price inflation that can be attributed purely to local demand, net of upstream cost pressures and debt dynamics. To do so, we extend equation 1 by including the local cost index and household debt stock as additional controls:

$$P_{i,j,t} = \alpha + \left(\sum_{m=-G}^{M} \beta_m \cdot D_{t-m} \cdot \log W_i \right) + \theta_1 \cdot \text{Cost}_{i,j,t} + \theta_2 \cdot \text{Debt}_i + X_{i,t} + \gamma_{j,t} + \epsilon_{i,j,t} \quad (2)$$

The inclusion of $\text{Cost}_{i,j,t}$ accounts for potential pass-through from wholesale prices to consumer prices, while Debt_i controls for differences in consumption-smoothing behavior across

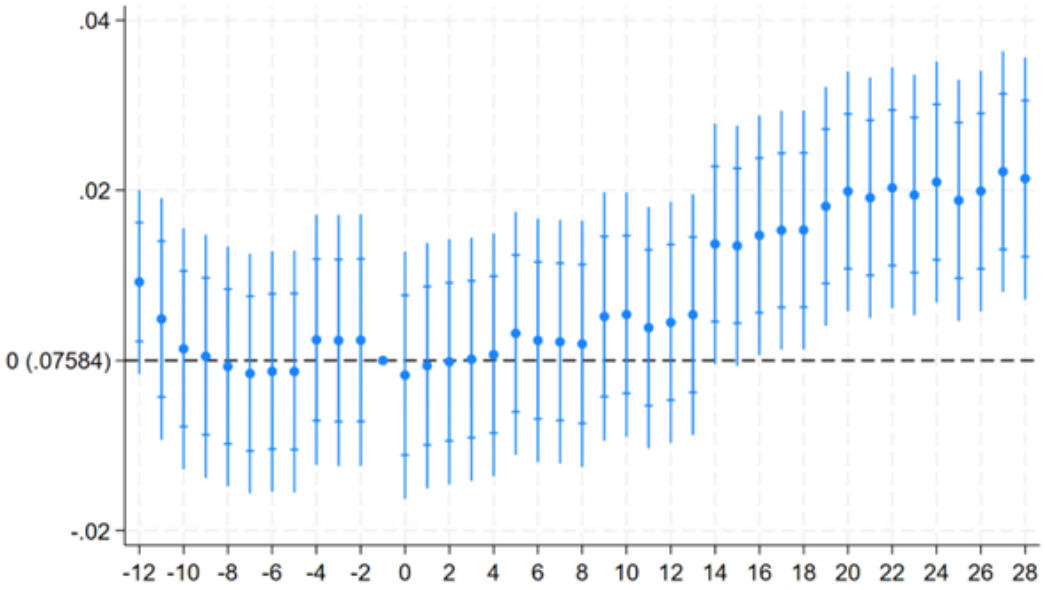


Figure 7: Event Study: Price Index Response by Withdrawal Intensity (with cost and debt as controls)

Note: Event study coefficients β_m estimated from equation 2, which controls for product-level input costs and household debt. Coefficients represent the elasticity of product-level prices with respect to a 1% increase in cumulative withdrawals.

municipalities. These variables help rule out alternative explanations for the observed inflation patterns—namely, that rising prices were driven by upstream supply costs or regional variation in debt repayment.

We interpret the coefficients β_m in this regression as the *net demand effect*: the portion of local price inflation attributable to withdrawal-induced demand that is not mediated by supplier cost shocks or household deleveraging. Figure 7 plots the dynamic response of prices to withdrawal intensity from this enriched specification.

The results in Figure 7 show that the estimated demand effect remains robust: the withdrawal coefficients β_m are statistically significant and closely track the magnitudes found in our earlier, bivariate specification. Although the point estimates are slightly attenuated, they still imply a persistent and economically meaningful relationship between withdrawals and local prices. This confirms that demand—not costs or debt—is the primary driver of the inflationary response.

Taken together, these results strengthen our interpretation of the earlier findings. The rise in prices observed in high-withdrawal municipalities cannot be explained by upstream supply shocks or regional differences in debt usage. Instead, they reflect a localized increase in consumer demand triggered by access to previously illiquid retirement savings. This decomposition offers direct microeconomic evidence that the post-COVID inflation in Chile was, at least in part, demand-driven.

3.7 Robustness and Additional Results

To assess the reliability of our findings, we conduct a series of robustness checks that address potential concerns related to data limitations, alternative modeling assumptions, and omitted variation in cost or debt dynamics. Across all specifications, we continue to find a statistically and economically significant relationship between local withdrawal intensity and food price inflation, consistent with the demand-side interpretation laid out in our main results. Full robustness results are reported in Appendix D.

We begin by addressing potential bias from missing data. In the baseline analysis, we include product–municipality pairs only if they have at least 90% monthly coverage (i.e., fewer than 6 missing months out of 60). To ensure that this filter does not introduce bias, we re-estimate equation 1 using a fully balanced panel that excludes any municipality–product pair with even a single missing observation. As shown in Appendix D.1, the results remain robust. The inflation elasticity falls modestly from 3% to 2.5%, but the dynamic pattern and significance persist, confirming that missing observations are not driving the results.

Next, we explore an alternative treatment definition that allows for progressive accumulation of withdrawals over time, rather than treating all three rounds as a lump-sum event occurring in August 2020. In this alternative specification, the treatment variable W_{it} updates each month to reflect cumulative withdrawals. As shown in Appendix D.2, this specification yields results that are consistent with the baseline, but slightly stronger: the price response becomes statistically significant earlier and reaches a somewhat larger magnitude. This finding supports the interpretation that the liquidity effect builds as withdrawals accumulate.

We also assess the sensitivity of our results to how the cost index is constructed. In the baseline, supermarket purchase prices are aggregated nationally and assigned to each municipality based on local supermarket market shares. As an alternative, we assign each supermarket the cost of its geographically closest supplier and aggregate to the municipality level. This approach better captures spatial variation in supplier relationships. Re-estimating the cost response using this new index (Appendix D.3) yields qualitatively identical results: there is no evidence of a cost response to withdrawals, reinforcing our conclusion that cost pass-through does not drive the observed inflation pattern.

In addition, we verify that our results are not sensitive to the weighting scheme used in index construction. Our baseline price and cost indexes use the number of transactions within each product category as weights. We re-estimate the analysis using value-of-sales weights instead, which give more prominence to higher-value goods. The results, shown in Appendix D.4, are unchanged in both sign and magnitude, confirming that the measured inflation response is not an artifact of the weighting strategy.

We also disaggregate the debt response by type to better understand the mechanisms behind deleveraging. Re-estimating the specification in Figure 6 separately for commercial, consumer, and mortgage debt (Appendix D.5), we find distinct patterns. Commercial debt falls sharply but briefly following the first withdrawal. Consumer debt exhibits a larger and more persistent decline, with levels gradually returning to baseline after roughly two years. Mortgage debt also

declines significantly in the early months post-withdrawal. These patterns suggest that pension withdrawals were used broadly across debt categories, and that the consumer debt margin in particular may have freed up constrained households for additional consumption over time.

In sum, the inflationary effects of pension withdrawals remain consistently strong across a wide array of empirical choices. These checks reinforce the interpretation that localized liquidity injections triggered persistent price increases—an effect that cannot be explained by data artifacts, supply shocks, or cost pass-through alone.

4 A TANK Model with Mandatory Savings

To provide theoretical grounding for our empirical findings, we present a simple two-period TANK (Two-Agent New Keynesian) model with mandatory savings. This framework captures how heterogeneity in household consumption behavior—interacting with institutional features of forced savings—can generate inflationary responses to liquidity shocks. The model helps rationalize why municipalities with higher pension withdrawals experienced stronger and more persistent inflation, consistent with the demand-driven mechanisms documented in Section 3. Our approach builds on the literature studying behavioral frictions in retirement savings decisions (e.g., Gelber et al., 2019; Beshears et al., 2018).

4.1 Environment

The economy consists of a unit mass of households, divided into two types. A fraction $\lambda \in (0, 1)$ are *behavioral* agents who consume myopically: they are fully rational within each period but exhibit a low subjective discount factor $\hat{\beta} \ll 1$, leading them to treat liquidity windfalls as immediate income. The remaining share, $1 - \lambda$, are *rational* agents who optimize consumption intertemporally with standard log utility and time discount factor β.

Each household receives an income of 1 in both periods. A fraction $s \in (0, 1)$ of period-0 income is mandatorily saved in a retirement account. Under normal circumstances, these savings are inaccessible until period 1. In the model's policy experiment, the government authorizes an early withdrawal of a share $\phi \in [0, 1]$ of the saved amount in period 0. The key question is how this liquidity release affects aggregate demand and inflation in period 0.

We assume prices are sticky in period 0 and flexible in period 1. Output is fully demand-determined in period 0, and inflation follows a standard New Keynesian Phillips Curve:

$$\pi_0 = \kappa \left(C_0 - 1 \right),$$

where $\kappa > 0$ is the slope of the Phillips curve and C_0 denotes aggregate consumption in period 0. Since income is normalized to 1, deviations of C_0 from 1 capture the extent of demand-driven inflationary pressure.

4.2 Household Behavior

Behavioral agents treat the savings mandate as a tax and consume all disposable resources each period without intertemporal smoothing. Their consumption is:

$$C_0^B = (1-s) + \phi s, \qquad C_1^B = (1-s) + (1-\phi)s.$$

That is, they treat the withdrawn portion ϕs as extra liquidity in period 0, and the remaining $(1-\phi)s$ as future consumption, without accounting for the intertemporal implications of the policy.

Rational agents, by contrast, solve:

$$\max_{C_0^R, C_1^R} \log C_0^R + \beta \log C_1^R,$$

subject to the intertemporal budget constraint:

$$C_0^R + \frac{C_1^R}{R} = (1-s) + \phi s + \frac{(1-\phi)s}{R},$$

where R is the gross real interest rate. The Euler equation implies:

$$\frac{1}{C_0^R} = \beta R \cdot \frac{1}{C_1^R} \quad \Rightarrow \quad C_1^R = \beta R\, C_0^R.$$

Substituting into the budget constraint yields:

$$C_0^R(1+\beta) = (1-s) + \phi s + \frac{(1-\phi)s}{R}, \qquad \Rightarrow \qquad C_0^R = \frac{(1-s) + \phi s + \frac{(1-\phi)s}{R}}{1+\beta}.$$

4.3 Aggregate Demand and Inflation

Aggregate consumption in period 0 is the weighted average of behavioral and rational consumption:

$$C_0 = \lambda C_0^B + (1-\lambda) C_0^R.$$

Substituting in the expressions above:

$$C_0 = \lambda\left[(1-s) + \phi s\right] + (1-\lambda) \cdot \frac{(1-s) + \phi s + \frac{(1-\phi)s}{R}}{1+\beta}.$$

Plugging this into the Phillips curve gives:

$$\pi_0 = \kappa \left[\lambda\left((1-s) + \phi s\right) + (1-\lambda) \cdot \frac{(1-s) + \phi s + \frac{(1-\phi)s}{R}}{1+\beta} - 1 \right].$$

4.4 Interpretation

This closed-form solution illustrates several core mechanisms underpinning our empirical results.

First, π_0 is increasing in λ. When the behavioral share is larger, a greater portion of the population treats the withdrawal as new income and immediately raises consumption, generating stronger inflationary pressure. In the empirical analysis, this corresponds to municipalities with higher withdrawal intensity exhibiting greater and more persistent inflation.

Second, the inflation response scales with both s (the size of the forced savings pool) and ϕ (the share withdrawn). If either parameter is close to zero, the liquidity injection is small and the inflationary effect negligible. In Chile, where up to 30% of accumulated savings could be withdrawn, both parameters were substantial—consistent with a sizable response.

Third, rational agents smooth consumption over time. As λ falls, aggregate demand in period 0 rises less in response to the policy, and the inflationary response attenuates. In the limiting case where $\lambda = 0$, the policy is intertemporally neutral and $\pi_0 = 0$. This theoretical prediction mirrors the empirical heterogeneity we document with respect to household debt: municipalities with higher indebtedness—a proxy for constraint severity—display stronger inflationary effects, suggesting a higher effective λ.

Finally, the model underscores why our empirical strategy is robust to national or global shocks. Because all municipalities face the same macroeconomic environment, variation in π_0 arises from local heterogeneity in behavioral responses to an exogenous policy. In this sense, realized withdrawal intensity serves as a reduced-form proxy for latent shifts in local demand, with the model offering a structural rationale for our identification strategy.

5 Conclusion

This paper investigates how large, localized liquidity shocks—specifically those arising from institutional savings mechanisms—affect consumer price inflation. We exploit a quasi-experiment from Chile's COVID-19 response, in which households were allowed to withdraw up to 30% of their pension savings across three rounds. These withdrawals injected over 15% of GDP into the economy, with sharp variation across municipalities driven by pre-existing differences in account balances.

Using newly linked administrative microdata—including transaction-level supermarket prices, supplier costs, and household debt—we construct a novel panel of local inflation and withdrawal exposure. Our results show that municipalities with higher withdrawals experienced significantly greater and more persistent food price inflation. These effects are not explained by supply-side pressures: cost inflation occurred later and was weakly correlated with withdrawal intensity, and household debt fell in high-exposure areas, consistent with deleveraging behavior. A decomposition exercise confirms that the inflationary effect of withdrawals remains strong even after controlling for both input costs and local debt stocks.

To interpret these findings, we develop a stylized two-period TANK model featuring mandatory savings and behavioral heterogeneity. The model rationalizes why only a subset of house-

holds treats the withdrawal as new income, while others smooth intertemporally. Municipalities with a higher share of behavioral agents—proxied by larger realized withdrawals—exhibit stronger demand responses and thus higher inflation. This mechanism closely mirrors our empirical results and helps clarify why inflation varied across space even in the absence of policy targeting.

Looking ahead, we plan to extend this work in several directions. First, we aim to calibrate a richer quantitative model that incorporates spatial heterogeneity, pricing frictions, and general equilibrium feedback. This will allow us to assess whether the observed magnitude and persistence of inflation differentials can be rationalized structurally. Second, we will explore additional mechanisms driving heterogeneity in price responses, including exposure to supplier networks, labor market dynamics, and variation in household credit access.

More broadly, our findings offer clean evidence that liquidity access—even when not funded by government transfers—can generate persistent inflation through a demand channel. This has immediate relevance for inflation measurement, monetary transmission, and the design of liquidity support policies. In particular, the unintended inflationary effects of pension access—especially when activated through behavioral channels—should be carefully weighed in macroeconomic policy frameworks, including in emerging markets where credit constraints and forced savings programs frequently coexist. Our results underscore the importance of combining high-frequency microdata with institutional variation to disentangle the drivers of inflation in real time. The Chilean case offers broader lessons for settings where households hold illiquid savings, policymakers face limited fiscal space, and inflation is shaped not just by aggregates but by the distribution and accessibility of liquidity

References

Acemoglu, Daron and Emmanuel Farhi, "Supply and Demand in Disaggregated Keynesian Economies," *Quarterly Journal of Economics*, 2020, *135* (2), 829–886.

Aruoba, S. Borağan, Andrés Fernández, Daniel Guzmán, Ernesto Pastén, and Felipe Saffie, "Pricing Under Distress," June 2024.

Baqaee, David and Emmanuel Farhi, "Supply and Demand in Disaggregated Keynesian Economies with an Application to the COVID-19 Crisis," *American Economic Review*, May 2022, *112* (5), 1397–1436.

Beshears, Jesse J., David Laibson, and Brigitte C. Madrian, "Framing and Claiming: How Information-Framing Affects Expected Social Security Claiming Behavior," *Journal of Public Economics*, 2018, *167*, 117–129.

Beshears, John, Hengchen Dai, Katherine L. Milkman, and Shlomo Benartzi, "Using fresh starts to nudge increased retirement savings," *Organizational Behavior and Human Decision Processes*, 2021, *167*, 72–87.

Cerrato, Andrea and Giulia Gitti, "Inflation Since COVID: Demand or Supply," *Empirical Economics*, 2022, *64*, 123–156. Exact details to be filled with publication info.

Cesa-Bianchi, Ambrogio and Andrea Ferrero, "The Transmission of Keynesian Supply Shocks," *LSE Working Paper*, 2021. Discussion Paper 2021-16.

di Giovanni, Julian, ebnem Kalemli-Özcan, Alvaro Silva, and Muhammed A. Yildirim, "Pandemic-Era Inflation Drivers and Global Spillovers," November 2023.

Elgin, Ceyhun, Gokce Yalaman, and Serdar Yasar, "Economic Stimulus Measures in the Pandemic: The Role of Fiscal Decentralisation," *Cambridge Journal of Regions, Economy and Society*, 2023, *16* (1), 167–187.

Ganong, Nathaniel, Daniel Mitchell, and Peter Soble, "Liquidity, Default, and the Effectiveness of Mortgage Modifications," *American Economic Review*, 2021, *111* (3), 767–808.

Gelber, Alexander, Adam Isen, and Jacob S. Goldin, "Automatic Contributions and the Retirement Savings of U.S. Households," *Journal of Public Economics*, 2019, *180*, 104084.

Hamilton, J., L. Liu, J. Miranda-Pinto, and G. Sainsbury, "A $100,000 Marshmallow Experiment: Withdrawal and Spending Responses to Early Retirement-Savings Access," *NBER Working Paper*, 2023, (w31618).

Kehoe, Patrick and Virgiliu Midrigan, "Prices are sticky after all," *Journal of Monetary Economics*, October 2015, *75*, 35–53.

MacKay, Alexander and Nathan Miller, "Estimating Models of Supply and Demand: Instruments and Covariance Restrictions," *American Economic Journal: Microeconomics*, 2021, *13* (1), 1–36.

Miranda-Pinto, Jorge, Daniel Murphy, Kieran James Walsh, and Eric R. Young, "Saving constraints, inequality, and the credit market response to fiscal stimulus," *European Economic Review*, 2023, *151*, 104355.

Pecher, Natalia, "The Effectiveness of Fiscal Policy Support During COVID-19: Cross-Country Empirical Evidence," *LBS Economics Working Paper*, 2021, (No. 14).

Shapiro, Adam, "Decomposing Supply- and Demand-Driven Inflation," *Working Paper*, 2020. Unpublished or working paper, details to be updated.

Weinberg, Alexander, "The Aggregate Effects of Fiscal Stimulus: Evidence from the COVID-19 Unemployment Supplement," *NBER Working Paper*, 2023, (w27576).

Appendix

A Withdrawals data

A.1 The Chilean pension system

Since 1981, the Chilean Pension System has been based on individual capitalization. Each member has an account in which his/her social security contributions are deposited. These are capitalized and earn the yield on the investments made by the administrators with the resources from the funds. When an individual retires, the fund is used to buy a pension, generally an annuity. The amount of the pensions will depend on the amount of savings, thus there is a direct relation with personal effort, as well as with the return on the financial investment and the pension obtained. The Pension System is managed by private institutions known as Pension Fund Administrators (AFPs).

A.2 Data analysis of withdrawals at the municipality level

The first withdrawal started on July 30, 2020, and in each one of them, most of the withdrawals occurred within the first month, and they are in the same order of magnitude, although the first withdrawal was somewhat larger than the others. Figure A.1 presents the time distribution of withdrawals, in which each dot represents the share of withdrawals in each month as a fraction of the total amount of each withdrawal. Almost 80% of each withdrawal event occurs within the first month of implementation. As for the number of people who withdrew money from their individual savings accounts in each of the three events, the numbers were 10.9 million, 9.0 million, and 8.7 million, respectively (Table A.1). In terms of the amount of money each withdrawal involved, these were 18.147 USD million, 15.522 USD million, and 14.570 USD million.

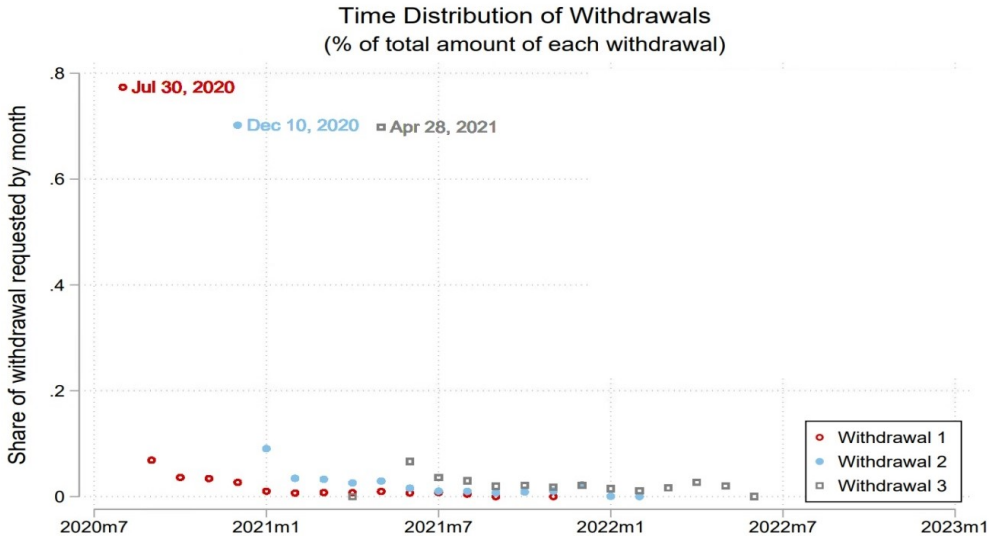


Figure A.1: Time Distribution of Withdrawals

Number of Withdrawals	Total Individuals
First	10,910,323
Second	9,031,663
Third	8,709,189

Table A.1: Table of Individuals with Withdrawals

Another interesting dimension of heterogeneity is the difference in the amount of money withdrawn over three withdrawal events across municipalities. Figure A.2 shows the per capita total withdrawals among the three events, with the left panel showing the top ten municipalities in terms of labor income and the right panel showing the bottom ten. People in the top ten high-income municipalities withdraw around twice what people in the bottom ten municipalities did. Two factors seem to drive this heterogeneity in the amount of withdrawals across municipalities. First, people in higher-income municipalities had, on average, larger savings in their pension accounts, so the maximum 10% they were allowed to withdraw meant larger withdrawals at those locations. Second, if the saving amount in the individual account was below $\$1,500$ USD (approx.), people were allowed to withdraw all of their money, meaning that in poor municipalities, more people ran out of savings after the first or second event becoming unable to withdraw any money in the third event.

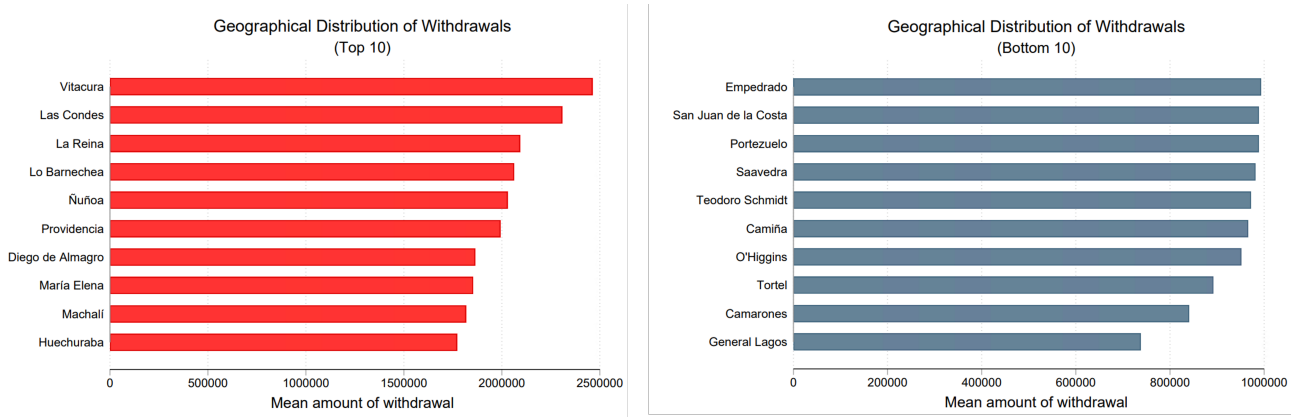


Figure A.2: Geographical distribution of withdrawals at the muncipality-level

B Supermarket Transaction Data and Price Index Construction

B.1 Data description

To analyze the dynamics of prices around the COVID-19 period, we use the Electronic Invoice data (EI) from the Chilean IRS that covers the universe of firm-to-firm transactions in Chile. We focus the analysis on food products sold by large supermarkets in Chile. There are several reasons for this decision. First, although the EI data registers the transactions made among firms, not between firms and households, supermarkets sell their products at the same price regardless of whether the buyer is a person or a firm.[4] Therefore, the price recorded in the EI is the actual price at which a supermarket sells goods to all its customers, making it a good source of administrative data to keep track of prices.[5] Along with the selling price, the EI also provides information on the following variables at the transaction level: origin and destination firm tax ID, quantity, string description of product/service, standardized product categories, origin and destination municipality, and form of payment, among other information. The coverage of the EI data available at the CBC is the universe of formal firms in Chile since 2018. Second, we focus the analysis on food product prices only because these sorts of goods present a higher frequency data, which provides us with better quality data, and because food products are common goods sold by supermarkets, which minimizes the likelihood of a bias arising from different types of goods being sold across municipalities. Because we are interested in studying price evolution before, during, and after the COVID-19 episode, we built the price indexes at a monthly frequency between January 2018 and December 2022.

B.2 Price index construction

The unit of analysis is a product defined as a combination of supermarket, municipality, and product description. For instance, each type of apple sold by a supermarket of a particular brand in a particular municipality is a different product to which we keep track of its price. We work only with large supermarkets, according to the Chilean IRS classification.[6]

We build price series for each product at a daily frequency using the mode of the prices at which a product was sold during the day. Over a day, a product might present different prices due to special discounts or certain benefits that some kind of customers may have, so the mode function allows to deal with the noise in the price data associated with those marketing policies.

Next, we keep only products that have at least one observation per week, and we apply to them the procedure proposed by Kehoe and Midrigan (2015) to filter the price series of each product from outliers.[7] Then, we compute the daily price change rates using the price series that

[4] In Chile, supermarkets by law can issue two different types of tax records at the time of sale: *"boleta"* to register transactions with individuals and *"factura"* to register transactions with firms.

[5] We cannot use *"boleta"* because its data is available only since January 2022 at the CBC.

[6] Only supermarkets belonging to classification "estrato=4" are included in the sample.

[7] If a product changes its text description in the EI documents, we consider it as a new product.

survive the filter procedure. Finally, to deal with the remaining possible outliers, we winsorize the tails of the price change distribution at a daily frequency at the 5% and 95%.[8]

After computing the price variation of each product, we construct a synthetic municipality-product price index for each of the 76 categories in the CPI basket at a monthly frequency. To do this, we group each product in a particular CPI category and use the share of the number of transactions as weights to generate the category price change in monthly frequency at the municipality level.[9] Then, using the resulting category price change series, we built the category-municipality price indexes. The result is an unbalanced panel with price information for 73 categories (out of 76 in the CPI basket) and 345 municipalities (out of 365) at a monthly frequency between January 2018 and December 2022.

Figure B.1 presents the resulting food price index along with the official food CPI index.

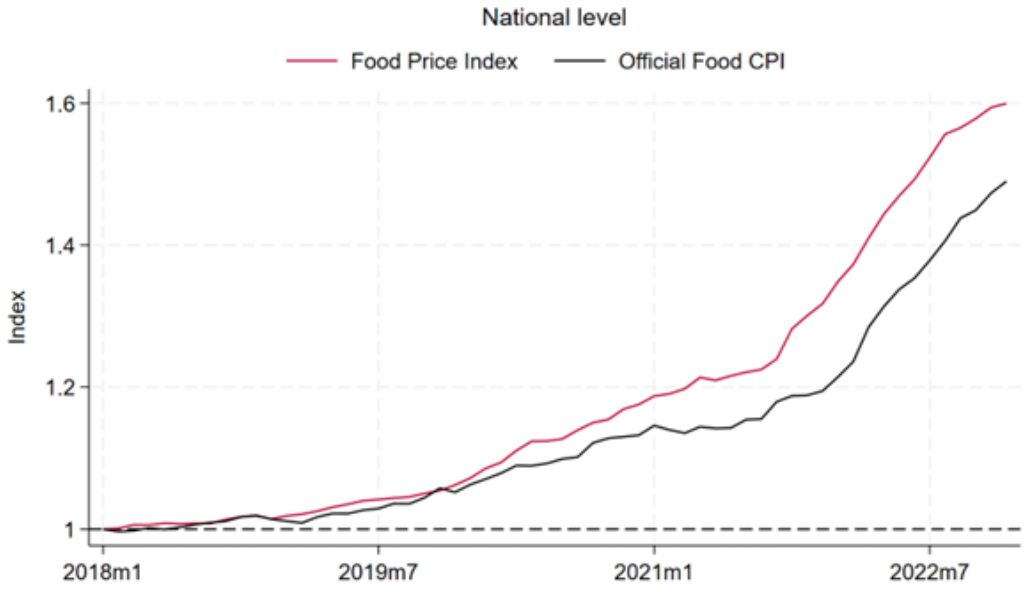


Figure B.1: Price Index comparison with Official Food CPI Index

B.3 Cost index construction

To build the cost index, we start by identifying the suppliers of each supermarket-product unit and generating the price series of the transactions. We filter the resulting purchase price series following the same procedure described in B.2. Next, we use the filtered purchase price series of each product to build a national supermarket-product cost index. Then, we build the municipality-supermarket-product cost index as a weighted average of the national supermarket-product cost index, using the share of sales of each supermarket within a municipality as weights.

Figure B.2 presents the resulting national cost index along with the official food CPI index.

[8] We worked on four different approaches to deal with the remaining outliers.

[9] The construction involved two alternative approaches for weighting: by sales and number of transactions. We chose to use the weights built on the number of transactions.

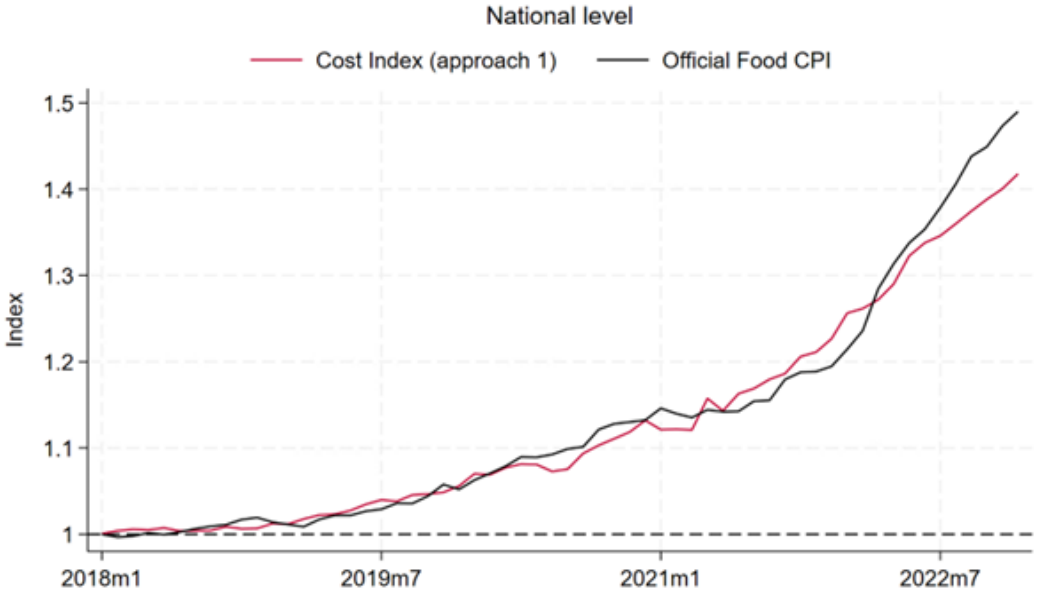


Figure B.2: Cost Index comparison with Official Food CPI

B.4 Cost index construction: Alternative Approach

Results from the exercise in which we study the response of the cost index by intensity of withdrawals, presented in Figure 5, show no significant effect from withdrawals on the cost index. To be sure that this is not due to our approach to building the cost index is unable to capture the heterogeneity in costs across municipalities, we build the cost index following an alternative approach.

First, as we did in the original approach, we start by identifying the suppliers of each supermarket-product unit and generating the filtered purchase price series. Next, using the filtered purchase price series, we build a cost index at the supermarket-product-supplier's municipality level. Then, for each municipality-supermarket-product unit, we search for the closest supplier (we calculate the geographical distance in kilometers) and we assign it the cost index of that supplier. By doing so, each municipality-supermarket-product unit ends up with a unique supplier and cost index. Finally, to build the municipality-product index we combine the cost index of all supermarkets selling a product within a municipality as a weighted average using their share of sales as the weights.

The resulting national cost index built following this alternative construction approach is presented in Figure B.3.

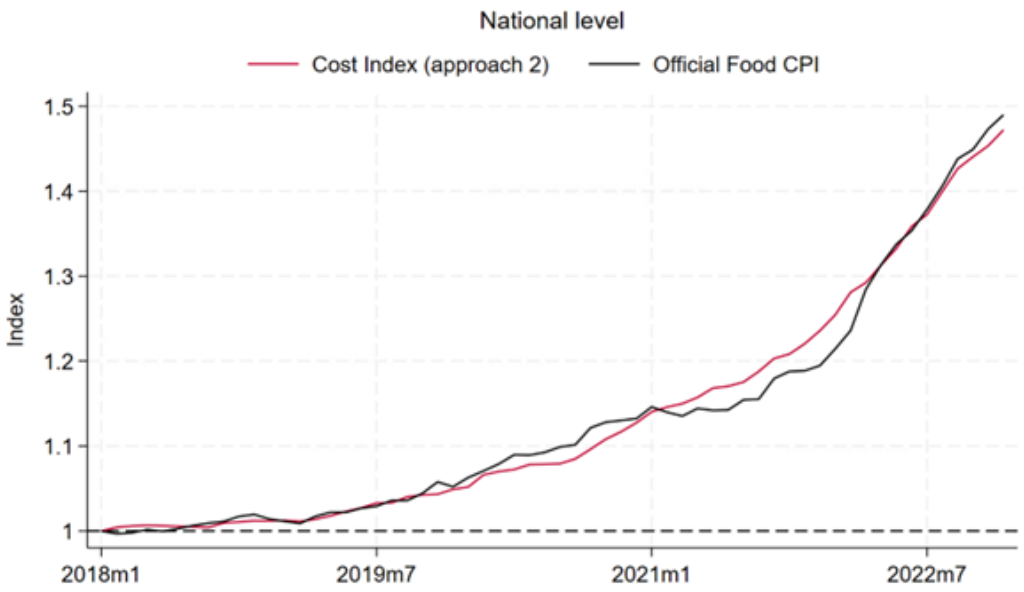


Figure B.3: Cost Index comparison with Official Food CPI

C Debt Data

C.1 Evolution of the number of individuals with liabilities

Figure C.1 shows the evolution of the number of people reported with liabilities over time. We observe a sharp decline of 400,000 individuals after the beginning of the first withdrawal round, which suggests that there were people who used the money from the withdrawals to fully repay their exisitng debt.



Figure C.1: Number of individuals with liabilities

D Event Study: Robustness

D.1 Event Study: Price Index Response with balanced panel

Figure D.1 shows the results from estimating equation 1 but now using a balanced panel without municipality-product units exhibiting gaps. The results from the original specification remain (Figure 4), but the size of the price elasticity at the end of the time horizon becomes a little smaller (2.5% vs 3%).

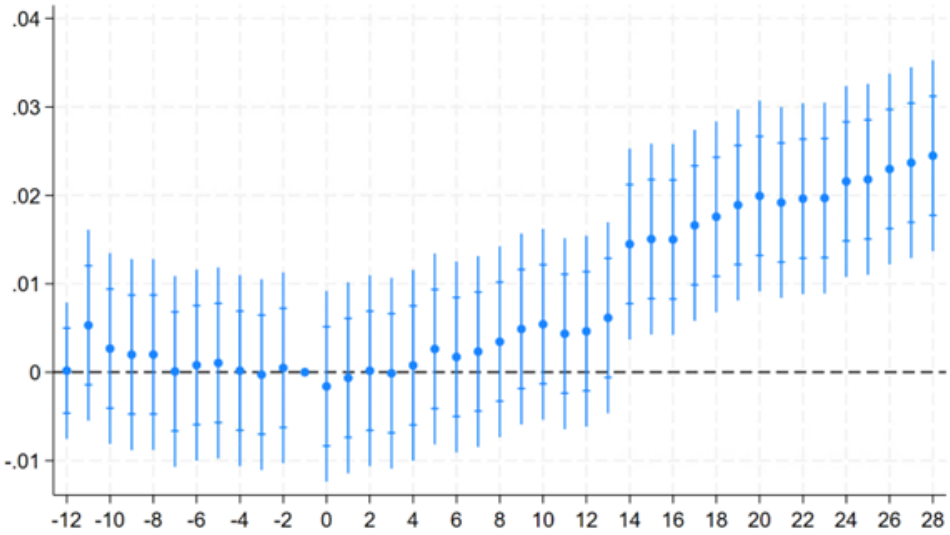


Figure D.1: Event Study: Price Index Response by Accumulated Withdrawal Intensity with balanced panel

D.2 Event Study: accumulated withdrawals

$$P_{i,j,t} = \alpha + \left(\sum_{m=-G}^{M} \beta_m \cdot D_{t-m} \cdot WA_{i,t}) \right) + X_{i,t} + \gamma_{j,t} + \epsilon_{i,j,t} \tag{3}$$

where P_{ijt} is the log price index of product j in municipality i at time t, normalized to 1 in January 2018. D_m are month dummies relative to the baseline month ($m = 0$ corresponds to August 2020, the beginning of the first withdrawal). WA_{it} is the log of the progressive cumulative amount withdrawn in municipality i over time t, in logs. X_{it} includes controls for municipality income and population. γ_{jt} are product-by-time fixed effects, which capture aggregate inflation trends, national shocks, and supply chain disruptions at the product level.

The results are presented in Figure D.2. In comparison with the results from the baseline specification presented in Figure 4, now the estimated coefficients are somewhat larger and become statistically significant a few months earlier.

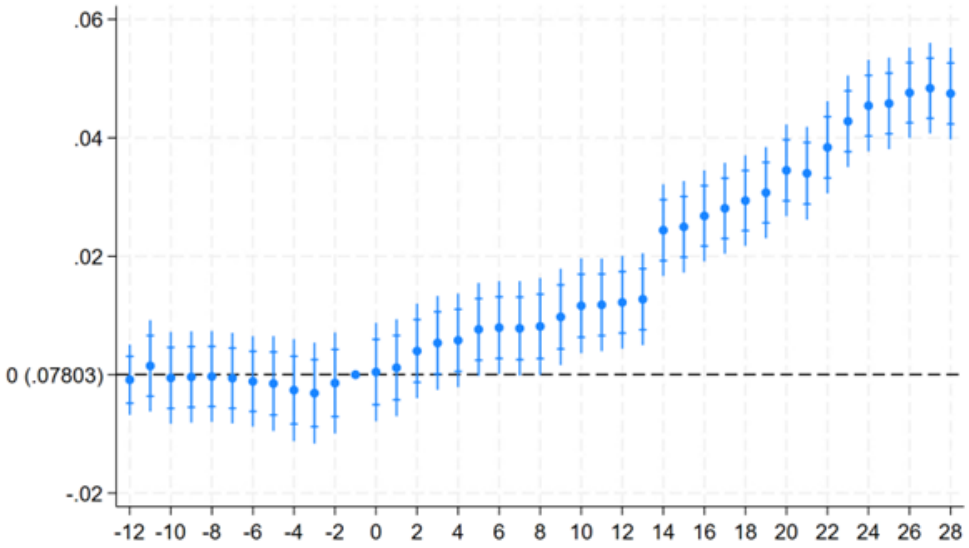


Figure D.2: Event Study: Price Index Response by Accumulated Withdrawal Intensity

D.3 Event Study: Cost Index Response by Withdrawal Intensity with alternative index construction approach

Figure D.3 presents the results for the cost index response by withdrawal intensity under the alternative construction approach for the index. The results are qualitatively the same as those from the original approach presented in Figure 5. There is no signficant effect of withdrawals on the cost index.

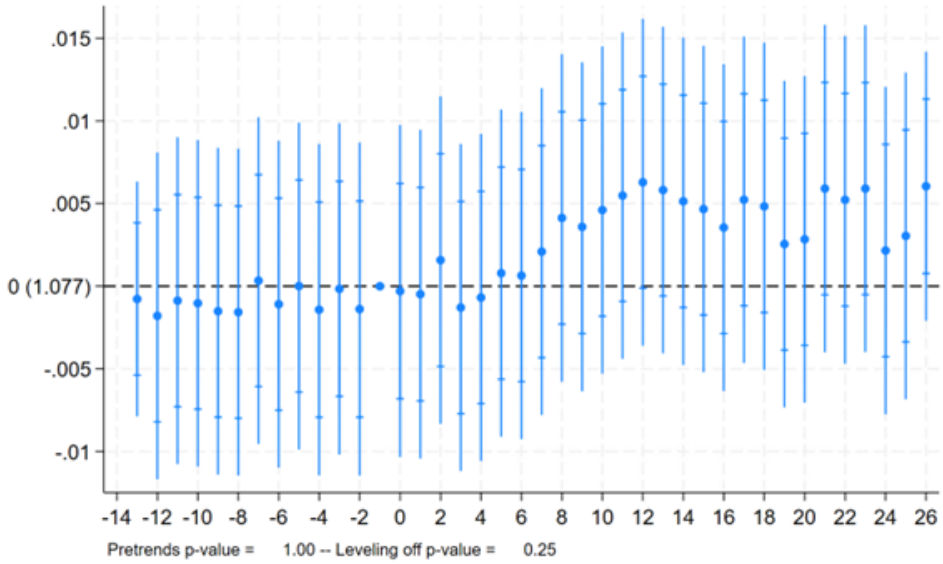


Figure D.3: Event Study: Cost Index Response by Withdrawal Intensity with alternative index construction approach

D.4 Event Study: Price Index Response by Withdrawal Intensity using a price index built with share of sales as weights

Figure D.4 shows the price index response by withdrawal intensity, but with the price index of the municipality-supermarket-product unit being built using the share of sales instead of the share of transactions as weights.

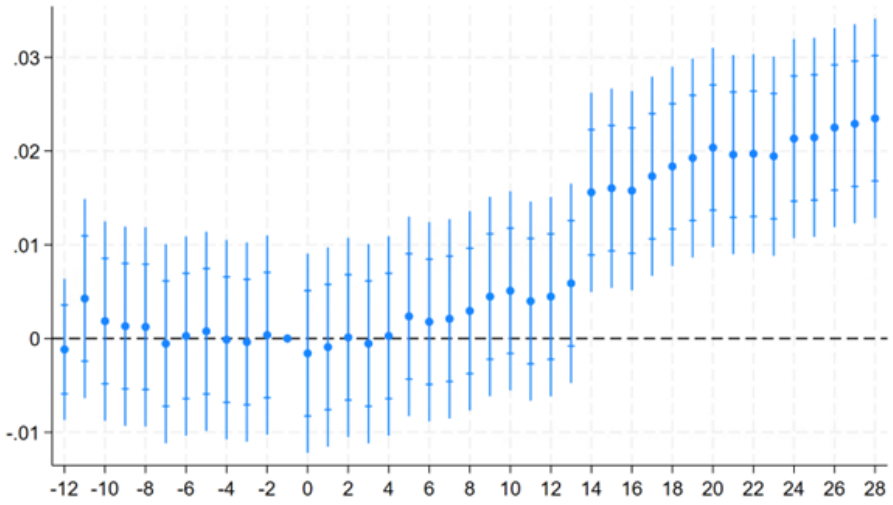


Figure D.4: Event Study: Price Index Response by Withdrawal Intensity using a price index built with share of sales as weights

D.5 Event Study: Debt Response by Withdrawal Intensity by type of debt

Figures D.5, D.6, and D.7 present the debt responses to withdrawals for commercial, consumer, and mortgage household debt, respectively.

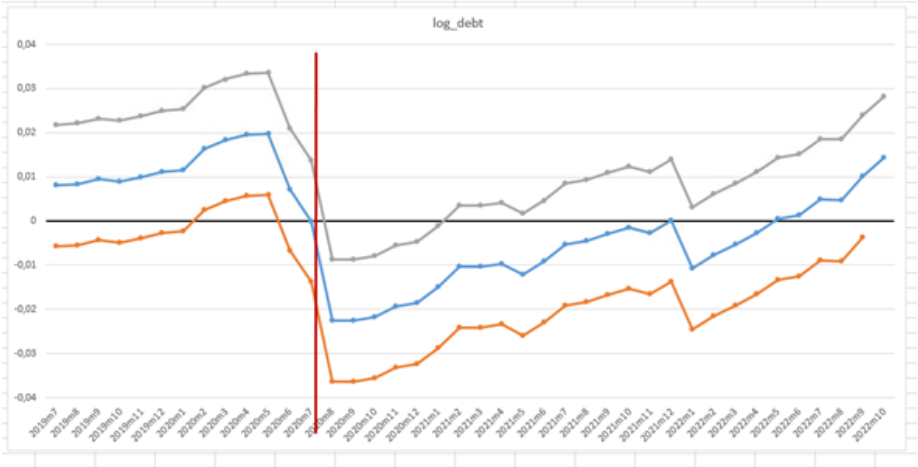


Figure D.5: Event Study: Commercial Household Debt Response by Withdrawal Intensity

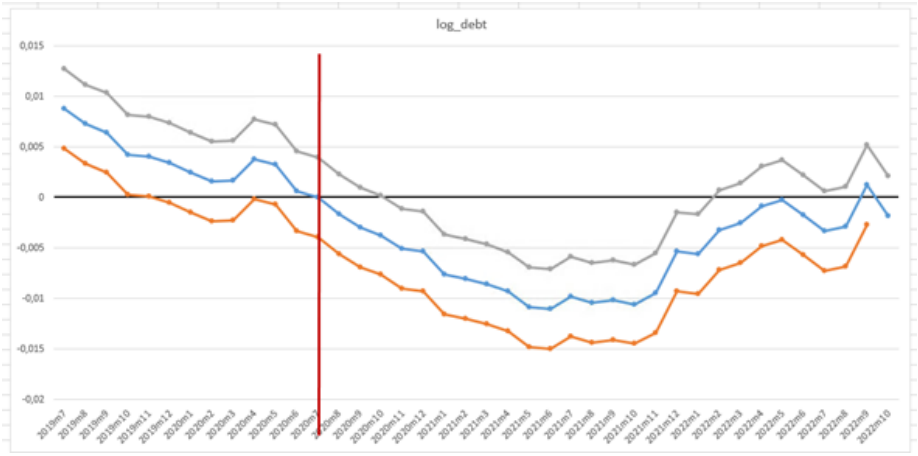


Figure D.6: Event Study: Consumer Household Debt Response by Withdrawal Intensity

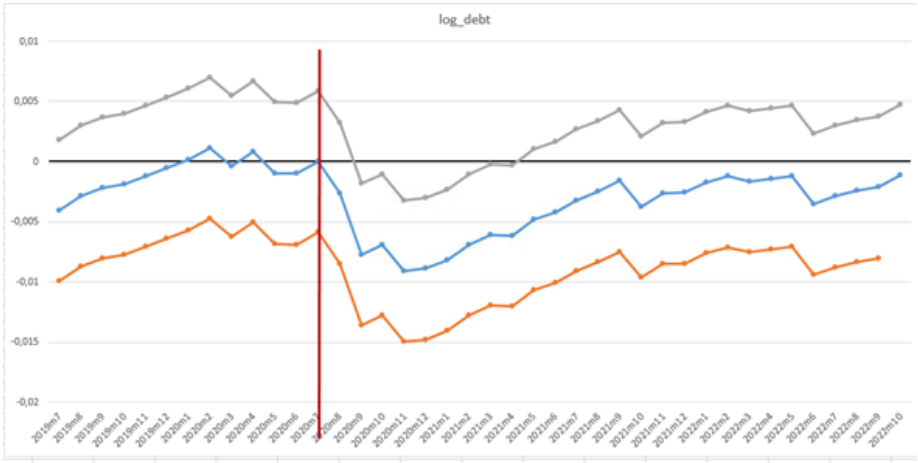


Figure D.7: Event Study: Mortgage Household Debt Response by Withdrawal Intensity