Recurrent Anticipated Liquidity Shocks and Household Expenditure *

Hector Cardozo † Damian Pierri ‡

November 20, 2024

Abstract

We exploit a novel panel of thousands of monthly bank accounts to examine households' responses in Argentina to a predictable and periodic liquidity shock—the regular biannual bonus (RBB). We find household spending highly responsive to the RBB, with durable goods rising sharply in maintenance and operational costs. Also, households use the RBB to cancel debt. We develop a model that successfully replicates expenditure patterns and underscores the risks of durable goods. Our study highlights the critical role of these goods in shaping spending responses to anticipated and recurrent liquidity shocks.

Keywords: anticipated liquidity shocks, durable goods, expenditure.

*We would like to thank Gustavo Ventura, Paula Calvo, Esteban Aucejo, Domenico Ferraro, Clodomiro Ferreira, Gianluca Violante, Agustin Casas, Manuel Arellano, and the participants in the macro workshop at Arizona State University.

†Arizona State University. Email: `hcardozo@asu.edu`.

‡ESCP Business School, Universidad Autónoma de Madrid and Instituto Interdisciplinario de Economía Política. Email: `damian.pierri@gmail.com`.

1 Introduction

Understanding how households respond to income shocks has long been a central focus of economic research. A substantial body of literature has estimated elasticities and marginal propensities to consume following income changes (for comprehensive surveys, see Jappelli and Pistaferri, 2010 and Fuchs-Schündeln and Hassan, 2016). Yet, these studies are often limited by data constraints and struggle to capture all relevant aspects of household finances. Even when an agent's income, spending, and wealth are observable, limitations related to the frequency of observations and the ability to track agents over time can hinder the analysis. Moreover, as Kaplan and Violante (2014) note, despite the extensive empirical literature, there are significantly fewer quantitative studies analyzing income shocks within dynamic models of household behavior.

This paper studies how households adjust their spending in response to a significant, predictable, and recurrent liquidity shock, Argentina's regular biannual bonus (RBB). To our knowledge, this is the first attempt to estimate the effects of this type of shock. The RBB is a legally mandated bonus equivalent to an extra month's salary, paid in two installments: the first at the end of June, which is the focus of this study, and the second in December. The paper offers detailed insights into household financial behavior using a novel dataset that provides monthly financial observations from thousands of bank accounts. Our findings show that, after receiving the RBB, households significantly increase their spending, with a substantial portion directed toward durable goods. Within this category, spending on repair and maintenance costs plays a significant role. Moreover, the paper highlights the liquidity dynamics of households. Despite holding few liquid assets, households are not credit-constrained. This distinction is explained by the fact that durable goods are often purchased on credit. When households receive the RBB, they use it to pay down existing debt, allowing them to take on new credit for further purchases. This behavior underscores the importance of liquidity and credit availability in shaping household spending responses.

To explain this behavior, we develop a model of income fluctuations with two types of goods. The model incorporates an anticipated and recurring income bonus, such as the RBB, depreciation shocks, and maintenance costs for durable goods. Two key channels are identified in this framework. First, depreciation shocks increase the demand for durable goods due to the higher risk premium associated with maintenance costs. Second, the predictable and recurrent nature of the RBB introduces an additional state variable. After receiving the bonus, households anticipate a long interval before the next payment, lowering their expected short-term income and generating precautionary savings, raising the demand for durable goods. This second channel relates to working costs, which impose a severe strain on household budgets, a strain that is further amplified by the extended period before the next RBB.

We estimate agents' responses to the RBB using a unique dataset from one of the largest banks in Argentina for 2022. We employ a difference-in-difference regression within an event study framework to address potential identification threats. The control group consists of agents who do not receive income through payroll or pensions but exhibit significant expenditure and checking account activity. These agents do not receive the RBB because they are not in an employer-employee relationship; they are typically self-employed workers or entrepreneurs. We find significant excess sensitivity to the RBB as agents' expenditure increases by 3.4% relative to their annual average.

We calculate the aggregate expenditure response relative to the income changes associated with the RBB, a proxy for the standard marginal propensity to consume (MPC)[1]. We estimate the anticipated income increase to be 27.9%, leading to a relative expenditure response of 12.3% at the monthly level. We also assess the impact of liquidity constraints by estimating a triple-difference regression that includes a dummy variable to identify agents with lower levels of liquid wealth. Our results indicate that liquidity-constrained agents drive most of the observed expenditure increases, responding to the RBB by increasing their spending by 3.6% more than their more liquid counterparts.

[1]Due to the lack of adequate income data for the control group, we do not directly estimate agents' marginal propensity to consume. Instead, we use the relative expenditure response to approximate the relationship between these variables.

We classify expenditures into durable and non-durable goods to further examine the excess sensitivity. We argue that spending on durable goods involves *more* than purchasing new items. We identify two types of expenditures related to durable goods that account for a significant portion of agents' total purchases: maintenance (repairs) and working costs[2]. Both categories show significant excess sensitivity and contribute substantially to the overall expenditure response. We estimate that maintenance spending on durable goods increases by 9.7% relative to its annual average for agents receiving the RBB. Meanwhile, working costs exhibit an excess sensitivity of 4.1%. The significant increase in maintenance spending suggests that agents delay repairs until they receive the RBB, using the bonus to address postponed expenses. Regarding working costs, we argue that these expenses are proportional to the value of the durable goods they are associated with. Thus, the observed excess sensitivity in working costs suggests that agents have increased their stock of durable goods through large, infrequent purchase[3].

We then aim to account for our empirical findings within a model. We build on the standard heterogeneous agent incomplete-markets framework with one asset and an uninsurable, idiosyncratic income process. There are two primary deviations from the benchmark model: (i) the inclusion of an anticipated income bonus every six periods and (ii) the introduction of working costs and depreciation shocks to the stock of durable goods. As a result, the model incorporates time *distance* to the income bonus (the RBB) and integrates durable goods into an otherwise standard framework. The solution displays an invariant distribution across all six periods, meaning the model remains stationary when conditioned on the time distance to the bonus. We calibrate the model using critical moments from our dataset to align it with the ob-

[2]Maintenance refers to any spending necessary to repair durable goods following malfunctions or breakdowns. Working costs include expenses required to use a durable good, such as fuel for a car or cellphone service.

[3]For example, spending on electricity, insurance, and taxes represents a share of the durable goods an agent owns. This reasoning helps us address certain limitations in our dataset, such as its inability to capture purchases of specific durable goods (e.g., houses, cars, motorcycles) through credit or debit card transaction data.

served data[4]. Our calibrated model's responses for total expenditure, repair, and working costs on durable goods closely reproduce their empirical counterparts. Depreciation shocks increase the risk of holding durable goods relative to liquid assets. Moreover, working costs heighten the risk of durable goods by tightening households' budget constraints, especially among illiquid households, compounding the effects of depreciation shocks. To hedge against these risks, agents over-accumulate durable goods when they receive the RBB. This mechanism is akin to the precautionary savings motive: due to incomplete markets, agents over-accumulate risky assets. At the same time, agents hedge against the compound risks associated with durable goods by maintaining a fraction of liquid assets in their balance sheets. Agents respond strongly to the RBB through inter-temporal arbitrage by accumulating wealth in liquid assets and durable goods.

Contribution to the Literature. This paper contributes to several strands of literature. It is closely aligned with the research on household consumption responses to anticipated income changes. This body of work has tested a fundamental insight from the life-cycle and permanent income hypotheses (Modigliani and Brumberg, 1954; Friedman, 1957): that current consumption should not respond to anticipated income changes. This prediction has been extensively studied through variations of the excess sensitivity test. Early studies used macroeconomic data (Hall, 1978; Flavin, 1981), but more recent research has utilized micro-level data from sources like the PSID, CEX, surveys, and proprietary datasets (Zeldes, 1989; Parker, 1999; Souleles, 1999; Hsieh, 2003; Johnson et al., 2006; Aaronson et al., 2012; Gelman et al., 2014; Misra and Surico, 2014; Ganong and Noel, 2019). Comprehensive reviews by Jappelli and Pistaferri (2010) and Fuchs-Schündeln and Hassan (2016) cover the extensive literature testing these predictions. Many studies have found evidence challenging the theoretical insight that consumption does not react

[4]Argentina is among the few middle-income countries with persistent inflation. As a result, agents hold only a small percentage of liquid assets relative to income. In our database, the ratio of hand-to-mouth agents (those with liquid wealth lower than half their monthly regular income) is 64%.

to anticipated income changes. Consequently, various explanations have been proposed to account for this apparent deviation from the model's prediction. Attanasio (1999) reviews several possible explanations, including borrowing constraints, non-separabilities in preferences, habits, and the durability of goods. Some studies have successfully explained consumption excess sensitivity by incorporating one or more of these additional features into their models. Gelman et al. (2014) attribute much of the expenditure sensitivity they observe to liquidity constraints. However, the results across the literature are mixed, and none of them address recurrent income changes. Our paper contributes to this vast literature by estimating the expenditure excess sensitivity to an entirely predictable and periodic income change in Argentina. Moreover, we explore the roles of borrowing constraints and durable goods expenditure.

Our paper also contributes to the literature that examines the implications of consumption excess sensitivity within the context of quantitative models of household behavior. Standard dynamic models rely on income shocks and borrowing constraints to explain this behavior, as surveyed by Heathcote et al. (2009). Kaplan and Violante (2014) introduce the concept of "wealthy hand-to-mouth" to replicate the excess sensitivity observed in empirical studies. Some researchers have also proposed various behavioral models to account for excess consumption sensitivity. Graham and McDowall (2022) provide an overview of this literature, while Kaplan and Violante (2022) solve and calibrate several of these models. We contribute to developing a two-goods model where durable goods involve non-trivial costs associated with their ownership, which plays a crucial role in explaining observed behavior.

Paper Structure. The rest of the paper is organized as follows. Section 2 describes the database we use in this paper. We present our empirical strategy and main results in Section 3. The quantitative model is presented in Section 4. Section 5 discusses the calibration strategy, solves the model, and analyzes the model results. Section 6 concludes and highlights avenues for future research.

2 Data

The database was provided by one of the largest banks in Argentina. The literature used similar data before, but our database's content is unique for at least two reasons. First, we can observe a monthly panel of thousands of individual anonymized bank accounts for 2022. With the same granularity, we observe regular income, which may come from wages, pensions, self-employed workers, and expenditures. We have detailed information on assets and liabilities from each account. This allows us to track the total expenditure and crucial spending categories of liquidity-constrained households over time, which will be extremely useful in properly studying the effects of RBB. Second, to our knowledge, no other paper has analyzed the consumption patterns in a middle-income country with persistent inflation.

2.1 Database Working Sample

The dataset comprises seven million bank accounts. Because people have many bank accounts, we observe several accounts with very little activity. To control for this fact, we impose some restrictions on the dataset. We use a similar method in Ganong and Noel (2019): we limit the sample to include only those bank accounts with "significant" expenditure. We impose that they must be above the poverty line. The Argentinian National Institute of Statistics and Censuses (INDEC) releases the CPI report together with an estimation of the income needed not to be poor, i.e., the poverty line. We restrict our sample to observations that have expenditures above this threshold. Furthermore, we work with a balanced panel, so we only keep those accounts appearing at every point. Thus, the working sample for the paper is a balanced panel made up of the accounts that earn income and spend above the poverty line every month in 2022. By excluding agents with low spending, we try to identify only primary bank accounts to study their monthly inflows and outflows.

The dataset provides a wide range of information about a particular account at a given point in time. We categorize the main financial information we can observe from each account according to Table 1.

Table 1: Financial Information per Account

Assets	Liabilities	Income	Expenditure	Interest Payment
Checking account	Visa credit card balance	Net wages	Groceries	Personal loans payments
Time deposits	Mastercard credit card balance		Gas	Mortgages payments
	Personal loans		Pharmacy	
	Mortgages		Clothing	
			Telephone services	
			TV	
			Insurance	
			Taxes and utilities	
			Bars and restaurants	
			Fast food	
			Electronics	
			Hardware store	
			Car Repair	
			Health	
			Construction	
			Flights	
			Others	

Notes: The table shows the financial information in each client's account.

Due to the persistently high inflation and the lack of financial development, time deposits are the main financial instrument that agents use to save. Their yield is tightly linked to the interest rate set by the central bank. There are two things to notice regarding time deposits: i) in our dataset they represent 55% of the total liquid assets held by the agents. On the other hand, durable goods-related expenditures add up to 21% of total expenditure: electronics (5.0%), hardware store (0.8%), car repair (2.5%), gas (6.3%), telephone and internet (2.7%), and insurance (3.8%). ii) Inflation-adjusted time deposits averaged only 5.7% out of total time deposits during 2022. Thus, agents save part of their income in liquid nominal assets. As it will be clear in future sections, durable goods are essential not only to understand how agents hedge against inflation but also to how they respond to income shocks, and at the same time, they will allow us to explain the persistent demand for liquid nominal assets even in an inflationary environment.

Now, we move to discuss the credit market in Argentina. Mortgage loans are very small compared to other countries. According to some calculations by Helgi Library, the ratio of mortgage loans to GDP was about 1.44% for Argentina in 2020, while in the US this ratio is closer to 50%. So it is not surprising that the amount of accounts with mortgages is close to 2%. However, a significant number of Argentinians have personal loans, since they are easier to get as they require only a paycheck as collateral. In our dataset, over 34% of the agents have been granted a personal loan. This is relevant to our results. As we only observe maintenance and working costs associated with durable goods, we know households purchase durable units using credit. In that sense, they leverage precautionary savings. They use their credit capacity to hedge against inflation, as durable goods are real assets. They use their net financial income to pay the costs associated with durable goods, smoothing consumption through the flow of services provided by these goods.

Additionally, descriptive statistics for the entire sample and by income quintiles about assets, liabilities, income, and expenditure are displayed in the Appendix. On top of the rich financial information we have from each account, we can also observe some additional information about the account holder. We can see their employment status, whether they are working for the private or public sector or if they are retired. Furthermore, if they work for the public sector we can see their occupation. And if they are employed in the private sector, we know the particular sector they work in. Some descriptive statistics about these characteristics are also presented in the Appendix.

3 Expenditure Response to the RBB

In this section, we show that expenditure responds significantly to the RBB even though it is a predictable and periodic income variation. We further show that some expenditure categories react more than others.

3.1 Empirical Strategy

In Argentina, the RBB is a legally required bonus equivalent to an extra monthly salary, divided into two annual payments. The first half is paid at the end of June, and the second in December. Although originally intended for workers, the RBB is now mandatory for all formal sector earners, extending even to retirees and social security beneficiaries. However, self-employed workers are not entitled to receive it.

One of the most significant threats to identifying the impact of the RBB stems from its timing, as it coincides with holidays. The December RBB overlaps with the Austral summer holidays, while the July RBB aligns with the winter school break. Since the winter break is relatively shorter and does not affect all workers, we focus on the July RBB payment.

We estimate a difference-in-difference regression. In Argentina, all formal sector workers[5], as well as retirees and social security beneficiaries, receive an RBB. Consequently, our control group consists of self-employed individuals who are not on a payroll and do not receive regular pensions but still exhibit significant expenditures, assets, and liabilities. This group serves as the control in our difference-in-difference estimation. Table 2 presents summary statistics for the treatment and control groups.

Table 2: Characteristics of the Control and Treatment Groups

	Treated	Control
Sample share	90.1%	9.9%
Have commercial debt	0.5%	11.0%
Avg Balance	111,615	90,790
	(251,625)	(399,583)
Asset	248,098	293,874
	(819,682)	(1,398,545)
Liabilities	109,672	45,323
	(212,207)	(96,211)
Expenditure	88,694	122,117
	(62,036)	(106,365)

Notes: Averages values at constant prices.

The treatment group represents 90% of our sample, which certifies that every formal worker in Argentina receives an RBB. One way to test whether the control group captures self-employed workers involves examining if these agents have commercial debt. Among those receiving the RBB, fewer than

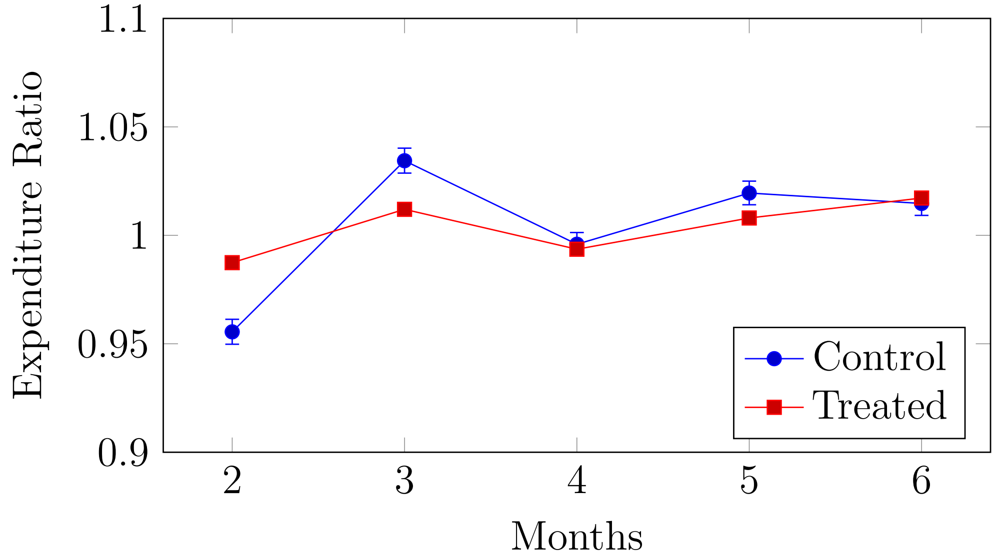
[5]As our database is exclusively composed of bank account holders, we do not observe informal workers who do not receive the RBB.

1% have commercial debt, while 11% of the control group have commercial liabilities. This suggests that many entrepreneurs and business owners are correctly identified within the control group. These individuals have no payroll income in their bank accounts, but their checking accounts show substantial activity. Compared to the treated group, the control group maintains smaller balances in their checking accounts but holds more assets, primarily through term deposits. They are generally wealthier, as they have lower debt levels, likely due to their lack of stable, contractual income, which reduces their ability to offer loan collateral. Notably, aside from the months when agents receive the RBB, the differences between the treatment and control groups in expenditure profiles and composition are *not significant*, making the selected control group appropriate for testing the effects of recurrent and anticipated income shocks.

The recurring nature of the RBB presents challenges in establishing definitive proof of parallel trends between the treatment and control groups. Anticipation and lingering effects may influence behavior in the months preceding and following an RBB payment. Moreover, since the RBB is distributed biannually, the time window to verify parallel trends is limited. However, we test the hypothesis by analyzing the average expenditure ratio across both groups. The expenditure ratio for an individual i at month t is calculated as the ratio of i's expenditure in month t to their average expenditure over the entire sample period. This measure helps control for any baseline differences between agents and groups.

Figure 1 illustrates the average expenditure ratio for the treatment and control groups during the five months leading up to the RBB paid in July, specifically from February to June (months 2 to 6). The figure shows that the expenditure patterns of both groups closely mirror each other. The most pronounced differences in expenditure occur in the months furthest from the RBB payment, particularly in February and March (months 2 and 3). However, in April, May, and June (months 4, 5, and 6), the expenditure profiles of both groups align closely, with no significant differences observed in April and June. This suggests that, as agents approach the month of the RBB, the control group's behavior becomes increasingly similar to that of the treatment

Figure 1: Groups' Expenditure Before the RBB



Notes: Months 2 to 6 represent February to June.
Expenditure Ratio is the average ratio of expenditure at a given time to the average expenditure over the period for each group.

group, supporting the parallel trends assumption necessary for our difference-in-difference estimation.

3.2 Estimation

We rely on a methodology similar to the one used in Gelman et al. (2014) but combine the event study component with a diff-in-diff estimation. Our main regression is the following:

$$c_{it} = \beta_0 + \beta_1 T_i + \sum_{k=2}^{11} \beta_{2,k} M_k + \sum_{k=2}^{11} \beta_{3,k} M_k \times T_i + \Gamma' X_{it} + \epsilon_{it}, \tag{1}$$

where c_{it} is the ratio of expenditure of individual i at time t to i's average expenditure over the entire period. T is a dummy variable, such that $T = 1$ if an agent receives RBB (treated group). M_k are dummy variables for each month in the sample (from February to November). Our main focus is on $M_k \times$

T_i that captures the differences in expenditure from receiving the RBB with respect to not receiving it (i.e., those agents are in the control group). Thus, the coefficient $\beta_{3,k}$ measures *deviations with respect to the average expenditure of the treated relative to the control group* in the months surrounding the RBB. This event study specification allows us to estimate the effect of the RBB before and after it is paid to the agent. We can capture both anticipated and delayed responses to the expected income change. The coefficient β_0 is a constant term, and the variable X represents a set of controls like assets, liabilities, average balance, etc.

We also tackle other components associated with the seasonality of RBB. Schools and the justice system close in July for two weeks due to the winter holidays. The specific weeks change every year, but they usually occur during July. Fortunately, we can identify these types of workers in our dataset. Since neither teachers nor judicial workers are in our control group, the diff-in-diff does not help us address this concern. Thus, we drop them from the sample according to our preferred specifications.

A source of potential concern is that every worker may be subject to the effects of the winter break. To address this fact, we run a specification in which we restrict the sample to retirees (besides the control group). These agents are no longer working, so they should not be exposed to the effects of winter holidays. Moreover, retirees are unlikely to have school-age children; hence, the school break should not impact their consumption patterns.

We present the results for the expenditure elasticities for different specifications in Table 3. In the first row we show the estimates for $\beta_{2,7}$, that is, the elasticity of expenditure of the control group at month 7 when the RBB is paid. This estimate captures the seasonality component of July. In the next row we present the results for $\beta_{3,7}$, the excess sensitivity of expenditure to receiving the RBB.

In column 1 we show the estimates for the entire sample. We remove teachers in column 2, and also get rid of the judicial workers in column 3. Finally, we consider a sample containing only retirees and the control group in column 4.

Table 3: Response of Expenditure to the RBB

	(1) Sample	(2) No Teachers	(3) No Teachers, No Judicial	(4) Retirees
$\beta_{2,7}$	0.0343***	0.0343***	0.0343***	0.0343***
$\beta_{3,7}$	0.0560***	0.0358***	0.0344***	0.0307***
Teachers	Y	N	N	N
Judicial workers	Y	Y	N	N
Rest of workers	Y	Y	Y	N
Retirees	Y	Y	Y	Y
Observations	2,844,750	2,203,490	2,072,650	935,240

Notes: P-values less than 0.05, 0.01, and 0.001 are flagged with *, **, and ***, respectively. This table reports the expenditure responses to RBB for the full sample and for different subsamples.

The results for $\beta_{2,7}$ show that the seasonality of July is significant. Expenditure during that month increases by 3.4% over its annual average. Hence, failing to control for it properly in our diff-in-diff estimation would greatly bias the results. Given that our sample contains many teachers, it is not surprising to see that including them in the estimation amplifies the expenditure response to RBB (column 1). Thus, we view the specification in column 3 as *our main result*. Moreover, excluding teachers but leaving judicial workers in the sample (column 2) does not seem to change our results much relative to column 3. More importantly, we show that the results in column 4 do not differ much from the ones in the preferred specification. Thus, we argue that after excluding teachers and judicial workers, our estimate of 3.4% captures the *causal effect* of the RBB in households' expenditure. That is, our results properly control for the holiday component in July.

To put these results in perspective, we can calculate the aggregate response of consumption to changes in income associated with the RBB. We call this estimate *consumption response relative to income* (CRI) to differentiate it from the standard marginal propensity to consume, MPC. We estimate Equation 1 using the ratio of the checking account balance of individual i at time t to i's average checking account balance over the entire sample period as the dependent variable. The estimate for $\beta_{3,7} = 0.2792$. Hence, we compute the CRI by dividing the coefficient in column 3 of Table 3 by this value. That is:

$$CRI_{3,7} = \frac{0.0343}{0.2792} = 0.1229$$

Thus, we calculate a CRI out of the RBB of 12.3% at the monthly level. Our estimate for the CRI is in line with the value of the MPC found in previous estimates in the literature (see, for instance, Souleles (1999) Gelman et al. (2014), Misra and Surico (2014), etc.). However, as Gelman et al. (2014) points out, the differences in the time frame used to measure the spending response make the MPC estimates challenging to compare.

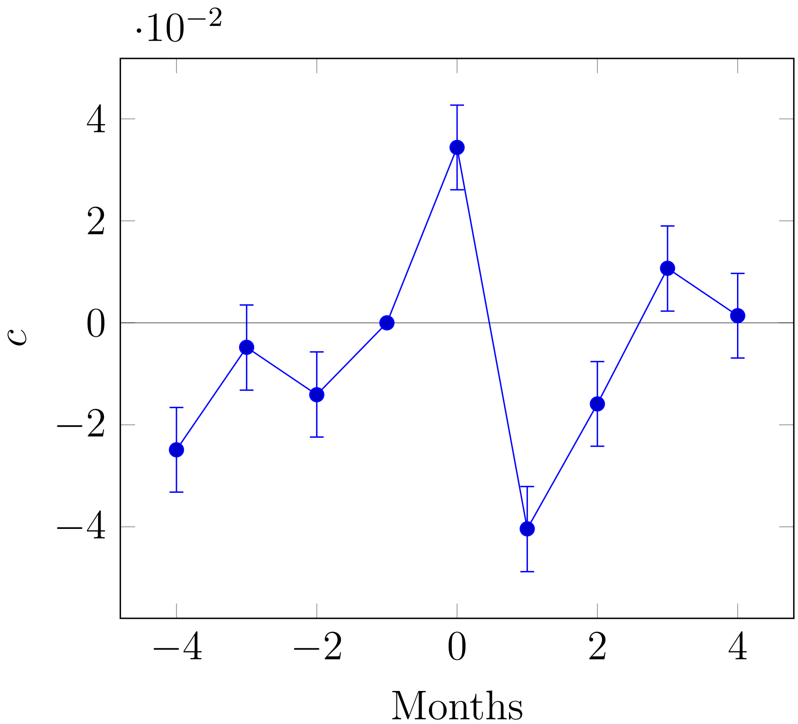
We show the results for $\beta_{3,k}$, with $k \in \{-4, ..., 0, ...4\}$, from our preferred specification in Figure 2. As we can see, agents anticipate the reception of the RBB. Moreover, expenditure decreases significantly afterward. We see this last pattern as suggestive evidence of agents accumulating certain goods. We analyze agents' expenditure composition in the next subsection to verify this hypothesis.

3.3 Decomposing Total Effect

In this subsection, we investigate which components drive the response of aggregate expenditure. As explained before, spending on durable goods has become a beneficial saving mechanism for Argentinians. Unfortunately, we cannot observe all the durable goods purchases agents make. For instance, our dataset cannot identify agents buying houses, cars, motorcycles, and some home appliances. However, we can capture two types of spending related to durable goods: expenditure in maintenance (or repair) and working costs. Below, we will carefully define these two types of expenditure.

First, by maintenance, we mean the spending households must incur whenever a durable good malfunctions or breaks down. Behind this category is the notion that a good does not depreciate linearly. At the monthly level, we can think of durable goods suffering a depreciation shock that forces agents to spend to repair them. For instance, in the case of a car, these shocks would

Figure 2: Response of Expenditure to the RBB



Notes: Month 0 represents the reception of RBB (July).
c is the ratio of expenditure at a given time to the average expenditure over the period.

be a flat tire, a traffic accident, or a mechanical malfunction that impacts the utility the agent derives from the car. These shocks are infrequent but can have sizeable effects on the stock of durable goods. In our dataset, we classify as durable repair or maintenance the variables *Car repair, Construction,* and *Hardware store*. All these categories represent around 5.4% of the total expenditure we observe.

Second, by working cost of durable goods, we mean taxes, insurance, gas, telephone service, and any other spending needed to use a durable good regularly. Without paying for insurance, taxes, or even gas, an agent cannot derive utility from a car. The same goes for cell phones, TVs, and other house appliances: they need a cellphone service, TV subscription, and electricity to generate utility for the agent. In our dataset, we identify as working cost the sum of variables *Gas, Telephone services, TV, Taxes and utilities,* and *Insurance*. These categories represent around 16.9% of total expenditure.

We believe these two categories of durable goods are essential to explain expenditure patterns in Argentina. Notice that purchasing these goods differs from acquiring a real estate unit, which is a more infrequent decision. Thus, the mechanisms behind our results significantly impact frequent households' choices. However, they have not been studied adequately in the literature before. In most cases, the lack of precise data by category can be a limiting factor. Thus, highlighting the *role of expenditure in maintenance and working costs* in understanding the response of agents to changes in the environment is one of our main contributions.

After defining several expenditure categories, we study their response to the RBB. Using the specification in Equation 1, we estimate their excess sensitivity in Table 4.

Table 4: Response of Expenditure Categories to RBB

	(1)	(2)	(3)
	Total Expenditure	Repair	Working Costs
$\beta_{2,7}$	0.0343***	0.1202***	0.0510***
$\beta_{3,7}$	0.0344***	0.0971***	0.0407***
Teachers	N	N	N
Judicial workers	N	N	N
Rest of workers	Y	Y	Y
Retirees	Y	Y	Y
Observations	2,072,650	2,072,650	2,072,650

Notes: P-values less than 0.05, 0.01, and 0.001 are flagged with *, **, and ***, respectively. This table reports the responses to RBB for total expenditure and for different categories.

In column one, we show the estimates for the total expenditure from our preferred specification where, as before, we remove teachers and judicial workers (column 3 from Table 3). In column two, we show the response to RBB of expenditure on repairs and maintenance, which increases significantly above any other reported category. Intuitively, agents do not always pay to fix their durable goods. However, when they receive the RBB, everyone is in better conditions to afford it. We present the elasticity for the working costs in column three. This category also exhibits excess sensitivity with respect to total expenditure. If we assume the working costs represent a fraction of the total value of durable goods, then this elasticity can be interpreted as an increase in the stock of durable goods, which suggests the presence of a lumpy expenditure decision. This interpretation aligns with the idea that Argentinians use durable goods as a store of value when they receive the RBB.

Combining the results in tables 3 and 4, we compute some back-of-the-envelope calculations. First, we estimate the excess sensitivity of durable goods. As the sum of repair and working cost amounts to 22.3% of total expenditure, the *joint elasticity* of durable goods is 5.51 and of non-durable goods 2.87. Durable goods are twice as sensitive to the RBB. Second, we can estimate the savings response to the RBB in a broad sense. That is, we can compute the joint response of the demand for *net* liquid assets and durable goods-related expenditure to a recurrent and anticipated income shock. Some back-of-the-envelope calculations suggest that a) the contribution of durables, repair, and working cost to the CRI is 35.2%. That is, as the relative response of consumption to income is $CRI_{3,7} = 12.29\%$, the CRI of durable goods is 4.33% and of non-durable goods is only 7.96%. b) The joint response of durable goods and net liquid assets to income is 92.04%. *More than* 90% of a recurrent and anticipated income shock is devoted to durable goods or to increasing liquid net wealth. Notice that a CRI of 12.29% implies that households use 87.71% of the hike in income due to the RBB to either save in liquid assets (i.e., term deposits) or to cancel debt or both. Thus, we observe a significant increase in net liquid wealth.

In our dataset, we cannot observe the lumpy decision to purchase a durable unit. However, working costs suggest that there has been an increase in the stock of durable goods. Furthermore, we can test for this mechanism by analyzing the agents' liabilities whenever they increase their working costs. This is natural, as lumpy expenditure decisions are typically paid with credit. To test this hypothesis, we run a simple regression between liabilities and working costs spending:

$$\text{Liabilities}_{i,t} = \alpha_0 + \alpha_1 \text{WorkingCost}_{i,t} + \epsilon_{i,t}$$

and find that $\alpha_1 = 0.96$. This result suggests that working costs are linked to the stock of durable goods, and agents purchase these goods using credit. Combining the response of gross liabilities and net liquid wealth, we can further characterize agents' response to the RBB. As they can borrow up to a limit, households deleverage, reducing the gross debt accumulated until $t-1$, or purchase liquid gross assets. As most households have a small stock of gross liquid assets [6], the latter tends to dominate the former. In this sense, the joint behavior of gross assets, gross liabilities, and durable-related expenditure *can account* for the response of households to recurrent and anticipated income shocks.

Moreover, these results suggest that agents are not credit-constrained. However, they could be illiquid. The fraction of liquid assets with respect to current income may be low, and at the same time, the stock of outstanding credit per agent could be high. We investigate this possibility in the next section.

3.4 Role of Liquidity

The previous subsection points to an exciting result: illiquid hand-to-mouth agents may respond differently to a change in the environment when compared with liquid households. We find evidence that they cancel debt and/or acquire durable goods after a recurrent and anticipated income shock. This implies that even though both consumers save through durable goods, their elasticities can differ. Illiquid agents increase their net nominal wealth through deleveraging. Thus, they are more indebted when compared with liquid agents. More to the point, this debt has an origin: a strong preference for durable goods. Thus, after receiving the RBB, they may respond by purchasing more durable

[6] We observe that 64% of households in the dataset have less than half their salary in (gross) liquid assets.

goods than liquid households.

To assess the role of liquid assets in our estimates, we propose a variation of our previous regression. We estimate a triple difference estimator (diff-in-diff-in-diff) where we introduce a new dummy that identifies agents with less liquid wealth. The new parametric regression is the following:

$$
\begin{aligned}
c_{it} = \beta_0 + \beta_1 T_i + \beta_2 L_i + \beta_3 T_i \times L_i + \sum_{k=2}^{11} \beta_{4,k} M_k + \sum_{k=2}^{11} \beta_{5,k} M_k \times T_i + \\
\sum_{k=2}^{11} \beta_{6,k} M_k \times L_i + \sum_{k=2}^{11} \beta_{7,k} M_k \times T_i \times L_i + \Gamma' X_{it} + \epsilon_{it},
\end{aligned}
\tag{2}
$$

where we set $L = 1$ if the agent has low levels of liquidity according to a specific criterion to be defined below. As before, T is a dummy variable that equals one if the agent gets treated (i.e., she receives the RBB). $\{M_k\}_k$ are the month dummies. The main variable of interest is the triple interaction term $M_k \times T_i \times L_i$, with $k = 7$. This term captures the differences in expenditure from receiving an RBB and being liquidity constrained relative to liquid. Thus, we focus on the estimate for $\beta_{7,7}$.

We use two definitions of low liquidity. First, we rank agents based on how much assets they have relative to their expenditure levels. We calculate the gross assets ratio (mainly composed of check accounts and term deposits) over expenditure for each account and average it over time. We use these values to calculate the median ratio for the sample across agents. An agent is assumed to have low liquidity if her liquid asset position is below such median. This criterion is similar to the literature's standard definition of hand-to-mouth agents. Namely, an agent is hand-to-mouth if she holds less than half her salary in liquid assets. We cannot apply these criteria because we do not observe wages for agents in the control group. So, we must rely on the agents' asset holdings and expenditure needs. Second, we use information on the accounts' savings behavior. We define a low liquidity agent as one that does not have time deposits by the month of RBB. The motivation behind this criteria comes from the fact that, in Argentina, term deposits are the main instruments used by households to save and protect themselves against inflation. Thus, an agent who holds money in their balance but does not save through term deposits is assumed to have low liquidity because she cannot set money aside for saving and consumption smoothing.

We present the results for $\beta_{5,7}$ and $\beta_{7,7}$ in Table 5. The former shows the effect in average expenditure from receiving an RBB and being a liquid agent. The latter coefficient captures the differences in average expenditure from receiving an RBB and having low liquidity relative to being liquid and paid the RBB. In column one, we show the estimates for our first definition of low liquidity agents (i.e., those agents in the bottom half of the average assets-to-expenditure ratio distribution). In column two, we present the estimates for the second definition of illiquid agents (i.e., those without term deposits).

Table 5: Response of Expenditure to RBB

	(1) Low assets/expenditure	(2) No Term Deposits
$\beta_{5,7}$	0.0164**	0.0066
$\beta_{7,7}$	0.0327***	0.0365***
L/Sample	50%	76%
L/T	51%	75%
Observations	2,072,650	2,072,650

Notes: P-values less than 0.05, 0.01, and 0.001 are flagged with *, **, and ***, respectively. This table reports the expenditure responses to RBB for liquid and illiquid agents.

The results for $\beta_{5,7}$ and $\beta_{7,7}$ show that a *large part* of the excess elasticity can be attributed to low liquidity agents. In column one, the bottom half of the asset-to-consumption ratio distribution shows a significantly larger sensitivity. These agents react 3.3% more than the top half more liquid agents. Similarly, in column two, the average expenditure of agents that do not have term deposits rises by 3.4% more than their more liquid counterparts. These results indicate the importance of considering liquidity when studying excess sensitivity of expenditure to the RBB. We also show the fraction of agents classified as low liquidity in the sample (L/Sample) and among those that perceive an RBB or treated (L/T). As seen in the third and fourth columns of table 5, these shares do not change much across groups. This suggests we are not capturing a composition effect among treated and control groups but rather the causal effect of having little liquid assets.

We can also analyze the expenditure response for the different categories introduced previously. That is, estimate the differential response of expenditure related to durable goods for agents with low liquid assets. For this purpose, we use the second definition of illiquid agents, i.e., those without time deposits. We prefer this criterion because it captures a fundamental difference between agents. As term deposits have an average maturity of slightly above 30 days, they can be used to afford the repair costs of durable goods. Thus, the RBB may not significantly affect these types of liquid agents. We present the results for $\beta_{5,7}$ and $\beta_{7,7}$ in Table 6.

Table 6: Response of Expenditure Categories to RBB

	(1) Total Expenditure	(2) Repair	(3) Working Costs
$\beta_{5,7}$	0.0066	0.0883	0.0029
$\beta_{7,7}$	0.0365***	0.0152	0.0476**
Teachers	N	N	N
Judicial workers	N	N	N
Rest of workers	Y	Y	Y
Retirees	Y	Y	Y
Observations	2,072,650	2,072,650	2,072,650

Notes: P-values less than 0.05, 0.01, and 0.001 are flagged with *, **, and ***, respectively. This table reports the responses to RBB for total expenditure and different categories.

The results show that the expenditure on the working cost of durable goods rises more among the illiquid agents. This suggests that agents with lower liquid assets purchase *more* durable goods with their RBB. These results support the hypothesis that Argentinians rely on durable goods as a saving mechanism. Specifically, low liquidity, indebtedness, and durable goods are deeply related. Illiquidity relates to a strong preference for durable goods, which we observe through expenditure on working costs. Due to the lumpy nature of durable goods, illiquid households are also relatively more indebted, generating another form of wealth-hand-to-mouth: these agents may have negative net liquid wealth, which improves after we add the stock of durable goods to compound total net wealth. Due to the persistence in the consumption patterns and because there are limits to the indebtedness levels, agents need to reduce gross debt to acquire additional durable goods. Thus, they use the extra resources obtained from the RBB to deleverage.

4 A Model with Durable Goods

We develop an analytical framework to characterize the empirical findings. The model is a variation of the standard heterogeneous agent incomplete-markets economy. It features an uninsurable and idiosyncratic income process, a borrowing constraint, and an endogenous wealth distribution in a recursive environment. There are durable and non-durable goods. The main departure from benchmark models is the existence of an anticipated income bonus every six periods. This fact affects the value function of each agent, creating an additional state variable with respect to the canonical version of the model. Thus, we add time, more precisely, time distance, to the income bonus that mimics the RBB. Agents understand that after receiving the bonus, they will receive the next one precisely six periods ahead. They are aware of this repeating cycle and choose their consumption profile accordingly. Given our data and primary focus on the agents' decisions, we solve the model in partial equilibrium. We hypothesize that the RBB does not alter the relative price structure in the economy, although it is affected by it. The equilibrium features a stationary distribution conditional on the time period that repeats itself every six periods.

4.1 Description of the model

The economy consists of a unit measure of households. Time is discrete, and there is no aggregate uncertainty. Agents derive utility from current perishable consumption, c, and the next-period stock of durable goods, D'. Households choose how much to save in next-period liquid assets, a', consume perishable goods, and the level of durable goods they would like next period, D'. They discount the future with a factor β and have expectations over future shock realizations. Agents are endowed with an uninsurable stochastic stream of income that evolves according to an AR(1) Markov process.

An agent's expenditure on durable goods is denoted as e. The agent's stock of these goods, D, depreciates at a non-linear rate $\delta(\omega) \in (0, 1)$. We model the depreciation as a stochastic process that depends on the idiosyncratic shock realization ω. This variable represents the probability that the depreciation shock occurs at a given period and the agent's stock of durable goods gets reduced. We assume durable goods do not depreciate linearly, but they suffer shocks that cause breaks and malfunctions. For instance, in the case of a car, these shocks could be a flat tire, a traffic accident, or a mechanical malfunction that impacts the utility the agent derives from the car. Even though these shocks are infrequent, they can significantly affect the stock of durable goods. The assumptions concerning the depreciation rate are realistic and better suited for calibrating monthly data in the next section. Hence, the stock of durable goods evolves according to the standard law of motion $D' = e + (1 - \delta(\omega))D$. It is worth noting that agents can spend e for two reasons: i) repair a depreciated unit and ii) increase the stock of durable goods. Even though we do not differentiate them here, we will bring this distinction back in the next section.

Another critical component of durable goods is their working costs, denoted γ. We assume that these costs are proportional to the value of the desired stock, pD', so an agent has to pay $\gamma pD'$ to enjoy these goods. In practice, working costs are taxes, insurance, gas, telephone service, and any other spending needed for a durable good to be used by the agent. For instance, without paying for insurance, taxes, or even gas, an agent cannot derive utility from a car. The same goes for cell phones, TVs, and other house appliances; they need a cellphone service, TV subscription, and electricity to generate utility for the agent.

The environment described above can be formalized as follows:

$$V(a, D, z, p, t, \omega) = \max_{c,a',D'} u(c, D') + \beta E[V(a', D', z', p', t', \omega')]$$

subject to:

$$c + a' + p(D' - (1 - \delta(\omega))D) = a(1 + r) + z(1 + g\mathbb{1}(t = 0)) - \gamma p D'$$

$$a' \geq \underline{a} \quad (\lambda)$$

$$e = D' - (1 - \delta(\omega))D, \quad c \geq 0.$$

The agents' value function depends on their level of assets a, the initial stock of durable goods, D, income shock realization, z, price of durable goods, p, time distance to RBB, t, and the realization of the depreciation shock, ω. Time distance to RBB takes values $t \in \{0, 5, 4, 3, 2, 1\}$, where $t = 0$ is the RBB month. In the budget constraint, the time distance to RBB t enters as an indicator variable that grants agents with $(1{+}g)$ additional income when RBB is being paid.

4.2 Characterization

In this model, durable goods have a dual role: they generate utility and can also be used to transfer resources across time. The first role is straightforward since the stock of durable goods is part of the flow utility function. The second role requires comparing the return on saving in liquid assets and durable goods. In Argentina, the ex-post interest rates are negative due to persistently high inflation. The return on saving in liquid assets is such that $r < 0$. This alone would force agents to save almost exclusively on durable goods. However, holding these goods requires paying the working cost, which reduces its return.

Moreover, the risk of experiencing a depreciation shock $\delta(\omega)$ exists. Thus, agents face an interesting trade-off between saving in liquid assets or durable goods. More to the point, the presence of working costs and depreciation shocks implies that is possible to demand liquid assets even in the presence of an ex-post negative real rate r.

To further characterize this trade-off, we derive the model's first-order conditions:

$$u_c(c) - \lambda = \beta(1+r)E[u_c(c', D'')] \tag{3}$$

$$u_c(c, D')p(1+\gamma) - u_d(c, D') = \beta E[u_c(c', D'')(p'(1-\delta(\omega')))] \tag{4}$$

Equation (3) is a standard Euler equation. Equation (4) is an arbitrage equation for durable goods: the net expected return of increasing the stock of these goods $E[u_c(c', D'')(p'(1-\delta(\omega')))]$, appropriately discounted, must equal its cost in terms of perishable goods net of the marginal utility of durable goods. From equation (3) and (4) we get:

$$\beta(1+r)E[u_c(c', D'')] + \lambda = \frac{\beta(RP + CG) + u_d(c, D')}{(1+\gamma)p}, \tag{5}$$

where $RP \equiv cov\,[u_c(c', D''), (p'(1-\delta(\omega')))]$ and $CG \equiv E[u_c(c', D'')]E[(p'(1-\delta(\omega')))]$. RP stands for *risk premium* and represents the risk associated with a higher depreciation cost in the future. Moreover, CG stands for *capital gains* and represents the benefits of an increase in the future price of durables. Thus, after a decrease in the real interest rate, in the absence of the risk premium and the capital gains, the agent reacts by increasing the demand for durables through u_d. However, as RP is negative, this effect is buffered. More to the point, an expected capital loss (i.e., CG/p goes down) would also prevent agents from reducing the demand for liquid assets after a decrease in the interest rate. Note that *this mechanism is robust to the presence of a negative real interest rate* $r < 0$. In the calibrated model, RP suffices to match data as we assume that p is constant through time.

Now we analyze the effect of the RBB. To do that, we add the time index t into the system form by equations (3) and (4).

$$u_c(c; t = 0) - \lambda = \beta(1 + r)E[u_c(c', D''; t = 5)] \tag{6}$$

$$u_c(c, D'; t = 0)p(1 + \gamma) - u_d(c, D'; t = 0) = \beta E[u_c(c', D'')(p'(1 - \delta(\omega'))); t = 5], \tag{7}$$

where we can split the right hand side of equation (7) in two terms: $E[u_c(c', D''); t = 5]E[(p'(1-\delta(\omega'))); t = 5]$ and $cov\,[u_c(c', D''), (p_+(1 - \delta(\omega'))); t = 5]$. The time index captures the time-conditional stationarity induced by the RBB, which asymmetrically affects the demand for liquid assets and durable goods. First, note that the time index in the dynamic program, through envelope theorems, generates a strong reaction of the composite $a' + pD'$ as it simultaneously affects the left-hand-side (when $t = 0$) and the right-hand-side (when $t = 5$) of both Euler equations. This is due to the *recurrent* nature of the RBB and explains the reduction in relative consumption observed in figure 2 after households receive the RBB. More to the point, this can also account for the strong joint response of liquid assets and durables found in data (i.e., the CRI of non-durables is only 7.96% and the relative response of the composite $a' + pD'$ is 92.04%). Intuitively, the RBB increases available resources today and decreases them tomorrow, forcing a strong inter-temporal re-balancing. Second, $E[u_c(c', D''); t = 5]$ captures the reduction of income after receiving the RBB in both equations. However, the risk premium amplifies this effect through $cov\,[u_c(c', D''), (p'(1 - \delta(\omega'))); t = 5]$. Thus, the response of durables is stronger when compared with non-durables because the latter is riskier due to depreciation shocks, as we assume that relative prices do not change over time. Due to incomplete markets, households hedge this risk through *precautionary* saving in durables, which accounts for the excess sensitivity of these goods.

5 Mapping the Model to Data

In this section, we present the parameter values that we use in our model. First, we show the estimated parameters for the income process, together with some additional robustness checks. Then, we discuss the intuition behind some parameters and their calibration.

5.1 Income Process Estimation

Proper estimation of the income process is critical in our calibration. Due to Argentina's high and persistent inflation environment, the agents' real income may be considerably more volatile than in other countries. Hence, we estimate the real income process using the time-invariant model proposed by Storesletten et al. (2004). The real income of agent i at time t is defined as:

$$\ln Y_{i,t} = \beta_t + f(X_{i,t}) + u_{i,t},$$

where $Y_{i,t}$ is the monthly real income. We control for demographic characteristics and time-fixed effects with the time-invariant function $f(X_{i,t})$. The time-series process for the idiosyncratic stochastic earnings component $u_{i,t}$ is defined as:

$$u_{i,t} = \alpha_i + \eta_{i,t} + \epsilon_{i,t}$$

$$\eta_{i,t} = \rho\eta_{i,t-1} + \nu_{i,t},$$

where $\alpha_i \sim (0, \sigma_\alpha^2)$, $\epsilon_{i,t} \sim (0, \sigma_\epsilon^2)$, $\nu_{i,t} \sim (0, \sigma_\nu^2)$, so $E(u_{i,t}) = 0$. We assume that these shocks are iid ($\alpha_i \perp \epsilon_{i,t} \perp \nu_{i,t}$). The variable α_i is the permanent income component, while $\nu_{i,t}$ and $\epsilon_{i,t}$ are the persistent and transitory shocks, respectively.

The parameters' estimates for the real income process are presented in Table 7. In Section 3, we mentioned that we do not observe wages for the untreated group. So, naturally, we do not include them in this estimation. Moreover, some of the treated agents receive very small wage payments. Since we only observe net wages, it may be the case that these agents suffer from additional deductions to their income. Thus, in order to control for this possibility, we only estimate the income process using those agents with a level of wages above the poverty line.

Table 7: Real Income Process Estimates

	Shocks Variance			
	Permanent σ_α^2	Transitory σ_ϵ^2	Persistent σ_ν^2	ρ
Sample	0.1806	0.0000	0.0237	0.5646
Workers	0.1740	0.0000	0.0298	0.5837
Private sector	0.1439	0.0000	0.0438	0.5362
Public sector	0.1799	0.0000	0.0274	0.6083

Notes: This table reports the parameter estimates for the real income process in our dataset for the full sample and for different subsamples. σ_α^2 is the variance of the permanent component of income, σ_ϵ^2 is the variance of the transitory shock, σ_ν^2 is the variance of the persistent shock, and ρ is the persistence parameter of the AR(1) process.

For the calibration, we use the estimates for the entire sample (first row). One of the main results is that the estimated income process has a significantly low persistence relative to estimates for the US. We estimate a persistence parameter ρ of 0.56 monthly, while Storesletten et al. (2004) estimate ρ to be closer to 0.98 yearly. Given $\rho = 0.56$, a shock loses almost half its effect by the first period. After five periods, only six percent of the impact remains, and by period ten, the shock completely disappears. This result implies that short-lived shocks do not send agents into persistent income paths. On the contrary, the income process is quite volatile, which should profoundly impact the agents' consumption patterns. Our estimated values for the shocks' variance align with the results that Storesletten et al. (2004) obtain for the US using PSID yearly data.

In Table 7 we also provide estimates of the real income process for all workers, private and public sector workers. The parameter estimates do not vary much across the different subsamples, which gives us confidence that our results are robust to various specifications.

5.2 Calibration

We calibrate the model to our dataset spanning from February to November 2022 in Argentina and set its frequency to be monthly.

Preferences. First, the preference parameters in the flow utility are among the most important parameters to calibrate. We use the following utility representation:

$$u(c, D') = \frac{(c^{\alpha} D'^{1-\alpha})^{1-\sigma}}{(1-\sigma)}$$

That is, consumption and durable goods are combined through a Cobb-Douglas function. Besides that, we rely on a standard constant relative risk aversion (CRRA) utility form for the composite consumption good. We follow the literature and set the relative risk aversion parameter σ equal to 2. As for the share, α will be calibrated to generate a realistic fraction of expenditure on durable goods over total expenditure. In our dataset, that fraction is equal to 4.6% and is given entirely from *Electronics*. However, the high elasticity of the working costs in durable goods that we estimated in Section 3, suggests we are not capturing the entire spending on durable goods done by the agents. For instance, we observe spending in *Construction* that represents 2% of total expenditure. However, we cannot determine how much is spent on repairing and how much is allocated to building/expanding a house. So we have decided to half its weight and add it to the expenditure on durable goods. The remaining 1% is considered durable goods repair spending, described below. Hence, our measure of expenditure on durable goods represents 5.6% of total spending.

Depreciation Shock. We suppress the dependence of δ on ω to economize on notation. We model the depreciation shock δ as follows:

$$\delta = \begin{cases} \frac{\delta_M}{\omega} & \text{with probability } \omega \\ 0 & \text{with probability } 1-\omega, \end{cases}$$

where δ_M is the monthly depreciation rate. The logic is as follows: with probability ω, an agent receives a shock δ to its stock of durable goods. The magnitude of the shock is such that, on the aggregate, the stock of durable goods gets reduced at the monthly depreciation rate of the economy (δ_M). This implies that, for a given probability ω, we can match the monthly depreciation rate using the rate δ. In the limit when $\omega = 1$, every agent receives the shock and $\delta = \delta_M$. In the model, however, some agents receive the shock, and others do not. But, at the aggregate level, the stock of durable goods depreciates linearly through $\omega\delta$. Given the type of durable goods we are studying have a short lifespan, we use an annual depreciation rate of 20% (houses are not a usual investment in Argentina).This yearly rate translated into a monthly rate of $\delta_M = 1 - (1 - 0.20)^{(1/12)} = 0.0184$.

Repair Spending. In Section 3, we highlighted the importance of durable goods repair spending and showed they represent a non-trivial share of total expenditure. In the model, we do not explicitly distinguish between spending to increase the stock of durable goods and to repair them. Agents choose the level of D' they desire based on their state variables. To capture the spending on repairs, we assume that only those agents who suffer from the shock ω can repair their durable goods. We model durable repair as follows:

$$\text{Repair} = \begin{cases} D' - D(1-\delta) & \text{if } D(1-\delta) < D' \leq D \text{ , and } \delta = \frac{\delta_M}{\omega} \\ D\delta & \text{if } D' > D \text{ , and } \delta = \frac{\delta_M}{\omega} \\ 0 & \text{if } \delta = 0 \end{cases}$$

In the first case, agents that receive a depreciation shock repair part or all of the damaged goods. In the second case, agents decide to fully repair the stock of durable goods and even increase it. In the third case, agents that did not receive the depreciation shock cannot spend on repair. Using this definition, we can measure how much agents spend repairing durable goods in the model. We use the depreciation shock probability ω to target the share of durable goods repair spending in the total expenditure. In our dataset, that share is equal to 5.4%. However, one of the spending categories in this group is *Construction*. As explained before, the weight of *Construction* in total expenditure is 2%, and we decided to use half that for durable goods repair. The remaining 1% goes to our measure of expenditure on durables goods. Hence, we target a share of durable goods repair spending of 4.4%.

New Durable Spending. Similarly to repair spending, we model spending on new durable goods as follows:

$$\text{New Durable goods} = \begin{cases} 0 & \text{if } D(1-\delta) < D' \leq D \text{ , and } \delta = \frac{\delta_M}{\omega} \\ D' - D & \text{if } D' > D \text{ , and } \delta = \frac{\delta_M}{\omega} \\ D' - D & \text{if } D' > D \text{ , and } \delta = 0 \end{cases}$$

In the first case, agents only repair the damaged durable goods from the depreciation shock, so no new durable goods are purchased. In the second and third cases, agents spend more on new durable goods than their current stock. In the calibration, we use this measure to target the share of 5.6% that we observe in the data.

Working Costs. Parameter γ is calibrated to target the share of the working cost of durable goods spending on total expenditure. In our dataset, working costs amount to 16.9% of total expenditure.

Discount Factor. We use the discount factor β to target the median wealth over income. As explained before, we do not observe income for the untreated group. So, we only consider this measure for those agents that receive an RBB. In our dataset, the median wealth-to-income ratio is 0.247. In the model, we take the median values for income and wealth from a ten-period window that mirrors the data. In such a window, the parameter t (time distance to RBB) starts at $t = 5$, goes down to $t = 0$ (RBB period), then $t = 5$ again and finishes at $t = 2$. We also consider that, in the model, agents can receive a stream of income from selling their durable goods. Hence, we include that additional source of revenue in their total income. If $D' < (1-\delta)D$, we add this value to income.

Interest Rate. We calibrate the interest rate $r = 0$ to analyze an economy where liquid assets do not yield a positive return.

Remaining Parameters. Additionally, we assume that asset holdings cannot be negative, so $\underline{a} = 0$. Since we work in a partial equilibrium, we set the price of durables at $p = 1$. Finally, the value of the RBB increase in real income g is calculated as the median variation in agents' checking account balances between July and June 2022, equal to 32%.

Table 8 presents all the externally calibrated parameter values. At the same time, the internally calibrated ones are shown in Table 9.

Table 8: Externally Calibrated Parameter Values

Parameter	Value	Description
σ	2	From literature
ρ	0.5646	Estimated
σ_α^2	0.1806	Estimated
σ_ν^2	0.0237	Estimated
σ_ϵ^2	0	Estimated
p	1	Set
$\underline{a}$	0	Set
g	0.32	From data
r	0%	Set

Notes: This table reports the parameter values used for the calibration of the model.

Table 9: Internally Calibrated Parameter Values

			Moments	
Parameter	Value	Description	Data	Model
β	0.9924	Median wealth/income	0.247	0.240
ω	0.26	Repair exp/Total exp	0.044	0.044
δ	0.07	Depreciation rate of 0.0184		
α	0.735	Durables exp/Total exp	0.056	0.055
γ	0.074	Working cost exp/Total exp	0.169	0.171

Notes: This table reports the parameter values used for the calibration of the model.

From Table 9 we can see that the model does a very good job reproducing the targeted moments. The discount factor β equals 0.9924 monthly, which implies an annual rate of almost 0.91. The depreciation shock ω occurs with a probability of 26%. This means that to generate the aggregate monthly depreciation rate (δ_M) of 1.84%, the depreciation shock $\delta = \frac{\delta_M}{\omega} = 7.1\%$. The model matches the shares of durable spending and working cost spending we observe in our database.

5.3 Results and Discussion

First, we estimate the expenditure elasticities from the model and compare them to our empirical estimates from Section 3. To calculate the elasticities in the model, we take agents starting from the stationary distribution at $t = 5$. Then, we simulate them for ten periods from $t = 5$ to $t = 0$, then $t = 5$ to $t = 2$. For each type of expenditure, we estimate a simple regression using only time dummies, as follows:

$$c_{it} = \beta_0 + \sum_t \beta_t M_t + \epsilon_{it} \tag{8}$$

We run 1000 simulations of this regression and take the median of the estimates to get the model elasticities. We show the elasticities for total expenditure, durable goods repair spending, and working costs on durables goods in Table 10.

Table 10: Response of Expenditure Categories to RBB in the Model

	(1)	(2)	(3)
	Total Expenditure	Repair	Working Costs
Data	0.0344	0.0971	0.0407
Model	[0.0129 - 0.1037]	0.0925	0.0505

Notes: This table compares the responses to RBB for total expenditure and different categories from the data and the calibrated model. The value range for total expenditure arises from the treatment of durable goods purchases. The lower bound represents the elasticity of total expenditure net of durable goods spending. The upper bound represents the elasticity when spending on durable goods is included. The data estimate lies somewhere in between, suggesting we observe some but not all durable goods purchases in our dataset.

The values in the first row are the estimates for $\beta_{3,7}$ from Table 4. In the first column, we present the results for total expenditure for the model. In the model, the increase in working costs must be matched with an equally significant rise in durable goods. This increases the total expenditure significantly more than we observe due to the limitations in our dataset in observing all purchases of durable goods. To control for this, we calculate the effect on total expenditure net of durable goods spending as a lower bound of an interval. Our model generates a response to RBB of 1.3%, which is smaller than the empirical estimate. However, if we include durable goods spending, the total expenditure response to RBB rises to 10.4%, which is the upper bound of the interval. Part of the explanation for this significant response comes from our criteria for identifying expenditures for durable goods in the model. Agents spend little on new durable goods during most periods since a large fraction goes to repairs. However, agents choose significantly larger D' when $t = 0$, so most durable goods spending is concentrated in the RBB period. The discussion in section 4.2 suggests that this fact can be explained by the joint effects represented in equations (5) and (7). Due to the risk premium associated with durables, the model predicts a strong response in this type of goods. The precautionary motive combined with depreciation shocks forces agents to over-accumulate durable goods. Moreover, equation (7) can account for the concentration of this type of expenditure when agents receive the RBB. The effect of time as an additional state variable reduces the return on durables immediately after the RBB. To balance the Euler equation, durable goods must respond significantly to this event. Our empirical estimates are in between the two model extreme elasticities. Hence, we could argue that our dataset includes some but not all of the durable goods purchases agents make.

The simulated model responses for total expenditure, repair, and working costs on durable goods can replicate their empirical counterparts closely. Total expenditure response to RBB generates a range that captures the data estimates. Furthermore, the estimates for durable goods repair and working costs are almost identical to our dataset's empirical ones. This indicates that agents spend a significant share of their RBB in durable goods-related expenditures, as highlighted in this paper.

Our results suggest that it is necessary to move beyond benchmark models that assume a single good to fully explain the expenditure responses to RBB observed in the data. This paper explores a two-goods model in which holding durable goods is risky due to maintenance costs and stochastic depreciation shocks. These features can replicate the expenditure patterns we estimate and explain why agents might choose to hold liquid assets even in an environment with zero or negative real interest rates.

6 Conclusion

We use a unique dataset for Argentina to study the impact on expenditure of a fully predictable and periodic income variation, namely the RBB. We argue that the RBB has several advantages over previous sources of anticipated income change that the literature has studied before.

We measure the elasticity of expenditure to the RBB and find that: i) durable goods are more reactive than non-durable expenditure, ii) durable goods expenditure is more than just new goods, maintenance and working costs matter a lot, iii) despite low real interest rate, households still save a significant fraction of the RBB in liquid assets because durable goods are risky. We find two main sources of risk: depreciation shocks and expensive working costs. While the first one is standard, the working costs channel has not being well documented and, as we show, it is important to explain how agents react to anticipated income shocks.

We develop a model that accommodates for the periodicity of RBB to study this event. Moreover, we estimate the real income process for the workers in our dataset and find that income profiles show little persistence. The model helps us to give a structural interpretation to the empirical results in the paper.

Our results are relevant for Argentina, which is affected by inflation. As we are the first to estimate and interpret the effects of a recurrent and anticipated income shock and we only have data for this country, we believe that there is scope for future research to other, more stable, countries.

References

Aaronson, D., Agarwal, S., & French, E. (2012). The spending and debt response to minimum wage hikes. *American Economic Review*, *102*(7), 3111–3139 (cit. on p. 5).

Attanasio, O. P. (1999). Consumption. *Handbook of macroeconomics*, *1*, 741–812 (cit. on p. 6).

Flavin, M. A. (1981). The adjustment of consumption to changing expectations about future income. *Journal of political economy*, *89*(5), 974–1009 (cit. on p. 5).

Friedman, M. (1957). *Theory of the consumption function*. Princeton university press. (Cit. on p. 5).

Fuchs-Schündeln, N., & Hassan, T. A. (2016). Natural experiments in macroeconomics. In *Handbook of macroeconomics* (pp. 923–1012, Vol. 2). Elsevier. (Cit. on pp. 2, 5).

Ganong, P., & Noel, P. (2019). Consumer spending during unemployment: Positive and normative implications. *American economic review*, *109*(7), 2383–2424 (cit. on pp. 5, 7).

Gelman, M., Kariv, S., Shapiro, M. D., Silverman, D., & Tadelis, S. (2014). Harnessing naturally occurring data to measure the response of spending to income. *Science*, *345*(6193), 212–215 (cit. on pp. 5, 6, 12, 15).

Graham, J., & McDowall, R. A. (2022). Consumption behavior across the distribution of liquid assets (cit. on p. 6).

Hall, R. E. (1978). Stochastic implications of the life cycle-permanent income hypothesis: Theory and evidence. *Journal of political economy*, *86*(6), 971–987 (cit. on p. 5).

Heathcote, J., Storesletten, K., & Violante, G. L. (2009). Quantitative macroeconomics with heterogeneous households. *Annu. Rev. Econ.*, *1*(1), 319–354 (cit. on p. 6).

Hsieh, C.-T. (2003). Do consumers react to anticipated income changes? evidence from the alaska permanent fund. *American Economic Review*, *93*(1), 397–405 (cit. on p. 5).

Jappelli, T., & Pistaferri, L. (2010). The consumption response to income changes. *Annu. Rev. Econ.*, *2*(1), 479–506 (cit. on pp. 2, 5).

Johnson, D. S., Parker, J. A., & Souleles, N. S. (2006). Household expenditure and the income tax rebates of 2001. *American Economic Review*, *96*(5), 1589–1610 (cit. on p. 5).

Kaplan, G., & Violante, G. L. (2014). A model of the consumption response to fiscal stimulus payments. *Econometrica*, *82*(4), 1199–1239 (cit. on pp. 2, 6).

Kaplan, G., & Violante, G. L. (2022). The marginal propensity to consume in heterogeneous agent models. *Annual Review of Economics*, *14*, 747–775 (cit. on p. 6).

Misra, K., & Surico, P. (2014). Consumption, income changes, and heterogeneity: Evidence from two fiscal stimulus programs. *American Economic Journal: Macroeconomics*, *6*(4), 84–106 (cit. on pp. 5, 15).

Modigliani, F., & Brumberg, R. (1954). Utility analysis and the consumption function: An interpretation of cross-section data. *Franco Modigliani*, *1*(1), 388–436 (cit. on p. 5).

Parker, J. A. (1999). The reaction of household consumption to predictable changes in social security taxes. *American Economic Review*, *89*(4), 959–973 (cit. on p. 5).

Souleles, N. S. (1999). The response of household consumption to income tax refunds. *American Economic Review*, *89*(4), 947–958 (cit. on pp. 5, 15).

Storesletten, K., Telmer, C. I., & Yaron, A. (2004). Consumption and risk sharing over the life cycle. *Journal of monetary Economics*, *51*(3), 609–633 (cit. on pp. 28, 29).

Zeldes, S. P. (1989). Consumption and liquidity constraints: An empirical investigation. *Journal of political economy*, *97*(2), 305–346 (cit. on p. 5).

Appendix

Database Descriptive Statistics

Table 11: Descriptive Statistics for the Sample and by Income Quintile

		Sample	Quintile 1	2	3	4	5
Assets	Mean	228,920.80	117,585.50	143,466.40	177,292.80	244,778.40	461,476.60
	Median	60,423.84	29,458.71	42,194.14	55,146.17	78,037.86	142,261.80
Liabilities	Mean	113,640.30	66,828.27	84,491.73	104,398.40	121,801.60	190,679.90
	Median	41,583.57	30,542.53	35,930.26	41,193.58	45,349.64	61,178.18
Income	Mean	135,278.30	68,785.72	97,091.44	122,180.00	151,349.10	236,983.30
	Median	120,290.40	68,122.07	93,955.87	117,685.30	145,295.30	214,253.80
Expenditure	Mean	88,686.90	68,786.48	76,663.14	83,622.91	93,048.74	121,233.10
	Median	73,550.30	58,954.80	66,424.30	72,535.13	80,411.63	99,927.39

Notes: This table reports some descriptive statistics about the agents for the full sample and by income quintile.

Table 12: Agents' Employment Status

Employment Status	Sample	Quintile 1	2	3	4	5
Public Sector	58.93%	59.61%	59.63%	60.50%	59.60%	55.30%
Retirees	28.30%	24.01%	24.59%	27.51%	28.92%	36.49%
Private Sector	12.15%	16.23%	15.51%	11.48%	10.32%	7.19%
Bank Employees	0.57%	0.10%	0.22%	0.44%	1.11%	0.95%
Others	0.06%	0.05%	0.05%	0.07%	0.06%	0.08%

Notes: This table shows the employment status distribution for the agents in the full sample and by income quintile.

Table 13: Composition of Public Sector Workers

Public Sector	Sample	Quintile 1	2	3	4	5
Teacher	42.68%	37.72%	42.73%	55.96%	53.08%	22.24%
Municipal	14.95%	22.33%	16.52%	11.85%	11.90%	12.00%
Provincial entities	11.82%	13.04%	13.98%	11.90%	10.16%	9.91%
Police	9.69%	11.41%	13.98%	9.15%	10.21%	3.22%
Judicial	8.66%	1.32%	3.87%	3.71%	6.12%	29.89%
Healthcare	8.44%	14.02%	8.35%	6.53%	6.14%	7.10%
Bank employee	3.32%	0.00%	0.06%	0.41%	1.93%	15.07%
National entities	0.37%	0.08%	0.45%	0.44%	0.42%	0.45%
Others	0.07%	0.08%	0.06%	0.06%	0.04%	0.12%

Notes: This table shows the main occupations that the public sector workers have in the full sample and by income quintile.

Table 14: Composition of Private Sector Workers

Private Sector	Sample	Quintile 1	2	3	4	5
Services	60.71%	59.02%	58.65%	64.55%	61.39%	61.89%
Manufacturing	18.33%	13.88%	16.26%	18.68%	24.39%	23.60%
Commerce	15.69%	20.74%	20.43%	12.28%	9.63%	8.22%
Agricultural	2.55%	3.56%	2.21%	1.85%	1.97%	2.95%
Construction	1.69%	1.60%	1.56%	1.61%	1.63%	2.36%
Others	1.04%	1.20%	0.89%	1.03%	1.00%	0.98%

Notes: This table shows the main sectors that the public sector employees work at in the full sample and by income quintile.