Credit Market Experiences and Macroeconomic Expectations: Evidence and Theory *

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Using the NY Fed Survey of Consumer Expectations, I show that individuals overweigh personal credit rejections when forecasting aggregate credit markets, unemployment, stock prices, and inflation, challenging standard belief-formation theories. A selective memory model explains this: rejections cue recall of negative experiences, inflating pessimism. The data supports key predictions: (i) rejected individuals recall tighter credit conditions, (ii) experience-driven belief heterogeneity correlates with demographics, (iii) adverse shocks generate disagreement and overreaction. Embedding these beliefs into a consumption-saving model, I find rejection-induced pessimism amplifies durable consumption declines, accounting for 12% of the drop, particularly among younger, lower-SES households, and magnifying aggregate shocks.

Keywords: experiences, memory, expectations, disagreement, consumption

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1 Introduction

It is well established that people's expectations about economic outcomes –such as inflation, unemployment, and stock prices– are shaped by their past economic experiences (Malmendier and Nagel, 2011, 2016; Kuchler and Zafar, 2019). Prior research suggests these effects remain domain-specific: they do not affect beliefs outside the domain where they occur. For example, aggregate stock market experiences affect expectations about the stock market but not expectations about bond markets (Malmendier, 2021), or local house price experiences affect expectations about house prices but not about inflation (Kuchler and Zafar, 2019).

This paper shows that these effects can be much broader, shaping expectations about multiple macroeconomic outcomes –even when the experience itself is idiosyncratic. Using micro-level data from U.S. household surveys, I find that personal credit rejections induce a robust pessimism not only about nationwide credit conditions but also about unemployment, stock prices, and inflation. This poses a puzzle under standard models of expectation formation: these personal rejections have no predictive power for actual macro outcomes, nor can their effect be attributed to particular applicant characteristics or common shocks. Why, then, do individuals assign such excessive weight to their own credit rejections when forming macroeconomic beliefs, and what are the implications?

To understand this puzzle, I develop a model of selective and associative memory, building on Bordalo et al. (2022) and psychological evidence on contextual retrieval (Kahana, 2012). When a household experiences a loan rejection, the event enters their memory database and simultaneously shifts their financial "context" toward a more pessimistic state. This pessimistic context makes negative episodes more accessible in memory, leading to a distorted recalled set and, consequently, systematically pessimistic forecasts. Consistent with this mechanism, I show that rejected individuals recall overly tight past credit conditions, which directly correlates with more negative macroeconomic expectations. The model further predicts –and the data confirm– that these belief distortions are strongest among younger and lower-SES individuals, and during recessions. This results in both systematic heterogeneity in beliefs across demographic groups and aggregate overreaction to downturns.

Finally, I examine the economic implications of these findings by embedding memory-based beliefs into a standard consumption-saving model. In this setting, rejections reduce consumption both directly (via lower ability to spend) and indirectly (via lower willingness to spend). Using survey data on planned durable consumption, I find that this belief-driven channel accounts for 12% of the total decline in durable spending among rejected households, with the strongest effects among younger, lower-income individuals. Crucially, I show that during downturns, this belief distortion amplifies aggregate demand contractions: individuals who have previously been rejected are more likely to overreact to negative macro shocks, reinforcing pessimism and deepening economic slowdowns.

I begin by leveraging micro-level data from the NY Fed Survey of Consumer Expectations (SCE), presented in Section 2. The Core Module provides individuals' demographic characteristics and macroeconomic forecasts, while the Credit Access Module tracks credit applications and outcomes in the past 12 months, letting me classify respondents into "applied and accepted," "applied and rejected," and "didn't apply". This classification is ideal for isolating how idiosyncratic credit experiences affect broader economic beliefs. In Section 3, I show that those recently rejected for credit consistently exhibit greater pessimism about nationwide credit market conditions, unemployment, stock prices, and inflation. Why then, when asked about the same macro outcomes, household rely on their idiosyncratic experiences?

Standard Bayesian or information-based models would only give substantial weight to personal rejections if those events carried informative signals about future macro trends –a hypothesis for which I find no support. Indeed, households who experienced rejections systematically make larger forecast errors, over-weighting these idiosyncratic events with zero predictive power. This pattern can neither be attributed to observed or unobserved applicant characteristics: the result remains robust after controlling for a wide range of variables (age, gender, race, education, numeracy, income, employment), loan types (mortgage, credit card, student loan), reported credit scores, and aggregate shocks, as well as after using individual fixed effects and matching methods to ensure comparability with households who were accepted or did not apply.[1] Hence, we require a different mechanism to explain *why* households attach such outsize importance to their personal event.

To address this, in Section 4, I propose a selective and associative memory framework building on Bordalo et al. (2022) and the concept of contextual retrieval (Kahana, 2012). In the model, individuals form beliefs about future economic conditions by drawing on both statistical data and personal memories. This process operates through two key steps: (*i*) *which* experiences are recalled and (*ii*) *how* those recalled experiences shape probability judgments. First, recall is *selective and associative*: individuals are more likely to retrieve experiences that are both similar to the event they are forecasting and congruent with their current personal context (Kahana, 2012; Bordalo et al., 2023). Here, context refers to the household's internal mood or state –captured by their financial situation– that shapes which experiences come to mind. Second, recalled memories shape beliefs through *simulation*: people use retrieved experiences to construct or imagine scenarios, making it easier to mentally simulate certain economic outcomes (Kahneman and Tversky, 1981; Schacter et al., 2012; Bordalo et al., 2023).[2]

Under this framework, a negative personal experience –such as a credit rejection– plays a dual role. First, it enters the memory database, becoming available for recall. Second, it alters

[1]These exercises also reveal that, while rejections are associated with economic pessimism, acceptances do not induce optimism.

[2]This process of simulation is a form of reasoning by analogy which gets easier when experiences are similar to the event, even if they are from different domains (Kahneman and Tversky, 1981), and it is well documented in psychology and neuroscience (Dougherty, Gettys and Thomas, 1997; Schacter, Addis and Buckner, 2007, 2008; Schacter et al., 2012; Biderman, Bakkour and Shohamy, 2020).

the individual's context, shifting it toward a more pessimistic state. This shift affects recall: a negative context reduces the perceived distance to other bad episodes in memory, making them more likely to be retrieved and integrated into expectations. Intuitively, when asked about future credit conditions while in a negative personal context, individuals may recall not only official statistics but also disproportionately more negative personal episodes, including their own rejection and subsequent financial struggles. This recall bias increases the ease of imagining similar hardships for others, leading to a systematic overestimation of adverse macroeconomic scenarios. Although idiosyncratic rejections provide no true signal about future unemployment or inflation, recalling financial struggles can make it easier to imagine other hardships, fuelling more pervasive pessimism across domains.

I formalise this mechanism and demonstrate that subjective probabilities of downturns can deviate from frequentist estimates due to similarity-based recall and simulation. Specifically, individual rejections matter because they increase the recall probability of tighter economic conditions, leading to a more pessimistic recalled set and thus more pessimistic beliefs. The SCE allows me to test this directly, as it asks respondents to recall past experiences but also 'overall credit conditions from the past year'. In particular, I find that rejected individuals over-remember tight credit environments resulting in higher "recalled errors" when compared to objective measures of past credit conditions. Moreover, the pessimism induced by personal rejections diminishes substantially once I account for what people remember about aggregate conditions –suggesting that memory is the key channel through which idiosyncratic rejections spill over into general economic beliefs. Likewise, this recalled pessimism in one domain (credit) extends to other domains (unemployment, stock markets, inflation), in line with the idea that once people retrieve negative experiences, they are more likely to "simulate" or imagine similar negative states in other areas.

I then use this memory-based framework to characterise households' excess sensitivity to personal rejections and derive three key predictions about which households are most affected and under what conditions.[3] Each prediction is confirmed in the data. First, there are predictable spillovers: personal rejections induce pessimism across multiple markets, but the strongest impact occurs in the credit market –the domain most similar to the rejection itself (e.g., +10 percentage points for perceived future credit tightness vs. +2 for unemployment). Second, experience-driven heterogeneity correlates with demographics: younger households (with fewer past experiences to recall) and lower-SES households (for whom rejections are costlier) are disproportionately affected. This helps explain why these groups are consistently found to be more pessimistic about the economy (Das, Kuhnen and Nagel, 2020). Third, the

[3]Having an empirical measure of recalled conditions is crucial, as it allows me to test the specific model predictions on imperfect recall, for which the evidence provides support. Nevertheless, this measure captures the broad recalled set of individuals and is thus potentially noisy. The key advantage from my setup is that I can pinpoint a specific idiosyncratic event –the credit rejection– within the broader recalled set. Because this event is both self-reported and highly specific, it captures the memory effect cleanly, avoiding ambiguity about what households are exactly recalling.

memory bias is state-dependent: in bad macroeconomic states, negative personal experiences become even easier to recall due to stronger similarity, amplifying pessimism disproportionately among rejected households. In downturns, then, these households overreact to bad news, which feeds into aggregate overreaction in expectations.

These findings have significant macroeconomic implications, which I explore in Section 5. Using a three-period consumption-saving model, I isolate two channels through which rejections influence behaviour: (i) a direct channel, via tighter credit constraints, and (ii) an indirect channel, via lower willingness to spend by inducing pessimism about future economic states. Empirically, I quantify this indirect belief channel using data on planned durable consumption from the SCE Spending Module. Mediation analysis shows that roughly 12% of the total negative effect of rejections on durable consumption stems from macroeconomic pessimism alone. This belief-driven impact is most pronounced among younger, lower-income, and less-educated households, consistent with the predictions of the memory-based framework.

The interaction between the recall of personal rejections and current aggregate conditions amplifies these effects during downturns. Combining survey data with model equations, I show that when unemployment rises (a proxy for bad macroeconomic states), overall pessimism increases more than standard models would predict due to stronger recall of past negative experiences among previously rejected households. A counterfactual analysis indicates that if pessimism from past rejections were to remain constant across economic states, aggregate consumption would decline by about 0.8%. However, because this bias intensifies during downturns, the drop in aggregate consumption is estimated to be 30 basis points higher. Thus, personal financial setbacks do not just affect individual households –they can contribute to amplifying macroeconomic shocks by feeding back into aggregate demand through selective memory and belief formation.

Related Literature. This paper contributes to research on how individual experiences shape macroeconomic beliefs, building on work documenting that aggregate shocks often influence domain-specific expectations (Malmendier and Nagel, 2011, 2016; Kuchler and Zafar, 2019). In contrast, I show that recent *idiosyncratic* shocks –like personal credit rejections– matter beyond the known determinants and can spill over into multiple, potentially less related domains (inflation, unemployment, stock prices). This work also complements earlier findings on individual-level labor market or goods-market experiences (e.g., Malmendier and Shen, 2018; D'Acunto et al., 2021), while focusing on credit, a key but less studied arena of personal experiences. Moreover, the rich dataset I employ allows me to both identify experience effects on beliefs and quantify their impact on behaviour, distinguishing direct and indirect (belief-driven) channels.

I also connect to the literature on memory-based belief formation. Although existing experience-effect models typically assume domain-specific learning (Malmendier, 2021), I find broader influences consistent with memory theories emphasising the importance of perceived similarity.

Relatedly, Taubinsky et al. (2024) show that individuals' inflation expectations can be overly sensitive to their own income changes, and present evidence of selective recall. My paper therefore aligns with a broader line of research on memory and expectations (Enke, Schwerter and Zimmermann, 2020; Malmendier and Wachter, 2021; Bordalo et al., 2021*a*; Nagel and Xu, 2022; Andre et al., 2022; Afrouzi et al., 2023; Jiang et al., 2023; Bordalo et al., 2023), and specifically builds on Bordalo et al. (2022), who formalise how people use recalled (rather than purely informative) experiences to simulate and form novel risk assessments. Here, I use that framework to show how personal rejections can bias households' macroeconomic beliefs and then trace those distortions into consumption decisions.

Finally, my findings complement work on deviations from Full Information Rational Expectations (Coibion and Gorodnichenko, 2015; Bordalo et al., 2020; Broer and Kohlhas, 2022; Born et al., 2022; Kohlhas and Walther, 2021) by documenting predictable, memory-driven belief errors at the household level. This approach clarifies why households with negative experiences become particularly pessimistic in recessions, linking associative memory processes to overreactions in aggregate outcomes. More broadly, it contributes to research on demand-driven cycles and the role of sentiment in macro fluctuations (Bianchi, Ilut and Saijo, 2023; Angeletos and Lian, 2022; Maxted, 2023; Krishnamurthy and Li, 2020; Bordalo et al., 2021*b*; Benhabib, Wang and Wen, 2015; Lorenzoni, 2009; Bhandari, Borovička and Ho, 2022; Bordalo, Gennaioli and Shleifer, 2018). By building a memory-based model of household sentiment and embedding it into a macro framework, I show that personal rejections can amplify credit and spending cycles, especially for younger, low-income, and less educated individuals who overreact more strongly, offering a new perspective on how personal circumstances can shape aggregate demand dynamics.

2 Data

This section describes the main sources of information used, defines the key variables and provides descriptive statics for the main sample. Further details can be found in Appendix A.

2.1 Main Data Source and Variable Definition

Data Sources. The main source of data is the Survey of Consumer Expectations (SCE) from the Federal Reserve Bank of New York (Federal Reserve Bank of New York, 2013-2022). The SCE is a representative monthly survey composed of a rotating panel of approximately 1200 households heads who remain in the survey for up to a year. Each month new respondents are added to the survey, as others drop out. The Core Module of the survey contains detailed information about households' expectations and spans from June 2013 till February 2022.

A key feature of the SCE is its various specialised modules, which can be matched to the

Core Module. The Credit Access Module, administered three times a year (February, June, and October) since October 2013, provides unique insights into households' past experiences with the credit market and their expectations regarding future credit applications and outcomes.[4] By integrating this module with the Core Module, I create a final sample of 28241 person-month observations enriched with information on households' credit market experiences and economic expectations.

In addition to the Core and Credit Access Modules, the SCE includes a Spending Module and an Annual Household Finance Module, which I can also match to my main sample. The Spending Module, conducted three times a year from December 2014, allows me to link credit experiences and expectations to spending attitudes. The Annual Household Finance Module, administered once a year from August 2014 to 2019, includes 6809 observations and offers information on annual changes in individuals' savings and net wealth.

Throughout the paper, I use additional data sources to test the external validity of my results and to conduct supplementary analyses. A key source is the Survey of Consumer Finances (SCF) (Federal Reserve Board, 1989-2021), a triennial survey conducted since 1989. Unlike the SCE, the SCF provides a cross-sectional snapshot of households every three years. While it places less emphasis on expectations, the SCF offers advantages, including a longer time series (1989-2021) and more comprehensive information on household balance sheets and credit experiences. Specifically, it details the types of information households use when borrowing, the extent of their search efforts, and whether they have reapplied for credit.

Variable Definition. The SCE provides the ideal set up to analyse the role of personal experiences. I here describe the key variables for my analysis –experiences, expectations and controls– and in Online Appendix A I report the exact questions used.

Measure of Experiences in the Credit Market. The primary explanatory variable captures individuals' past experiences in the credit market. Respondents indicate whether they applied for any of seven credit types (i.e. credit cards, credit card limit increases, mortgages or home based loans, auto loans, increases in the limit of an existing loan, mortgage refinances, and student loans) within the last 12 months. Applicants are classified as "Applied and Accepted" if all their applications were approved (fully or partially) or "Applied and Rejected" if any application was denied. Individuals who did not apply are further categorised as "Didn't Apply, Discouraged" (those who avoided applying due to anticipated rejection) or "Didn't Apply, Other" (those who did not seek credit for other reasons). This classification distinguishes between individuals who refrain from applying out of preference and those deterred by pessimism about their acceptance prospects. For the main analysis, the experience variable does not differentiate by loan type, although I later explore differential effects based on the type of rejection.

[4] This paper uses data from the Credit Access Module up to October 2021. It spans 25 waves with approximately 1100 observations per wave (3300 per year), with a total of 28241 observations. The sample includes 13053 unique individuals, with 5518 responding three times, 4101 twice, and 3417 once.

Measures of Expectations. I focus on four variables that measure individuals' 12-month-ahead macroeconomic expectations: 1. future credit market conditions for everyone (tightening (=1), no change (=0), loosening (=-1)), 2. probability of higher US unemployment (scale from 0 to 100), 3. probability of higher stock prices in the US stock market (scale from 0 to 100), and (4) inflation rate (continuous). To have a measure of aggregate macroeconomic optimism, I follow Das, Kuhnen and Nagel (2020) and construct an Optimism Index. This index is an average of the standardised values of responses to the questions about credit, unemployment and stock prices.

Other Variables. The SCE also contains detailed demographic and socioeconomic characteristics such as respondents' age, gender, race, college attainment, marital status, employment status, income category, income expectations and numeracy category. The latter is constructed based on respondents' answers to seven basic questions about probabilities and interest rates. Households also report their credit score range, and other measures of financial conditions such as level of debt, timing of payments, and considerations of bankruptcy.

The Spending Module allows me to investigate the link between experiences, beliefs and behaviour. To have a measure of their individuals' spending attitude, I rely on their reported percent chance of buying durables within the next 4 months. Durables are defined as home appliances, electronics, computers or cell phones, furniture.

2.2 Descriptive Statistics

Appendix Table A.1 presents summary statistics of respondents' characteristics, their past experiences in the credit market and their expectations. The average age is 51 years, with 50% female and nearly 50% holding some college education. Regarding income distribution, 28% earn over \$100k annually, 30% between \$50k and \$100k, and 41% under \$50k.[5] Over two-thirds of respondents are in the high numeracy category, and almost three-quarters own a home. Approximately 50% of the sample participated in the credit market in the past year, with 7.2% not applying due to anticipated rejection. Acceptances constitute nearly 40% of the total sample, while rejections account for 7.6%. Among participants, the average rejection rate is 18%. The sample includes panel data, with 295 transitions from acceptance to rejection and 318 from rejection to acceptance.

With respect to expectations about the economy, respondents assign an average of 35.58% to the probability that US unemployment will increase in the next year, and an average of 40% to the probability that stock prices will increase in the next year. For inflation, I present summary statistics for the reported point estimates of expected inflation, but also for the mean expected inflation that emerges from a fitted distribution constructed based on their answers to a probabilistic question (see Armantier et al., 2017 for a complete description). The reported

[5]For empirical analysis, income is categorised more granularly into 11 groups.

expected inflation is 5.63 with a dispersion of 9, both moments considerably higher than the ones from the fitted distribution with a mean of 2.82 and dispersion of 5.4. Additionally, nearly half of the sample expects credit conditions to remain unchanged, while over 30% anticipate tightening credit conditions.

The Credit Access Module also elicits respondents' credit scores, which fall into four broad ranges: over 720 (55%), between 720 and 680 (10.5%), below 680 (20%), and uncertain (the remainder). Appendix Table A.2 provides a summary. Unsurprisingly, the share of rejections among applicants varies considerably across these categories. However, while credit scores are important for understanding loan approvals, they are also endogenous, because an application's outcome can itself affect a borrower's score. In Section 3, I discuss how I use this credit-score information in the analysis.

3 Idiosyncratic Rejections and Macro Expectations

Figure 1 illustrates significant heterogeneity in macroeconomic expectations based on credit experiences. Among individuals rejected for credit applications in the past year, nearly 50% anticipate tighter credit market conditions in the next year, compared to 30% or less among those who did not apply or were accepted. This heterogeneity extends to other domains, including labor market conditions, stock prices, and inflation. Interestingly, the pattern observed for those rejected is very similar to the one observed for those who did not apply because they thought they would not be accepted. Individuals' experiences within the credit market seem to correlate strongly with how they think about the economy as a whole.

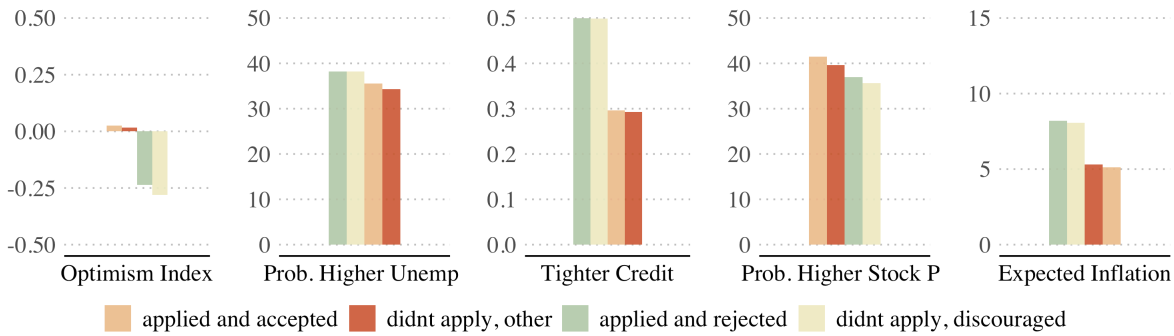


Figure 1: Average Expectations by Credit Market Experience

Notes: The table shows average expectations for each credit market experience category. Colour green refers to those rejected, orange to those accepted, red to those who did not apply and yellow for those discouraged.

The remaining of this section aims to identify the effect, if any, of individual rejections on macroeconomic expectations, and understand why such experiences might matter.

3.1 Empirical Specification

To analyse the role of personal credit market experiences on respondents' expectations about the macroeconomy, I estimate the following regression:

$$E_{i,k,t}(Y_{t+1}) = \alpha + \sum_{k=1}^{3} \beta_k \mathrm{T}_{i,k,t} + \beta_y \mathrm{LifetimeExp}^{Y}_{i,t} + \delta X_{i,k,t} + \chi_{st} + e_{i,k,t} \tag{1}$$

The unit of observation is a survey response by individual i in experience group k during month-year t. The variable $k = 1, 2, 3$ represents the categories of the key explanatory variable $\mathrm{T}_{i,j,t}$, which are dummy variables capturing individual i's past experience in the credit market reported at time t. "Applied and Accepted" is the reference category, while $T_{i,1,t}$ equals 1 if "Applied and Rejected", $T_{i,2,t}$ equals 1 if "Didn't Apply, Other" and $T_{i,3,t}$ equals 1 if "Didn't Apply, Discouraged". The coefficients β_1, β_2, and β_3 capture the heterogeneity in beliefs among accepted versus rejected applicants, accepted versus those who didn't apply for other reasons, and accepted versus those who were discouraged from applying, respectively.

The dependent variable $E_{i,k,t}(Y_{t+1})$ represents individual i's expectation in group k at time t regarding a future variable Y_{t+1}. Specifically, $E_{i,k,t}(Y_{t+1})$ can be optimism index (OPTM), expected credit market conditions for everyone (FCredit), percent chance that US unemployment will be higher 12 months from now (UNEMP), percent chance that stock prices will be higher 12 months from now (StockP), and expected economy-wide inflation (INFL).[6]

To isolate the effect of credit market experiences from other determinants, I include state-month-year fixed effects (χ_{st}) to control for time-varying local shocks. Additionally, I incorporate a measure of lifetime experiences, $\mathrm{LifetimeExp}^{Y}_{it}$, following Malmendier and Nagel's approach. This measure is a weighted average of individual i's past lifetime experiences with aggregate variable Y from birth until time t, with declining weights assigned to older experiences.[7] $X_{i,k,t}$ is a vector of control variables, including age, income, employment status, gender, education, numeracy, marital status, and race. Equation 1 is estimated using OLS with robust standard errors clustered by date and respondent.

Identifying Assumptions. I start by exploring the relationship between past personal credit experiences and individuals' macroeconomic expectations by relying on cross sectional estimates that control for covariates that are commonly thought of as affecting both experiences and beliefs. The primary identifying assumption is that credit rejections can be treated as a random treatment conditional on these covariates, with variability in experiences stemming from supply-side randomness. In addition to the previously mentioned controls, I conduct robustness checks incorporating loan type, expected personal income, reported credit scores and more. A potential important concern is selection bias, which I discuss and address in Section 3.3.

[6] Results are based on reported point estimates, but they are robust to using the fitted distribution mean.

[7] Lifetime experience of variable Y for individual i at time t is defined as $\mathrm{LifetimeExp}^{Y}_{it} = \sum_{h=1}^{H_i} w_{i,t}(h) Y_{t-h}$, where $w_{i,t}(h)$ are linearly declining weights that assign higher values to more recent experiences of Y.

3.2 Pessimism associated with Rejections

Table 1 presents the estimates from Equation 1, where each column corresponds to a different outcome variable. Across all variables, individuals who experienced a credit rejection in the past year exhibit significantly more pessimistic expectations compared to those who were accepted. Specifically, rejected individuals anticipate tighter credit conditions for everyone, a higher probability of increased U.S. unemployment, lower chances of rising stock prices, and higher inflation rates. These findings indicate substantial heterogeneity in macroeconomic expectations driven by credit market experiences. For instance, a credit rejection is associated with an increase in expectations about credit tightening by approximately 32% of its standard deviation, while for expectations about unemployment it represents 11% of its standard deviation.[8]

All specifications include the full set of previously introduced controls, covering socio-economic status, race, gender, and employment. Fixed effects let me compare individuals who live in the same US state and answer in the same month-year, thus facing similar local economic shocks and survey timing. These controls mitigate concerns about time-varying local conditions that might jointly affect both rejections and overall expectations. Results remain robust if I include other economic experiences, such as income or unemployment changes, and "lifetime-experience" measures, which capture generational exposure to past macro shocks. While I find that these lifetime experiences also matter for individuals' macro forecasts, recent idiosyncratic events like rejections still play a larger role, even if they come from a different domain. For instance, a one-standard-deviation increase in lifetime experienced inflation leads to a 0.3 increase in inflation expectations, but the coefficient on rejections is 1.461, underscoring the importance of personal credit denials.

A related group is those who did not apply because they anticipated rejection. Table 1 shows that these discouraged individuals are also more pessimistic across all domains than those who were accepted. Further analysis reveals that *past* rejections increase the likelihood of being discouraged from future credit applications by 48 percentage points (Appendix Table B.5), indicating that discouragement strongly ties to prior rejections. In contrast, households who did not apply for other reasons (unrelated to rejection fears) do not differ significantly from accepted households in their average optimism.[9] This pattern implies that the observed differences stem largely from rejection-related pessimism rather than acceptance-related optimism, a pattern I investigate further in Section 3.3.

[8] Additionally, a rejection correlates with a 16% increase in expected inflation and a 6% decrease in expected stock prices, relative to their respective standard deviations.

[9] For the other measures of expectations, the pattern is less clear. If anything it seems that those who "didn't apply, other" are more optimistic than those accepted (except for stock prices), which would also leads us to conclude that rejected are more pessimistic than the rest.

Table 1: Credit Market Experiences and Macroeconomic Expectations

	OPTM	↑UNEMP	FCredit	↑StockP	INFL
Idiosyncratic Experiences					
Applied and Accepted			(omitted)		
Applied and Rejected	-0.175^{***}	2.480^{***}	0.223^{***}	-1.296^{*}	1.461^{***}
	(0.019)	(0.728)	(0.023)	(0.730)	(0.268)
Didn't apply, Discouraged	-0.172^{***}	1.680^{**}	0.249^{***}	-0.885	0.744^{**}
	(0.020)	(0.776)	(0.023)	(0.787)	(0.293)
Didn't apply, Other	0.008	-0.950^{***}	-0.022^{*}	-0.838^{**}	-0.220^{**}
	(0.009)	(0.361)	(0.011)	(0.359)	(0.096)
Lifetime Experiences					
Life-Experience, US Unemp		5.259^{**}			
		(2.278)			
Life-Experience, US Credit Cond			0.242^{***}		
			(0.066)		
Life-Experience, US Stock Prices				5.739^{***}	
				(1.035)	
Life-Experience, US Inflation					0.633^{***}
					(0.142)
Demographics	Y	Y	Y	Y	Y
State-Month-Year FE	Y	Y	Y	Y	Y
R^2	0.106	0.073	0.087	0.109	0.130
Observations	25161	25132	25161	25135	24770
Mean Dep Var	−0.02	35.58	0.13	40.03	5.72

Notes: The table presents regression estimates from Equation 1. The tittle of each column specifies the dependent variable used. All columns control for individual level controls and state-month-year fixed effects. Individual level controls include gender, race, employment status, married, college, income, income expectations. The reference category for the credit experience is "Applied and Accepted" and for employment status is "Employed". The table only includes the results of the comparison with those unemployed, but also controls for the other possible categories (out of labor force, retired, student). Age is not included, as controlling for age and month-year fixed effect would completely absorb the effect of aggregate personal experiences. Including age and age squared does not have an impact on the coefficient of own rejection. Standard errors are clustered at the respondent and date level. Significance levels: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Overall, these results suggest that household-level credit-market experiences are important determinants of individuals' macroeconomic expectations across multiple macro domains. This contrasts with much of the earlier literature, which has emphasised domain-specific experience effects (Malmendier, 2021). One reason may be that I focus on recent, idiosyncratic, self-reported events rather than large aggregate shocks, potentially offering a cleaner identification of these cross-domain spillovers. In concurrent work, Taubinsky et al. (2024) likewise show that household income shocks can shape inflation expectations, further illustrating the cross-domain patterns documented in Table 1.

Hence, even when households are asked about the same macro variables, their beliefs diverge depending on whether they have personally experienced a credit rejection. This raises a natural question: *why* do these idiosyncratic events generate such pronounced differences in macroeconomic forecasts? The next section delves into this puzzle in more detail.

3.3 Why Do Households Overweight Credit Rejections?

I now investigate the mechanisms behind this idiosyncratic rejection-based pessimism. One possibility is that households *learn* genuine signals from rejections, adjusting their beliefs in accordance with valuable aggregate information. Another is that they *over-weight* these purely idiosyncratic experiences, yielding excess sensitivity and heterogeneity in forecasts. In what follows, I explore both explanations, demonstrating that (1) the observed pessimism is not explained by informational content; (2) people indeed assign disproportionate weight to personal rejections; and (3) these patterns persist even when accounting for confounds or selection bias.

No Evidence for Informational Content. The informational content of credit rejections may vary depending on the type of loan applied for, the household's personal characteristics, and their initial level of economic information. I test, through several exercises, whether the observed effects align with the informativeness of the rejection.

Heterogeneity by credit type. Individuals might apply for credit for different reasons: either buying a new house or refinancing a mortgage, asking for a credit card or extending current limits. Although all type of loan applications are significant decisions, certain types, like mortgages, may lead to more information collection –they involve more research and extensive application processes, and have lower rejection rates (see Appendix Table A.4 for summary statistics). Appendix B.6 examines the robustness of the rejection-induced pessimism across different loan types and finds that the negative impact of rejections on economic expectations is consistent across all categories, suggesting no differential learning.

Heterogeneity by households' characteristics. To test whether rejections provide useful macroeconomic signals, I examine the correlation between macroeconomic conditions and *rejection shares* –the fraction of applicants rejected within a given group (see Appendix Figure B.1).[10] Results show that only "high" types –those with high income and college degrees– have rejection shares that comove with macro indicators, likely because their credit access depends more directly on the state of the economy. If individuals relied on rejections as macro signals, one would expect high types to use them more. Yet, the data reveal that lower-income, non-college individuals –whose rejection shares are acyclical– place greater weight on personal rejections

[10] Individual rejections are largely idiosyncratic and uncorrelated with aggregate outcomes. By contrast, if a group's rejection share systematically varies with macro conditions, it suggests that members of that group may learn more from these signals.

in forming their forecasts (see Appendix Table B.7). This finding suggests that households over-weight personal rejections regardless of their potential informational content.

Heterogeneity by information levels. Appendix Table B.2 demonstrates that the results hold in the Survey of Consumer Finances (SCF), a cross-sectional survey from 1989 to 2019. The effects are consistent regardless of the extent of individuals' search efforts or their initial level of economic information when applying for the loan.

Excess Weight to Idiosyncratic Experiences. I directly test for excess sensitivity to idiosyncratic rejections by exploring how individuals' forecasts compare to realised economic outcomes. In particular, I construct individuals' forecast errors, defined as $Y_{t+1} - F_{it}(Y_{t+1}|I_{it})$ (Appendix Table B.9 describes the datasets). Under this definition, a household who is too pessimistic about credit markets, unemployment or inflation has a negative error while a household who is too pessimistic about stock prices has a positive error. I test whether households' forecast errors are predictable by their idiosyncratic credit experiences by running the following OLS regression:

$$Y_{t+1} - F_{it}(Y_{t+1}|I_{it}) = \hat{\alpha} + \hat{\delta}\, r_{it} + \hat{\nu}\, d_{it} + \hat{\gamma} X_{it} + \hat{e}_{it} \quad (2)$$

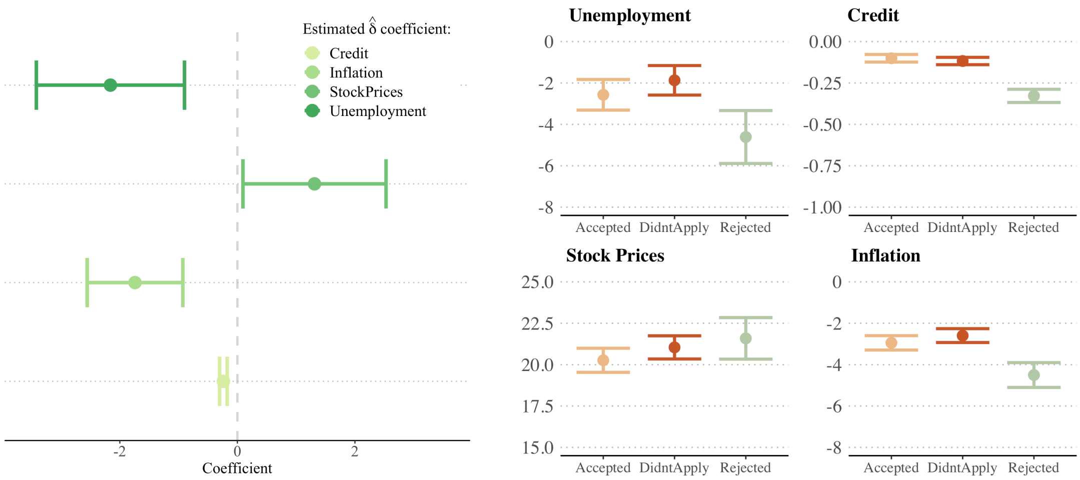
The outcome variable is individuals' i forecast error at time t. X_i are the individual-level controls described in Section 3.1, and r_{it} is a dummy that takes value 1 if the individual experienced a rejection in the past year while d_{it} takes value 1 if she chose not to apply. The coefficient of interest is $\hat{\delta}$. Since individuals' past rejections are in their information set when making the forecast, optimal use of information predicts $\hat{\delta} = 0$ –their forecast errors cannot be predicted by any information in their dataset at the time of making the forecast, otherwise, they wouldn't be using this information in the best way possible.

Figure 2a graphically shows the estimated coefficient using Equation 2 and considering each outcome variable, while Figure 2b shows the forecast error predicted by the OLS regression for each credit experience when all other regressors are at their sample mean. Results do not support the hypothesis of optimal use of limited information: the estimated coefficient is significantly different from zero for all variables.[11]

Results show that compared to realised outcomes, households assign too much weight to their individual-level rejections, which suggests that they are not using these experiences optimally according to their informational content. Looking at the predicted forecast errors, we see that individuals are on average pessimistic about the economy, although there is considerably heterogeneity depending on credit market experiences. While individuals who do not apply to

[11] Several other papers have found that individuals' FE are predictable (Bordalo et al., 2020; Broer and Kohlhas, 2022; Born et al., 2022; Kohlhas and Walther, 2021, for example). While most of the literature has focused on the predictability coming from news or aggregate outcomes, I focus on the role of personal experiences. An advantage of my set up is that I do not need to make assumptions about individuals information sets, as respondents' report their own experience when interviewed at time t. $r_{it} \in I_{it}$ is enough to test whether $(Y_{t+1} - F_{it}Y_{t+1}|I_{it}) \perp I_{it}$.

loans tend to have similar errors to those accepted, those rejected have higher forecast errors on the pessimistic side.



(a) Estimated Coefficient on Rejection **(b)** Predicted FE by Credit Experience

Figure 2: Predictable Forecast Errors

Notes: Figure (a) presents estimated regression coefficients $\hat{\delta}$ from Equation 2 from Appendix Table B.9. Figure (b) shows predicted forecast errors based on regression results from the same Table B.9. Predicted values are computed while holding all other explanatory variables at their sample mean.

In concurrent work Taubinsky et al. (2024) formalise this test and propose an additional one: to understand whether households' forecasts F_i exhibit excessive sensitivity to information in a household-level variable Z_i, run the following two separate linear regressions, $Y = \alpha + \eta Z_i + e_i$ and $F_i Y = \hat{\alpha} + \hat{\eta} Z_i + \hat{e}_i$, where $Cov(e_i, Z_i) = Cov(\hat{e}_i, Z_i) = 0$. Under minimal assumptions, the standard assumption of limited information rational expectations (LIRE) implies $\eta = \hat{\eta}$ or equivalently $\eta - \hat{\eta} = \hat{\delta} = 0$. I find that $\hat{\delta} \neq 0$ throughout, but by running both equations separately, one can grasp a better understanding of the comovement of individual rejections with aggregate variables versus the comovement with their forecasts about those variables. I show the results for this test in Appendix Table B.10: rejections have very weak or null associations with actual economic variables, while they have very strong associations with individuals' forecasts about these variables.

No Evidence for Selection into Rejection. This excessive sensitivity to personal rejections may alternatively arise from selection bias: households that are rejected might be different from those who aren't, and regression controls might not suffice (see Table A.3). The ideal experiment would consist of two individuals who are comparable –for example in age, income category, type of loan they applied to– but one gets randomly rejected while the other accepted. I aim to get closer to this ideal set up by using matching methods. Another related explanation for the excess sensitivity could be unobservables and mainly, prior bias: rejected individuals are consistently more pessimistic about the macroeconomy, irrespective of their experience.

I exploit the availability of a panel component in the SCE to show this is not the case. The following evidence suggests these alternatives cannot explain the findings.

Estimates in a Matched Sample. I use matching techniques to increase comparability between treated and control groups (for a complete description refer to Appendix B). First, I split the sample into three groups: (1) only participants in the credit market with accepted as control and rejected as treated, (2) non-participants as control and rejected as treated, (3) non-participants as control and accepted as treated. Throughout the analysis, the category "non-participants" refers to those classified as "Didn't Apply, Other". Then, I apply the matching procedure based first on a conservative selection of covariates such as gender, race, age, income, numeracy category, college attainment, and type of credit application when applicable.[12] Matching improves covariate balance for all variables, with all standardised mean differences below 0.1 (see Appendix Figures B.3a and B.3b). Finally, for each matched sample, I run linear regressions of individuals' macroeconomic expectations on the treatment variable and the covariates used for matching, controlling for state-month-year fixed effects. Cluster-robust standard errors account for pair-membership. Table 2 presents the estimated average effect on the optimism index.[13]

Table 2: Credit Market Experiences and Macro Expectations – Matched Samples

(1) Rejected & Accepted		(2) Rejected & Didn't Apply		(3) Accepted & Didn't Apply	
Dep.Var.:	OPTM	Dep.Var.:	OPTM	Dep.Var.:	OPTM
Accepted	(omitted)	Didn't Apply	(omitted)	Didn't Apply	(omitted)
Rejected	-0.176^{***}	Rejected	-0.182^{***}	Accepted	-0.009
	(0.027)		(0.027)		(0.015)
Covariates	Y	Covariates	Y	Covariates	Y
State-Time FE	Y	State-Time FE	Y	State-Time FE	Y
Observations	3320	Observations	3330	Observations	23019
R^2	0.319	R^2	0.327	R^2	0.100

Notes: The table reports OLS estimates from $E_{i,t}(Y_{t+1}) = \alpha + \beta \mathrm{T}_{i,t} + \delta X_{i,t} + \gamma_t + \gamma_s + e_{it}$ using three matched samples. Specification (1) tests rejection effects on optimism with accepted individuals as control while Specification (2) uses non-participants as the control. Specification (3) examines acceptance effects with non-participants as the control. All models include matching covariates and state-month-year fixed effects. Standard errors are cluster-robust by pair. Significance levels: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Specification (1) and (2) show that rejections have a statistically significant negative effect on individuals' macroeconomic expectations, regardless of whether the control group consists of accepted applicants or non-participants. The magnitude of the effect is similar to that of the estimates of Table 1 Column 1. Specification (3) indicates that acceptances do not have a sig-

[12] While I exclude covariates potentially influenced by rejection (e.g., reported credit scores), I perform robustness checks by including them either during matching or as controls in the outcome model (Stuart, 2010).

[13] Appendix Figure B.5 summarises the results when credit score is used as control and also in the matching procedure. Appendix Table B.11 shows the estimated effects for the full set of outcome variables (credit market conditions, unemployment, stock prices, inflation).

nificant effect when compared to non-participants, suggesting an asymmetry where rejections induce pessimism, but acceptances do not induce optimism.[14]

Prior Beliefs. The strong association between personal rejections and macroeconomic expectations might be driven by prior beliefs. Individuals who are intrinsically more pessimistic may be more likely to experience rejections. Appendix Table B.14 presents a further robustness test, by focusing on a sub-sample of individuals for which matching can be performed based on covariates and level of pre-optimism. Overall, results are consistent.

Additionally, leveraging the panel component of the survey data, I show that within individuals, experiencing a rejection leads to increased pessimism about the economy (see Appendix Table B.15). Overall, results are consistent with a rejection-induced pessimism hypothesis, albeit coefficients are smaller and standard errors are higher.[15]

Robustness and Roadmap. Appendix B presents regression tables, and robustness to the inclusion of households' reported credit score in Table B.5. Online Appendix B presents further robustness checks, including the use of matched samples and individual fixed effects for the forecast-error regressions, which mitigate concerns about prior bias.

The evidence consistently shows that households over-weight their personal rejections when forming macroeconomic expectations. This bias cannot be explained by the informational content of these experiences, nor by individual confounds or selection bias. A quasi-Bayesian model with misperceived correlations could plausibly account for this sensitivity, but it leaves unanswered the deeper question of *why* households interpret personal credit rejections as strongly correlated with future macroeconomic conditions.

Recent research suggests that *selective and associative memory* may offer a key to this puzzle (Taubinsky et al., 2024). Negative personal episodes can cue the recall of other negative events because of similarity (rather than informativeness), inflating perceived probabilities of adverse macroeconomic outcomes. Extensive psychological evidence supports this view: memory is both *selective* –only certain experiences are recalled at a given time– and *associative* –retrieval is often cued by the features of the hypothesis being evaluated and the emotional or cognitive context in which it is evaluated (Kahana, 2012; Bordalo et al., 2023). Once recalled, similar experiences, whether statistically relevant or not, help individuals *imagine* specific scenarios, inflating their subjective probability of occurrence (Schacter et al., 2012; Kahneman and Tversky, 1981). Therefore, memory-based models not only account for biased weighting but also provide a mechanism (recall and simulation) for how these misperceptions arise.

For instance, even if the objective correlation between a personal credit rejection and broader

[14] Among applicants, acceptances are potentially viewed as the default –they simply confirm people's baseline expectation of not being turned down– and are thus less salient.

[15] This estimation approach, while addressing internal validity concerns, has limitations. The survey's narrow resampling window and infrequent loan applications limit the number of transitions. Furthermore, within-individual estimation captures variations from both moving from acceptance to rejection and vice versa. If acceptances do not fully counteract the pessimism from prior rejections, individual fixed effects may bias the estimates.

economic conditions is low, memory processes can foster the *illusion* of a strong connection through similarity-based recall and simulation. Recent studies have shown the potential of using these well-established insights from psychology to understand economic beliefs and behaviour. For example, Bordalo et al. (2022) demonstrate that both relevant and irrelevant yet similar experiences influence beliefs about new risks through a priming experiment. Jiang et al. (2023) show how positive market conditions cue the recall of favorable past experiences, fostering optimism about future returns. Similarly, Charles (2022) document how associative recall systematically distorts attention and financial market pricing.

In what follows, I build on these insights and develop a memory-based model of belief formation that puts structure on the documented role of personal rejections, and I then demonstrate its important economic implications.

4 Understanding the Mechanism: Memory-Based Beliefs

The analysis in this section consists of three steps. First, I present a belief formation process based on selective memory building on Bordalo et al. (2022, 2023), and on the well-established concept of contextual retrieval (Kahana, 2012). This framework allows me to characterise the over-weighting that I documented in the data and derive new predictions. Then, in the second step, I provide empirical evidence suggesting that memory indeed drives the over-weighting of personal rejections using data on households' "recalled credit conditions". Finally, I show how the model can shed light on households' excessive sensitivity to personal rejections and study, both theoretically and empirically, how this sensitivity varies (who is most prone to it and when it is most likely to occur).

4.1 Model Setup & Key Mechanisms

There are three key elements to be defined: (1) the database, which captures what can be recalled; (2) the recall process, which tells us which memories are actually retrieved (and how), (3) the simulation process, which explains how retrieved information and experiences are used to form beliefs.

The Setup and Database. Households form probabilities about transitioning to an economic state next period by recall from memory and simulation from the recalled experiences. The state of the economy can be either High (H) or Low (L), governed by a 2-state Markov process $\theta_t \in \{\theta_H, \theta_L\}$ with transition probabilities $p(\theta_{t+1} = \theta_j \mid \theta_t = \theta_i) = p_{ij}$.

Each household has a memory database $M = \{\Theta, E\}$ consisting of: (1) past macroeconomic transitions between states i and j (stored in Θ), and (2) other personal experiences or events (stored in E). Each experience $m \in M$ is represented by three key features: its type ($f_1 \in \{\theta, e\}$ either a macroeconomic transition or other experiences/event), its "current" state ($f_2 \in \{L, H\}$), and its "future" state ($f_3 \in \{L, H\}$).[16] For example, a macro transition from L to L is stored as $\theta_{LL} \in \Theta$ with features (θ, L, L), while a negative personal experience –such as a rejection– is stored as $e_{LL} \in E$ with features (e, L, L). Hence, the memory database is represented as: $M = \{\Theta, E\}$, with $\{\Theta\} = \{|\theta_{HL}|, |\theta_{HH}|, |\theta_{LH}|, |\theta_{LL}|\}$, and $\{E\} = \{|e_{HL}|, |e_{HH}|, |e_{LH}|, |e_{LL}|\}$, where $|x_{ij}|$ denotes the number of stored experiences transitioning from state i to state j for $x \in \{\theta, e\}$.

Cued-Recall. Having established the memory database, the next step is to define how memories are recalled. The key concept here is similarity: individuals are more likely to recall experiences that resemble both the event they are evaluating and their current context (e.g., financial state).

The Cue and Similarity. Following the psychology literature on *contextual retrieval*, memory retrieval is guided by a combination of the event's features (e.g., a macro transition from low state to a high state) and the individual's current context (Kahana, 2012). Context refers to an individual's *internal* state (e.g., mood or emotion) and relevant *external* factors (e.g., temporal or environmental) that shape which memories come to mind. For our purposes, individuals' context can be interpreted as their perceived current financial situation.

Let the cue be $[\theta_{ij}, c]$, representing a transition from state i to j under context c. This cue prompts the retrieval of stored experiences in M that have higher similarity to both the hypothesis and the context. For instance, if one is thinking about transitioning to a tighter credit market, then past tight-market episodes become more salient; if the individual's personal context is negative (for example, because of a recent loan rejection), negative experiences of any kind are more likely to be retrieved.

To capture this formally, I define a similarity function $S(m, [\theta_{ij}, c]) = \exp\{-d(m, [\theta_{ij}, c])\}$, which depends on the distance between the stored experience m and the joint cue $[\theta_{ij}, c]$. The distance function can be broken into two components: $d(m, [\theta_{ij}, c]) = \alpha \times d(m, \theta_{ij}) + \beta \times d(m, c)$. Here, α and β represent the relative importance of the macro hypothesis (θ_{ij}) and the individual's context (c). The component $d(m, \theta_{ij})$ captures how closely m's features match the features of the macro event θ_{ij}. For instance, a macro transition θ_{LL} aligns closely with itself (distance $d = 0$) but less closely with a personal experience e_{LL}, which shares features but differs in type (i.e. all else equal, $1 = S(\theta_{LL}, [\theta_{LL}, c]) > S(e_{LL}, [\theta_{LL}, c]) > 0$). The second component $d(c, m)$ captures how well m aligns with the individual's context c. For example, a negative context has a small distance with negative experiences, thereby increasing similarity and boosting recall of "L" instances.

In this setup, recent experiences of credit denial play a dual role. First, they are added to the memory database M (as e_{LL}), and can thus can be recalled. Second, they worsen households' financial situation and thus change their context c to a more pessimistic or negative state, af-

[16] In principle, these attributes can include many facets such as time, location, or emotion. For simplicity, each experience $m \in M$ is fully characterised by three features.

fecting *what* is recalled. In other words, credit rejections push households' financial context to a more pessimistic state, thus making them more likely to recall past negative experiences when judging the hypothesis θ_{ij} –since these are now more similar to the joint cue $[\theta_{ij}, c]$.[17]

Recall Process. Having defined how people make associations between the hypothesis and the memories in M, the next step is to define what $m \in M$ are recalled and with what probability. Formally, *Cued-Recall* states that when evaluating the transition θ_{ij} in context c, the probability of recalling a memory $m \in M$ is:

$$r(m, [\theta_{ij}, c]) = \frac{S(m, [\theta_{ij}, c])}{\sum_{m' \in M} S(m', [\theta_{ij}, c])} \quad \in [0, 1] \tag{3}$$

Hence, an experience m with higher similarity to $[\theta_{ij}, c]$ is recalled more often, but it also competes with any other experiences that share features with the cue.

Simulation. Once a set of experiences is recalled, households must decide how those experiences inform their probability judgments. Formally, a recalled memory m is used to simulate the future state with probability $\sigma(m, \theta_{ij})$, which is increasing in similarity. This process is a form of reasoning by analogy which gets easier when experiences are similar to the event, even if they are from different domains (Kahneman and Tversky, 1981).[18]

Putting these pieces together, the memory-based probability of transitioning from i to j is:

$$p_{ij}^{M} = \sum_{m \in M} r(m, [\theta_{ij}, c]) \sigma(m, \theta_{ij}) = \frac{\sum_{m \in M} S(m, [\theta_{ij}, c]) \sigma(m, \theta_{ij})}{\sum_{m \in M} S(m, [\theta_{ij}, c])} \quad \in [0, 1] \tag{4}$$

In principle, $\sigma(.)$ could vary between 0 and 1, but I adopt a simplifying assumption: once m is recalled, if m "matches" the future state j in its features $(f_2 = j)$, then $\sigma = 1$; otherwise $\sigma = 0$. That is, when thinking about the transition to j, only recalled experiences that share that feature are used with probability 1. Moreover, for simplicity, I focus on forecasts of a Low state $(j = L)$, and define the complementary event $(j = H)$ as $1 - p_{iL}^{M}$. These assumptions discipline the model and suffice to explain my empirical findings, but can be easily relaxed.

In sum, similarity drives which experiences are recalled. Simulation drives how those experiences shape probability judgments. In doing so, personal events (e.g. rejections) can matter even if informationally irrelevant, because they share features with a negative future state. Likewise, a rejection shifts one's context, further tilting recall toward negative episodes. The next

[17] Consistent with my interpretation of context, I see that those rejected feel that their financial situation has gotten worst during the last 12 months. Specifically, individuals who were rejected are 10.3 percentage points more likely to report that their financial conditions worsened compared to those who were not rejected. This finding is statistically significant.

[18] Although simulation is well documented in psychology (Dougherty, Gettys and Thomas, 1997; Schacter, Addis and Buckner, 2007, 2008; Schacter et al., 2012; Biderman, Bakkour and Shohamy, 2020), Bordalo et al. (2022), and are the first ones to formalise it through the $\sigma(.) \in [0, 1]$ function while also providing a priming experiment that supports the modelling assumptions and highlights how the role of simulation can be tested.

sections show how this memory-based process explains the over-weighting of personal rejections and yields testable predictions about heterogeneity across individuals and states.

4.2 Recall and Beliefs: Predictions and Evidence

Whether beliefs are distorted from statistical probabilities or not depends on the role of non-domain specific and potentially uninformative experiences –whether they are recalled and how they are used thereafter. For example, if only historical macro transitions from state i are retrieved, irrespective of the personal context c, and only transitions to L are used to simulate the event,[19] then probabilities are unbiased and given by the frequentist estimate: $p_{iL} = \frac{|\theta_{iL}|}{|\theta_{iL}|+|\theta_{iH}|}$. Intuitively, only macro transitions from current state i are recalled, as this are the relevant pieces of information to evaluate transitions from such a state. Among those recalled datapoints, only the ones that reflect transitions to the state of interest j will be helpful to imagine such event.

But since memory is selective and associative, other experiences might come to mind influencing households' subjective probability of transitioning to a low state p^M_{iL} according to their similarity. Equation 4 can then be re-written as:

$$p^M_{iL} = p_{iL} + \Delta \tag{5}$$

$$\text{with } \Delta = \underbrace{(1-p_{iL}) \times \left(\frac{s^e_{LL} + s^e_{HL}}{W}\right)}_{Simulation\ Term} - \underbrace{p_{iL} \times \left(\frac{s^e_{LH} + s^e_{HH}}{W}\right)}_{Interference\ Term} \tag{6}$$

where $W = (|\theta_{iH}|+|\theta_{iL}|+s^e_{LL}+s^e_{HL}+s^e_{LH}+s^e_{HH})$ and $s^e_{ij} = S(e_{ij},[\theta_{iL},c])\,|e_{ij}|$ for $i,j \in \{H,L\}$. A proof of the derivation is relegated to Appendix C.

The first term p_{iL} captures the perfect recall of past macroeconomic transitions to the state of interest, while the second term Δ –defined as the subjective recalled set– captures additional information and experiences that come to mind because of similarity and are projected onto beliefs. This term considers recalled experiences that are useful to *simulate* the future event and thus lead to overestimation (i.e. $s^e_{LL} + s^e_{HL}$) but also those that are recalled and *interfere* with relatively more useful experiences, therefore reducing the probability assigned to L (i.e. $s^e_{LH} + s^e_{HH}$).

Model Predictions. Recalled personal experiences affect the recalled set, which is then projected onto beliefs about aggregate conditions. The link between personal experiences, recalled conditions and beliefs can be summarised as follows:

Proposition 1. Consider two households, R (Rejected) and A (Accepted), who differ only in whether they have experienced a credit rejection. Then:

1. Household R has an additional negative personal memory e_{LL} in its database, which can

[19] Only type θ memories are recalled and used with $S(\{i,j\},\{i,j\}) = S(\{i,i\},\{i,j\}) = \sigma(\{i,j\},\{i,j\}) = \sigma(\{j,j\},\{i,j\}) = 1$ and 0 otherwise.

be used to simulate a future Low state L.

2. Because of this rejection, household R's context is also more negative, increasing the recall of all negative experiences (both personal and aggregate). Formally, when they evaluate the event θ_{iL} in their (negative) context c_R, the recall weights for negative memories satisfy

$$s^{e,R}_{LL} > s^{e,A}_{LL} \quad \text{and} \quad s^{e,R}_{HL} > s^{e,A}_{HL}$$

Consequently, relative to A, household R has a strictly higher recalled set $d^R > d^A$, leading to a higher subjective probability of transitioning to a Low state:

$$p^R_{iL} \;=\; p_{iL} \;+\; \Delta^R \quad > \quad p_{iL} \;+\; \Delta^A \;=\; p^A_{iL}$$

Intuitively, R holds a personal rejection e_{LL} in memory, and so it adds directly to the recalled set of negative experiences. Moreover, the rejection also creates a more pessimistic personal context c_R. This context lowers the "distance" to all negative memories –so both θ_{LL} (aggregate states) and e_{LL}-type (personal) experiences are more likely to be recalled. These differences in recalled sets translate directly into differences in expectations. These ideas are summarised in the proposition and in the following testable predictions:

Prediction 1. (Recalled Set) Rejected individuals are more likely to remember negative aggregate and personal conditions, leading to a more pessimistic recalled set.

Prediction 1b. (Recalled Errors). Recalled conditions deviate relatively more from the objective conditions for those rejected, leading to relatively higher recalled errors. To see this, define a "recalled error" as the gap between subjective and objective probabilities, $(p^M_{iL} - p_{iL})$, then the extra negative experience in R's set means: $[p^R_{iL} - p_{iL}] = \Delta^R > \Delta^A = [p^A_{iL} - p_{iL}]$

Prediction 2. (Recalled Set and Beliefs) Recalled conditions –aggregate and personal, relevant and non-relevant– are projected onto beliefs. Tighter recalled credit conditions and recalled rejection translate into higher overestimation of future tighter credit conditions: $\Delta^R > \Delta^A \Rightarrow p^R_{iL} > p^A_{iL}$.

Prediction 2b. (Recalled Set and Beliefs Spillovers) If negative memories in one domain (credit) share features with a different domain (i.e. unemployment, inflation, or future stock returns), then they will also be recalled and used to simulate a negative future in the other domain. Thus "past tight credit conditions" or "personal credit rejection" can raise pessimism about all macro conditions.[20]

Test of Model Predictions. These specific predictions of selective memory can be tested.

[20] Any negative memory with a "Low" feature can enter the similarity function in the numerator and thus shift p^M_{iL}. If domain boundaries are fuzzy (similar features), that negative memory has positive similarity even in a new domain.

Beyond asking households about their credit experiences and macroeconomic expectations, the SCE asks them to recall aggregate credit conditions in the last 12 months (just before asking them about their expectations for credit conditions in the next 12 months). This allows me to have information about their beliefs in the credit domain, their recalled aggregate credit conditions in that domain (the recalled set), and also a particular experience in that domain (which belongs to the broader recalled set). Table 3 presents evidence in favour of the models' predictions.

In line with Prediction 1. and 1b., I find that those who experienced a credit rejection also recall tighter credit conditions (Column 1) and exhibit higher "recalled errors" (Column 6): rejected individuals tend to perceive past credit conditions to be tighter than they actually were (Column 4 versus 5). In line with Prediction 2., these tighter recall credit conditions are projected onto tighter expected credit conditions. Column 3 shows that when controlling for recalled aggregate credit conditions, the role of personal rejections is considerably reduced, suggesting that the link between personal experiences and economic expectations is indeed mediated by what people recall about those economic conditions.

Table 3: Personal Rejections and Recalled & Expected Credit Conditions

	Tighter Credit Conditions (CC)			Errors in Recalled CC		
	(1)	(2)	(3)	(4)	(5)	(6)
	recalled	expected	expected	realised	recalled	error
Applied and Rejected	0.250^{***}	0.220^{***}	0.012	-0.030^{*}	0.250^{***}	-0.282^{***}
	(0.019)	(0.019)	(0.010)	(0.018)	(0.019)	(0.025)
Didn't Apply	−0.004	-0.021^{**}	-0.018^{***}	0.013	−0.004	0.028^{**}
	(0.010)	(0.010)	(0.005)	(0.009)	(0.010)	(0.013)
Tighter Recalled CC			0.836^{***}			
			(0.003)			
Controls	Y	Y	Y	Y	Y	Y
R^2	0.041	0.035	0.715	0.003	0.041	0.066
Observations	25161	25161	25161	25161	25161	25161

Notes: Columns 1-3 have as dependent variable individuals' recalled credit conditions and expected credit conditions (higher values represent tighter credit), while Column 4-6 have realised credit conditions in the past 12 months, individuals' recalled credit conditions and the difference between the two. Regressors include personal credit experiences and recalled credit conditions. Significance level: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Interestingly, as predicted by Prediction 2b., this is not limited to expectations about credit: what people recall about aggregate credit conditions and what they personally experienced in that domain (i.e. their rejections) affects their economic expectations across domains (see Table 4). Overall, the evidence suggests that memory is an important mechanism driving the over-weighting of idiosyncratic credit rejections when forming economic beliefs.

Table 4: Expectations about the Macro on Rejections and Recalled Credit Conditions

	OPTM	↑UNEMP	FCredit	↑StockP	INFL
Applied and Rejected	-0.048^{***}	1.233^{**}	0.015	0.047	0.893^{***}
	(0.013)	(0.616)	(0.010)	(0.607)	(0.209)
Didn't apply, other	0.007	-0.876^{***}	-0.017^{***}	-0.922^{***}	-0.312^{***}
	(0.007)	(0.314)	(0.005)	(0.309)	(0.106)
Tighter Recalled CreditC	-0.494^{***}	4.759^{***}	0.835^{***}	-4.092^{***}	0.834^{***}
	(0.004)	(0.206)	(0.003)	(0.203)	(0.070)
Controls	Y	Y	Y	Y	Y
R^2	0.411	0.073	0.723	0.120	0.130
Observations	25157	25128	25157	25131	24740

Notes: The table presents regression estimates from Equation 1 plus an additional regressor: Tighter Recalled Credit Conditions. All columns control for individual-level controls and state-month-year FE. Significance level: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Taking Stock. Although useful to test the role of memory, "recalled credit conditions" is a broad and potentially noisy measure that can englobe many different types of information and experiences. The key advantage of my setup is that I can observe a specific past experience, "credit rejection", that belongs to the recalled set and can be used to isolate and study the impact of recall on beliefs. This is not only a cleaner measure but it also captures memory, as it is a past experience that people report in the survey themselves, although in a different module than the one in which expectations are elicited (and thus it is not necessarily primed). For the rest of the analysis I thus focus on the rejection experience and, to simplify notation, I refer to the joint cue $[\theta_{iL}, c]$ as simply θ_{iL}.

4.3 Recalled Rejections and Beliefs: Predictions and Evidence

Instead of analysing the role of the entire recalled set, I focus here on the effect of recalling one particular experience –namely, a credit rejection– and the heterogeneity it generates. Specifically, let the database of a rejected individual be expressed as $M^R = M \cup R$, where $R \equiv e_{LL}$ is the prior rejection experience, and M includes all other data points. Then Equation 5 can be rewritten to isolate the effect of the experience R as follows:

$$\hat{p}^R_{iL} = \hat{p}_{iL} + \underbrace{r(R, \theta_{iL}) \times (1 - \hat{p}_{iL})}_{\text{bias from recalling } R \,\equiv\, \beta_r} \tag{7}$$

where $\hat{p}_{iL} = \frac{\sum_{m \in M} S(m,\theta_{iL})\sigma(m,\theta_{iL})}{\sum_{m \in M} S(m,\theta_{iL})}$, and $r(R, \theta_{iL}) = \frac{S(R,\theta_{iL})}{S(R,\theta_{iL}) + \sum_M S(m,\theta_{iL})} \equiv \omega_{iL}$. Intuitively, $\hat{p}_{iL}$ is the estimated probability absent the rejection event, and $r(R, \theta_{iL})$ is the probability that the rejection R is recalled.[21] Thus, selective memory places structure on households' misperceived correlations between their personal rejection and macroeconomic outcomes, here captured by β_r, allowing for a deeper exploration of this bias.[22]

Model Predictions. This framework predicts that idiosyncratic experiences produce heterogeneity in macroeconomic beliefs:

Proposition 2. (Heterogeneity) Let $\hat{p}_{iL}^R$ denote the probability estimate of those rejected and $\hat{p}_{iL}^A$ denote the probability estimate of those accepted. Suppose that the only systematic difference between rejected and accepted individuals is their rejection experience. Then, the difference in their beliefs can be attributed to the recall bias from this extra experience, such that: $\hat{p}_{iL}^R - \hat{p}_{iL}^A = r(R, \theta_{iL}) \times (1 - \hat{p}_{iL}) = \beta_r > 0$.

Importantly, this heterogeneity persists even if both individuals share the same historical macro experiences. For instance, Malmendier and Nagel (2016) show that entire generations differ in inflation expectations due to distinct histories. Here, I show that idiosyncratic rejections can also drive disagreement, even conditional on the same macro history (see Table 1).

The model further implies that the magnitude of this experience-driven heterogeneity varies with certain parameters: the size of the database (i.e. M), the ex-ante subjective probability of the event (i.e. $\hat{p}_{iL}$), and the similarity between the event and the rejection (i.e. $S(R, \theta_{iL})$).

Prediction I. (Heterogeneity across demographics) The experience-driven heterogeneity in macroeconomic expectations correlates with households' demographics.

a. Households with smaller databases are more strongly affected by a personal rejection. Formally, the recall probability $r(R, \theta_{iL})$ declines with the size of M. Under the assumption that age is a good proxy for size of M, $\beta_{young}^R > \beta_{old}^R$.

b. For households with lower wealth and/or socio-economic status, credit rejections are arguably more costly and thus lead to a more negative personal context, increasing the similarity between their rejections and negative aggregate outcomes: $\beta_{low}^R > \beta_{high}^R$.

Prediction II. (Heterogeneity across (un-)likely events) When the future Low state is perceived as less likely, recalling a negative personal experience has a bigger marginal impact on the subjective probability. That is, $\frac{\partial \beta_r}{\partial \hat{p}_{iL}} < 0$.

Prediction III. (Heterogeneity across domains) Recalling a rejection in credit markets has the strongest effect on beliefs within the credit domain, because $S(R, \theta_{LL}^{credit}) > S(R, \theta_{LL}^{\bar{d}})$, $\beta_r^{credit} > \beta_r^{\bar{d}}$ where $\bar{d}$ refers to any other domain beyond "credit".

Prediction IV. (State dependency and overreaction) If the current macro state is already Low, then negative personal experiences share more "Low" features and are recalled more readily.

[21] In principle, the model also predicts roles for acceptances, but it explains why rejections have a larger effect: (i) a negative focal state (L) discards acceptances (they do not simulate low scenarios), and (ii) even if the focal point is high, acceptances face more positive interference. As a result, rejections dominate empirically.

[22] Online Appendix D further compares a memory-based model with a Bayesian updating framework.

Formally, $r(R, \theta_{LL}) > r(R, \theta_{HL})$. Thus, rejections fuel even greater pessimism in bad times, driving an overreaction to negative shocks at the aggregate level.[23]

These predictions have significant macro implications. First, belief heterogeneity arises from purely idiosyncratic shocks and is more pronounced among younger or lower-SES households. Second, negative rejections spill over to multiple domains, even if uninformative. Finally, a bad aggregate shock amplifies recall of negative personal events, producing an "overreaction" at the aggregate level. The next subsection examines whether the data aligns with these predictions.

Test of Model Predictions. I start by testing Prediction 1. First 1a. suggests that the size of the beliefs heterogeneity driven by recalling a rejection depends on the database that it is incorporated. I test this by using age as a proxy for database size, hypothesising that younger individuals, with fewer prior experiences, rely more on their rejection experience. Point b. suggests that it also depends on other demographic characteristics, as those households with lower socio-economic status incur higher costs from credit denial, leading to stronger associations of this negative experiences with negative aggregate outcomes and thus higher overestimation. To test this, I interact a household' s past rejection with proxies for socio-economic status (e.g., no college attainment, lower income, lower net wealth). Note that this contradicts what a theory based on partial information would predict: because rejections for low-income or non-college individuals are not correlated with aggregate conditions, they should, in theory, assign less weight to such experiences, rather than more (see Section 3.3).

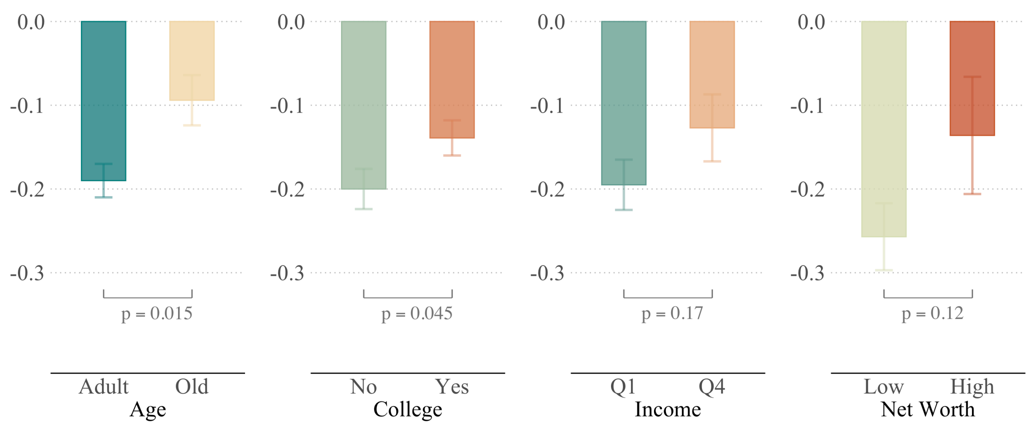


Figure 3: Heterogeneity in Estimated Coefficient on Personal Rejection

Notes: The figure plots the estimated rejection coefficient across subgroups, along with p-values for subgroup differences. The outcome variable is optimism index. Details are in Table B.7.

The data supports the predictions of the memory-based belief model, summarised in Figure 3. Individuals who are younger, or have no college attainment, or lower income, or lower net

[23] Aggregate beliefs overreact to the current low state relative to the case in which memory is not state dependant: suppose the economy can be divided into a share λ who experienced a rejection and $1 - \lambda$ who didn't, then aggregate beliefs $P_{iL} = \lambda \hat{p}^R_{iL} + (1 - \lambda)\hat{p}^A_{iL}$ are increasing in the memory channel $\lambda r(R, \theta_{iL})$.

wealth assign a higher weight to their idiosyncratic experiences of rejections when forecasting future economic states. Interestingly, these findings also provide a microfoundation for the well-known correlation between lower socio-economic status and more pessimistic macroeconomic expectations (Das, Kuhnen and Nagel, 2020). Due to costlier rejections (and other negative personal experiences), lower-SES households develop a more pessimistic personal context,[24] which amplifies the recall of negative events when assessing the economy –leading to systematically lower forecasts. This analysis thus demonstrates how such pessimism can emerge endogenously from selective memory and contextual retrieval.

Next, I turn to Predictions II and III, which examine how the perceived likelihood of the event and the similarity between the experience and the hypothesis shape recall. In particular, β_r can be higher because (1) $\hat{p}_{iL}$ is lower (the event is unlikely), (2) similarity and thus recall $r(R, \theta_{iL})$ is higher. To test them, I first calculate $\hat{p}_{iL}$ as the average probabilities for the whole sample who has not experienced a rejection. Then, I use the model equations and the estimated coefficients on rejection to calculate an implied probability of recalling a personal rejection: $r(R, \theta_{iL}) = \beta_r/(1 - \hat{p}_{iL})$.

Table 5 presents the estimates. To test Prediction II on unlikely events I use the probabilistic questions about inflation included in the SCE and analyse the effect of rejection on individuals' perceived probability of inflation being higher than 4% and probability of it being higher than 8%. The idea is that the similarity between a rejection experience and the inflation event is relatively constant, while the likelihood of these events two events varies.

Table 5: Implied Similarity Across Domains and Ranking

(1) Outcome	(2) Avg. Prob. in Sample $\hat{p}_{iL}$	(3) Estimated Coeff. on Rejection β_r	(4) Implied Recall
Tighter Credit Conditions	0.304	0.158	0.226 ≈ 23 pp
Higher Unemployment	0.356	0.020	0.031 ≈ 3.0 pp
Inflation higher than 4%	0.346	0.022	0.034 ≈ 3.5 pp
Inflation higher than 8%	0.176	0.031	0.037 ≈ 3.5 pp

Notes: Column 2 reports the sample weighted average response, excluding rejected individuals, and Column 3 the estimated coefficient on rejection for each of the outcome variables (see Appendix Table C.16). The last column presents the implied recall probability and the suggested ranking, when simulation equals 1. Lower values of simulation increase the value of the implied recall, but the ranking prevails. The results thus provide a lower bound for implied recall.

As predicted, personal credit rejections strongly relate to expectations about credit markets, reflecting higher perceived similarity and, thus, greater recall probability (Column 4). Rejections also generate pessimism about unemployment and inflation, but to a lesser degree.

[24]In line with the model, I find that rejected individuals with lower income and no-college perceive a worse personal context: they are more likely to say that their financial situation has gotten *much* worse in the past year.

Although average probabilities do not differ substantially across scenarios, the varied effects of rejections arise from differences in implied recall as suggested by Prediction III.

Regarding Prediction II, the average probability assigned to inflation exceeding 4% is almost twice that of exceeding 8%, indicating the latter is viewed as less likely. Columns 3 and 4 show that while the rejection coefficient is larger for the 8% scenario, the implied similarity is nearly identical. Consistent with the prediction, rejections more strongly influence unlikely events not because of differing similarity, but because personal rejections help imagine rare outcomes.[25]

According to Prediction IV, since negative experiences (such as rejections) share more features with a "Low" macro state, during economic downturns, they become even easier to recall, amplifying pessimism and driving overreaction to bad news. To test this, I interact past personal rejections with a binary variable that takes value 1 if the individual answered the survey during the COVID induced recession of 2020, and regress this onto individuals' Optimism Index. The left figure in Figure 4 presents the results.

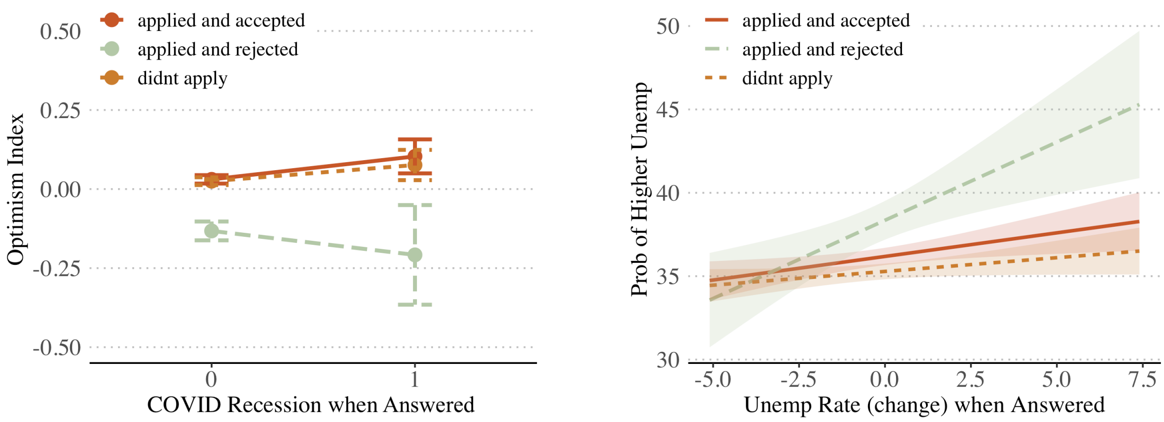


Figure 4: State Dependency in Beliefs

Notes: The figure plots interaction effects shown in Appendix Table C.17. The left panel refers to Optimism Index as outcome variable and Recession interaction dummy, while the right panel refers to Probability of Higher Unemployment as outcome variable and Unemployment Rate (change) as interaction variable. Solid dark orange refers to those accepted, dotted orange to those who didn't apply and dashed green to those rejected.

Being rejected in the last year is associated with a strong pessimism about the future economic state, and the effect is almost doubled when respondents' expectations are elicited during the recession period. Interestingly, beliefs of those who were accepted move closely to beliefs of those who chose not to apply, irrespective of the economic state. For robustness, the right figure looks at state dependency when individuals are forecasting unemployment and assesses

[25] The model also suggests that other economic outcomes that are further away in terms of similarity from personal rejections would not be influenced by such an experience. One example of this could be individuals' reported probability of increases in "the level of U.S. government debt". Although related to the economic outlook, personal rejections are arguably less similar to increases in government debt than increases in unemployment. Indeed, I find that those rejected in the past are not statistically different than those accepted when it comes to their expectations about government debt.

how the recall of rejections changes with the current unemployment rate. Overall, the cuing effect is robust: the recall of idiosyncratic negative experiences such as rejections leads to further disagreement in beliefs during low economic states.

Table 6 further illustrates how the impact of rejections depends on the current aggregate state. Consistent with the model, when unemployment is higher (i.e., the macro state is worse), negative personal memories are more likely to be recalled, thereby raising the subjective probability of a bad outcome. For example, a one-standard-deviation increase in aggregate unemployment rates raises individuals' expected probability of higher unemployment by about 0.68 percentage points (Column 3). In addition, the marginal effect of recalling a personal rejection varies with the unemployment rate: at average rates, rejections add roughly 2 percentage points to the perceived probability of higher unemployment, but this figure grows to 4.5 percentage points when unemployment is one standard deviation above average (Column 2). The implied recall probability thus increases from 0.029 to 0.071 as the state deteriorates, underscoring that the same negative experience exerts a stronger effect once the economy weakens (Column 5). Overall, this evidence highlights a state-dependent recall channel that can generate "overreaction" in downturns, since households with negative personal histories become more pessimistic when unemployment is high because of stronger recall of these past negative experiences. In Section 5.3, I explore the broader economic implications of this mechanism and provide suggestive evidence of its significance for aggregate outcomes.

Table 6: Marginal Effects and Implied Similarity in Good and Bad Times - Unemployment

	Marginal Effect of Rejection	Marginal Effect of Unemp	$\hat{p}_{iL}$: Avg. Prob. Unemp↑	$r(R, \theta_{iL})$: Implied Recall
Avg. Unemp	1.889	-0.083	35.517	0.029
1 Std. Dev. Unemp	4.524	0.684	36.284	0.071

Notes: Aggregate Unemployment refers to unemployment rates from FRED (change from year ago, percent), with a mean of -0.30 and standard deviation of 2.48. Columns 2-3 present marginal effects of aggregate unemployment and personal rejection on individuals' subjective probability of higher unemployment. Complete regression results can be found in Table C.17. Column 4 shows the average subjective probability of higher unemployment when current unemployment rates are at their average value and when they are higher by 1 standard deviation. Column 5 presents the implied recall probabilities calculated based on the estimated probabilities and the derived model equation $\beta_r = r(R, \theta_{iL})(1 - \hat{p}_{iL})$.

Extrapolation and overreaction to aggregate states, as formalised in models like diagnostic expectations (Bordalo et al., 2020), have been widely documented. Negative news about the current state tend to make negative future states more prominent in individuals' minds, leading to their over-estimation. These models have proven valuable in studying overreactions to aggregate shocks and their economic consequences. For instance, Bianchi, Ilut and Saijo (2023) demonstrate how diagnostic beliefs can lead to boom-bust cycles following a monetary policy shock. The findings in this paper suggest that overreaction is not solely tied to recent news;

rather, its extent depends on the experiences triggered by the news.

Robustness and Roadmap. Appendix C provides detailed regression tables (and robustness) for the exercises in this section.[26] Overall, the results confirm the memory-based predictions and show that memory indeed matters for belief heterogeneity. In the next section I show evidence that it also matters for behaviour.

5 Implications for Economic Behaviour

In this section, I incorporate memory-based beliefs into a three-period consumption-saving model to isolate the mechanisms through which memory impacts household behaviour and the aggregate economy. I then test the model predictions using the SCE survey data.

5.1 Model Setup & Key Mechanisms

Consider a continuum of ex-ante identical households who live for three periods, $t = 0, 1, 2$. As before, there are two aggregate states, High (H) and Low (L), governed by a two-state Markov process P. Households observe the current state and form beliefs about future transitions using both macro-level information and personal experiences, as previously discussed in Section 4.

At the start of each period, households receive an endowment. In periods $t = 1$ and $t = 2$, the endowment depends on the macroeconomic state, taking value y_t^H if $\theta_t = \theta_H$ and y_t^L if $\theta_t = \theta_L$. In period $t = 0$, the endowment is deterministic and satisfies the inequality $y_0 < \frac{1}{2}E(y_1 + y_2)$, capturing the idea that households are initially "young" and expect rising income on average.

Households can save or borrow through a credit market to transfer resources across periods. Before $t = 0$, they choose whether to participate in this market. Those who opt out remain unable to shift consumption across time. Those who participate anticipate higher future income and are willing to borrow at $t = 0$. A bank supplies loans at interest rate R, subject to an exogenous credit limit $\bar{B}_t$. In the spirit of Calomiris, Longhofer and Jaffee (2008), if total credit demand exceeds $\bar{B}_t$, the bank randomly rejects a fraction λ_t of applicants. In period $t = 0$, this limit is binding ($\lambda_0 > 0$), so some fraction of households are refused credit and thus must consume their initial endowment. In period $t = 1$, the constraint is no longer binding ($\lambda_1 = 0$), and all households wishing to borrow can do so, subject only to their individual borrowing limits.

More formally, at $t = 0$ a fraction $(1 - \lambda_0)$ of participants is accepted and borrows an amount b_1, while the remaining λ_0 is rejected and must set $b_1 = 0$. Each household faces borrowing

[26] I argued that rejections affect the personal context. I test for robustness of the main exercises when controlling for a broad proxy of personal context –reported personal financial situation– and show that (1) rejected perceive a more pessimistic personal context (2) rejections still matter for beliefs when controlling for this broad proxy of context, showing that recalling a rejection can also have a direct impact (because it belongs to M and can be recalled, beyond its impact on c).

constraints based on the lowest discounted value of future income, ensuring that individuals cannot borrow more than the minimum present value of (y_1^L, y_2^L). For simplicity, I assume quadratic utility, $u(c) = b\,c - \frac{1}{2}c^2$, $b > 0$, $b < c$ together with $\beta = \frac{1}{R}$. Online Appendix E provides further details on the structure of the model.

The model is solved by backward induction. In period $t = 1$, households observe the current state $i \in \{H, L\}$, receive their endowment y_1^i, and choose b_2 to maximise expected utility. They face the budget constraints $c_1 = y_1^i - R\,b_1 + b_2$ and $c_2 = y_2 - R\,b_2$, where b_1 is either chosen at $t = 0$ (for those accepted) or set to zero (for those rejected). Under quadratic preferences, the Euler equation implies $c_1 = \hat{E}_1(c_2)$, which yields

$$b_2^{h,i} = \frac{1}{1+R}\left[\hat{E}_1^h(y_2) - y_1^i + R\,b_1^h\right],$$

where $h \in \{a, r\}$ indicates whether the household was accepted (a) or rejected (r) at $t = 0$, and $\hat{E}_1^h(y_2)$ is the household's subjective expectation of period-two income.

At $t = 0$, all households start with y_0. A fraction λ_0 is randomly rejected, thus constrained to $b_1^r = 0$, so they consume $c_0^r = y_0$. The remaining $(1 - \lambda_0)$ is accepted and borrows

$$b_1^a = \frac{1}{1+R(1+R)}\left[\hat{E}_0^a(y_2 + R\,y_1) - y_0\,(1+R)\right].$$

This setup implies that, if beliefs are unbiased and all else is equal, the only difference between accepted and rejected households emerges from a direct liquidity constraint: being forced to borrow zero at $t = 0$.

However, if beliefs incorporate personal memories –potentially uninformative but salient experiences such as a credit rejection– then heterogeneity in these experiences systematically affects expectations, amplifying differences in choices. Let $\hat{p}_{iL}$ be the baseline (memory-based) probability of a future Low state, and let ω_{iL} represent the probability that a past rejection is recalled at state i. If a household recalls its rejection, it increases the perceived likelihood of the Low state by $\omega_{iL}\left(1 - \hat{p}_{iL}\right)$, as in Equation (7). This added pessimism reduces the household's willingness to borrow and thus lowers its consumption.

Formally, a rejected household faces two effects. The direct effect is the inability to borrow at $t = 0$. The indirect (belief) effect arises if the household recalls that rejection and use it to form the probability of a Low state. Combining these effects shows that in period $t = 1$ the household's borrowing $b_2^{r,i}$ is further reduced by the "memory distortion" term $\omega_{iL}\left(1 - \hat{p}_{iL}\right)\left(y_2^H - y_2^L\right)$.

It is helpful to separate these channels explicitly. In an unbiased scenario with $\omega_{iL} = 0$, rejected households differ from accepted ones only via the forced borrowing limit at $t = 0$. In contrast, if $\omega_{iL} > 0$, then there is an additional, indirect effect on behaviour at $t = 1$. Denoting $\omega_{iL}\,(1 - \hat{p}_{iL})\,(y_2^H - y_2^L)$ by IE (for the indirect, or memory, effect) and $R\,b_1^a$ by DE (for the direct effect), it follows that

$$b_2^a - b_{2,\,\omega>0}^r = \frac{1}{1+R}\Big[\underbrace{R\,b_1^a}_{\text{DE}} + \underbrace{\omega_{iL}\left(1-\hat{p}_{iL}\right)\left(y_2^H - y_2^L\right)}_{\text{IE}}\Big] > 0.$$

Thus, rejected individuals who recall their credit denial suffer a larger reduction in borrowing and consumption, as both the direct and indirect channels work against them.

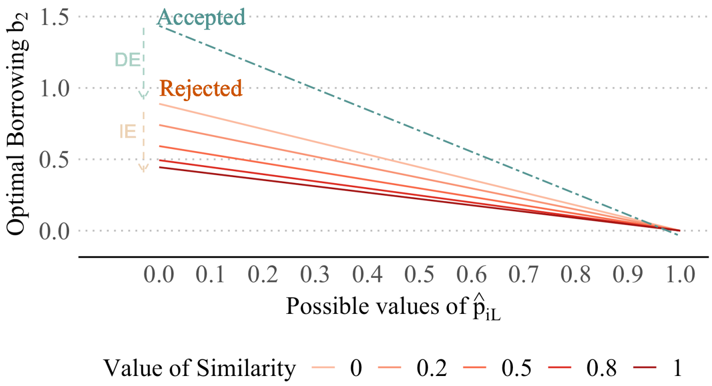


Figure 5: Optimal Borrowing – varying $\hat{p}_{iL}$ and similarity values

Notes: The figure plots optimal borrowing b_2 for accepted and rejected, with and without memory-based beliefs, across different probabilities and similarity values. Simulation values are $\beta = \frac{1}{R}$, $R = 1.25$, $y^L = 1$, $y^H = 3$.

Figure 5 illustrates the impact of these two channels on optimal borrowing for accepted and rejected households, as $\hat{p}_{iL}$ and similarity vary. The green line represents the borrowing path of an accepted household, while the light red line reflects a rejected household experiencing only the direct constraint. The darker red lines incorporate progressively larger similarity between the rejection and the event L (i.e., greater recall probability), highlighting how personal memory amplifies the difference in borrowing even further. The figure emphasises the role of heterogeneity: households who rely more on their personal experiences (for example, younger and low SES individuals) reduce their desired borrowing even more, leading to lower consumption through the belief channel.

5.2 Direct and Indirect Effect in the SCE Data

The model highlights how rejections impact consumption through both a direct constraint effect and an indirect (belief) effect. I now use the SCE Spending Module and a standard mediation framework (Imai et al., 2011; Tingley et al., 2014) to measure these two channels.

First, I combine the SCE data on expectations, credit access and spending as explained in Section 2. The key consumption measure is households' reported percent chance of buying durables within the next four months.[27] Then, I use this data to estimate the direct and indirect effect following standard methodology in mediation analysis.

The first step consists of a regression of individuals' macroeconomic beliefs on their experiences of rejections (as done in Section 3): $\text{OPTM}_{it} = \beta_0 + \beta_1 \text{Rejection}_{i,t-1} + \delta X_{it} + \gamma_{st} + v_{it}$. The second step consists of a multivariate regression of rejections and beliefs on individuals' spending attitudes, while controlling for a broad set of variables and fixed effects: $\text{Spending}_{it,t+1} = \alpha_0 + \alpha_1 \text{Rejection}_{i,t-1} + \alpha_2 \text{OPTM}_{it} + \delta X_{it} + \gamma_{st} + u_{it}$. The idea is as follows: if rejections shape beliefs (measured by β_1) and beliefs shape spending (measured by α_2), then part of rejection's impact on spending can be 'mediated' by memory-driven pessimism (measured $\beta_1 \times \alpha_1$). Table 7 provides the results based on the estimation strategy proposed in Imai et al. (2011) and Tingley et al. (2014), while Appendix E.2 describes the underlying and assumptions and shows robustness using the steps approach.

Table 7: Direct and Indirect Effect of Rejection

	Estimate	p-value
Indirect Effect (IE)	-0.455	$< 2^{-16}$
Direct Effect (DE)	-3.223	0.004
Total Effect (TE)	-3.678	$< 2e^{-16}$
Proportion Mediated (IE/TE)	$0.123 \approx 12\%$	$< 2e^{-16}$
Mean Durables Spending	16.55	

Notes: The table presents point estimates and p-values for the average direct, indirect, and total effects using the R mediation package described in Tingley et al. (2014). Uncertainty estimates are calculated using 1000 simulations with a quasi-Bayesian Monte Carlo method based on normal approximation. White's heteroskedasticity-consistent estimator is used for the covariance matrix. The last row shows the average probability that respondents assign to spending in durables in the next four months.

This analysis shows that rejections have a total negative effect on households' spending attitudes, as predicted: households who recently experienced a rejection are 3.7 percentage points less likely to buy durable goods in the next 4 months. From that total negative effect, 12% can be attributed to their rejection-induced pessimism about the macroeconomy, while the rest can be attributed to other factors related to the rejection but not to differences in the optimism index. This is a sizeable effect considering the average spending probability. To see this, consider a person whose probability of spending in durables is the average probability in sample (i.e. 16.55%), then experiencing a rejection directly reduces this probability to 13.33% and the

[27] The SCE questions states: "Now looking ahead, what do you think is the percent chance that a member of your household (including you) will make any of the following large purchases within the next 4 months?". I construct an average percentage chance using households responses to home appliances, electronics/computers/cell phones, furniture, home repairs/improvements/innovations. Therefore, the outcome variable in this exercise refers to spending *attitudes* or intentions. I construct an aggregate measure of these spending intentions and corroborate that it is highly correlated with realised durable demand during those 4 months (corr= 0.57, p-value= 0.02). The source for aggregate contemporaneous monthly demand for durable goods is the FRED database of the Federal Reserve Bank of St. Louis.

memory bias induces an extra reduction of 0.455, leading to a final probability of spending of 12.87%.

The model predicts that this belief channel is also heterogeneous across demographics. In particular, it should be stronger for younger individuals and those with lower socioeconomic status (SES), as the pessimism bias from personal rejections is more pronounced for these groups.[28] I test this hypothesis by examining the indirect effect across different age and SES groups. Table 8 shows that the belief channel is indeed stronger and statistically significant for younger, non-college-educated, and lower-income individuals, accounting for a higher proportion of the total effect compared to older and higher-SES individuals.

Table 8: Moderated Mediation: Indirect Channel by Age and SES

	Indirect Effect (IE)	Direct Effect (DE)	Proportion Mediated (IE/TE)
College	-0.08	-2.7	0.03
	(0.08)	(0.01)	(0.09)
No College	-0.39	-1.32	0.16
	(0.00)	(0.41)	(0.27)
Income>= 60k	-0.19	-5.6	0.03
	(0.04)	(0.00)	(0.04)
Income< 60k	-0.18	-0.99	0.10
	(0.01)	(0.40)	(0.31)
Age> 60	-0.10	-1.8	0.05
	(0.06)	(0.14)	(0.16)
Age<= 40	-0.21	-2.33	0.08
	(0.00)	(0.05)	(0.03)

Notes: The table presents the estimated direct and indirect effects using the R mediation package described in Tingley et al. (2014), allowing for moderation by age group and socio-economic status (SES), proxied by college attainment and income levels. The median of income in the sample is \$60.000. p-values are presented in parenthesis. Uncertainty estimates are calculated using 1000 simulations with a quasi-Bayesian Monte Carlo method based on normal approximation. White's heteroskedasticity-consistent estimator is used for the covariance matrix. The third column calculates the ratio between the indirect effect and the total effect.

More broadly, I find that this excess sensitivity of beliefs to past rejections correlates with other important measures of households' financial behaviour. Using the SCE and SCF data sets I find that rejections are also associated with lower likelihood of applying again even if desired (Appendix Table B.5), increases in savings due to fear of tighter credit conditions (Online Appendix Table E.14), and lower holdings of risky assets (Online Appendix Table E.15).

5.3 Aggregate Overreaction: Mechanism & Quantification

Excessive reliance on rejection memories not only amplifies individual choices but can also induce overreaction to negative economic shocks at the aggregate level. Typically, when a

[28] Data limitations prevent analysis based on wealth differences.

negative shock hits, people revise their probability judgments downward. However, if recalling past rejections is more likely in a bad state, an additional idiosyncratic pessimism is introduced, contributing to a larger decline in aggregate demand.

Below, I integrate the empirical findings on state-dependent recall from Section 4.3 with the model's equations to illustrate the relevance of the memory channel for aggregate demand.

Parameters. I use the average rejection rate observed in the SCE data (i.e. $\lambda_0 = 0.18$). Given that the aggregate state in the model affects individuals' income, I define a low state as one where unemployment rates increase by one standard deviation, and I focus on individuals' expectations about higher U.S. unemployment in the upcoming year. As outlined in Table 6, the average probability assigned to rising unemployment increases as the state worsens (i.e. $p_{HL} = 0.355 < p_{LL} = 0.363$). Crucially, the recall of a personal rejection is higher when the state is low than when it is high (i.e. $\omega_{LL} = 0.07 > \omega_{HL} = 0.03$).

Impact on Aggregate Demand. At time $t = 1$, aggregate consumption in state $i \in \{H, L\}$ is given by $C_1^i = (1 - \lambda_0)c_1^{a,i} + \lambda_0 c_1^{r,i}$. Hence, both the direct and indirect (belief) effects of rejection matter, weighted by the fraction of rejected individuals λ_0. More specifically,

$$C_1^i = c_1^{a,i} + (1+R)^{-1}\,\lambda_0 \left[\underbrace{Rb_1^a}_{DE}\underbrace{-\omega_{iL}(1-\hat{p}_{iL})\Delta y_2}_{IE}\right] \tag{8}$$

Even in favourable states, some individuals recall past rejections, overestimating the probability of transitioning to a low state, which slightly reduces aggregate consumption. In low states, this effect intensifies as adverse conditions increase the likelihood of recalling personal rejections ($\omega_{LL} > \omega_{HL}$). Table 9 quantifies the reductions in aggregate consumption due to the memory channel in both states. Relative to a "no-memory" scenario, aggregate consumption is depressed in both states, but especially during low ones.

Table 9: Effect of Memory Channel or IE on Aggregate Consumption

(1) High State	(2) Low State
-0.22%	-0.52%

Notes: Estimated percentage change in C_1^i once we allow memory recall of rejections. Computed as $(C_1^{i,\omega=0} - C_1^i)/C_1^i = ((1+R)^{-1}\lambda_0\omega_{iL}(1-p_{iL})\Delta y_2)/C_1^{i,\omega=0}$, with $R = 1.25$, $y_2^H = 3y_2^L$, $y_2^L = 1$ and $\lambda_0 = 0.18$.

In the data, rejected individuals are consistently more pessimistic whereas accepted individuals do not compensate through higher optimism, leading to aggregate pessimism. Even if accepted individuals where to compensate through higher optimism, individual's reliance on personal memories matters for aggregate demand because of the state-dependency: rejections (and negative experiences as a whole) are more likely recalled during downturns. The following exercise highlights this.

Overreaction During State Transitions. Instead of doing comparative statics across states, we can look at the role of memory when we transition from a H to a L state. The change in aggregate consumption at time 1 is given by:

$$\Delta C_1^{H \to L} = \underbrace{(y_1^H - y_1^L)}_{\substack{\text{(1) Income} \\ \text{Channel} > 0}} + \frac{1}{1+R} \left(\overbrace{\underbrace{E_1^H(y_2) - E_1^L(y_2)}_{\substack{\text{(2) Probability} \\ \text{Channel} > 0}} \underbrace{- [\omega_{HL}(1 - p_{HL}) - \omega_{LL}(1 - p_{LL})]}_{\text{(3) Memory Channel} > 0}}^{\text{Belief Channel}} \lambda_0 \Delta y_2 \right) \tag{9}$$

The transition to a low economic state reduces aggregate consumption through an income channel and a probability channel by decreasing resources and altering perceived probabilities about future economic states. Additionally, it triggers the recall of negative personal experiences, distorting probability judgments (memory channel). To focus on changes in beliefs, I assume the income channel is zero and quantify the importance of state-dependent pessimism bias through a counterfactual exercise presented in Table 10.

Table 10: Decline in C_1 through Belief Channel (%)

No Recall	Constant Recall	State-Dependent Recall
$\omega_{HL} = \omega_{LL} = 0$	$\omega_{HL} = \omega_{LL}$	$\omega_{HL} < \omega_{LL}$
−0.813%	−0.811%	−1.11%

Notes: The table presents estimated percentage change in aggregate consumption that results from changes in beliefs, calculated based on Equation 9 and parameters in defined in text plus $y_2^H = 3y_2^L$, $y_2^L = 1$.

If $\omega_{HL} = \omega_{LL}$, memory matters but rejections are recalled equally in both states, and thus the transition mostly reflects the standard probability channel (Columns 1 and 2). But since the data shows $\omega_{HL} < \omega_{LL}$, the memory channel compounds the shock: consumption drops an additional 0.30 percentage points in the state-dependent case (Column 3). Thus, past personal rejections interact with a current aggregate shock in the labor market through selective recall, and this interlinkage across markets can have relevant aggregate implications.

While the model is stylised, it provides valuable insights into the potential impact of the memory channel on aggregate demand. The estimates presented are conservative lower bounds, focusing on unemployment expectations (non-domain-specific) and not accounting for expectations about future credit market tightening (within-domain experiences), which could have more pronounced effects in models with long-lived agents participating in credit markets multiple times.

6 Conclusion

Despite being highly idiosyncratic, credit rejections exert a disproportionate influence on individuals' macroeconomic expectations. Rejected individuals are excessively pessimistic about credit conditions, unemployment, stock prices, and inflation –irrespective of demographics, loan type, or access to information. These findings cannot be fully explained by the informational context of the experience, nor by selection or individual confounds, challenging standard belief-formation models. I interpret this through a selective memory model, where personal credit rejections cue negative past experiences, shaping aggregate expectations. This mechanism generates systematic belief heterogeneity across socio-economic groups and amplifies average overreaction in beliefs during recessions, with empirical data supporting the model predictions.

Incorporating these memory-based beliefs into a consumption-saving framework reveals significant economic implications. Rejections affect consumption directly through credit constraints and indirectly by inducing pessimism about future macroeconomic conditions. This "belief channel" explains about 12% of the decline in planned durable consumption, particularly among younger and lower-SES households. Additionally, past rejections are associated with increased savings, discouragement from future credit market participation, and lower holdings of risky assets. At the aggregate level, beliefs overreact following downturns because of associative recall, amplifying contractions in aggregate demand.

Understanding how households think about the economy –and how personal experiences shape their beliefs– is crucial for understanding economic behaviour and aggregate dynamics. From a policy perspective, the results highlight the unintended consequences of increased credit rejections, particularly for vulnerable groups, and underscore the importance of crafting policies and communications that account for how individuals interpret economic signals through their own experiences.

At the same time, these findings open new avenues for research. Exploring how personal experiences and memory influence households' economic behaviour, especially their interlinkages across markets, is a promising direction for future research. Understanding these mechanisms will deepen our ability to anticipate how shocks propagate through the economy.

Appendix

A Descriptive Statistics

Table A.1: Summary Statistics: Experiences, Expectations and Controls

	Mean	Standard Deviation	Min	Median	Max
Experiences in the Credit Market					
Applied and Accepted	0.39	0.63	0	0	1
Applied and Rejected	0.076	0.27	0	0	1
Didn't Apply, Other	0.46	0.68	0	0	1
Didn't Apply, Discouraged	0.072	0.27	0	0	1
Demographics					
Age	51	7.12	17	51	85
Female	0.5	0.7	0	0	1
White	0.84	0.92	0	1	1
Black	0.09	0.3	0	0	1
Married	0.64	0.8	0	1	1
College	0.49	0.7	0	1	1
Employment Status					
Employed	0.65	0.81	0	1	1
Looking for a job	0.03	0.17	0	0	1
Retired	0.21	0.46	0	0	1
Out of labor force	0.08	0.28	0	0	1
Income Category					
Below 50k	0.41	0.64	0	0	1
Between 50k and 100k	0.3	0.55	0	0	1
Above 100k	0.28	0.53	0	1	1
Home Owner	0.72	0.85			
Numeracy Category					
Low	0.34	0.81	0	0	1
High	0.65	0.59	0	1	1
Aggregate Expectations					
Optimism Index	-0.02	0.6	-2.23	-0.02	2.53
Unemployment	35.58	23.33	0	33	100
Stock Prices	40.03	23.35	0	48	100
Inflation (mean of distribution)	2.82	5.41	-25	3	36
Inflation (reported point estimate)	5.63	9.06	-25	3	50
Credit conditions					
tighten	0.32	0.46	0	0	1
no change	0.49	0.5	0	0	1
loosen	0.18	0.38	0	0	1

Notes: The table shows summary statistics of the respondents' experiences, characteristics and expectations. Values account for the weights provided by SCE to make the sample representative of the US. The reported point estimate of inflation has been winsorized at the 1% level (original data varies from −100% to 200% inflation).

Table A.2: Application and Rejection Rate by Credit Score

Credit Score Cat.	Share of Pop.	Application Rate (%)	Rejection Rate (% Applicants)
< 680	0.1992	0.534	0.44
>= 680& < 720	0.104	0.573	0.13
>= 720	0.549	0.465	0.042
DK	0.147	0.32	0.19

Table A.3: Summary Statistics for Credit Market Participants, by Experience

	Mean Accepted	Mean Rejected	t-stat	p-value
Age	48.3	46	6.63	3.97e-11
Female	0.47	0.6	-10.66	5.37e-26
White	0.85	0.76	8.29	1.80e-16
Black	0.08	0.17	-9.75	5.40e-11
Married	0.69	0.54	11.29	2.98e-29
College	0.72	0.56	12.77	3.56e-36
Employment Status				
Employed	0.75	0.72	2.31	2.10e-02
Looking for a job	0.02	0.045	-5.11	3.58e-07
Retired	0.16	0.09	8.66	7.95e-18
Out of labor force	0.053	0.11	-7.45	1.35e-13
Income Category				
Below 50k	0.26	0.54	-22.67	6.83e-103
Between 50k and 100k	0.37	0.31	5.16	2.64e-07
Above 100k	0.36	0.14	23.51	1.53e-112
Home Owner	0.76	0.5	21.45	4.84e-93
Numeracy Category				
Low	0.24	0.4	-13.24	1.30e-38
High	0.76	0.6	13.23	1.42e-38
Reported CrScore>= 720	0.77	0.30	42.21	2.07e-293

Notes: The table shows summary statistics of respondents' characteristics by credit market experiences experiences. Values account for the weights provided by SCE to make the sample representative of the US. Column 2 shows mean averages for those accepted and Column 3 for those rejected. Column 4 and 5 report the result of running t-test of differences in mean.

Table A.4: Share of applications and rejections by credit type

	New Loans				Existing Loans		
	Credit Card	Mortg.	Auto Loan	Student Loan	↑ Credit Card Limit	↑ Limit Loan	Refinance Mortgage
% pop. (App. Rate)	0.28	0.07	0.15	0.03	0.12	0.08	0.13
% among applicants	0.57	0.16	0.32	0.07	0.22	0.13	0.23
% rejections among app.	0.22	0.16	0.14	0.21	0.36	0.40	0.09

Notes: The first row shows the application rate over the past twelve months for each credit type, the second row the share that applied to each credit type among all the applicants and the third row the rejection rate among applicants for each type. All shares are constructed as weighted means, using the provided weights to be representative of US population. Rows might not sum to 1, as respondents might have applied to more than one type of credit.

B Regression Results

Rejections future discouragement.

Table B.5: Discouragement from Rejections – SCE (2013-2021) and SCF (1999-2019)

	SCE 2013-2021	*SCF 1999-2019*
Applied and rejected	0.477***	0.317***
	(0.013)	(0.008)
Didn't apply	−0.039***	0.020***
	(0.005)	(0.004)
Individual Level Controls	Y	Y
FE	State×Month×Year	Year
R^2	0.531	0.217
Observations	8790	42205
Mean Dep. Var.	12.8	12.5

Columns 1 and 2 use data from the SCE (2013-2021) and SCF (1999-2019), respectively. Each column reports results from regressing respondents' past credit rejections on a dummy for discouragement from applying due to fear of rejection. The SCE regressions control for state-month-year fixed effects, income category, income expectations, gender, age, race, employment status, college attendance, and marital status. The SCF regressions control for year fixed effects, income category, income expectations/perceptions, gender, age, race, recent unemployment, home ownership, college attendance, and marital status. Significance level: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Not related to information. I present regression estimates of the exercises discussed in the main text.

By Credit Type. I construct subsamples across loan types to evaluate whether the role of rejection differs according to each loan type.

Table B.6: Credit Market Rejection and Aggregate Pessimism by loan type - New Loans

Dep.Var: Optimism Index	(1)	(2)	(3)	(4)
Applied and Rejected	−0.209***	−0.169***	−0.163***	−0.229***
	(0.027)	(0.044)	(0.036)	(0.046)
Sample	CreditCard	Mortgage	Auto Loan	Student Loan
Controls	Y	Y	Y	Y
R^2	0.162	0.279	0.224	0.368
Observations	6686	2012	3605	854

Notes: The table presents regression estimates from equation 1 where each column refers to a different sample. The dependant variable is the Optimism Index. All columns control for demographics (include age, gender, race, employment status, married, college, income, income expectations.), state-month-year fixed effects. Standard errors are clustered at the respondent and date level. Significance level:$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

By Households' Characteristics. I explore whether rejection rates among different types of applicants correlate with macroeconomic conditions, and if households' reliance on rejections aligns with these patterns. Using SCE data, I calculate rejection rates by income and education levels and compare them to the adjusted national financial conditions index (ANFCI) from the Chicago Fed. Figure B.1 shows scatter plots of these relationships. Rejection rates among college-educated and high-income applicants positively correlate with tight financial conditions, while no significant correlation exists for non-college-educated or low-income groups. Similar analyses with other macroeconomic outcomes yield consistent results (see Online Appendix B.1).

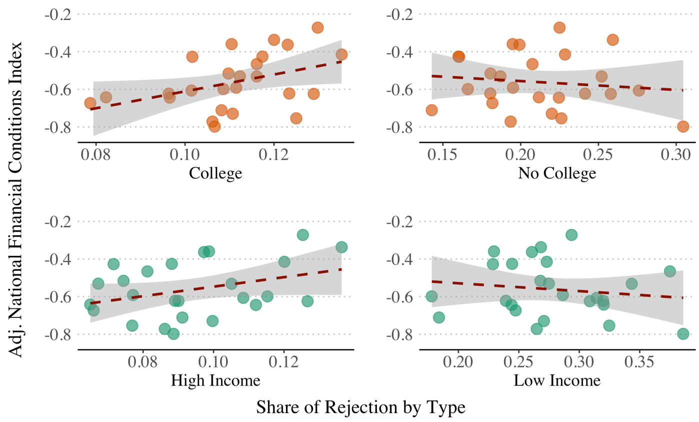


Figure B.1: Share Of Rejections by Individuals' Type and Financial Conditions

Notes: Upper left panel shows correlation between ANFCI and rejection rate for college-educated applicants ($\rho = 0.42$, p-value= 0.04); upper right for non-college-educated ($\rho = -0.12$, p-value= 0.55); lower left shows high-income applicants ($\rho = 0.35$, p-value= 0.08); lower right for low-income applicants ($\rho = -0.14$, p-value= 0.49)

Table B.7: Rejection and Optimism Index by Respondent Characteristics

	(1)	(2)	(3)	(4)
Applied and Rejected * Young	-0.151^{***}			
	(0.030)			
Applied and Rejected * Adult	-0.187^{***}			
	(0.023)			
Applied and Rejected * Old	-0.083^{*}			
	(0.045)			
Applied and Rejected * College			-0.127^{***}	
			(0.023)	
Applied and Rejected * No College			-0.204^{***}	
			(0.029)	
Applied and Rejected * High Income				-0.142^{***}
				(0.025)
Applied and Rejected * Low Income				-0.173^{***}
				(0.028)
Didn't apply	-0.010	-0.011	-0.010	-0.011
	(0.010)	(0.010)	(0.010)	(0.010)
Controls	Y	Y	Y	Y
Stat. Diff.	$p = 0.01$	$p = 0.01$	$p = 0.04$	$p = 0.17$
Observations	25146	25146	25147	25146
R^2	0.105	0.103	0.105	0.105

Notes: The table presents regression estimates from equation 1. The dependant variable is the Optimism Index. All columns control for demographics (age, gender, race, employment status, married, college, income, income expectations) and state-month-year fixed effects. Standard errors are clustered at the respondent and date level. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

By Information Levels. Using SCF data, I construct an indicator for past credit rejection and measure economic expectations via the question: "Over the next five years, do you expect the U.S. economy to perform better (=1), worse (=0), or about the same (=1) as the past five years?" To assess households' information levels when applying for credit, I consider two measures: (1) Search Intensity, rated from 0 (none) to 10 (extensive), and (2) Sources of Information, such as financial advisors or friends. Households listing financial advisors as their primary source are classified as "financially informed."

Rejected individuals are categorised by search intensity (low, medium, or high) and financial information levels. The hypothesis is that well-informed individuals rely less on personal experiences when forming macroeconomic expectations. Logit regressions of credit rejection on economic expectations, controlling for individual characteristics and time fixed effects, reveal that rejected individuals are 15% more likely to be pessimistic than accepted ones. However, financial information and search intensity do not significantly mitigate this pessimism, suggesting that reliance on personal credit experiences persists, regardless of prior knowledge or search effort.

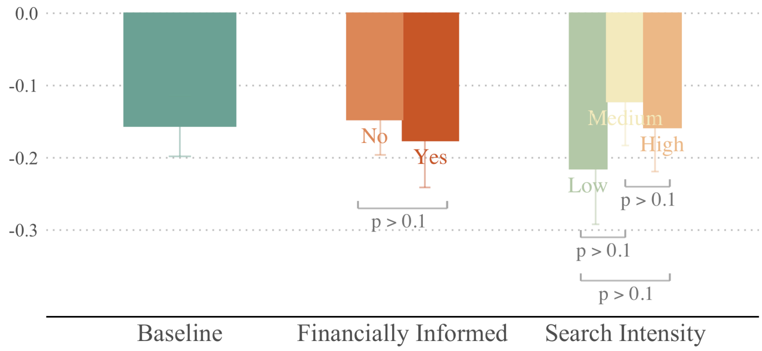


Figure B.2: Estimated coefficient on personal rejection, baseline and by info level

Notes: Estimated coefficients on binary measures of past personal rejection from logit estimation. The regression controls for individual characteristics (age, gender, education, marital status, race, unemployment status, income - category, perception and expectation) and year fixed effects. Reference category refers to accepted.

Excess Sensitivity - Forecast errors. For the credit conditions variable, I used different measures – (1) Senior Loan Officer Opinion Survey on Bank Lending Practices from FRB, (2) National Financial Conditions Index from Chicago Fed (baseline index, adjusted index, and credit focused). Results are robust to both of them. Importantly, the key for my analysis is the heterogeneity in forecast errors across individuals, rather than the level of their forecast errors.

Table B.8: Description of Variables used for constructing Forecast Errors

Variable	*Source*	*Question*	*Coding*	*Average*
Credit Cond.				
Expectation	Survey of Consumer Expectations (SCE)	"12 months from now it will generally be harder or easier for people to obtain credit or loans?"	harder (1) no change (0) easier (-1)	0.1
Outcome	Senior Loan Officer Opinion Survey on Bank Lending Practices	changes in consumer lending at your bank over the last 3 months (annualized)	tightening (1) no change (0) loosening (-1)	-0.535
Inflation				
Expectation	Survey of Consumer Expectations (SCE)	"Over the next 12 months, I expect the rate of inflation/deflation to be ... %"	continuous	3.6
Outcome	US Bureau of Labor Statistics (BLS)	Realized inflation over the next 12 months after each individual answered the survey	continuous	1.66
Unemployment				
Expectation	Survey of Consumer Expectations (SCE)	"percent chance that 12 months from now the unemployment rate in the U.S. will be higher than it is now?"	continuous [0, 100]	37.1
Outcome	FRED	Unconditional probability of a positive change in unemployment rate	continuous [0, 100]	33.56
Stock Prices				
Expectation	Survey of Consumer Expectations (SCE)	"percent chance that 12 months from now, on avg, stock prices in the US stock market will be higher than they are now?"	continuous [0, 100]	40.02
Outcome	Shiller S&P Composite Stock Price Index	Unconditional probability of a positive change in stock price index	continuous [0, 100]	57

The following tables show regression estimates.

Table B.9: Idiosyncratic Rejections on Individuals' Forecast Error

	FE Unemp	FE Credit	FE Stock	FE Infl
(Intercept)	-4.625^{**}	-0.027	10.684^{***}	-2.842^{**}
	(1.973)	(0.105)	(1.966)	(1.242)
Applied and Accepted		(omitted)		
Applied and Rejected	-2.160^{***}	-0.238^{***}	1.312^{**}	-1.742^{***}
	(0.643)	(0.033)	(0.621)	(0.415)
Didn't Apply	0.943^{***}	0.031^{*}	0.834^{***}	0.479^{***}
	(0.314)	(0.017)	(0.310)	(0.138)
R^2	0.013	0.016	0.045	0.068
Observations	25005	21825	21761	25008
Mean Dep.Var.	−2.65	−0.47	22.4	−3.69

Notes: All specifications control for respondents characteristics. Standard errors are clustered at the individual and date level. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table B.10 reports estimates for (1) η from regressing idiosyncratic rejections on realised macro outcomes and (2) $\hat{\eta}$ from regressing idiosyncratic rejections on beliefs about macro outcomes, for each macro variable of interest (as suggested in Taubinsky et al. (2024)). Although the estimated correlation between idiosyncratic rejections and aggregate outcomes is close to zero for all aggregate variables, respondents' believe this correlation to be very high and strong. Moreover, they not only vastly overestimate the correlation between r_{it} and the macro, they also make associations for which there is no support in the data: the estimated $\hat{\eta}$ is at least 20 times bigger than the estimated η, and in some cases, $sign\{\hat{\eta}\} \neq sign\{\eta\}$.

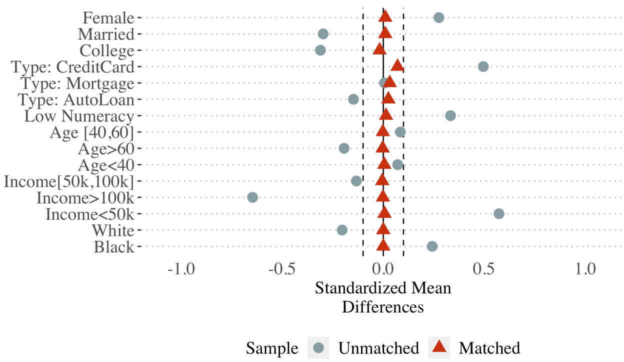
Table B.10: Idiosyncratic Rejections on Future Macro Outcomes and Macro Beliefs

	Prob Unemp ↑		Tighten Credit		Prob StockPrices ↑		Avg Infl.	
	η	$\hat{\eta}$	η	$\hat{\eta}$	η	$\hat{\eta}$	η	$\hat{\eta}$
(Intercept)	33.487***	36.357***	0.001	0.072***	63.240***	42.846***	1.637***	4.890***
	(0.010)	(0.217)	(0.070)	(0.007)	(0.003)	(0.218)	(0.007)	(0.103)
Rejected	−0.001	2.468***	0.046	0.263***	0.002	−4.271***	0.028	2.921***
	(0.026)	(0.583)	(0.187)	(0.017)	(0.009)	(0.586)	(0.018)	(0.276)
Didn't Apply	−0.079***	−0.840***	−0.433***	0.032***	0.033***	−1.536***	0.027***	0.218
	(0.013)	(0.290)	(0.094)	(0.009)	(0.005)	(0.292)	(0.009)	(0.138)
Obs.	28236	27311	26013	28236	28236	27313	28233	27280

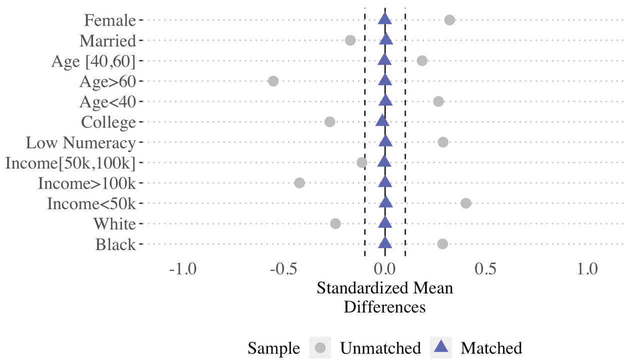
Notes: The table presents results from regressions (1) $Y_{t+1} = \alpha + \eta r_{it} + \gamma X_{it} + e_{t+1}$ (2) $E(Y_{t+1}|I_{it}) = \hat{\alpha} + \hat{\eta} r_{it} + \hat{\gamma} X_{it} + v_t$, for each aggregate variable. Significance level: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

No evidence for selection into rejection. I present regression tables and robustness tests for the exercises discussed in the main text.

Matching. The figures show balance improvement after matching, and the regression tables present the estimates in each matched sample. Online Appendix B.2 provides a detailed description of the approach.



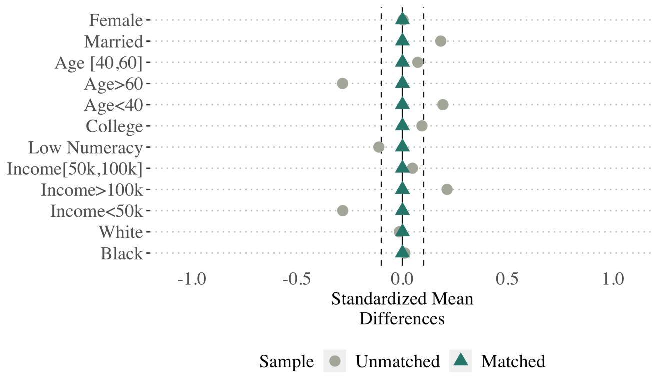
(a) Std. Mean Diff.: Rejected vs. Accepted



(b) Std. Mean Diff.: Rejected vs. Didn't Apply

Figure B.3: Standardised Mean Differences – Matched and Unmatched

Notes: Matching method is 1 : 1 nearest neighbour matching on Mahalanobis distance without replacement. y-axis presents covariates, x-axis shows standardised mean differences, with unmatched sample in grey dots and matched sample in triangles.



(a) Std. Mean Diff.: Accepted vs. Didn't Apply

(b) Standardised Mean Differences – Matched and Unmatched

Notes: Matching method is exact matching. y-axis presents covariates, x-axis shows standardised mean differences, with unmatched sample in grey dots and matched sample in triangles.

Table B.11: Rejections and Expectations – Matched Sample of Rejected and Accepted

	OPTM	UNEMP	FCredit	StockP	INFL
Rejected	-0.176^{***}	2.321^{**}	0.228^{***}	-0.743	1.275^{**}
	(0.027)	(1.070)	(0.032)	(1.053)	(0.613)
Individual level Controls	Y	Y	Y	Y	Y
State-Month-Year FE	Y	Y	Y	Y	Y
R^2	0.319	0.292	0.304	0.312	0.281
Observations	3320	3315	3320	3313	3315

Notes: The table presents OLS estimates from equation $E_{i,t}(Y_{t+1}) = \alpha + \beta \mathrm{T}_{i,t} + \delta X_{i,t} + \gamma_{st} + e_{it}$. The title of each column specifies the dependent variable used. All columns control for state-month-year fixed effects and individual-level covariates (employment status, gender, race, age, marital status, college attainment, type of loan, income category, numeracy category). Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table B.12: Rejections and Expectations – Matched Sample of Rejected and Non-Participants

	OPTM	UNEMP	FCredit	StockP	INFL
Rejected	-0.182^{***}	3.015^{***}	0.218^{***}	-0.630	2.360^{***}
	(0.027)	(1.105)	(0.033)	(1.088)	(0.758)
Individual level Controls	Y	Y	Y	Y	Y
State-Month-Year FE	Y	Y	Y	Y	Y
R^2	0.327	0.291	0.298	0.318	0.305
Observations	3330	3323	3330	3321	3324

Notes: The table presents OLS estimates from equation $E_{i,t}(Y_{t+1}) = \alpha + \beta \mathrm{T}_{i,t} + \delta X_{i,t} + \gamma_{st} + e_{it}$. The title of each column specifies the dependent variable used. All columns control for state-month-year fixed effects and individual-level covariates (employment status, gender, race, age, marital status, college attainment, type of loan, income category, numeracy category). The treated group is composed of rejected individuals while the control group is composed of those who chose not to apply. The matching method is $1:1$ nearest neighbour matching on Mahalanobis distance without replacement on the covariates. Cluster-robust standard errors account for pair membership. Standard errors are reportes in parenthesis. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table B.13: Rejections and Expectations – Matched Sample Accepted and Non-Participants

	OPTM	UNEMP	FCredit	StockP	INFL
Accepted	-0.009	1.026	0.023	1.457^{***}	0.032
	(0.015)	(0.636)	(0.016)	(0.544)	(0.248)
Individual level Controls	Y	Y	Y	Y	Y
State-Month-Year FE	Y	Y	Y	Y	Y
R^2	0.100	0.080	0.084	0.126	0.099
Observations	23019	22994	23019	22997	22957

Notes: The table presents OLS estimates from equation $E_{i,t}(Y_{t+1}) = \alpha + \beta \mathrm{T}_{i,t} + \delta X_{i,t} + \gamma_{st} + e_{it}$. The title of each column specifies the dependent variable used. All columns control for state-month-year fixed effects and individual-level covariates (employment status, gender, race, age, marital status, college attainment, type of loan, income category, numeracy category). The treated group is composed of accepted individuals while the control group is composed of those who chose not to apply. The matching method is $1:1$ nearest neighbour matching on Mahalanobis distance without replacement on the covariates described above. Cluster-robust standard errors account for pair membership. Standard errors are reportes in parenthesis. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Robustness to Matching based on Covariates and Optimism.

Table B.14: Rejection and Expectations – Matched Sample (covariates & pre-optimism level)

	OPTM	Unemp	FCredit	StockP	INFL
(Intercept)	0.040	33.281^{***}	0.049	39.305^{***}	4.954^{***}
	(0.031)	(1.260)	(0.038)	(1.264)	(0.513)
Rejected	-0.126^{***}	3.981^{**}	0.145^{***}	0.348	2.025^{**}
	(0.040)	(1.806)	(0.053)	(1.720)	(0.876)
Individual level Controls	Y	Y	Y	Y	Y
State-Month-Year FE	Y	Y	Y	Y	Y
R^2	0.012	0.01	0.011	0.00	0.01
Observations	650	649	650	650	649

Notes: The table presents OLS estimates from equation $E_{i,t}(Y_{t+1}) = \alpha + \beta \mathrm{T}_{i,t} + \delta X_{i,t} + \gamma_{st} + e_{it}$. The title of each column specifies the dependent variable used. All columns control for state-month-year fixed effects and individual-level covariates (employment status, gender, race, age, marital status, college attainment, type of loan, income category, numeracy category). The treated group is composed of individuals who start the sample by not being rejected and are then treated, while the control group is composed of those who never experienced a rejection. The matching method is $1:1$ nearest neighbour matching on Mahalanobis distance without replacement on the covariates described above. Cluster-robust standard errors account for pair membership. Standard errors are reportes in parenthesis. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Individual Fixed Effects. The following table presents regression estimates when both time and individual fixed effects are included. This estimation approach, while addressing internal validity concerns, has limitations. The survey's narrow resampling window and infrequent loan applications limit the number of transitions. Furthermore, within-individual estimation captures variations from both moving from acceptance to rejection and vice versa. If acceptances do not fully counteract the pessimism from prior rejections, individual fixed effects may bias the estimates.

Table B.15: **Table B.15:** Credit Market Rejection and Aggregate Pessimism within individuals

	OPTM	UNEMP	FCredit	StockP	INFL
Applied and Rejected	-0.061^{***}	1.438^{**}	0.061^{***}	-0.413	0.162
	(0.016)	(0.639)	(0.019)	(0.596)	(0.275)
Didn't Apply, Discouraged	-0.034^{**}	0.339	0.069^{***}	0.023	0.112
	(0.016)	(0.744)	(0.019)	(0.645)	(0.334)
Didn't Apply, Other	-0.008	-0.306	-0.019^{**}	-1.373^{***}	-0.020
	(0.007)	(0.313)	(0.009)	(0.306)	(0.103)
Ind. Level Controls	Y	Y	Y	Y	Y
Month-Year FE + Ind. FE	Y	Y	Y	Y	Y
R^2	0.034	0.043	0.024	0.041	0.028
Observations	27337	27293	27337	27294	26891

Notes: The table presents regression estimates from equation 1 plus individual fixed effects. Controls include demographic characteristics that change through time such as income category, expected income and employment status. Standard errors are clustered at the date level. Significance level: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Robustness to the inclusion of Credit Score. The ideal experiment would account for individuals' credit scores as a covariate, provided the credit score was not affected by rejection. However, credit scores could influence rejection decisions and also be affected by past rejection, which poses a challenge. In the SCE data, 72.3% of respondents reported checking their credit score in the past year, 22.3% over a year ago, and 5.4% never checked it.

To evaluate robustness, I conducted four analyses incorporating credit score information differently. The blue bar in Figure B.5 shows the estimated coefficient when credit score is not included as a control (from Table B.11). The green bar represents the coefficient after adding credit score as a control variable (from Online Appendix Table B.10). In the next exercise, I included individuals' reported credit score in both the matching procedure and as a control. This coefficient is represented by the orange bar (from Online Appendix Table B.11). However, this approach can be problematic because matching variables should ideally be pre-treatment. To address this concern, the fourth exercise restricts matching to individuals who had not checked their credit score in the last year. Within this subset, individuals are matched based on covariates and a binary variable, Old Credit Score, which equals 1 if their credit score was above 680 when they last checked 12 months ago and 0 otherwise. This stricter approach results in a smaller matched sample of approximately 550 individuals, and the coefficient from this analysis is represented by the pink bar in Figure B.5 (from Online Appendix Table B.12).

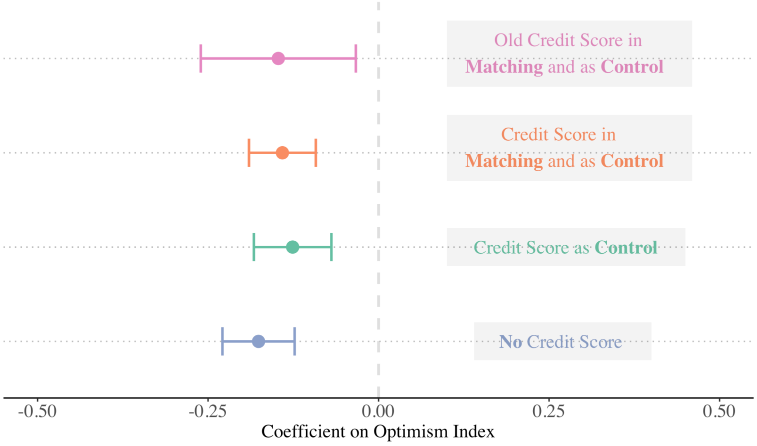


Figure B.5: Robustness to the inclusion of Reported Credit Score

Notes: Figure shows the estimated coefficients on the binary variable *rejected* when the outcome variable is OPTM. All specifications control for state-month-year fixed effects and individual-level covariates (employment and marital status, gender, race, age, college, type of loan, income and numeracy category). *Old Credit Score* refers to the credit score that individuals reported to have checked more than 12 months ago. The matching method is $1:1$ nearest neighbour matching on Mahalanobis distance without replacement. Cluster-robust standard errors account for pair membership. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

C Memory-Based Model

Proof of Expression 5.

Suppose:

1. past relevant macro transitions are perfectly recalled and used: they satisfy $S(\{i,j\},\{i,j\}) = S(\{i,i\},\{i,j\}) = \sigma(\{i,j\},\{i,j\}) = \sigma(\{j,j\}\},\{i,j\}\}) = 1$ and 0 otherwise
2. other experiences (either macro or personal) $\in E$ come to mind with positive similarity as long as they share some feature with θ_{iL}, and then they are used with probability 1 if they share feature $f_2 = j$

Although not necessary, Assumption 1 simplifies analysis and allows us to focus on deviations from the frequentist benchmark. Another way to interpret this is to think that households are informed and know about the frequentist probability, but they still recall other things with positive probability and use them to imagine the scenarios, thus inflating that probability.

In this setup, relevant transitions from i to j that $\in \Theta$ are not distorted by similarity. Nevertheless, when forecasting a transition to L, experiences from E can also come to mind with positive similarity: since e_{LL}, e_{HL}, e_{LH} have a negative feature, they have positive similarity irrespective of i. If $i = H$, also e_{HH} can come to mind with a positive probability. Once recalled, only e_{LL}, e_{HL} are useful to imagine the transition to L. For expositional clarity, define $D = S(.)|e_{LL}| + S(.)|e_{HL}| + S(.)|e_{LH}| + S(.)|e_{HH}|$ and $X = S(.)|e_{LH}| + S(.)|e_{HH}|$, such that $D - X = S(.)|e_{LL}| + S(.)|e_{HL}|$, then:

$$\hat{p}_{iL} = \frac{|\theta_{iL}| + S(.)|e_{LL}| + S(.)|e_{HL}|}{|\theta_{iL}| + |\theta_{iH}| + S(.)|e_{LL}| + S(.)|e_{HL}| + S(.)|e_{LH}| + S(.)|e_{HH}|}$$

$$= \frac{|\theta_{iL}| + |\theta_{iH}|}{|\theta_{iL}| + |\theta_{iH}|} \times \left[\frac{|\theta_{iL}|}{|\theta_{iL}| + |\theta_{iH}| + D}\right] + \left[\frac{S(.)|e_{LL}| + S(.)|e_{HL}|}{|\theta_{iL}| + |\theta_{iH}| + D}\right]$$

$$= p_{iL} + \left[\frac{|\theta_{iL}| + |\theta_{iH}|}{|\theta_{iL}| + |\theta_{iH}| + D}\right] + \left[\frac{S(.)|e_{LL}| + S(.)|e_{HL}|}{|\theta_{iL}| + |\theta_{iH}| + D}\right]$$

$$= p_{iL} + \left[1 - \frac{D}{|\theta_{iL}| + |\theta_{iH}| + D}\right] + \left[\frac{S(.)|e_{LL}| + S(.)|e_{HL}|}{|\theta_{iL}| + |\theta_{iH}| + D}\right]$$

$$= p_{iL} + \left[1 - \frac{D - X + X}{|\theta_{iL}| + |\theta_{iH}| + D}\right] + \left[\frac{D - X}{|\theta_{iL}| + |\theta_{iH}| + D}\right]$$

$$= p_{iL} + (1 - p_{iL}) \times \left[\frac{D - X}{|\theta_{iL}| + |\theta_{iH}| + D}\right] - p_{iL} \times \left[\frac{X}{|\theta_{iL}| + |\theta_{iH}| + D}\right]$$

$$= p_{iL} + \underbrace{(1 - p_{iL}) \times \left(\frac{s^e_{LL} + s^e_{HL}}{W}\right)}_{Simulation\ Term} - \underbrace{p_{iL} \times \left(\frac{s^e_{LH} + s^e_{HH}}{W}\right)}_{Interference\ Term}$$

where $s^e_{LL} = S(\theta_{iL}, e_{LL})|e_{LL}|$, $s^e_{HL} = S(\theta_{iL}, e_{HL})|e_{HL}|$, $s^e_{LH} = S(\theta_{iL}, e_{LH})|e_{LH}|$ and $s^e_{HH} = S(\theta_{iL}, e_{HH})|e_{HH}|$ for $i = \{H, L\}$. The simulation Term captures all recalled experiences that are used because they ease simulation for L events, while the Interference Term captures all recalled experiences that are not used for simulation but still retrieved and thus interfere with other more relevant experiences.

Proof of Expression 7. Follows from the expression above, by assuming $|e_{LL}| = 1$ and isolating its role.

Predictions of Memory Model.

Table C.16: Rejections and Expectations about the Macro - Implied Similarity Exercise

	Tighter Credit Mkt	Higher Unemp	Inflation>= 4%	Inflation>= 8%
Applied and rejected	0.158^{***}	2.010^{***}	2.197^{**}	3.114^{***}
	(0.013)	(0.627)	(0.903)	(0.705)
Didn't apply, disc	0.156^{***}	1.245^{*}	2.635^{***}	2.975^{***}
	(0.014)	(0.678)	(0.976)	(0.762)
Didn't apply, other	-0.030^{***}	-0.846^{***}	-2.111^{***}	-1.366^{***}
	(0.006)	(0.321)	(0.462)	(0.361)
Controls	Y	Y	Y	Y
R^2	0.035	0.014	0.055	0.086
Observations	25161	25132	25161	25161
Mean Dep Var	0.30	35.3	34.6	17.1

Notes: Table presents the regression coefficients used for the implied similarity exercise. All specifications control for individuals demographic and socioeconomic characteristics and for state-month-year fixed effects. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table C.17: State Dependency in Beliefs across Macro Outcomes

	OPTM	↑UNEMP
(Intercept)	0.207^{**}	43.054^{***}
	(0.103)	(3.992)
Applied and rejected	-0.163^{***}	2.173^{***}
	(0.016)	(0.626)
Didn't apply	-0.005	-0.935^{***}
	(0.008)	(0.310)
Recession	0.069^{**}	
	(0.028)	
Applied and rejected×recession	-0.148^{*}	
	(0.086)	
Didn't apply×recession	-0.018	
	(0.037)	
UNEMPrate		0.276^{**}
		(0.110)
Applied and rejected×UNEMPrate		0.672^{**}
		(0.300)
Didn't apply×UNEMPrate		-0.107
		(0.141)
Individuals' Controls	Y	Y
R^2	0.053	0.018
Observations	25161	25132

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

D Economic Implications

Robustness of the Belief Channel/Indirect Effect. I here implement the causal model of mediation analysis by following the "steps approach" (Baron and Kenny, 1986; Rucker et al., 2011; Imai et al., 2011; Pearl, 2014, 2022).

In the first step, I run a regression of individuals' macroeconomic beliefs on their experiences of rejections (as done in Section 3):

$$\text{OptimismIndex}_{it} = \beta_0 + \beta_1 \text{Rejection}_{i,t-1} + \delta X_{it} + \gamma_{st} + v_{it} \tag{10}$$

In the second step, I run a multivariate regression of rejections and beliefs on individuals' spending attitudes, while also controlling for a broad set of variables and fixed effects. To measure individuals' spending attitudes, I use their reported percent chance of buying durables within the next four months:

$$\text{Spending}_{it,t+1} = \alpha_0 + \alpha_1 \text{Rejection}_{i,t-1} + \alpha_2 \text{OptimismIndex}_{it} + \delta X_{it} + \gamma_{st} + u_{it} \tag{11}$$

The indirect effect is then calculated as the multiplication of the estimated effect of rejections on beliefs (β_1) and the estimated effect of beliefs on spending attitudes (α_2). Table D.18 presents results from regression 10 in Column (1) and regression 11 in Column (2). The direct effect of a rejection reduces the percent chance of buying durables in the near future by approximately 2.8 percentage points. The indirect effect or belief-channel is calculated as $-0.161 \times 2.968 = -0.478$. Thus, the total effect of a rejection on spending attitudes is a reduction of 3.3 points on the percent chance. The importance of the indirect effect can be measured as the ratio of the indirect effect over the total effect: the rejection induced pessimism accounts for almost 15% of the reduction in spending attitudes.

Assumptions for Identification of the Effect. First, the rejection should be random conditional on the covariates, an assumption that was discussed in Section 3. Here as well I include the full set of controls and run robustness with the matched sample. We can also rule out concerns about reverse causality, since spending attitudes were measured after beliefs (different modules in SCE) and beliefs were measured after rejections occurred. It may be further argued that macroeconomic beliefs and spending attitudes are both influenced by a third variable related to individuals' own assessment about their future income. To alleviate such concerns, I include expected income as control. Finally, there should be no measurement error in the mediator variable. Unfortunately, expectations tend to be a hard object to measure and can be subject to mood fluctuations and error. I follow Das, Kuhnen and Nagel (2020) and instrument individuals' current beliefs about the macroeconomy with their first-ever reported belief.[29]

	Direct α_1	Indirect $\beta_1 \times \alpha_2$	Total	Indirect/Total
Durables	-2.784	-0.478	-3.262	14.65%

Table D.18: Direct and Indirect Effect of Rejections on Spending Attitudes

	(1) OPTM	(2) DUR
Optimism Index		2.968^{***}
		(0.885)
Applied and rejected	-0.161^{***}	-2.784^{***}
	(0.023)	(1.039)
Didn't apply	-0.008	-2.597^{***}
	(0.017)	(0.756)
Demographics	Y	Y
State-Month-Year FE	Y	Y
R^2	0.043	0.193
Observations	14169	6786
Mean Dep. Var.	0.01	16.55

Notes: Column (1) reports estimated coefficients of Equation 10 relating past personal rejections to Optimism Index, while Column (2) presents estimated coefficients of Equation 11 relating both past rejections and beliefs to spending attitudes. Individuals' beliefs are instrumented by their first-ever reported belief (Weak Instrument statistic 1563.168 with p-value$< 2e-16$, Wu-Hausman statistic 4.398 with p-value$= 0.036$). Both specifications control for age, age squared, gender, race, marital and employment status, college, expected income, income, numeracy, type of credit (either credit card, mortgage or auto loan) and state-month-year fixed effects. Standard errors are clustered at the respondent-time level. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

[29] To do so, I restrict the sample to those individuals who participated in the survey more than once and keep their last responses. To such data set I add their first-ever reported belief to be used as an instrument. As stated in Das, Kuhnen and Nagel (2020), "if measurement error has sufficiently low persistence that it is not predictable with beliefs measured months earlier, then this IV approach removes the inconsistency caused by these distortions."

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