Credit Market Experiences and Macroeconomic Expectations: Evidence and Theory *

Josefina Cenzon†

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Abstract

Using the NY Fed Survey of Consumer Expectations, I show that individuals give excessive weight to their personal credit rejections when forecasting U.S. credit markets, unemployment, and inflation –relative to present or past macro outcomes. This evidence challenges standard belief-formation theories. I explain it through an associative memory model in which a rejection cues memories of bad aggregate conditions and experiences, thereby inflating pessimism about the macroeconomy. The data support three main predictions: (i) rejected individuals recall tighter credit conditions and project them onto more pessimistic forecasts, (ii) this forecast heterogeneity correlates with demographics, and (iii) during adverse shocks, there is not only disagreement but also aggregate overreaction. Incorporating these findings into a consumption-saving model and using data on planned durable consumption, I find that rejection-induced pessimism accounts for about 12% of the total negative impact on consumption –particularly for younger and lower-SES households, and in downturns– leading to amplified contractions in aggregate demand.

Keywords: experiences, memory, expectations, disagreement, consumption

JEL Classifications: D83, D91, E21, E44, G51

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†Bocconi University, 20136 Milano MI, Italy, josefina.cenzon@unibocconi.it. Cenzon is a UniCredit and IGIER fellow.

1 Introduction

It is well established that people's expectations about economic outcomes –such as inflation, unemployment, and stock prices– reflect their prior macroeconomic experiences (Malmendier and Nagel, 2011, 2016; Kuchler and Zafar, 2019). However, past 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 such effects can be much broader, influencing expectations about aggregate outcomes even when the experience 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 information-based views: 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 negative event like a loan rejection, that event enters their memory database but also shifts the household's "context" in a more pessimistic direction – making negative states more likely to be remembered when forecasting future states. In line with this selective recall mechanism, I show that individuals who experienced credit rejections are more likely to recall overly tight aggregate credit conditions thus leading to overly pessimistic forecasts. I then use this framework to characterise the excessive sensitivity in forecasts arising from personal rejections, and I show, theoretically and empirically, that such bias is stronger for young, low socio-economic-status (SES) individuals, and during economic recessions, leading to both cross-sectional belief heterogeneity and aggregate overreaction during recessions.

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). Exploiting survey data on spending attitudes, I show that the latter, "belief-driven" effect is sizeable and amplifies declines in planned durable consumption. Consistent with the model, this amplification is heterogeneous across age and SES groups. Moreover, combining the model with survey estimates, I illustrate how a negative aggregate shock to the economy can be magnified via the overreaction of households who have experienced credit rejections in the past.

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, 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 events, even for unrelated domains like inflation or unemployment.

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, people form beliefs about future economic events using both statistical data and memories of personal experiences, guided by two key steps: (*i*) *which* experiences are recalled, and (*ii*) *how* those recalled experiences are *used*. First, recall is *selective and associative*: a memory is more likely to come to mind if it is similar to the outcome being forecasted and to the household's personal "context" (Kahana, 2012; Bordalo et al., 2023). Here, context refers to the household's internal mood or state that shapes which experiences are retrieved. Second, those recalled experiences help construct "similar scenarios" in a process known as *simulation* (Kahneman and Tversky, 1981; Schacter et al., 2012; Bordalo et al., 2023).

Under this lens, a negative personal event –like a rejection– both enters the memory database and shifts the context toward a more pessimistic or "negative" state. Concretely, this "negative context" narrows the distance to other bad episodes in memory, making them more likely to be recalled and used for forecasts. Intuitively, when asked about future credit conditions while in a negative personal context, individuals might recall not only official statistics but also relatively more negative episodes, including their own credit-denial experience and subsequent financial

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

stress. These memories help them picture others experiencing similar struggles and increases the likelihood they assign to bad aggregate 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. Essentially, a recent loan rejection serves as a "negative lens" through which households retrieve and project additional negative episodes.

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" similar negative states in other areas.

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. Consequently, the subsequent analysis focuses on credit rejections and how recalling this experience affects beliefs.

This framework puts structure to the observed experience driven heterogeneity in expectations and generates new predictions on whose beliefs are most affected and when. Specifically, the model yields three key predictions, each confirmed in the data. First, personal rejections induce pessimism across multiple markets, though strongest in the domain of the rejection itself (e.g., +10 percentage points for credit forecasts vs. +2 pp for unemployment). Second, the effect is larger for younger individuals (who have fewer experiences to recall) and for lower socio-economic status households (for whom rejections are more salient and costly leading to stronger recall of negative episodes) –offering new insights into why these groups tend to be more pessimistic about the economy (Das, Kuhnen and Nagel, 2020). Third, the bias intensifies during recessions, since negative personal experiences are more likely remembered when current economic conditions are also "negative". As a result, although weak economic conditions depress expectations overall, this effect is amplified among those who have personally experienced a rejection, leading to overreaction in expectations.

In Section 5 I show that this mechanism of belief formation has important macroeconomic implications. First, I incorporate the model in a simple dynamic consumption-saving setting to isolate the mechanisms through which memory impacts behaviour. This framework shows that rejections can influence individual choices both directly, via lower ability to spend through credit constraints, and indirectly, via lower willingness to spend by inducing pessimism about future economic states. Intuitively, rejected individuals reduce borrowing and current consumption in preparation for negative future shocks that they now perceive as more likely.

Second, I quantify this amplification channel by using additional data on individuals' planned durable consumption. Using mediation analysis on the SCE Spending Module, I find that this channel is sizable: 12% of the total negative effect of rejections on intended durable consumption can be attributed solely to macroeconomic pessimism. Consistent with the model's predictions, the belief channel is stronger for younger individuals and for those with low income and no college education. Rejected households are also more likely to increase their savings, anticipating tighter borrowing constraints, and they are less likely to reapply for credit because they expect to be turned down again.

Finally, I show that, since the pessimism stemming from personal past rejections becomes even stronger during economic downturns, average expectations tend to overreact to negative shocks which further depresses aggregate demand. Combining survey data with model equations, I demonstrate that an economic shock –proxied by a one-standard-deviation increase in unemployment– heightens overall pessimism and dampens aggregate demand. This effect is amplified by the overreaction of those previously rejected. A counterfactual analysis indicates that if pessimism from past rejections remained constant across economic states, aggregate consumption would decline by about 0.8%. However, because this bias intensifies during downturns, the drop is approximately 1.1%. Thus, past personal rejections interact with a current aggregate shock in the labor market, and this interlinkage across markets can have relevant aggregate implications.

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 *idiosyncratic* shocks –like personal credit rejections– can spill over into multiple, unrelated domains (inflation, unemployment, stock prices). This extends earlier findings on labor or goods-market exposures (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 perceived similarity rather than informativeness. Relatedly, Taubinsky et al. (2024) show that individuals' inflation expectations can be overly sensitive to their own income changes, highlighting 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; Bordalo et al., 2023), and specifically builds on Bordalo et al. (2022), who formalise how people use recalled (rather than purely informative) experiences to 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 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 (FRBNY). 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.[2] 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), 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 measures of credit market experiences, expectations and other variables that might relate to both experiences and expectations and are thus important for the analysis. I here describe these key variables and leave a detailed report of the SCE questions used for Online Appendix A.

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

[2]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.

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.

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 and their past experiences in the credit market. 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.[3] 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 (see Appendix Table A.2 for the full transition matrix).

The Credit Access Module asks individuals about their credit score range. Around 55% of respondents report a credit score of above 720, 10.5% between 720 and 680, 20% below 680

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

and the rest are uncertain. The share of rejections among applicants within each credit score category varies considerably (see Appendix Table A.3). Although important for the analysis, this measure is also endogenous. Credit scores are a determinant of loan application approvals but they are also affected by the outcome of such application. I discuss how I make use of this information in Section 3.

Appendix Table A.4 presents summary statistics for respondents 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 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.

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.

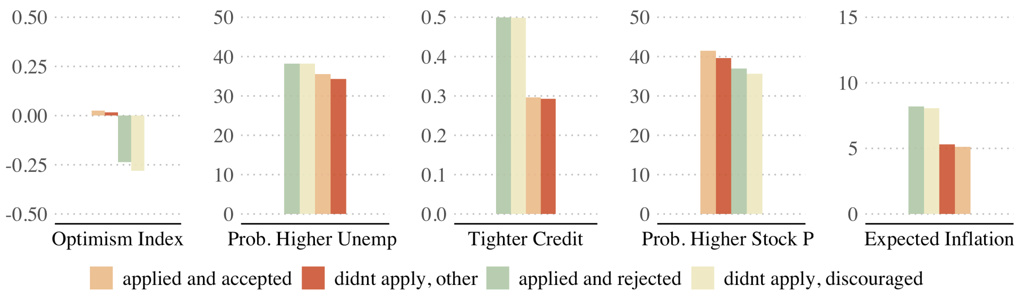


Figure 1: Average Expectations by Credit Market Experience

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).[4]

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.[5] $X_{i,k,t}$ 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

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

[5] 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.

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.

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, and an 11% increase in expectations about unemployment.[6]

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 state-month and thus face 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, notably the "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 strong effect 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.6), 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 optimism. This pattern implies that the observed differences stem largely from rejection-induced pessimism rather than acceptance-induced optimism, a theme I investigate further in Section 3.3.

[6] 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.

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 affect individuals' macroeconomic forecasts for both themselves and others, and across multiple macro domains. Contrary to prior research, which has emphasised domain-specific experience effects (Malmendier, 2021), this study uncovers broader spillovers. One possible reason is that I focus on *recent, idiosyncratic* experiences rather than aggregate-level shocks, potentially yielding a cleaner identification of cross-domain impacts. In concurrent work, Taubinsky et al. (2024)

similarly find that recent household-level income shocks affect inflation expectations, aligning with the cross-domain influence documented in Table 1.

Hence, even when households answer questions about the *same* macro variables, their beliefs differ depending on whether they have personally experienced a credit rejection. This raises a natural question: *Why* do these idiosyncratic events, which convey little obvious information about the broader economy, produce such variation in macroeconomic expectations? The next section turns to this puzzle in more detail.

3.3 Excess Weight to Personal Rejections – What is the Source?

In what follows, I investigate the mechanisms behind this idiosyncratic rejection-based pessimism. One possibility is that they learn valuable aggregate signals from these private events; another is that they over-weight these idiosyncratic rejection, leading to excess sensitivity and heterogeneity in beliefs. This section explores these competing explanations and demonstrates that (1) the observed pessimism cannot be explained by information, and (2) it also cannot be attributed to 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 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, involve more research and extensive application processes, and have lower rejection rates (see Appendix Table B.7 for summary statistics). Appendix B.8 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.

Heterogeneity by households' characteristics. Analysing the correlation between macroeconomic conditions and rejection shares across different groups reveals that only rejection shares among "high" types –characterised by high income and college education– are strongly correlated with macroeconomic conditions (see Appendix Figure B.1 and Tables B.9, B.10). If individuals use their experiences as informative signals, one would expect these "high" types to rely more on their rejections. Contrary to this, the findings show that individuals with lower income and no college education exhibit a greater reliance on personal rejections, despite their rejection shares being acyclical (see Appendix Table B.11).

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 $Y_{t+1} - F_{it}(Y_{t+1}|I_{it})$ (see Appendix B.2 for a complete description). 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 forecast errors are predictable by their idiosyncratic credit experiences by running the following OLS regression:

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

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.

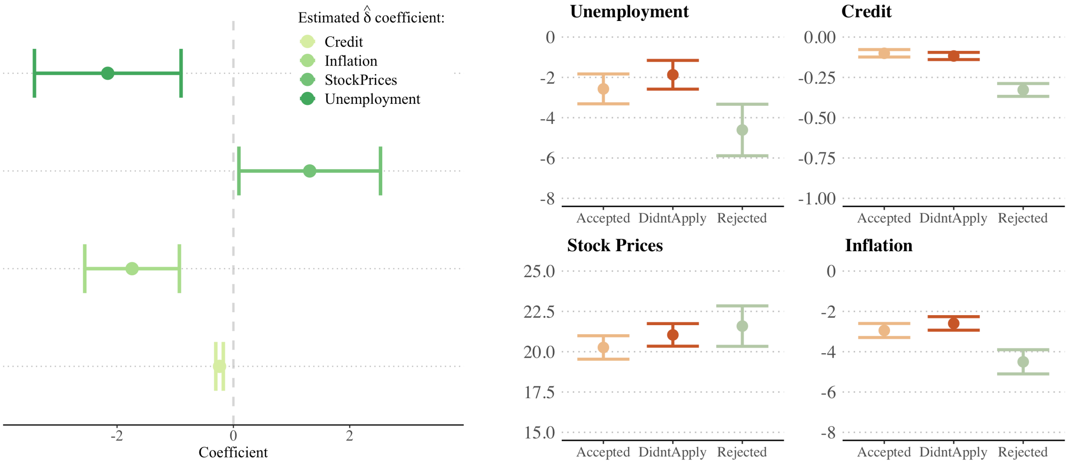
The coefficient of interest is $\hat{\delta}$. Since individuals' past rejections are in their information set when making the forecast, optimal use of information predicts $\hat{\delta} = 0$. Nevertheless, the estimated coefficient is significantly different from zero for all variables, as shown in Figure 2a.[7] Figure 2b shows the forecast error for each outcome variable predicted by the OLS regression on credit experiences when all other regressors are at their sample mean. 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 loans tend to have similar errors to those accepted, those rejected have higher forecast errors on the pessimistic side.

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.

In concurrent work Taubinsky et al. (2024) formalise this test. To understand whether households' forecasts F_i exhibit excessive sensitivity to information in a household-level variable Z_i, they propose to run the following linear regressions: $Y = \alpha + \eta Z_i + e_i$ v.s. $F_i Y = \hat{\alpha} + \hat{\eta} Z_i + \hat{e}_i$, where $Cov(e_i, Z_i) = Cov(\hat{e}_i, Z_i) = 0$. They show that 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 individual forecasts. I show the results for this test in Appendix Table B.14: rejections have very weak or null associations with actual economic

[7] 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 $(Y_{t+1} - F_{it} Y_{t+1}|I_{it}) \perp I_{it}$.

variables while they have very strong associations with individuals' forecasts about these variables.



(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.13. Figure (b) shows predicted forecast errors based on regression results from the same Table B.13. Predicted values are computed while holding all other explanatory variables at their sample mean.

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.5). 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 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.2). 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, and numeracy category, college attainment, and type of credit application when applicable.[8] Matching

[8]While I exclude covariates potentially influenced by rejection (e.g., reported credit scores), I perform ro-

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.[9]

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

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 $E_{i,t}(Y_{t+1}) = \alpha + \beta T_{i,t} + \delta X_{i,t} + \gamma_t + \gamma_s + e_{it}$ 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: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

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.18 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

bustness checks by including credit scores either during matching or as controls in the outcome model (Stuart, 2010).

[9] Appendix Figure B.5 summarises the results when credit score is used as control and also in the matching procedure. Appendix Table B.15 shows the estimated effects for the full set of outcome variables (credit market conditions, unemployment, stock prices, inflation).

Table B.19). Overall, results are consistent with a rejection-induced pessimism hypothesis, albeit coefficients are smaller and standard errors are higher.[10]

Robustness and Roadmap. Appendix B.2 presents detailed tables and robustness checks, including the use of matched samples and individual fixed effects for the forecast-error regressions (see Tables B.20, **??** and **??**), which mitigate concerns about prior bias.

Overall, the evidence indicates that households over-weight their individual rejections when forming macroeconomic expectations. A quasi-Bayesian model with misperceived correlations could account for the excessive sensitivity, but it leaves open the deeper question of *why* households treat personal credit rejections as so strongly correlated with future macro conditions.

Recent research points to *selective and associative memory* as a key factor (Taubinsky et al., 2024), whereby negative personal episodes can affect the recall of other negative events (including personal ones) and thus inflate perceived probabilities of dire events. Indeed, extensive psychological evidence shows that 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 context in which it is evaluated (i.e. mood, emotions) (Kahana, 2012; Bordalo et al., 2023). Once a "similar" (either statistically relevant or irrelevant) experience is recalled, it helps the individual *imagine* a particular scenario, thus elevating the subjective probability of its occurrence (Schacter et al., 2012; Kahneman and Tversky, 1981). Then even if the objective correlation between one's personal experience and the broader economy is low, memory can foster an "illusion" of strong correlation simply because that event is viewed as relevant via similarity-based recall and simulation.

Such insights have been formalised in memory models and applied across various economic setups. For example, Bordalo et al. (2022) show, through a priming experiment, that both relevant (ID-theft crime) and seemingly irrelevant but similar experiences (financial struggles) are recalled and used to form beliefs about a cyberattack. Jiang et al. (2023) find that good market conditions cue more positive recall of past experiences, fostering optimism about future returns, while Charles (2022) document how these associative processes can systematically distort attention and prices in financial markets.

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

[10] 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.

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

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 database of memories $M = \{\Theta, E\}$ that collects both the set of past aggregate transitions from state i to state j for all i, j (Θ) and other information or personal experiences (E). Each stored experience $m \in M$ is characterised by a small vector of features (f_0, f_1, f_2), where $f_0 \in \{\theta, e\}$ denotes the type (macro transition or personal event), $f_1 \in \{L, H\}$ marks the "current" state, and $f_2 \in \{L, H\}$ marks the "future" state.[11] For example, a macro transition from L to L is stored as $\theta_{LL} \in \Theta$ with features (θ, L, L), while a personal experience $e_{LL} \in E$ might be a negative, persistent event 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 $x \in \{\theta, e\}$.

The Cue and Similarity. Following the psychology literature on *contextual retrieval* (Kahana, 2012), I assume that memory retrieval is cued by both the *features* of the hypothesis being evaluated (macro and negative) *and* by the individual's *context* (e.g., temporal or emotional cues). Formally, let the cue be θ_{ij}, which denotes a potential transition from state i to j next period. This induces the retrieval of stored experiences in M that are relatively more similar to θ_{ij} and the current context c.

In line with 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

[11] 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.

come to mind. 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. For our purposes, individuals' context can be interpreted as their perceived current financial situation.

To capture this formally, I define a similarity function $S(m,[\theta_{ij},c]) = \exp\{-d(m,[\theta_{ij},c])\}$, where θ_{ij} is the hypothesis, c is the personal context, and $m \in M$ is a stored experience with attributes (f_0, f_1, f_2). The distance function $d\big(m,[\theta_{ij},c]\big)$ measures how far m is from the joint cue $[\theta_{ij},c]$. We can interpret this distance function as being composed of two terms:$d(m,[\theta_{ij},c]) = \alpha \times d(m,\theta_{ij}) + \beta \times d(m,c)$, where α and β weight how strongly each part of the cue matters. The component $d(m,\theta_{ij})$ captures how closely m's features match the features of the macro event θ_{ij}. For example, a macro transition from a L state to a L state (i.e. θ_{LL}) has 0 distance with itself, and a small but positive distance with a personal experience e_{LL} because of shared features $\{L,L\}$ (i.e. all else equal, $1 = S(\theta_{LL},\theta_{LL}) > S(e_{LL},\theta_{LL}) > 0$). The second component $d(c,m)$ captures how well m aligns with the individual's current 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}, say), 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, affecting *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 $[\theta_{ij},c]$.[12]

Recall. Formally, *Cued-Recall* states that when evaluating the transition θ_{ij} in context c, the probability of recalling a memory $m \in M$ is:

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

An experience m is thus recalled with higher probability if it shares relatively more features with both the macro hypothesis θ_{ij} and the individual's context c. For example, when thinking about the probability of transitioning to a future low state with tight credit markets, we are likely to remember negative experiences that we perceive as similar because of shared features, such as past instances of tight credit and personal rejections in the credit market. [13]

[12]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.

[13]While the numerator of Equation 3 is increasing in similarity, the denominator is increasing in the total number of experiences with positive similarity in the database. Overall, the probability that any given experience is recalled depends on how similar such experience is relative to all other experiences in the database.

Simulation. In the second step, households use retrieved experiences to form their beliefs about transition probabilities in the following way:

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

This depends on a process called *simulation* which regulates how experiences are used for probability judgements once they are recalled (Schacter et al., 2012; Bordalo et al., 2022). 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). Formally, the household remembers experience m when thinking about a transition from i to j with probability $r(m, [\theta_{ij}, c])$, and then she uses it to simulate the transition to state j with probability $\sigma(m, \theta_{ij})$ which is increasing in similarity. Although in principle simulation could vary between 0 and 1, I assume a simple step function: once recalled, experiences that share feature $f_2 = j$ are used perfectly for simulation, $\sigma(m_{hj}, \theta_{kj}) = 1$ for all h, k, while others are discarded.

Note that whether people think about transitions to low or high states is key, since the state tomorrow j acts like a focal point: when thinking about a transition from i to j in context c, personal experiences with i and j features are recalled because of similarity but only those with j help to simulate a j event tomorrow and thus these are used while others are discarded. For the purposes of this paper I focus on the case where individuals are trying to estimate the probability of transitioning from state i to a future low state L (i.e. p_{iL}), and assign $1 - p_{iL}$ to the alternative H state. This, and the above presented simplifying assumption, discipline the model and suffice to explain my empirical findings, but can be easily relaxed.[14]

The next sections explore how this imperfect recall mechanism (driven by similarity in shared features and context) impacts beliefs.

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 j are used to simulate the event,[15] then probabilities are unbiased and given by the frequentist estimate: $p_{ij} = \frac{|\theta_{ij}|}{|\theta_{ij}| + |\theta_{ii}|}$. 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

[14] 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.

[15] 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.

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_{iL}^{M} according to their similarity. Equation 4 can then be re-written as:

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

$$\text{with } \Delta = \underbrace{(\frac{s_{LL}^{\theta} + s_{L}^{e}}{D}) \times (1 - p_{iL})}_{simulation\ term} - \underbrace{(\frac{s_{ii}^{e}}{D}) \times p_{iL}}_{interference\ term} \tag{6}$$

where $D = (|\theta_{ii}| + |\theta_{iL}| + s_{LL}^{\theta} + s_{L}^{e} + s_{ii}^{e})$, $s_{jj}^{\theta} = S(\theta_{jj}, [\theta_{ij}, c])|\theta_{jj}|$, $s_{j}^{e} = S(e_{jj}, [\theta_{ij}, c])|e_{jj}| + S(e_{ij}, [\theta_{ij}, c])|e_{ij}|$, $s_{ii}^{e} = S(e_{ii}, [\theta_{ij}, c])|e_{ii}|$ where $i \in \{H, L\}$ and $j = \{L\}$.

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. $s_{LL}^{\theta} + s_{L}^{e}$) but also those that are recalled and *interfere* with relatively more useful experiences, therefore reducing the probability assigned to L (i.e. s_{ii}^{e}).

Model Predictions. Recalled personal experiences affect the recalled set of aggregate conditions, which is then projected onto beliefs about those 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 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

$$s_{LL}^{\theta,R} > s_{LL}^{\theta,A} \quad \text{and} \quad s_{L}^{e,R} > s_{L}^{e,A}$$

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:

$$p_{iL}^{R} \ = \ p_{iL} \ + \ \Delta^{R} \quad > \quad p_{iL} \ + \ \Delta^{A} \ = \ p_{iL}^{A}$$

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.[16]

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

[16]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.

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 looking at the role of the recalled set, I here focus on the role of recalling a particular experience, i.e. the rejection, and the heterogeneity it entails. For this, 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 datapoints. Then Equation 5 can be rewritten to isolate the effect of the experience R as follows:

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

where $\hat{p}_{iL} = \frac{\sum_{m \in M} S(m, \theta_{iL}) \sigma(m, \theta_{iL})}{\sum_{m \in M} S(m, \theta_{iL})}$ is the estimated probability without using the rejection experience, and $r(R, \theta_{iL}) = \frac{S(R, \theta_{iL})}{S(R, \theta_{iL}) + \sum_M S(m, \theta_{iL})} \equiv \omega_{iL}$ is the rejection-recall probability.[17] Selective memory puts structure on the households' misperceived correlations between their personal rejection and macroeconomic outcomes.[18]

Model Predictions. The model thus predicts that heterogeneity in idiosyncratic experiences generates heterogeneity in beliefs about aggregate outcomes:

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, any observed difference in beliefs between these groups can be attributed to the recall bias induced by this additional experience, such that: $\hat{p}_{iL}^R - \hat{p}_{iL}^A = r(R, \theta_{iL}) \times (1 - \hat{p}_{iL}) = \beta_r > 0$.

[17] In principle, the model predicts that both acceptances and rejections can impact economic beliefs, but it provides insights into the asymmetric effect observed in the data. First, if the focal point is a future negative state, acceptances, while potentially recalled when the current state is good, are typically discarded as they don't contribute to simulating negative future scenarios (as s_{ii}^e in Equation 5). Second, even if the focal point involves high states, acceptances are predicted to play a less significant role compared to rejections. This is because (1) they face greater interference from other positive experiences, making them less salient than rejections, and (2) the likelihood of transitioning to a high state is higher than a low state, so recalling a positive experience doesn't significantly increase its perceived probability.

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

Importantly, this heterogeneity emerges even when people are forecasting the same aggregate outcome and even if they hold the same experience of historical aggregate outcomes. For example, Malmendier and Nagel (2016) show that different generations have different inflation expectations today because they have experienced different inflation histories. This model would capture this through differences across databases but it goes further and suggests that even conditional on the same inflation history, idiosyncratic experiences affect inflation expectations. This is indeed what I document in Table 1 in which personal rejections lead to heterogeneity in economic expectations even when controlling by households' characteristics, experienced histories of the aggregate outcomes, and local and time varying shocks.

The model also suggests that the magnitude of this experience-driven heterogeneity will depend on specific 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, $\beta^R_{young} > \beta^R_{old}$.

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: $\beta^R_{low} > \beta^R_{high}$.

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 $S(R, \theta^{credit}_{LL}) > S(R, \theta^{d}_{LL})$, $\beta^{credit}_r > \beta^{\bar{d}}_r$ 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. 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.[19]

These predictions have important implications from a macroeconomic perspective. First, there is heterogeneity in beliefs about the economy stemming from idiosyncratic experiences,

[19] 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 $\lambda r(R, \theta_{iL})$.

and this heterogeneity is predicted to correlate with key demographics like age and socio-economic status. Second, the recall of these idiosyncratic rejection experiences can spillover across markets, affecting not only expectations about aggregate credit but also aggregate unemployment to varying extents. Finally, if there is a bad aggregate shock, idiosyncratic negative experiences are more likely to be recalled and thus lead to aggregate overreaction to the shock, not just heterogeneity. Does the data support 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. I test this by interaction the past rejection experience 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).

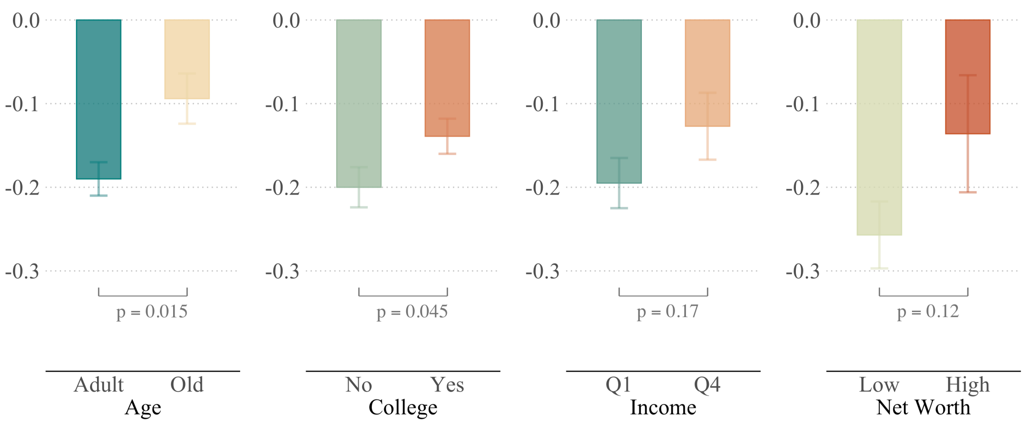


Figure 3: Heterogeneity in Estimated Coefficient on Personal Rejection

Notes: The figure shows the estimated coefficient on rejection that results from regressing personal past rejections interacted by an individual characteristic on optimism index. Each panel includes, in grey colour, the p-value from a test of statistical difference between the two categories. Table B.11 shows the regression results in detail.

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 wealth assign a higher weight to their idiosyncratic experiences of rejections when forecasting future economic states. Interestingly, this helps us rationalise prior findings in which people with lower socio-economic status are found to be more pessimistic about the economy (Das, Kuhnen and Nagel, 2020). My findings suggest that these individuals place greater weight on their rejections when forecasting the economy because for them these experiences are more costly and thus ease stronger recall and simulation of negative economic outcomes.

I now test Predictions II and III which suggest heterogeneity in the role of rejection depending on the characteristics of the event being forecasted. 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 (higher similarity between the experience and the hypothesis). 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.22). 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. 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.[20]

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.

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 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.

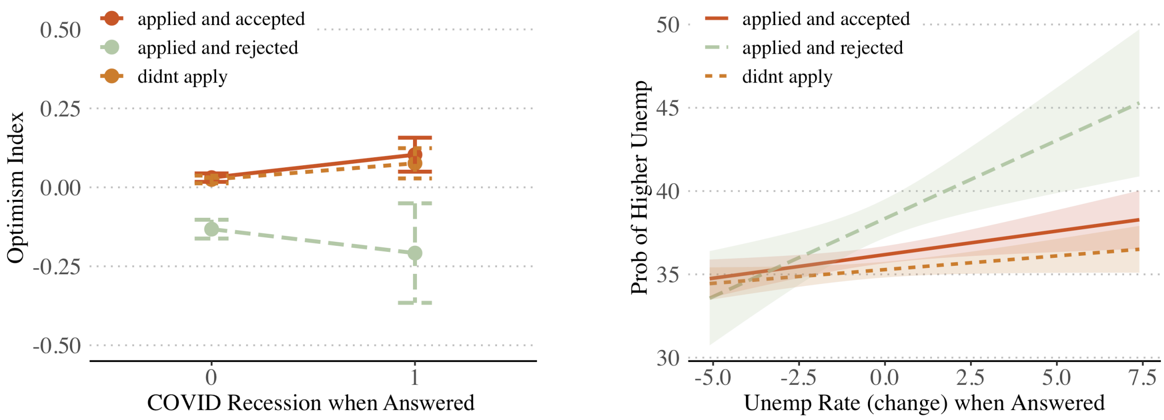


Figure 4: State Dependency in Beliefs

Notes: The figure plots interaction effects shown in Appendix Table C.23. 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.

In line with the model, the worse the aggregate state, the more likely a negative personal memory is recalled –thereby increasing the subjective probability of future negative outcomes. For example, when looking at individuals' subjective probabilities of higher unemployment,

[20] 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.

a 1 standard deviation increase in aggregate unemployment rates lead to an increase in individuals' expected probability of around 0.68 pp. How much recalling a personal rejection affects these probabilities depends on the current state of unemployment: for average rates of unemployment, the marginal effect of rejection is approximately 2 pp but it goes up to 4.5 pp when unemployment increases by 1 standard deviation (see Table 6). As shown in Table 6 the marginal impact of rejections grows, because the implied recall probability climbs from 0.029 to 0.071 once unemployment moves a standard deviation above average. On a macro level, this state-dependent recall suggests overreaction to downturns: many individuals with negative personal histories simultaneously become overly pessimistic when the economy. In Section 5.3 I explore the economic consequences of this and provide suggestive evidence on its economic relevance.

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.23. 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.[21]

The evidence overall shows that memory indeed matters for belief heterogeneity. In the next

[21] 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).

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, $t = 0, 1, 2$. 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 $b_1 = 0$. We assume quadratic utility, $u(c) = b\,c - \frac{1}{2}c^2$, together with $\beta = \frac{1}{R}$. Each household faces borrowing 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). Parameter assumptions that guarantee interior solutions under these constraints are provided in the appendix.

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 maximize expected utility. They face the budget constraints $c_1 = y_1^i - R\,b_1 + b_2, \quad c_2 = y_2 - R\,b_2$, 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.

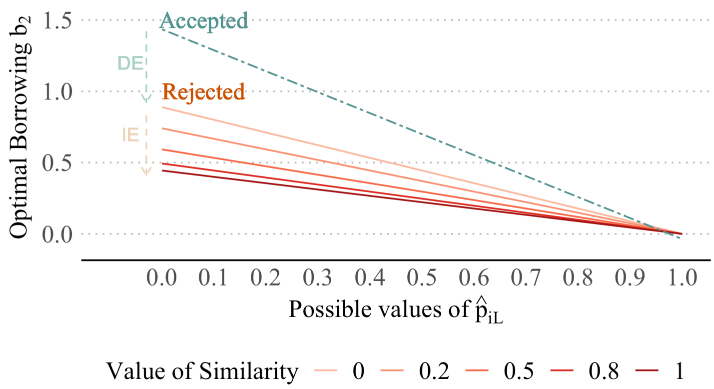


Figure 5: Optimal Borrowing – varying $\hat{p}_{iL}$ and similarity values

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 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.[22] Then, I use this data to estimate the direct and indirect effect following standard methodology in mediation analysis.

[22]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.

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_1), then part of rejection's impact can be 'mediated' by memory-driven pessimism (measured $\beta_1 \times \alpha_2$). Table 7 provides the results based on the estimation strategy proposed in Imai et al. (2011) and Tingley et al. (2014), while Online Appendix E.2 provides a detailed description of the exercise and further robustness.

This analysis shows that rejections have a total negative effect on households' spending attitudes, as predicted: households who recently experiences 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 memory bias induces an extra reduction of 0.455, leading to a final probability of spending of 12.87%.

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.

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.[23] 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,

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

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.6), 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 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 how the memory channel affects consumption within an economic state and during transitions between states.

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 Within States. 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 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, especially during low economic states. Thus, state-dependent pessimism further depresses consumption under adverse conditions, contributing to overreaction to a negative shock.[24]

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 $\lambda_0 = 0.18$.

Overreaction During State Transitions. The memory channel also contributes to overreaction when the economy transitions from a high to a low state. The change in aggregate consumption at time 1 is given by:

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

[24]In the data, rejected individuals are consistently more pessimistic whereas accepted individuals do not compensate through higher optimism, leading to aggregate pessimism. Beyond this asymmetry, individual's reliance on personal memories matters for aggregate demand because of the state-dependency of the results.

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 $\omega_{HL} = \omega_{LL}$, i.e. rejections are recalled equally in both states, then 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, 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 credit rejections being highly idiosyncratic experiences, I find that they exert an excessive influence in individuals' expectations about the macroeconomy: rejected individuals are too pessimistic about credit market conditions, unemployment, stock prices and inflation –irrespective of their demographics, what type of loan they apply to or how well informed they are. Individuals thus rely on their credit rejections to think about aggregate credit conditions but also about non-credit related variables. I interpret the findings through a model of selective and associative recall and show, both theoretically and empirically, that reliance on personal past rejections creates: i) systematic belief heterogeneity across age and other socio-economic groups, and ii) overreaction of average beliefs during recessions.

Understanding how households think about the economy and the associations they make before making financial decisions has important implications for both household finance and the broader economy. Incorporating the memory-based belief model into a dynamic consumption-saving framework shows that rejections influence individual choices both directly, through credit constraints, and indirectly, by inducing pessimism about future macroeconomic states. This leads to amplified contractions in consumption and reduced willingness to borrow again. Using SCE data, I estimate the impact of this belief channel on households' planned durable consumption. Additionally, analyses of both SCE and SCF data reveal that past rejections are associated with increased savings, discouragement from future credit market participation, and lower holdings of risky assets.

These insights underscore the significance of the documented household-level bias and its macroeconomic implications. Further exploration of how personal experiences and memory influence economic behaviour, particularly the interlinkages across markets, represents a crucial avenue for future research.

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Appendix

A Descriptive Statistics

Table A.1: Summary Statistics of Experiences 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

Notes: The table shows summary statistics of the respondents' characteristics and their experiences during the past year with the credit market. Values account for the weights provided by SCE to make the sample representative of the US.

Table A.2: Transition Matrix

Past Credit Status		Current Credit Status: Applied and Accepted	Applied and Rejected	Didn't Apply	Total
New Entrant	N	5522	965	6567	13054
	% row	42.3	7.4	50.3	100.0
Applied and Accepted	N	4272	295	1688	6255
	% row	68.3	4.7	27.0	100.0
Applied and Rejected	N	318	479	238	1035
	% row	30.7	46.3	23.0	100.0
Didn't Apply	N	1449	170	6273	7892
	% row	18.4	2.2	79.5	100.0
Total	N	11561	1909	14766	28236
	% row	40.9	6.8	52.3	100.0

Table A.3: Application and Rejection Rate by Credit Score

Credit Score Category	Share of Population	Application Rate	Rejection Rate among 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.4: Summary Statistics of Expectations

	Mean	Standard Deviation	Min	Median	Max
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' expectations used throughout the main analysis. Values account for the weights provided by SCE to make the sample representative of the US. The reported point estimate of inflation has been winsored at the 1% level (original data varies from −100% to 200% inflation).

Table A.5: 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.

B Regression Results

B.1 Rejections and Expectations

Table B.6: 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

Notes: Column 1 presents results from the Survey of Consumer Expectations (SCE) 2013-2021, and Column 2 presents results from the Survey of Consumer Finances (SCF) 1999-2019. The tables present the results from regressing respondents' past personal rejections in the credit market against a binary variable indicating whether individuals reported discouragement from applying due to fear of rejection. The coefficients were estimated using a probability linear model. Controls for SCE include state-month-year fixed effects, income category, income expectations, gender, age, race, employment status, college attendance, marital status. Controls for SCF include year fixed effects, income category, income expectations and perceptions, gender, age, race, recent unemployment, home-ownership, college attendance, marital status. Statistical Significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

B.2 Excess Sensitivity of Beliefs to Rejections

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

By Credit Type. Households can apply to different types of credit, all of which have different rejection rates. I thus construct subsamples to evaluate whether the role of rejection differs according to each loan type.

Table B.7: 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 applicants	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.

Table B.8: Credit Market Rejection and Aggregate Pessimism by loan type - New Loans

Dep.Var: Optimism Index	(1)	(2)	(3)	(4)
Applied and Accepted		(omitted)		
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
Demographics	Y	Y	Y	Y
State-Month-Year FE	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, month-year fixed effects and commuting zone fixed effects. Individual level controls include age, gender, race, employment status, married, college, income, income expectations. Standard errors are clustered at the respondent and date level. Significance level:$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

By Households' Characteristics. The next figure and tables investigate the correlation between the share of rejections and different macroeconomic outcomes. I am interested in understanding whether rejections rates among different types of applicants correlate differently with the economy, and whether households' reliance on their rejections matches this.

Using the SCE data, I calculate the share of rejections at each point in time by income category and college attainment. To have a summary of economic conditions, I use an adjusted index of national financial conditions (ANFCI) from the Chicago Fed. Figure B.1 shows scatter plots relating these measures.

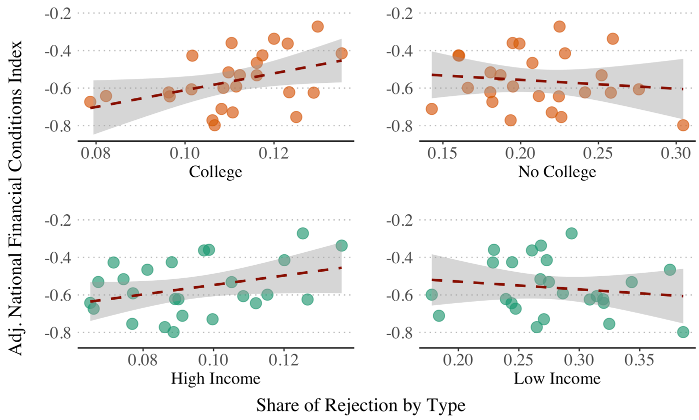


Figure B.1: Share Of Rejections by Individuals' Type and Financial Conditions

Notes: Upper left panel shows correlation between the ANFCI and the rejection rate among applicants with college attainment (ρ = 0.42, p-value= 0.04), while upper right without college attainment (ρ = −0.12, p-value= 0.55). Lower left panel shows the correlation between the ANFCI and the rejection rate among applicants with high income (ρ = 0.35, p-value= 0.08), while lower right with low income (ρ = −0.14, p-value= 0.49).

The y-axis reflects the ANFCI while the x-axis refers to the rejections rates. Rejection rates among applicants with college attainment and high income correlate positively with tightness in financial conditions, while rejection rates among those with no college attainment or low income have no statistically significant correlation.

The following tables provide similar correlation analyses with other macroeconomic outcomes such as unemployment, inflation and stock prices. The pattern is similar to the one described above: rejection rates among college attendants and high income applicants tend to correlate more strongly with the macroeconomy.

Table B.9: Share of rejection by Education and Macro Outcomes

	CreditTightness	UnempChange	InflRate	StockPGrowth
(Intercept)	-3.605^{**}	-6.742	3.600	0.372^{**}
	(1.603)	(4.348)	(2.207)	(0.131)
Share Rejection - Coll	29.539^{**}	86.385^{**}	-37.784^{*}	-1.981^{*}
	(13.242)	(35.921)	(18.230)	(1.079)
Share Rejection - No Coll	-0.995	-9.030	3.894	0.062
	(4.281)	(11.614)	(5.894)	(0.349)
R^2	0.708	0.617	0.769	0.830
Adj. R^2	0.500	0.344	0.604	0.709
Num. obs.	25	25	25	25

Notes: The table presents correlation estimates between rejections rates among college and non-college attendants with different macroeconomic variables. Column 1 refers to credit market tightness, Column 2 refers to unemployment rate changes (12-month change), Column 3 to inflation rate changes (12-month change) and Column 4 to stock prices growth. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table B.10: Share of rejection by Income and Macro Outcomes

	CreditTightness	UnempChange	InflRate	StockPGrowth
(Intercept)	-2.121	-1.734	1.319	0.278^{*}
	(1.654)	(4.829)	(2.049)	(0.137)
Share Rejection - High Inc	16.247^{*}	33.516	-23.718^{**}	-1.009
	(8.072)	(23.561)	(9.995)	(0.667)
Share Rejection - Low Inc	-0.616	-5.398	5.161	-0.004
	(4.337)	(12.658)	(5.370)	(0.358)
R^2	0.698	0.542	0.807	0.820
Adj. R^2	0.483	0.215	0.669	0.691
Num. obs.	25	25	25	25

Notes: The table presents correlation estimates between rejections rates among high income and low income with different macroeconomic variables. Column 1 refers to credit market tightness, Column 2 refers to unemployment rate changes (12-month change), Column 3 to inflation rate changes (12-month change) and Column 4 to stock prices growth. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table B.11: 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 * High Num		-0.138^{***}		
		(0.023)		
Applied and Rejected * Low Num		-0.196^{***}		
		(0.028)		
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)
Individual level Controls	Y	Y	Y	Y
State-Month-Year FE	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. The rejection indicator has been interacted with different households' characteristics. All columns control for demographics, state-month-year fixed effects. Individual level controls include age, gender, race, employment status, married, college, income, income expectations. Standard errors are clustered at the respondent and date level. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

By Information Levels (SCF data). To measure whether households were rejected in past credit applications, I construct an indicator variable. For expectations about the aggregate economy, I use the question: "Over the next five years, do you expect the U.S. economy as a whole to perform better (=1), worse (=0), or about the same (=1) as it has over the past five years?" To assess how informed households were when they applied for credit, I consider two measures: (1) Search Intensity: The amount of search done in pursuit of better credit terms, rated on a scale from 0 (no searching) to 10 (a great deal of searching); (2) Sources of Information: The sources used for credit decisions.

The most common sources of information are "friends and/or material from work/business contacts" (41.4% of respondents) and "financial advisors such as bankers, brokers, real estate brokers, builders, dealers, and/or insurance agents" (40% of respondents). I define households as "financially informed" if they list financial advisors as their top source of information.[25]

[25]For this analysis, households are classified as "financially informed" if they chose the option "financial advisors such as bankers, brokers, real estate brokers, builders, dealers, and/or insurance agents" among their top five

I categorise rejected individuals based on: (1) Search Intensity –Low, medium, or high–; (2) Financial Information –whether they were financially informed before applying for credit. The hypothesis is that individuals who extensively search for better terms or receive professional financial advice are more informed about credit market conditions and thus rely less on their own experiences when forming expectations.

To test this, I run logit regressions of credit experience on economic expectations, controlling for individual characteristics and time fixed effects. Figure B.2 illustrates the estimated coefficients. The baseline estimate confirms previous findings: rejected individuals are more pessimistic about future macroeconomic conditions than those accepted, even after controlling for other factors. The odds of being pessimistic are 15% higher for rejected individuals compared to accepted ones.

When examining the impact of being financially informed or the level of search intensity, the coefficients vary in magnitude but are not statistically significantly different. This suggests that being more informed about macroeconomic or credit conditions does not reduce the reliance on personal credit experiences, and such reliance does not align with the potential informativeness of the rejection.

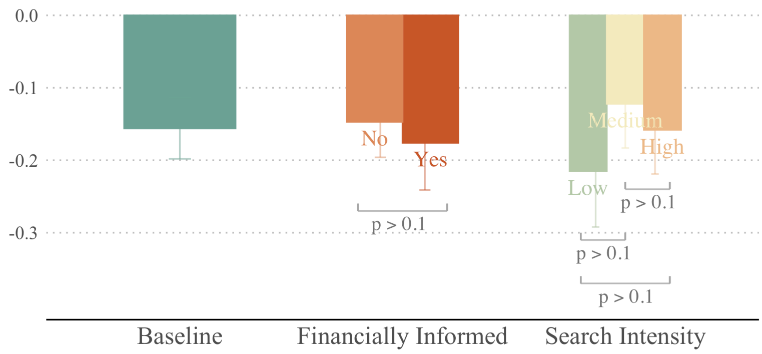


Figure B.2: Estimated coefficient on personal rejection, baseline and by info level

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.

Forecast errors. The following tables describe the datasets used for the construction of forecast errors and the regression estimates. 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.

sources. Results are robust to expanding this definition to include other positions in the list or additional types of information, such as financial planners, accountants, and lawyers.

Table B.12: 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

Table B.13: 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
Num. obs.	25005	21825	21761	25008
Mean Dep.Var.	−2.65	−0.47	22.4	−3.69

Notes: All specifications control for respondents characteristics and census region. "Applied and Accepted" is the reference category, "Didn't Apply" refer to those who didn't apply to any credit because they didn't want to or didn't need to (it excludes those discouraged). Standard errors are clustered at the individual and date level. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table B.14 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)).

Table B.14: Idiosyncratic Rejections on Future Macro Outcomes and Macro Beliefs

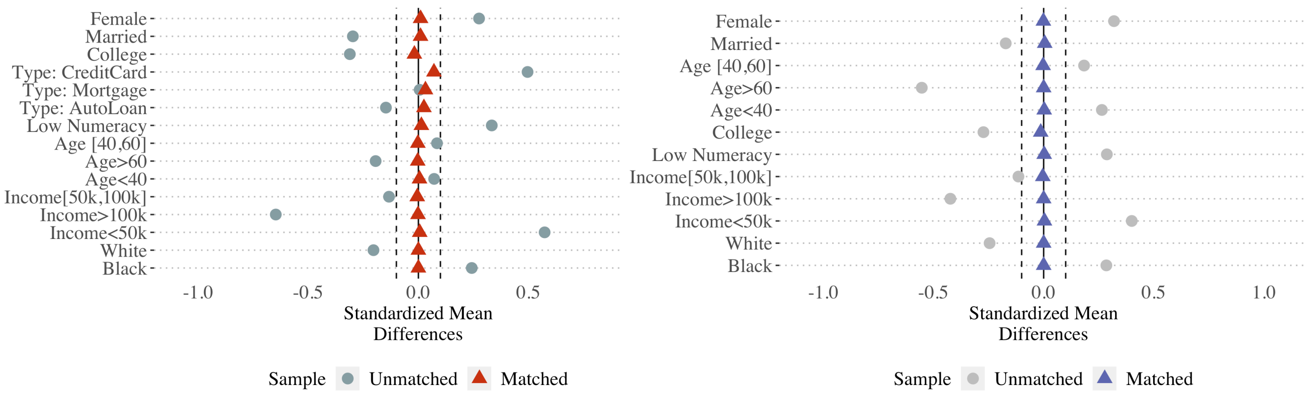
	Prob Unemp ↑		Tighten Credit		Prob StockPrices ↑		Avg Infl.	
	η	$\hat{\eta}$	η	$\hat{\eta}$	η	$\hat{\eta}$	η	$\hat{\eta}$
(Intercept)	33.487^{***}	36.357^{***}	0.001	0.072^{***}	63.240^{***}	42.846^{***}	1.637^{***}	4.890^{***}
	(0.010)	(0.217)	(0.070)	(0.007)	(0.003)	(0.218)	(0.007)	(0.103)
Rejected	-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: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

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, $sign\{\hat{\eta}\} \neq sign\{\eta\}$. An implication of this analysis is that individuals' forecast errors are predictable.

Selection. I present regression tables and robustness tests for the exercises discussed in the main text. Online Appendix B.2 provides a detailed description the assumptions.

Matching. The figures show balance improvement after matching, and the regression tables present the estimates in each matched sample.



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

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

Figure B.3: Standardised Mean Differences for Matched and Unmatched I

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.

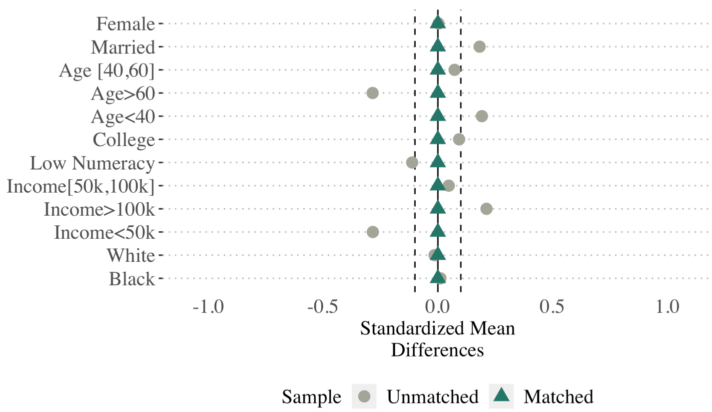


Figure B.4: Std. Mean Diff. for Matched and Unmatched: Accepted vs. Didn't Apply

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.15: 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.16: 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.17: 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. To corroborate that different levels of initial optimism are not driving the results, I focus on the sub-sample of people who started the sample by not being rejected and then at some point within the sample experienced such a rejection. These people can then be matched to other individuals who never experienced a rejection and are similar to them both in terms of covariates and their level of optimism when they started the sample. Table B.18 presents the results of running the OLS regression on such a matched sample.

Table B.18: 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.

Table B.19: Credit Market Rejection and Aggregate Pessimism within individuals

	OPTM	UNEMP	FCredit	StockP	INFL
Applied and Accepted			(omitted)		
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: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

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.

Robustness. I here describe the main robustness tests.

Robustness to the inclusion of Credit Score. The ideal experiment would also include individuals' credit score as a covariate, as long as the credit score was not affected by the rejection itself. SCE asks respondents about it and also when was the last time that they checked it. 72.3% of respondents have checked they credit score in the last year, 22.3% checked it more than a year ago, and 5.4% have never checked it. This represents a challenge as credit scores could have determined the rejection but, most likely, they could have also been affected by this past rejection.

With this in mind, I run different exercises that highlight the robustness of the result even to the inclusion of the reported credit scores either as control variables or as a covariate in the matching procedure. Figure B.5 summarises the findings when using Optimism Index as the outcome variable and "accepted" individuals as the control.

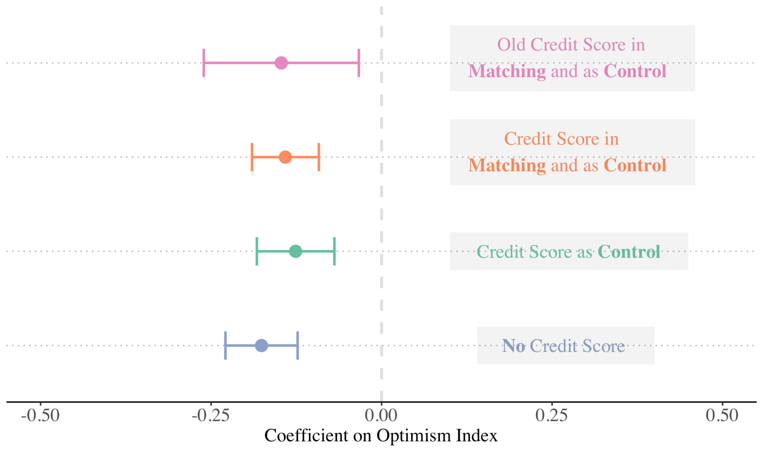


Figure B.5: Robustness to the inclusion of Reported Credit Score

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 status, gender, race, age, marital status, college attainment, type of loan, income category, numeracy category). The text in the figure explains when *Credit Score* is used as a control and when it is also used in the matching procedure. The variable *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 on the covariates. Cluster-robust standard errors account for pair membership. Standard errors are reportes in parenthesis. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

The blue bar (closest to the x-axis) shows the estimated coefficient when the variable *credit score* is not included as a control (first column in Table B.15) while the green bar shows the coefficient after including *credit score* as control (first column in Online Appendix Table B.10). In the last two exercises, I want to asses the robustness of the result to including information about individuals' credit score in the matching procedure. First, I choose a "naive" approach where I include individuals' reported credit score in the matching procedure and also as a control. The orange bar shows the coefficient on the treatment that results from this analysis (first column Online Appendix Table B.11). This specification can be problematic, as covariates used for matching have to be pre-treatment. To alleviate such concern, in the fourth exercise I only match individuals for which I know that they haven't checked their credit score in the last year. Within those, I match accepted and rejected based on the covariates mentioned before and a new binary variable - *Old Credit Score* - that takes value 1 if their credit score is above 680 and 0 otherwise. This leads to a smaller matched sample of approximately 550 individuals. The pink bar in the graph shows the estimated coefficient on the treatment using such sample and the covariates as controls (first column Online Appendix Table B.12).

Robustness of Forecast Errors results.

Table B.20: Individuals' Forecast Errors – With Individuals' Fixed Effects

	FE Unemp	FE Credit	FE Stock	FE Infl
Applied and Accepted		(omitted)		
Applied and Rejected	-1.347^{*}	-0.071^{*}	0.491	-1.127^{***}
	(0.761)	(0.037)	(0.712)	(0.385)
Didn't apply	0.611	−0.016	1.377^{***}	0.170
	(0.398)	(0.019)	(0.372)	(0.198)
R^2	0.000	0.000	0.001	0.001
Observations	27311	24941	24051	27313

Notes: All specifications include individuals' fixed effects. The dependent variable is adjusted such that higher $E_{it}(Y_{t+1})$ reflect higher pessimism for all variables and thus $Y_{t+1} - E_{it}(Y_{t+1}) < 0$ reflect higher movements of beliefs compared to the realized outcomes on the pessimistic side. Standard errors are clustered at the individual and date level, $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table B.21: Individuals' Forecast Errors – Matched Samples

	FE Unemp	FE Credit	FE Stock	FE Infl
(Intercept)	-35.813^{***}	-1.464^{***}	36.694^{***}	-9.952^{***}
	(10.752)	(0.414)	(7.502)	(3.183)
Accepted		(omitted)		
Rejected	-2.318^{***}	-0.274^{***}	1.483^{*}	-1.147^{**}
	(0.864)	(0.033)	(0.856)	(0.524)
R^2	0.06	0.36	0.08	0.07
Observations	3315	3022	3314	3017

	FE Unemp	FE Credit	FE Stock	FE Infl
(Intercept)	-22.579	-0.610^{*}	20.305	-9.272^{**}
	(14.309)	(0.335)	(13.124)	(4.010)
Didn't Apply		(omitted)		
Rejected	-3.723^{**}	-0.126^{**}	-1.650	-1.824^{*}
	(1.460)	(0.061)	(1.489)	(1.051)
R^2	0.05	0.35	0.10	0.06
Observations	3317	3054	3315	3048

Notes: The table reports estimated coefficients on the treatment using the matched sample of (1) participants: rejected are the treatment while accepted are the control group. All specifications control for respondents' characteristics, (2) rejected and non-participants: rejected are the treatment while those who didn't apply are the control group. All specifications control for respondents' characteristics. The dependent variable is adjusted such that higher $E_{it}(Y_{t+1})$ reflect higher pessimism for all variables and thus $Y_{t+1} - E_{it}(Y_{t+1}) < 0$ reflect higher movements of beliefs compared to the realized outcomes on the pessimistic side. Standard errors are clustered at the individual and date level, $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

C Memory-Based Model

Proof of Expression 7. To derive the expression for probability of rejected, one can multiply and divide by the sum of similarities across the database and re-arrange:

$$\hat{p}^B_{iL} = \frac{S(R)}{S(R) + \sum_{m\in M} S(m)}\sigma(R) + \frac{\sum_{m\in M} S(m)\sigma(m)}{S(R) + \sum_{m\in M} S(m)} \tag{10}$$

$$= \frac{S(R)}{S(R) + \sum_{m\in M} S(m)}\sigma(R) + \frac{\sum_{m\in M} S(m)\sigma(m)}{S(R) + \sum_{m\in M} S(m)} \times \frac{\sum_{m\in M} S(m)}{\sum_{m\in M} S(m)} \tag{11}$$

$$= \frac{S(R)}{S(R) + \sum_{m\in M} S(m)}\sigma(R) + \left(1 - \frac{S(R)}{S(R) + \sum_{m\in M} S(m)}\right)\frac{\sum_{m\in M} S(m)\sigma(m)}{\sum_{m\in M} S(m)} \tag{12}$$

$$= \omega_{iL}\sigma(R) + (1 - \omega_{iL})\hat{p}_{iL} \tag{13}$$

where $\omega_{iL} \equiv r(R, \theta_{iL}) = \frac{S(R)}{S(R)+\sum_{m\in M} S(m)}$ and $\hat{p}_{iL} = \frac{\sum_{m\in M} S(m)\sigma(m)}{\sum_{m\in M} S(m)}$.

Predictions of Memory Model.

Table C.22: Rejections and Expectations about the Macro - Implied Similarity Exercise

	Tighter Credit Mkt	Higher Unemp	Inflation>= 4%	Inflation>= 8%
Applied and accepted		(omitted)		
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)
Demographics	Y	Y	Y	Y
State-Month-Year FE	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.23: State Dependency in Beliefs across Macro Outcomes

	OPTM	↑UNEMP	FCredit	↑StockP	E(INFL)
(Intercept)	0.207^{**}	43.054^{***}	-0.367^{***}	47.269^{***}	4.575^{***}
	(0.103)	(3.992)	(0.123)	(4.359)	(1.342)
Applied and rejected	-0.163^{***}	2.173^{***}	0.349^{***}	-1.473^{**}	0.624^{*}
	(0.016)	(0.626)	(0.044)	(0.658)	(0.348)
Didn't apply	−0.005	-0.935^{***}	0.026	-0.914^{***}	−0.129
	(0.008)	(0.310)	(0.022)	(0.332)	(0.172)
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)			
CrCond			-0.109^{***}		
			(0.016)		
Applied and rejected×CrCond			0.140^{***}		
			(0.041)		
Didnt apply×CrCond			0.018		
			(0.021)		
STCKPgrowth				0.012^{***}	
				(0.003)	
Applied and rejected×STCKPgrowth				−0.001	
				(0.009)	
Didn't apply×STCKPgrowth				0.002	
				(0.005)	
INFLrate					0.647^{***}
					(0.054)
Applied and rejected×INFLrate					0.318^{**}
					(0.143)
Didn't apply×INFLrate					−0.032
					(0.072)
Individuals' Controls	Y	Y	Y	Y	Y
R^2	0.053	0.018	0.036	0.065	0.086
Observations	25161	25132	25161	25135	24744

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

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):

$$\text{OptimismIndex}_{it} = \beta_0 + \beta_1 \text{Rejection}_{i,t-1} + \delta X_{it} + \gamma_{st} + v_{it} \tag{14}$$

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:

$$\text{Spending}_{it,t+1} = \alpha_0 + \alpha_1 \text{Rejection}_{i,t-1} + \alpha_2 \text{OptimismIndex}_{it} + \delta X_{it} + \gamma_{st} + u_{it} \tag{15}$$

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.24 presents results from regression 14 in Column (1) and regression 15 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.[26]

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

[26]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."

Table D.24: 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 14 relating past personal rejections to Optimism Index, while Column (2) presents estimated coefficients of Equation 15 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: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$