Credit Market Experiences and Macroeconomic Expectations: Evidence and Theory*

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May 4, 2026

Abstract

Using the New York Fed Survey of Consumer Expectations, I document a robust "rejection gap" in macroeconomic expectations: households recently denied credit are more pessimistic than otherwise similar households about credit conditions, inflation, unemployment, and stock prices, make systematically pessimistic forecast errors, and remember recent aggregate conditions as worse than they actually were. Standard informational and selection explanations cannot account for these patterns. They are, however, consistent with a memory-based account: a credit rejection shapes which past experiences come to mind when households think about the economy, and the resulting pessimism is strongest for outcomes that feel most similar to a rejection, a similarity ordering I measure directly in a new survey. The rejection gap is largest among younger and lower-income households (those with higher marginal propensities to consume) and nearly doubles during recessions (when adverse experiences come to mind most easily). Larger gaps are associated with lower durable spending and higher precautionary saving, providing a channel through which credit-market experiences can amplify aggregate demand fluctuations.

Keywords: experiences, memory, expectations, disagreement, consumption

JEL Classifications: D84, E21, E71, G41, G51

*I am grateful to Alberto Martin, Vladimir Asriyan, Nicola Gennaioli and Jaume Ventura for their invaluable guidance and support. I thank Peter Andre, Larbi Alaoui, Malachy Gavan, Albert Marcet, Pierfrancesco Mei, Katrin Goedker, Victoria Vanasco, Maria Ptashkina, Andrei Shleifer, Edouard Schaal as well as seminar participants at CREI, HEC Paris Finance PhD Workshop, 21st Macro Finance Society Workshop, 7th Workshop on Subjective Expectations, 13th ifo Conference on Macroeconomics and Survey Data, EEA-ESEM Meetings, WE_ARE_IN Conference, Bocconi University, TSE, USC, SFU, HEC Montreal, Harvard Business School, Erasmus School of Economics, Bank of Spain, IESE Business School, Imperial College London, Kellogg Northwestern, Heidelberg University, 3rd BdF-CEPR-HEC-Oxford University PSE Paris Conference on the Macroeconomics of Expectations, Bocconi University, Copenhagen University, and Sixth Joint BoC-ECB-New York Fed Conference on Expectations Surveys for helpful comments. I gratefully acknowledge financial support from “la Caixa” Foundation (ID 10001434) with fellowship code LCF/BQ/DR20/11790004.

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1 Introduction

Expectations about the future are central to economic decision-making. How households form these expectations shapes consumption, saving, and ultimately aggregate demand. A large literature shows that individuals extrapolate from personal experience when forming beliefs (Malmendier, 2021), with most evidence focused on effects within the domain of the experience: aggregate stock-market experiences move beliefs about stocks but not bonds (Malmendier and Nagel, 2011), and local house-price experiences move beliefs about house prices but not inflation (Kuchler and Zafar, 2019). In parallel, a separate literature documents that broad, correlated shifts in sentiment are important drivers of macroeconomic fluctuations (Benhabib, Wang and Wen, 2015; Angeletos and Lian, 2022; Kamdar and Ray, 2025), but typically treats these shifts as exogenous, without linking them to individual household experiences. An important question therefore remains open: can broad, cross-domain movements in macroeconomic beliefs be traced to specific personal experiences?

This paper provides evidence that they can, and that they do so in structured and predictable ways. Using detailed micro survey data, I show that a salient idiosyncratic experience in credit markets (being denied credit) is systematically associated with broad pessimism spanning macroeconomic expectations beyond the credit domain. The pessimism has a clear ordering across outcomes (largest for credit, smaller for inflation and unemployment, smallest for stock returns) and is heterogeneous across households and macroeconomic states in predictable ways. The evidence points to an associative-memory mechanism: credit rejections shape what households recall about the aggregate environment, and the resulting pessimism is strongest for outcomes that feel most similar to a rejection. These distortions matter for household spending and for the propagation of credit-market shocks into aggregate demand.

I start by documenting three empirical facts using the New York Fed Survey of Consumer Expectations (SCE) and its Credit Access Module, a distinct survey module that allows me to match households' personal credit experiences with their macroeconomic expectations and, for credit conditions, their recollections of recent aggregate conditions.

The first fact is a robust cross-domain "rejection gap" in macroeconomic expectations: households rejected for credit in the past year are more pessimistic than otherwise similar accepted applicants and non-applicants across macroeconomic outcomes. Rejected households expect tighter nationwide credit conditions, higher inflation, higher unemployment, and lower stock prices than both other groups. Quantitatively, the differences are sizeable: relative to others, the rejected expect future credit conditions to tighten by 0.31 standard deviations (SD) more, inflation to rise by 0.16 SD more, unemployment by 0.10 SD more, and stock prices to fall by 0.05 SD more.[1] This pessimism declines monotonically from credit through inflation and

[1]The magnitude of the rejection gap is comparable to the low($<$ \$40k)-high($>$ \$100k) income tercile gap, which corresponds to 0.03-0.28 SD differences across outcomes.

unemployment to stocks. The gap is also asymmetric: acceptances are not associated with an equivalent optimism about macroeconomic conditions, a pattern I return to and explain.

The second fact is that the rejection gap is hard to reconcile with standard informational or selection explanations. Under the first interpretation, households could be using their rejections as informative signals about the macroeconomic environment. However, I find that personal rejections have little to no predictive power for subsequent macro outcomes and are associated with systematically more pessimistic forecast errors, consistent with overweighting of experiences rather than learning from them. Under the second interpretation, the gap could capture intrinsically more pessimistic households who are both more likely to be rejected and more likely to hold negative macro views. I find that the gap is robust to a rich set of controls (demographics, other experiences, credit history, loan types, and risk attitudes) as well as fixed effects, ruling out a wide range of observable and unobservable differences. The SCE panel structure allows a more direct test: by tracking households that transition into or out of rejection between survey waves, I can separate stable pessimism from short-run belief updates. If stable pessimism were the main driver, conditioning on prior beliefs should absorb the effect of both transitions. Instead, becoming rejected predicts a decline in optimism even after accounting for prior beliefs, while no longer being rejected does not.

Neither explanation accounts for the rejection gap, but the evidence suggests that an alternative grounded in cognitive psychology can: beliefs are formed from what comes to mind, and recall is selective, associative, and sensitive to contextual cues (Kahana, 2012; Gennaioli et al., 2024). Under this view, an idiosyncratic negative event can tilt which past episodes come to mind toward adverse ones, generating pessimistic beliefs and forecast errors even when the event itself carries no informative signal about future realisations. If this channel is at work, rejected households should not only hold more pessimistic expectations but also recall recent aggregate conditions differently. A distinctive feature of the SCE makes it possible to test this channel directly, because the credit module elicits respondents' expectations and also their recalled assessment of nationwide credit conditions over the previous twelve months.

The third fact is that rejected households exhibit systematically distorted recall of recent aggregate credit conditions, and these recall distortions help account for their pessimistic forecasts. Relative to accepted applicants and non-applicants, rejected individuals remember tighter credit conditions and exhibit larger recall errors: they recall conditions to have been tighter than objective measures indicate. Moreover, recalled credit tightness predicts subsequent forecasts, and controlling for recalled conditions substantially attenuates the relationship between personal rejections and macro forecasts. Together, these results point to a selective-memory channel: the rejection gap in beliefs operates, at least in part, through systematic differences in what recent aggregate conditions come to mind.

Motivated by these facts, I characterise the rejection gap with a model of belief formation based on contextual and associative memory, building on Bordalo et al. (2025) and evidence on contextual retrieval (Kahana, 2012). Households form expectations by recalling past experiences that are perceived as similar to the outcome being forecasted and to their current personal context. A credit rejection plays a dual role in this process: it adds a salient negative episode to the memory database, and it shifts the household's context toward a more adverse state. Both forces raise the probability of recalling other negative episodes when forming macro forecasts, generating systematic pessimism. The model yields two core testable implications. First, spillovers across macroeconomic beliefs are governed by perceived similarity between the personal experience and the outcome being forecasted, so the cross-domain ordering of the rejection gap should track the similarity ranking. Second, the magnitude of the rejection gap depends on primitives of the model, leading to predictable heterogeneity and state-dependency. I take each prediction to the data in turn.

A challenge for memory-based theories is that perceived similarity is typically latent. To discipline the first prediction directly, I designed and implemented a new online survey of 1,000 U.S. credit-market participants that elicits perceived similarity between personal credit experiences and macroeconomic outcomes. The resulting pattern closely mirrors the SCE: rejections are perceived as most similar to tight credit conditions, followed by high inflation and high unemployment, and least similar to low stock prices. The asymmetry noted earlier is also reflected in perceived similarity: rejections are viewed as strongly related to adverse macro conditions, whereas acceptances are only weakly related to favourable ones. This asymmetry is largely explained by a small set of experience attributes: relative to acceptances, rejections are rated as more unexpected, more unpleasant, more financially costly, and more vividly remembered, and these attributes in turn predict higher similarity ratings. Together, these findings provide direct evidence that households view rejections as salient and macro-relevant, consistent with the model's premise that perceived similarity shapes how personal experiences propagate into aggregate beliefs.

Turning to the second prediction, the model implies that macroeconomic disagreement reflects not only differences in exposure to common news, but also the cross-sectional distribution of personal experiences. A rejection shapes beliefs by influencing what comes to mind, and the strength of recall depends on three primitives: the size of the household's memory pool, the negativity of its context, and the similarity between the rejection and the prevailing macro state. The first two primitives generate cross-sectional predictions, supported in the SCE: the rejection gap is largest among younger households, who have fewer experiences, and among lower-SES households and those reporting worse financial conditions, for whom the context is more adverse. The third generates a state-dependent prediction. Interacting past rejections with the COVID-19 recession, I find that rejections are associated with stronger pessimism when the macro environment is adverse, even though the rejection itself occurred up to twelve months earlier. This state-dependence matters for aggregate dynamics: downturns make negative personal experiences more easily recalled, amplifying pessimism precisely when the economy is already contracting.

Finally, I examine the behavioural implications of these belief distortions. Embedding the mechanism into a simple consumption-saving framework, I distinguish two channels through which credit rejections may affect spending: a direct constraint channel (rejections reduce access to borrowing) and an indirect belief channel (rejections generate pessimism about future economic conditions). Using the SCE Spending Module, I find that rejected households are less likely to plan durable purchases, and a mediation analysis attributes roughly 8%[2] of this association to the belief channel alone. The data are therefore consistent with both channels operating, with a larger belief share among younger and lower-SES households, in line with the model's predictions. Rejected households also report higher saving flows and are more likely to cite expected borrowing difficulty as a saving motive, providing direct evidence that beliefs about future credit access shape saving decisions. A stylised aggregation, exploiting the state-dependence documented above, suggests that recall-induced pessimism could raise the sensitivity of aggregate consumption to income in downturns by roughly 30 basis points.

This paper contributes to the literature on the determinants of macroeconomic expectations and the role of personal experiences and circumstances (Das, Kuhnen and Nagel, 2020; D'acunto et al., 2023; Malmendier, 2021; Malmendier and Shen, 2018). Prior work has focused on experience-based extrapolation within the domain of the experience itself (Malmendier and Nagel, 2011; Kuchler and Zafar, 2019), with most evidence coming from inflation, asset returns, and house prices. I focus on a highly relevant but relatively less studied domain: the credit market, where nearly half of U.S. households apply for credit in a given year and roughly one in five applicants is denied. I document meaningful, ordered spillovers from idiosyncratic credit rejections to expectations outside the credit domain, and provide a mechanism grounded in well-established regularities in memory that explains both their existence and ordering.

The paper thus joins a growing literature on memory and expectations in economics (Enke, Schwerter and Zimmermann, 2020; Malmendier and Wachter, 2024; Bordalo et al., 2021; Andre et al., 2022; Afrouzi et al., 2023; Bordalo et al., 2023; Jiang et al., 2025). I build on the framework of Bordalo et al. (2025), which formalises how individuals form beliefs by simulating outcomes from recalled rather than purely informative experiences, and on evidence on contextual retrieval from cognitive psychology (Kahana, 2012). I bring their framework to the study of macroeconomic belief formation, deriving predictions about heterogeneity and state dependence that are specific to this setting, and provide new evidence on perceived similarity from a purpose-built survey.

The most closely related paper is contemporaneous work by Taubinsky et al. (2025), who show that inflation expectations are excessively sensitive to idiosyncratic income changes and provide evidence of distorted recall consistent with affect-cued retrieval. My focus is com-

[2]Although modest, this share is economically meaningful given that it reflects only one general measure of macroeconomic optimism rather than the full set of belief channels potentially activated by a rejection.

plementary. While both papers study how experiences in one domain affect expectations in another, Taubinsky et al. (2025) focus on a single experience-belief link (income changes and inflation), whereas I study how one experience maps onto multiple macro outcomes simultaneously. Studying multiple outcomes makes it possible to explore the ordering of spillovers across domains through perceived similarity, and to motivate a more structured retrieval mechanism in which recall is linked to similarity between the experience and the specific outcome being forecasted, generating the ordered gradient as a testable prediction. More broadly, the cross-domain structure speaks to how a single salient experience can propagate into broad, correlated pessimism across macroeconomic domains. I also trace these belief distortions to household spending and saving, distinguishing a direct borrowing-constraint channel from an indirect belief channel. Both of these distinctions have macroeconomic implications.

In particular, the results have implications for the literature studying demand-driven cycles and the role of sentiment in macroeconomic fluctuations (Benhabib, Wang and Wen, 2015; Angeletos and Lian, 2022; Bianchi, Ilut and Saijo, 2023). A large body of work in heterogeneous-agent macroeconomics shows that borrowing constraints are central for understanding aggregate consumption dynamics (Krusell and Anthony A. Smith, 1998; Krueger, Mitman and Perri, 2016). The evidence here points to a complementary margin: an indirect belief channel through which credit-market experiences can affect desired spending and precautionary saving even holding observed constraints fixed. Because this pessimism is most pronounced among younger and lower-SES households, groups with higher marginal propensities to consume (Johnson, Parker and Souleles, 2006; Amromin, De Nardi and Schulze, 2019), it represents a plausible channel through which credit-market experiences amplify aggregate demand, particularly in downturns. The findings also contribute to the sentiment literature by showing that experience-linked pessimism is not uniform across outcomes but follows a similarity-based ordering, a pattern that can inform how sentiment propagates in practice.

The rest of the paper is organised as follows. Section 2 describes the data. Section 3 documents the rejection gap in macroeconomic expectations and explores potential explanations. Section 4 introduces memory based beliefs, derives new predictions and tests them. Section 5 explores the economic implications, and Section 6 concludes.

2 Data

2.1 Data Sources

The primary dataset is the Survey of Consumer Expectations (SCE) of the Federal Reserve Bank of New York (Federal Reserve Bank of New York, 2013-2022). The SCE is a nationally representative monthly internet survey of about 1,200 household heads, structured as a rotating panel where respondents remain for up to 12 months. The design thus allows both cross-sectional and panel analysis of expectation formation and household behaviour.

The survey consists of a Core Module, fielded monthly since June 2013, and a set of specialised modules that can be linked to it. The Credit Access Module, introduced in October 2013 and repeated every February, June, and October, was developed to fill a gap in existing datasets by providing repeated household-level measures of credit applications and outcomes (Armantier et al., 2017). Other widely used data sources either aggregate supply and demand (e.g., the FRBNY Consumer Credit Panel), reflect only supply-side views (e.g., the Senior Loan Officer Opinion Survey), or are too infrequent to track short-run dynamics (e.g., the Survey of Consumer Finances). By contrast, the Credit Access Module provides timely information on households' actual interactions with credit markets, which I use to study how personal credit experiences are linked to expectations about macroeconomic conditions.

This paper uses 25 waves of the Credit Access Module, up to October 2021, yielding 28,241 person-month observations from 13,053 unique respondents.[3] Merging with the Core Module provides linked measures of credit experiences, macroeconomic expectations, and demographics. Additionally, I match the main dataset to the Spending Module (three times per year since December 2014), which captures past and planned spending, and the Annual Household Finance Module (2014-2019), which covers balance sheets and savings. For external validation, I also use the triennial Survey of Consumer Finances (SCF) (Federal Reserve Board, 1989-2021), which provides longer time coverage and richer detail on balance sheets, but without the same emphasis on expectations. Further details are provided in Appendix A.

2.2 Variable Definition

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

Credit market experiences. The main explanatory variable captures whether respondents applied for credit in the past 12 months and the outcome of those applications. The survey asks about seven categories of credit: credit cards, credit card limit increases, mortgages or home equity loans, auto loans, increases in existing loan limits, mortgage refinances, and student loans. I classify respondents into three mutually exclusive groups: (i) *Applied and Accepted* if all applications done in the past 12 months were approved (fully or partially), (ii) *Applied and Rejected* if at least one application was denied, and (iii) *Didn't Apply* if no applications were made.[4] In the baseline analysis, I aggregate across loan types to create a single measure of credit market experience. In later sections, I examine heterogeneity by loan type.

This variable provides a direct measure of recent personal interactions with the credit market,

[3] Among these, 5,518 participated three times, 4,101 twice, and 3,417 once.

[4] I focus on those who did not apply to credit because they did not need to or because they found it costly, while I exclude those who said they did not apply to any credit because they thought they wouldn't be approved.

which I then link to macroeconomic expectations.

Expectations. I focus on four variables measuring individuals' 12-month-ahead macroeconomic expectations: (1) expectations of credit availability over the next 12 months (coded as 1 if respondents expect tightening, 0 if they expect no change, and -1 if they expect loosening), (2) the probability of higher U.S. unemployment ($0-100$), (3) the probability of higher U.S. stock prices ($0-100$), and (4) the expected inflation rate. Since for stock prices the SCE elicits the probability of *higher* prices, I recode this measure as $100-$ *response* so that higher values correspond to more pessimistic expectations (i.e. stock prices remain flat or decline), consistent with the other outcomes.

To have a measure of aggregate macroeconomic optimism, I follow Das, Kuhnen and Nagel (2020) and construct an Optimism Index by first standardising and then averaging, for each individual, their expectations of credit, unemployment, and stock prices. The resulting index takes positive (negative) values if the respondent is relatively optimistic (pessimistic).

Controls and other measures. The SCE provides detailed demographic and financial information, including age, gender, race, education, employment status, income, credit score range, debt holdings, delinquency proxies, bankruptcy considerations, and numeracy skills. In later sections, I also use data from the Spending Module, which contains households' self-reported past purchases and the probability of purchasing durables in the next four months. These variables serve as behavioural outcome measures. Finally, the Annual Household Finance Module provides information on saving behaviour.

2.3 Descriptive Statistics

Appendix Table A.1 presents descriptive statistics. The average age is 51 years old, 50% are women, and nearly half have some college education. Household income is distributed with 28% above \$100k, 30% between \$50k and \$100k, and 41% below \$50k. Roughly two-thirds of respondents score high on numeracy, and nearly three-quarters are homeowners.

About half of the sample applied for credit in the past year. Of the full sample, 40% were accepted and 7.6% rejected. Among applicants, the average rejection rate is 18%. The panel structure allows tracking transitions within a 12 months window: 295 individuals move from acceptance to rejection across waves, and 318 in the opposite direction. The Credit Access Module also elicits respondents' credit scores, which fall into four broad ranges: over 720 (55%), between 720 and 680 (10.5%), below 680 (20%), and uncertain (the remainder).

With respect to expectations about the economy, respondents assign a 36% probability to rising unemployment and a 40% probability to rising stock prices (60% to flat or lower stock prices) over 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.

Figure 1 shows average differences in macroeconomic expectations across credit market experience groups. Consistently, those who were rejected for credit applications in the past year are more pessimistic than other groups. Nearly 50% of rejected applicants expect tighter credit conditions over the next year, compared with 30% or less among those who were accepted or did not apply. Similar differences emerge for expectations of unemployment, stock prices, and inflation.

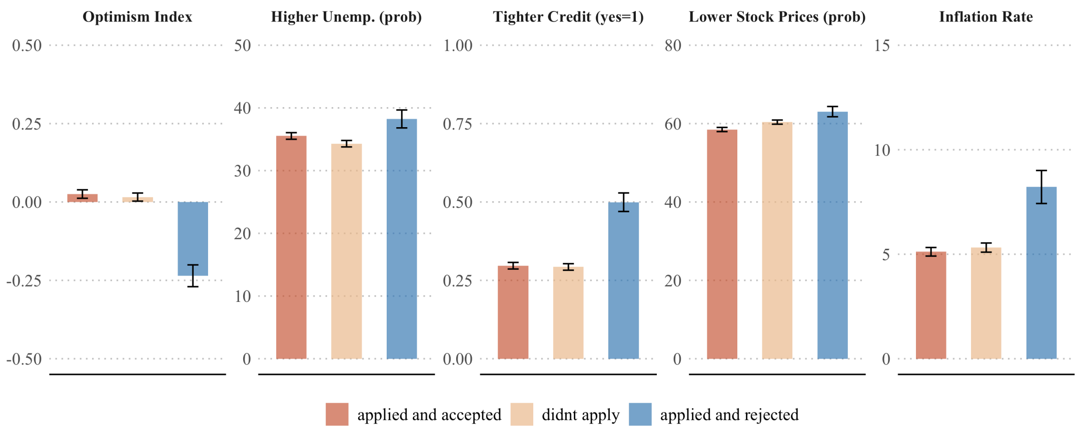


Figure 1: Average Expectations by Credit Market Experience

Notes: Bars report weighted means of each outcome by credit experience group (applied and accepted, did not apply, applied and rejected). Error bars are 95% confidence intervals. Outcomes are Optimism Index, reported probabilities of higher unemployment and lower stock prices, an indicator for expecting tighter credit conditions, and expected inflation rate.

3 Idiosyncratic Rejections and Macro Expectations

This section documents three empirical patterns linking personal credit experiences to macroeconomic expectations. First, a recent credit rejection is systematically associated with more pessimistic expectations across several macroeconomic domains, with a cross-domain ordering. Second, standard informational or selection-related explanations cannot account for this finding: personal rejections predict pessimistic forecast errors but not subsequent realisations, and their association with macro forecasts holds when controlling for beliefs prior to rejection. Third, the evidence is consistent with a selective-memory mechanism: experiencing a rejection is strongly associated with recalling credit conditions to have been tighter than they were, and controlling for this recall substantially attenuates the rejection-belief relationship.

3.1 Main Empirical Specification

To examine how personal credit market experiences relate to macroeconomic expectations, I estimate the following regression:

$$E_{i,t}(Y_{t+12}) = \alpha + \sum_{k=1}^{2} \beta_k T_{i,k,t} + \beta_y \text{LifetimeExp}_{i,t}^{Y} + \delta X_{i,t} + \chi_t + e_{i,t}, \quad (1)$$

where the unit of observation is an individual i in month t. The key explanatory variable is a set of dummies $T_{i,k,t}$ where k indicates credit market experience in the past 12 months. Respondents are classified as: (i) *Applied and Accepted* (reference group), (ii) *Applied and Rejected*, (iii) *Didn't Apply*. The coefficients β_k capture differences in expectations relative to accepted applicants. I use (i) as the reference group to focus on credit-market participants, but also provide robustness to using group (iii).

The dependent variable $E_{i,t}(Y_{t+12})$ denotes individual i's expectation at time t of outcome Y one year ahead. I consider the five measures previously introduced: optimism index (OPTM), expected aggregate credit conditions (FCredit), probability of higher U.S. unemployment (UNEMP), probability of lower U.S. stock prices (StockP), and expected inflation rate (INFL).[5]

The regression includes controls for standard determinants of macroeconomic expectations that may also be correlated with credit market experiences. In particular, I include state-of-residence×month×year fixed effects (χ_t) to absorb time-varying local shocks. As a result, the coefficients on $T_{i,k,t}$ capture within-location, within-time differences in macroeconomic expectations associated with individual credit market experiences, over and above shared local conditions. I also control for lifetime macroeconomic experiences, $\text{LifetimeExp}_{i,t}^{Y}$, constructed following Malmendier and Nagel (2011).[6] This control accounts for long-run belief formation based on individuals' cumulative exposure to aggregate outcomes.

Additionally, I control for individual characteristics that might relate to both personal rejections and macro beliefs, including age, gender, race, education, income, employment status and its duration (for the recently unemployed), marital status, and partner employment status when applicable. In robustness exercises, I extend the specification to include additional measures of respondents' recent financial profiles (e.g., loan type, delinquency indicators, involuntary account closures, reported credit score ranges, risk attitudes, and numeracy). I estimate equation (1) by OLS with heteroskedasticity-robust standard errors two-way clustered by individual and date.

[5] Results are based on point estimates but are robust to using the fitted distribution mean.

[6] This measure is constructed as a weighted average of past realisations of Y from birth to t, with declining weights on older observations. Formally, $\text{LifetimeExp}_{i,t}^{Y} = \sum_{h=1}^{H_i} w_{i,t}(h) Y_{t-h}$, where $w_{i,t}(h)$ are linearly declining weights.

3.2 The Rejection Gap in Macroeconomic Beliefs

Fact 1: A cross-domain rejection gap.

Table 1 reports baseline estimates of Equation 1 across expectation outcomes. Individuals who experienced a credit rejection in the past year are systematically more pessimistic than those who were accepted. Rejected applicants expect tighter aggregate credit conditions, assign higher probabilities to rising U.S. unemployment and falling stock prices, and anticipate higher inflation. This pattern is robust to alternative reference groups: relative to non-applicants, rejected respondents are more pessimistic in four of five domains.

This heterogeneity across experience groups persists after conditioning on a rich set of covariates, including demographics, socioeconomic status, other recent experiences, and state-of-residence×month×year fixed effects. Note that all respondents are forecasting the same aggregate outcomes so, under full-information rational expectations and conditional on time fixed effects, personal credit experiences should be irrelevant. I refer to this systematic pessimism associated with personal credit rejections as the "rejection gap" in macroeconomic expectations.

Table 1: Credit Market Experiences and Macroeconomic Expectations

	OPTM	UNEMP	FCredit	StockP	INFL
Applied and Rejected	-0.172^{***}	2.298^{***}	0.220^{***}	1.208^{*}	1.659^{***}
	(0.019)	(0.728)	(0.023)	(0.731)	(0.393)
Didn't apply	0.009	-0.876^{**}	-0.020^{*}	0.949^{***}	-0.466^{***}
	(0.009)	(0.360)	(0.011)	(0.360)	(0.140)
$Rejected - Didn't = 0$	$\rho < 0.001$	$\rho < 0.001$	$\rho < 0.001$	$\rho = 0.6$	$\rho < 0.001$
Controls	Y	Y	Y	Y	Y
Within R^2	0.054	0.013	0.036	0.058	0.041
Observations	25161	25132	25161	25135	25091
Mean Dep. Var.	−0.02	35.58	0.13	59.97	5.72

Notes: The table reports OLS estimates from Equation 1. All specifications include demographic and socioeconomic controls as well as state-month-year fixed effects. Standard errors are two-way clustered at respondent and date. Significance levels: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

To facilitate comparisons across outcomes, I standardise each dependent variable. Figure 2 plots the resulting coefficients and reveals a clear ordering: relative to accepted applicants, rejected applicants are 0.31 SD more pessimistic about future credit conditions, 0.16 SD on inflation, 0.10 SD on unemployment, and 0.05 SD on stock prices. The rejection gap is largest in the credit domain and attenuates as outcomes become less directly linked to household credit, consistent with a gradient in how personal credit experiences map into broader macroeconomic beliefs.

This ordering is robust to alternative reference groups: re-estimating the standardised models with "Didn't Apply" as the omitted category preserves the ranking and produces similar (if anything slightly larger) magnitudes (see Appendix Figure B.1). This suggests an asymmetry: rejections are associated with more pessimism but acceptances are not associated with an equivalent optimism about the wider macroeconomic environment.

Finally, the right panel of Figure 2 benchmarks the coefficient on recent rejection against a one-standard-deviation increase in lifetime, domain-specific experience (in the spirit of Malmendier and Nagel (2011)). While lifetime exposure matters, recent rejections have larger coefficients across almost all domains. Controlling for lifetime experience does not eliminate the rejection gradient, nor does it meaningfully change the coefficients, suggesting that idiosyncratic credit market events carry more weight in shaping macroeconomic beliefs than accumulated exposure to past macro shocks. As an alternative benchmark, Appendix Table B.2 shows that the rejection gap is larger than the low-high income tercile gap.

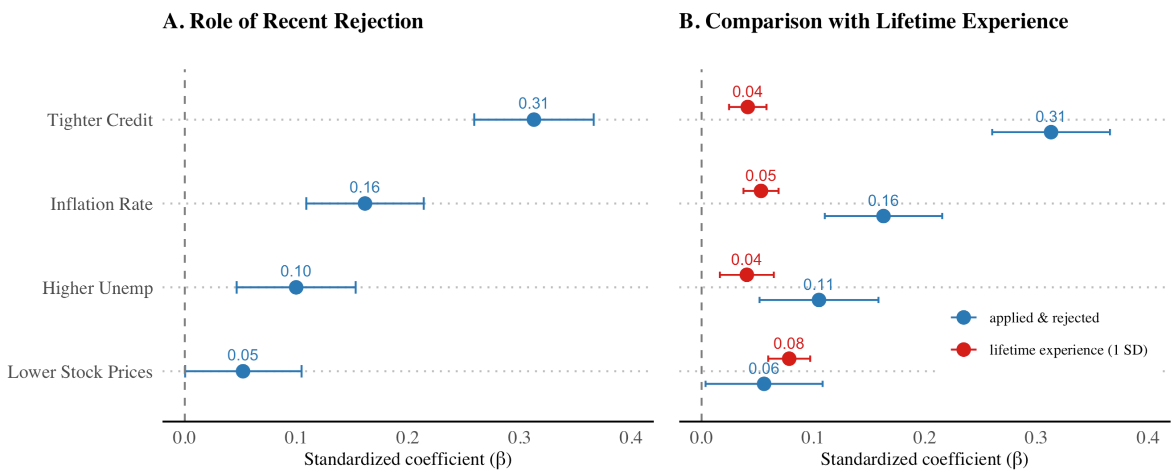


Figure 2: Recent Rejection versus Domain-Specific Lifetime Experience

Notes: The left panel reports standardised coefficients of rejections relative to accepted applicants. The right panel compares the magnitude of rejection effects (red) with the effect of one standard deviation in lifetime experience with the corresponding outcome (blue). All regressions include the same controls as in Table 1. Standard errors are two-way clustered at respondent and date.

Fact 2: The rejection gap is not consistent with informational or selection explanations.

Information. One possible interpretation of the rejection gap is that rejected applicants are learning from a private signal: a credit denial may carry idiosyncratic information about future macroeconomic conditions that is not available to accepted applicants or non-applicants. Under this view, rejections should have predictive power for subsequent realisations, and the more pessimistic forecasts of rejected households should reflect a genuine informational advantage rather than systematic forecast errors. If instead rejections predict pessimism but not realisations, the rejection is receiving more weight in belief formation than its actual informational content warrants.

To test this, I construct for each outcome a 12-month-ahead realised counterpart and define a forecast error FE_{it}^k as the realised value minus the household's forecast, with negative values indicating overly pessimistic beliefs.[7] I then estimate

$$FE_{it}^k = \alpha_k + \delta_k r_{it} + \gamma_k X_{it} + \mu_t + e_{it}^k,$$

where r_{it} indicates a rejection in the past 12 months, X_{it} are controls, and μ_t are survey-month fixed effects. The coefficient δ_k captures whether rejections systematically predict forecast errors: $\delta_k = 0$ implies that rejections do not predict forecast errors, while $\delta_k < 0$ implies that rejections are associated with systematically pessimistic errors. For inflation, unemployment, and stock prices, this specification is also a standard test of limited-information rational expectations (Coibion and Gorodnichenko, 2015; Bordalo, Gennaioli and Shleifer, 2018): since the SCE elicits a conditional mean and the rejection belongs to the information set at the time of making the forecast, $r_{it} \in I_{it}$, rational updating implies $\mathbb{E}[FE_{it}^k \mid I_{it}] = 0$ and thus $\delta_k = 0$.[8]

Figure 3 shows that $\hat{\delta}_k$ is negative across all domains: rejected respondents make systematically more pessimistic errors than accepted applicants. The figure also implements the coefficient-comparison decomposition of Taubinsky et al. (2025): rejections are strongly associated with forecasts (and hence forecast errors) but show no systematic relation with subsequent realised outcomes.

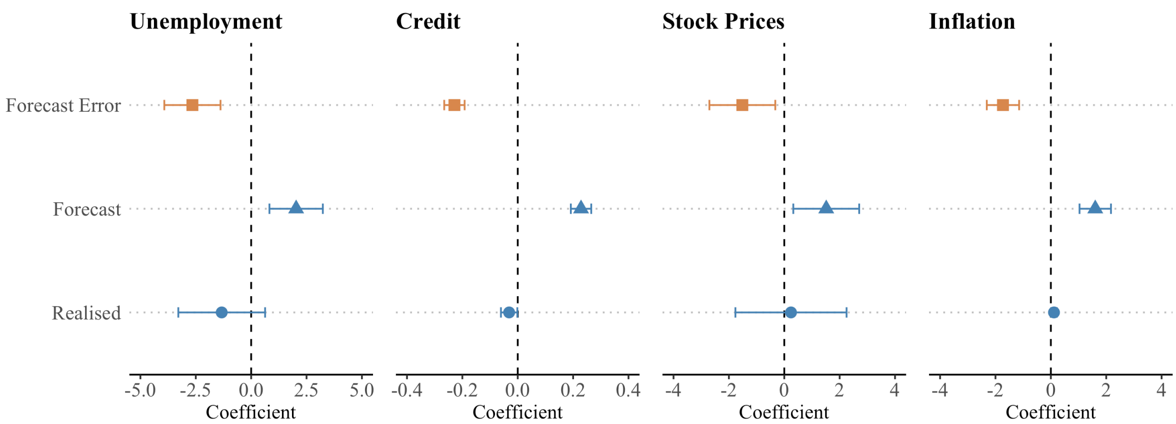


Figure 3: Over-Pessimistic Forecasts Among Rejected

Notes: Each panel reports the estimated coefficient on a binary indicator for having applied for and been rejected for credit, from separate regressions for (i) forecast errors (orange square), (ii) forecasts (blue diamond), and (iii) realised outcomes (blue circle). Points denote point estimates and horizontal bars show 95% confidence intervals. The domain of the outcome variable and forecast is shown in the panel title.

[7] For inflation, the realised counterpart is CPI inflation over the subsequent 12 months. For unemployment and stock prices, respondents report probabilities over binary outcomes, so I evaluate forecasts against indicators of higher unemployment and of weakly lower stock prices. For credit conditions, I construct an ordered index based on bank-reported tightening from the SLOOS. Appendix B provides details on series definitions and data sources.

[8] For credit, FE_{it}^c is an ordinal prediction error rather than a conditional-mean forecast error. The same regression is therefore interpreted as a test for systematic directional mistakes relative to the SLOOS-based benchmark.

Appendix Table B.3 confirms the same pattern when comparing rejected respondents to non-applicants. These results make a purely informational interpretation unlikely (see Appendix B.3 for additional tests). Instead, they are consistent with rejections receiving excessive weight in belief formation and pushing forecasts in a pessimistic direction.

Prior bias. A second potential explanation is that the rejection gap reflects stable differences in pessimism: individuals who are intrinsically more pessimistic may be both more likely to be rejected and more likely to hold negative macro beliefs. Appendix Figure B.2 shows that the rejection gap is robust to controls that could jointly affect credit outcomes and expectations, including numeracy, risk aversion, loan type, self-reported credit score, indicators of past delinquency, and time-varying household shocks.

To address the concern more directly, I exploit the panel structure of the SCE to separate stable cross-household differences in pessimism from short-run belief updates following a change in credit status. This exercise requires within-household variation in rejection status and is therefore identified off the subsample of respondents who transition between waves; while less representative of the population, it provides sharper evidence on belief dynamics.

Table 2: Entry into and Exit from Credit Rejection and Macroeconomic Optimism

Dep.Var.: OPTM	(1)	(2)
Entered Rejection	-0.119^{***}	-0.087^{***}
	(0.030)	(0.024)
Exited Rejection	-0.088^{***}	-0.033
	(0.027)	(0.022)
Lagged OPTM		0.584^{***}
		(0.005)
Within R^2	0.052	0.398
Observations	25157	23859

Notes: Outcome variable is OPTM (higher values = greater macro optimism). Other macro outcomes can be found in Appendix Table B.4. *Entered Rejection* indicates respondents moving from non-rejected to rejected between waves; *Exited Rejection* indicates the reverse; the omitted category is all other transitions. All models include the full control set (demographics, household and financial variables, numeracy, risk, loan type, and recent changes in residence, employment, and composition) and state-month-year fixed effects. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Column 1 of Table 2 shows that both entering and exiting rejection correlate with lower optimism, consistent with stable pessimistic types being present in the sample, but also with rejections having persistent effects on beliefs. Once we control for lagged optimism (Column 2), entering rejection continues to predict a sharp decline, whereas exiting rejection becomes small and statistically indistinguishable from zero. If stable pessimism were the main driver, conditioning on prior beliefs should absorb both effects. Instead, entering rejection produces short-run belief updates even after conditioning on prior beliefs, a pattern difficult to attribute solely to stable types.[9]

Fact 3: The rejection gap is consistent with selective recall.

Neither informational learning nor stable types accounts for the rejection gap. Insights from cognitive psychology suggest a natural alternative. People form beliefs based on retrieved memories, and retrieval is selective and associative: at any given time only a subset of past experiences comes to mind, and recall is guided by contextual cues and perceived similarity to the hypothesis under evaluation (Kahana, 2012; Bordalo et al., 2023). A salient negative personal credit event may therefore cue the recall of other negative episodes that feel similar, biasing beliefs toward adverse outcomes even when the objective link between an individual rejection and aggregate fundamentals is weak. Recent work in economics documents analogous patterns in other settings, showing that personal experiences can distort recall and predict biased forecasts (Taubinsky et al., 2025; Jiang et al., 2025; Bordalo et al., 2025).

A distinctive feature of the SCE allows me to test this mechanism directly within the credit domain. The credit module elicits not only respondents' (i) recent rejection experience and (ii) their expectations for aggregate credit conditions over the next 12 months, but also (iii) their *recalled* assessment of aggregate credit conditions over the past 12 months. This lets me ask whether rejected households differ in what they remember about the recent macro environment, and whether those differences in recall account for their differences in forecasts. I proceed in three steps: first, I test whether rejected individuals recall tighter credit conditions; second, whether they exhibit larger recall errors relative to objective measures; and third, whether controlling for recalled conditions attenuates the rejection-forecast relationship.

Figure 4 summarises the first two steps. Rejected respondents recall significantly tighter aggregate credit conditions (diamonds) and exhibit substantially more negative recall errors (squares), while rejections are not systematically related to realised aggregate credit conditions (circles). Panels A and B show that rejected respondents remember conditions to have been tighter than what they actually were relative to both accepted applicants and non-applicants; Panel C shows no meaningful difference between accepted applicants and non-applicants.

Table 3 implements the third step. Column (1) confirms that rejected applicants are more likely to recall tighter credit conditions. Column (2) shows that they report substantially more pessimistic forecasts. Column (3) shows that this rejection-forecast relationship is largely accounted for by recalled conditions: once recall is included, the rejection coefficient becomes small and statistically insignificant, while recalled tightening strongly predicts beliefs.

Together, these patterns provide direct evidence that the rejection gap operates, at least in part, through distorted recall of recent aggregate conditions. Rejected households remember a tighter macro environment than they actually experienced, and their pessimistic forecasts about

[9] The result also holds under two-way fixed-effects specifications, with a smaller but still significant rejection coefficient (Appendix Table B.5). The transition-based design is preferred because it separates entries from exits, an asymmetry that two-way FE estimates as a single average.

future credit conditions reflect those distorted recollections. This motivates the mechanism developed in the next section, which formalises how a salient personal experience can shape beliefs by reshaping what comes to mind.

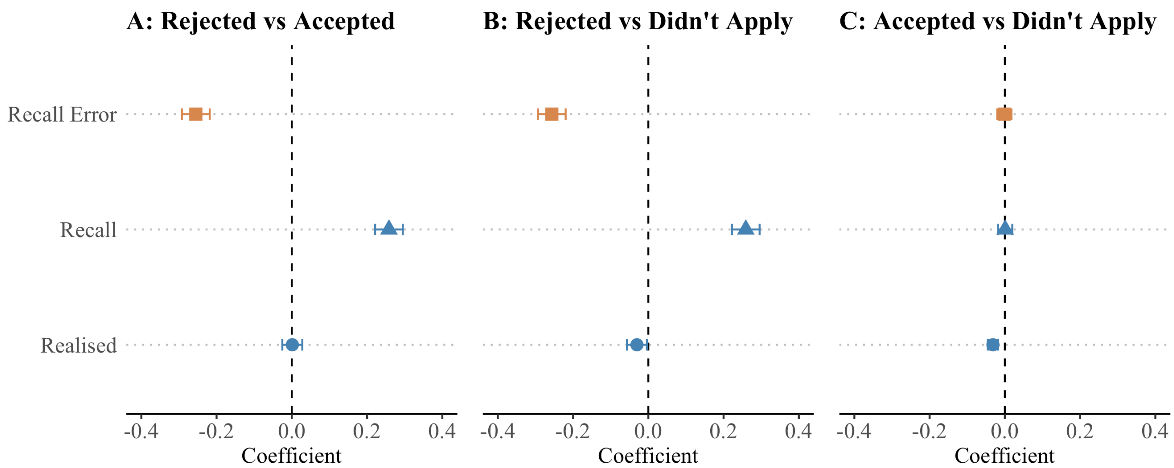


Figure 4: Over-Pessimistic Recall among Rejected

Notes: Each panel reports the estimated coefficient on a binary indicator for having applied for and been rejected for credit, from separate regressions for (i) recall errors (orange square), (ii) recall conditions (blue diamond), and (iii) realised outcomes (blue circle). Points denote point estimates and horizontal bars show 95% confidence intervals. The omitted category is the relevant comparison group shown in the panel title.

Table 3: Credit Experience, Recalled Conditions and Forecasts

Dep. Var.:	(1) Recall	(2) Forecast	(3) Forecast
Applied and Rejected	0.255***	0.229***	0.015
	(0.019)	(0.019)	(0.010)
Didn't apply	−0.001	−0.019*	−0.017***
	(0.010)	(0.010)	(0.005)
Recall			0.836***
			(0.003)
Within R^2	0.047	0.041	0.716
Observations	25157	25157	25157

Notes: Column (1) relates credit experiences to respondents' recalled assessment of aggregate credit conditions over the past 12 months. Column (2) relates credit experiences to forecasts for aggregate credit conditions over the next 12 months. Column (3) adds recalled conditions to the forecast regression. All regressions include household controls, state-of-residence fixed effects, and month-year fixed effects. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4 Mechanism: Memory-Based Beliefs

The section proceeds in three steps. First, I formalise belief formation under associative and selective memory, building on Bordalo et al. (2025, 2023) and contextual retrieval (Kahana, 2012). The model disciplines the rejection gap by linking personal experiences, recalled conditions, and expectations within a unified framework, and clarifies the conditions under which idiosyncratic experiences can translate into predictable aggregate pessimism. Second, I provide new evidence in line with the associative memory mechanism using an online survey specifically designed to elicit perceived similarities. Finally, I study the model's allocative consequences: because rejections are unevenly distributed across individuals and their impact varies by type, the model predicts systematic heterogeneity in beliefs, which I test using the SCE.

While other mechanisms may also contribute, the selective-recall framework generates distinctive predictions that do not naturally arise under alternative explanations, and I show that these predictions are supported by new evidence.

4.1 Model Setup & Key Mechanisms

Households forecast macro transitions by drawing on memory. Three ingredients matter: (i) the database M of stored experiences, (ii) a cued-recall process that selects which experiences come to mind given the forecasted event and the individual's context, and (iii) a simulation rule that maps recalled experiences into probability judgments.

Setup. The state of the economy can be either High (H) or Low (L), governed by a 2-state Markov process $\theta_t \in \{\theta_H, \theta_L\}$ with transition probabilities $p(\theta_{t+1} = \theta_j \mid \theta_t = \theta_i) = p_{ij}$. Each household has a memory database $M = \{\Theta, E\}$ consisting of past macroeconomic transitions between states i and j (stored in Θ), and other personal experiences or events e (stored in E).

Cued Recall. When individuals form expectations, they do not retrieve memories at random. Retrieval is guided by a cue, which combines features of the event being considered (e.g., a macro transition to a low state) and of the individual's current context (e.g., their perceived financial situation or mood) (Kahana, 2012).[10] Formally, let the cue be $[\theta_{ij}, c]$, where θ_{ij} is the macro event being evaluated (a transition from state i to j) and c the individual's context.

This cue triggers the retrieval of experiences in memory M that are most similar to it. In particular, following Kahana (2012) I define a features-based similarity function: each memory $m \in M$ receives a similarity weight $S(m, [\theta_{ij}, c]) \in [0, 1]$ that is increasing in shared features between m and the cue. For simplicity, I summarise features by type (macro vs. personal) and valence (current state i and future state j, with $i, j \in \{H, L\}$). A macro transition θ_{LL} thus shares all features with itself (highest similarity), while a personal negative episode e_{LL} shares

[10] Context refers to an individual's internal state (e.g., mood or emotion) and relevant external factors (e.g., temporal or environmental) that shape which memories come to mind.

valence but not type (intermediate similarity). I define a personal rejection $R \equiv e_{LL}$ as one such memory. The individual's context further influences this similarity:

Assumption A1 (Context monotonicity). A more negative context increases similarity to L-ending memories relative to H-ending memories.

Appendix Equation D.3 provides a standard functional form for the similarity function that reflects these dynamics. Moreover, I assume that rejections are linked to a more negative financial context, consistent with evidence from the SCE in which the probability of reporting a worsened financial situation in the past 12 months is 10 pp higher for those rejected in the past 12 months. Formally,

Assumption A2 (Rejection and negative context). Let c_1 be a more negative context than c_0. A recent rejection raises the likelihood of a more negative context: $\Pr(c_1 \mid R) > \Pr(c_1 \mid \neg R)$.

Recall Probabilities. When evaluating θ_{ij} in context c, the probability of recalling a memory $m \in M$ is given by:

$$r(m, [\theta_{ij}, c]) = \frac{S(m, [\theta_{ij}, c])}{\sum_{m' \in M} S(m', [\theta_{ij}, c])} \in [0, 1] \tag{2}$$

Hence, an experience that is perceived as more similar to the cue, relative to other experiences, has a higher probability of recall.

Simulation and Beliefs. Once a set of experiences is recalled, the individual uses them to form probabilities about the future event. In particular, a recalled memory is used to simulate the target event if and only if its *future feature* matches the target state: $\sigma(m, \theta_{ij}) = \mathbb{1}\{j(m) = j\}$. This simulation process is a form of reasoning by analogy that gets easier when experiences are similar to the event, even if they are from different domains (Kahneman and Tversky, 1981). A continuous $\sigma(\cdot) \in [0, 1]$ yields the same comparative statics.[11]

Combining cued recall and simulation yields the memory-based probability of transitioning from i to j:

$$p^M_{ij} = \sum_{m \in M} r(m, [\theta_{ij}, c]) \, \mathbb{1}\{j(m) = j\} = \frac{\sum_{m \in M: j(m) = j} S(m, [\theta_{ij}, c])}{\sum_{m \in M} S(m, [\theta_{ij}, c])} \in [0, 1]. \tag{3}$$

For the rest of the analysis, I focus on forecasts of a Low state ($j = L$), with $p^M_{iH} = 1 - p^M_{iL}$.[12]

[11] 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. (2025) formalize this process using a continuous mapping $\sigma(\cdot) \in [0, 1]$ that increases with similarity, and show experimentally that its behavioral implications align with the assumptions of memory-based forecasting. Adopting their more general specification would leave my comparative statics unchanged, since all predictions depend only on the ranking of similarities, not on the exact functional form of $\sigma(\cdot)$. For tractability, I use the step-function version in the main text.

[12] This assumption disciplines the model and suffices to explain my empirical findings, but could be relaxed.

The model delivers a simple mapping from experiences and context into beliefs: a rejection both enters the memory database ($R \in M$) and shifts the likelihood of a negative context (Assumption A2), which affects recall weights (Assumption A1) and thus beliefs as in Equation 3. The next subsection characterises how these forces distort beliefs relative to a frequentist benchmark and derives testable implications.

4.2 Experiences, Recall Set and Beliefs: Mechanism and Predictions

The role of the recalled set. Beliefs depend on what comes to mind. If households had perfect recall and drew exclusively on the historical record of macro transitions, their belief about the probability of a Low state would equal the frequentist benchmark

$$p_{iL} = \frac{|\theta_{iL}|}{|\theta_{iL}| + |\theta_{iH}|},$$

where $|\theta_{iL}|$ counts the historical transitions from state i to L. In this case, beliefs reflect only the relevant statistical record, and personal context plays no role. Selective, context-dependent retrieval relaxes this assumption. The set of episodes that come to mind is no longer restricted to relevant macro transitions: experiences from other domains can also enter the recalled set when they are perceived as similar. Appendix D.1 shows that memory-based beliefs can then be written as the benchmark plus a recall-driven deviation,

$$p^M_{iL}(c) = p_{iL} + \Delta(c), \tag{4}$$

where $\Delta(c)$ captures the effect of the recalled set beyond the relevant macro transitions. The deviation rises with the relative recall of L-ending experiences and falls with the relative recall of H-ending ones. Intuitively, a more negative context shifts the recalled set toward L, increasing p^M_{iL}.

Implication (Context raises pessimism). Let c_1 be more negative than c_0. Under Assumption A1, $\Delta(c_1) > \Delta(c_0)$ so $p^M_{iL}(c_1) > p^M_{iL}(c_0)$. A more negative context increases the retrieval weight on negative memories and thus the subjective probability of transitioning to L.

Corollary (Cross-sectional rejection gap). If rejected households are more likely to be in the negative context c_1, i.e. $\Pr(c_1 \mid R) > \Pr(c_1 \mid \neg R)$, then they recall a more negative set of experiences ($\Delta^R > \Delta^{\neg R}$) and form more pessimistic beliefs: $\mathbb{E}[p^M_{iL} \mid R] - \mathbb{E}[p^M_{iL} \mid \neg R] > 0$, where $\mathbb{E}[p^M_{iL} \mid g]$ denotes the average subjective probability among group g.

Rejections therefore shift both the database and the context, tilting recall toward negative experiences and increasing the probability assigned to adverse macro states. In the credit domain, recalled credit conditions provide a natural proxy for the recalled set, and recall errors proxy for its distortion relative to realised conditions. The mechanism therefore organises the empirical patterns in Figure 4. I now use the model to derive predictions about when and where the rejection gap should be strongest.

The role of a personal rejection. Since a rejection both augments the memory set with an experience $R = e_{LL}$ and shifts context from c_0 to c_1 (Assumption A2), there are two effects worth considering. Let $M^R = M \cup \{R\}$ be the database of a rejected household. Then, when forecasting a Low state L, the beliefs of those rejected are given by

$$p_{iL}^{M^R}(c_1) = p_{iL}^{M}(c_1) + r\big(R, [\theta_{iL}, c_1]\big)\left(1 - p_{iL}^{M}(c_1)\right) \tag{5}$$

where $r(R, [\theta_{iL}, c_1]) = \frac{S(R,[\theta_{iL},c_1])}{\sum_{m \in M^R} S(m,[\theta_{iL},c_1])}$ is the probability of recalling the rejection experience.

The first term is the *context reweighting* of existing memories under the more negative context c_1: the more negative the context, the higher the weight on L−ending memories. The second term is a *direct recall* effect from retrieving the memory R: the higher the similarity between the rejection and the hypothesis, the higher the probability of recalling that rejection experience.

Proposition (Rejected vs. Accepted). Let $\hat{p}_{iL}^{R} \equiv p_{iL}^{M^R}(c_1)$ denote the belief of rejected households and $\hat{p}_{iL}^{A} \equiv p_{iL}^{M}(c_0)$ those of accepted households (a proxy for the absence of R under a neutral context). Under Assumptions A1-A2, and if the only differences between groups are that (i) rejected households include $R = e_{LL}$ in their database and (ii) they face context c_1 while accepted households face c_0, then the rejection-acceptance gap in subjective beliefs equals

$$\hat{p}_{iL}^{R} - \hat{p}_{iL}^{A} = \underbrace{\left[p_{iL}^{M}(c_1) - p_{iL}^{M}(c_0)\right]}_{\text{Context reweighting (CR)}} + \underbrace{r\big(R, [\theta_{iL}, c_1]\big)\Big(1 - p_{iL}^{M}(c_1)\Big)}_{\text{Direct recall (DR)}} \equiv \beta_r > 0. \tag{6}$$

I refer to β_r as the rejection-acceptance gap in beliefs. Relative to accepted households, the rejected both (i) reweight existing memories toward "Low" states because their context is more negative (CR), and (ii) add a directly retrievable negative episode (DR), both forces increasing the perceived probability of a low state. If baseline contexts also differ across groups, an additional residual term appears.[13] Appendix D.7 presents the general formula and discusses its implications.

The model not only captures the baseline gap β_r but also delivers a set of testable heterogeneity predictions driven by two distinct forces: (i) perceived similarity (which governs how an idiosyncratic experience spills over across domains), and (ii) the allocation and context of experiences (which generate cross-sectional and state-dependent variation in the size of the gap). Formal proofs are in Appendix D.1.

[13] As long as this residual does not dominate, rejections remain a distinct source of belief heterogeneity through the context reweighting and direct recall channels. The empirical analysis in Section 3 suggests this residual is unlikely to dominate: the rejection gap is robust to a rich set of controls for observable differences across groups, time fixed effects, and conditioning on prior beliefs.

First, perceived similarity is the key object linking an idiosyncratic rejection to a macro outcome. When a rejection feels closer to a given domain, it is more likely to be recalled when forecasting that domain and more likely to be used in beliefs. Because retrieval is feature-based, the same experience can also spill over to other outcomes that share salient features with the rejection, with the strength of spillovers governed by perceived similarity.

Prediction H1 (Domain gradient). Similarity delivers a partial ordering across domains:

$$S\big(R,[\theta_{LL}^{\text{credit}},c]\big) > S\big(R,[\theta_{LL}^{d},c]\big) \;\Rightarrow\; \beta_r^{\text{credit}} > \beta_r^{d}, \quad d \in \{\text{unemployment},\ \text{inflation},\ \text{stocks}\}.$$

The rejection gap in beliefs is therefore largest for beliefs about credit and smaller (but positive) in other markets that share negative features. The order depends on individuals' perceived similarity between the experience and the macro outcome.

Second, a central implication of memory-based belief formation is that aggregate disagreement reflects not only differences in exposure to common news, but also the cross-sectional distribution of personal experiences. Credit rejections are disproportionately experienced by particular groups, and the same rejection can have different effects across households and states because recall depends on primitives such as the size of the memory pool, the intensity of context and the current state. The model therefore predicts systematic heterogeneity in β_r. The next predictions make these forces explicit.

Prediction H2 (Memory pool size). The rejection gap declines with the size of the memory pool M, $\partial\beta_r/\partial|M| < 0$, because the probability of recalling any given experience $r(\cdot)$ declines as the total size of the memory pool increases.

Prediction H3 (Context intensity). By Assumption A1, a more negative context raises the relative recall of L-ending memories, so the rejection gap in beliefs β_r increases with context negativity. Intuitively, rejections are more easily recalled for those in more adverse contexts and for whom such events are especially costly.

Prediction H4 (State dependence). When the prevailing macro state is Low, similarity between R and the cue is higher, because of shared valence:

$$S\big(R,[\theta_{LL},c]\big) > S\big(R,[\theta_{HL},c]\big) \;\Rightarrow\; r\big(R,[\theta_{LL},c]\big) > r\big(R,[\theta_{HL},c]\big) \;\Rightarrow\; \beta_r^{(LL)} > \beta_r^{(HL)}.$$

Thus, downturns amplify the rejection gap: personal rejections are more easily recalled leading to stronger pessimism in beliefs.

In the next subsection, I bring the model to the data and test whether variation in the rejection gap across demographics, macro states, and perceived similarity matches the mechanism's predictions.

4.3 Supporting Evidence

Perceived similarity. Prediction H1 is a mechanism test: if rejections are linked to beliefs through similarity-based retrieval, then cross-domain spillovers as documented in Figure 2 should line up with the similarity ranking of a rejection to each macro outcome.

A key challenge in testing memory-based mechanisms is that perceived similarity is typically latent. I address this directly by measuring similarity judgments for the relevant personal experience and macro outcomes in a new online survey. Quantifying perceived similarity matters because it pins down when an idiosyncratic event is treated as macro-relevant, and therefore when personal experiences can generate predictable wedges in aggregate expectations. While Bordalo et al. (2023, 2025) emphasise similarity as a primitive governing recall and belief distortions, direct measures of this primitive are rarely available in economic applications.[14] The survey provides such a measure in the context most relevant for this paper.

The survey was fielded in October 2025 to approximately 1,600 U.S. respondents recruited via Prolific. Although the survey was open to all U.S. residents to avoid selection into participation, the final sample focuses on credit market participants only, as having actually experienced the rejection is crucial for a test of the mechanism.[15] The final sample therefore consists of 970 individuals who applied to some form of credit in the last 12 months, among which 24% experienced a credit rejection, in line with average rates from the SCE.

Participants are asked whether they had applied to any credit in the last 12 months and what was the outcome of such application, using the same wording as in the SCE. Then, conditional on their experience, they start a similarity task. Participants are asked to rate on a scale from 1 (not similar at all) to 7 (extremely similar) how similar they perceive their personal credit experience to several macroeconomic outcomes: credit conditions, unemployment, inflation, and stock prices, each described in two valences L and H (e.g., "credit becomes easier" vs. "credit becomes tighter"). They also evaluate key attributes of the recalled event: its vividness, perceived impact, how pleasant the memory is, and degree of surprise. The study received ethical approval from the Bocconi University IRB (Protocol EA000997) and was pre-registered on AsPredicted.org (Registration 250249). Design, sampling, and measures are provided in Appendix C.

Figure 5 provides a tight link between the model and the data: the domain pattern of rejection gaps in the SCE (Panel A) tracks the perceived similarity of a rejection to each outcome measured independently in the survey (Panel B). Personal rejections are perceived as highly similar to tight credit markets, followed by high inflation, high unemployment, and lastly low stock

[14]For example, Bordalo et al. (2025) elicit perceived similarity between COVID-19 and other risks such as crime or theft in experimental tasks. In contrast, I elicit similarity for a concrete, personally experienced credit outcome and link it directly to macroeconomic expectations.

[15]After providing informed consent, respondents were asked whether they had applied for any form of credit in the past 12 months. Those who had not were thanked and screened out.

prices,[16] mirroring the SCE domain gradient in beliefs.

Since in the survey people use a scale to state their perceived similarity, one might be concerned that participants may differ in how they used the similarity scale. To account for this, all respondents first completed a short task rating the similarity between everyday objects unrelated to the macro. This exercise served as both a practice example and a benchmark for individual scaling behaviour. Adjusting similarity responses using each respondent's range from this benchmark leaves the domain ranking unchanged (Appendix Figure C.3).

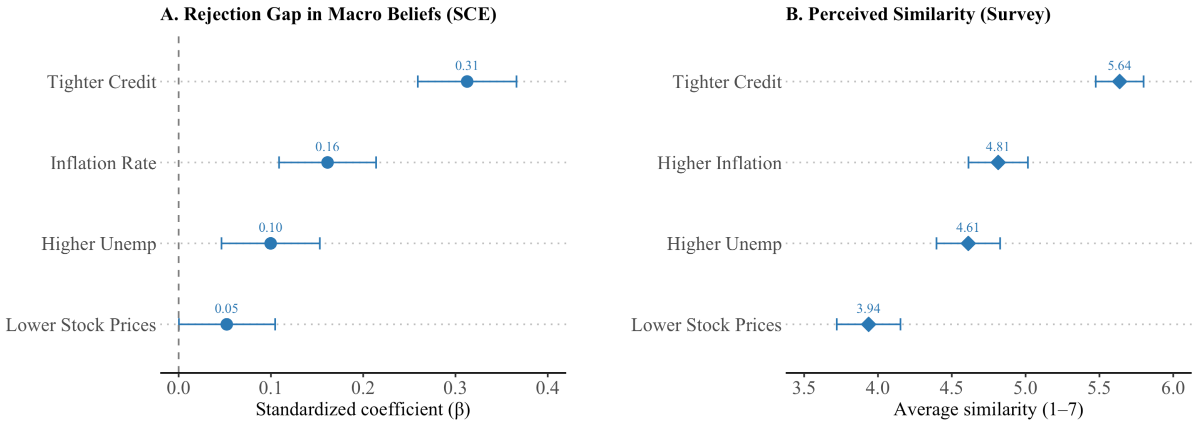


Figure 5: Rejection Gap in Beliefs and Perceived Similarity

Notes: Panel A plots the rejection-acceptance gap in macroeconomic expectations using SCE data as in Section 3.2. Panel B reports perceived similarity between personal credit experiences and macroeconomic outcomes from the online survey (among rejected individuals).

A second advantage of eliciting similarity is that it provides a direct way to evaluate the source of the asymmetry in beliefs (i.e. rejections are associated with pessimism about the macroeconomy, acceptances are not associated with corresponding optimism). In the model, any past experience can in principle be recalled when forecasting the macro state, with its influence proportional to its perceived similarity $S(m,\theta)$ to the target. The framework therefore does not require symmetry between positive and negative cues; an asymmetry in beliefs will arise whenever negative and positive experiences are encoded as differentially similar to Low versus High macro states. This observation suggests a direct empirical test in the survey data.

To implement this test, I construct for each respondent a model-based measure of perceived similarity, the *Low-state Similarity Share* (LSS): the share of similarity weight assigned to adverse ("Low") rather than favorable ("High") macro outcomes,

$$\mathrm{LSS}(m)^d = \frac{S(m,\theta^d_{iL})}{S(m,\theta^d_{iL}) + S(m,\theta^d_{iH})}, \text{ where } m \in \{A, R\}.$$

[16]Rejected households rate the similarity between a personal credit rejection and stock prices as essentially neutral (4 on a 1-7 scale), consistent with the near-zero rejection gap in that domain.

which I average across domains d to get one summary measure per individual. An LSS of 0.5 reflects equal perceived similarity of experience m to Low and High states, while values above (below) 0.5 indicate that the experience feels closer to adverse (favorable) macro conditions. Empirically, the average LSS among rejected respondents is 0.653 ($p < 0.001$), significantly above 0.5, whereas for accepted respondents it is 0.494 ($p = 0.19$), statistically indistinguishable from 0.5. This compact summary mirrors the model's similarity weighting and shows that rejections are perceived as macro-relevant and negatively valenced, while acceptances remain largely neutral. Appendix Table C.6 presents alternative ways of measuring this asymmetry and shows that the differences remain statistically and substantively large after adjusting for individual scale use. In line with the associative-recall mechanism, the asymmetry in expectations is thus reflected in an asymmetry in perceived similarity.

Because the similarity function is feature-based, the attributes or features with which an experience is encoded should matter. In the survey, respondents report several attributes of their most recent credit experience. Compared to acceptances, rejections are rated as more unexpected, more unpleasant, financially more negatively consequential, and more vividly remembered (Appendix Figure C.4). These attributes matter for perceived similarity. For example, conditional on rejection, the more unexpected, vivid and negatively impactful, the stronger the perceived similarity of the rejection to tighter credit (Appendix Table C.7). When I control for these attributes of the experience, the rejection-acceptance gap in Low-state Similarity Share (LSS) is reduced by about 43% (Appendix Table C.8). Thus, a sizeable fraction of the asymmetry can be accounted for by a small set of observed features of the experience. A fuller exploration of these channels underlying the asymmetry lies beyond the scope of the present paper but offers a promising direction for future research.[17]

Overall, the SCE and survey evidence jointly support the similarity-based recall channel: the cross-domain pattern and asymmetry in beliefs are mirrored by the corresponding similarity map elicited at the individual level.

Allocative consequences of memory. A distinctive implication of the model is that disagreement can be traced to *who experiences* rejections and *when* those experiences are most likely to come to mind. Because rejections are unevenly distributed across the population, and because recall depends on primitives such as the size of the memory pool and the intensity of context, the model predicts systematic heterogeneity in the rejection gap. Predictions H2–H4 translate this idea into three comparative statics that I test in the cross section: experience-pool attenuation, context amplification, and state-dependence.

[17]More broadly, the asymmetry in similarity is what one would expect if negative experiences are more likely than positive ones to be encoded as diagnostic of adverse macro states: rejections are salient negative experiences encoded with features that make them feel similar to Low macroeconomic outcomes, whereas approvals are more likely to be encoded as personally favourable but only weakly similar to High macro states. This pattern is also consistent with evidence from psychology and neuroscience that negative events are processed more deeply and weigh more heavily on subsequent judgment, and that people maintain self-serving, positively biased interpretations of favorable outcomes (Rozin and Royzman, 2001; Baumeister et al., 2001; Mezulis et al., 2004).

To operationalise these forces, I use age as a proxy for the size of the memory pool and two proxies for context negativity: recent changes in the household's financial situation and socio-economic status (education and income). While these measures are imperfect, they are directly observable and map naturally to the model's primitives.

Prediction H2 implies experience-pool attenuation: the rejection gap should be smaller for older respondents, for whom any single experience represents a smaller share of the recalled pool. Prediction H3 implies context amplification: the gap should be larger when the household's context is more adverse, proxied by a worsening financial situation and low SES. Results are summarised in Figure 6.

Consistent with the predictions, the rejection gap is smaller among older respondents, larger among those who report their financial situation has become much worse, and larger among low-SES than high-SES households. These findings also align with evidence that lower socioeconomic status correlates with more pessimistic macro expectations (Das, Kuhnen and Nagel, 2020). Consistent with the retrieval channel, Appendix D.3 shows that these same groups also recall tighter credit conditions. Conditioning on recalled tightness substantially attenuates the rejection coefficient within groups, suggesting that the amplification operates through differences in what comes to mind when beliefs are formed.[18]

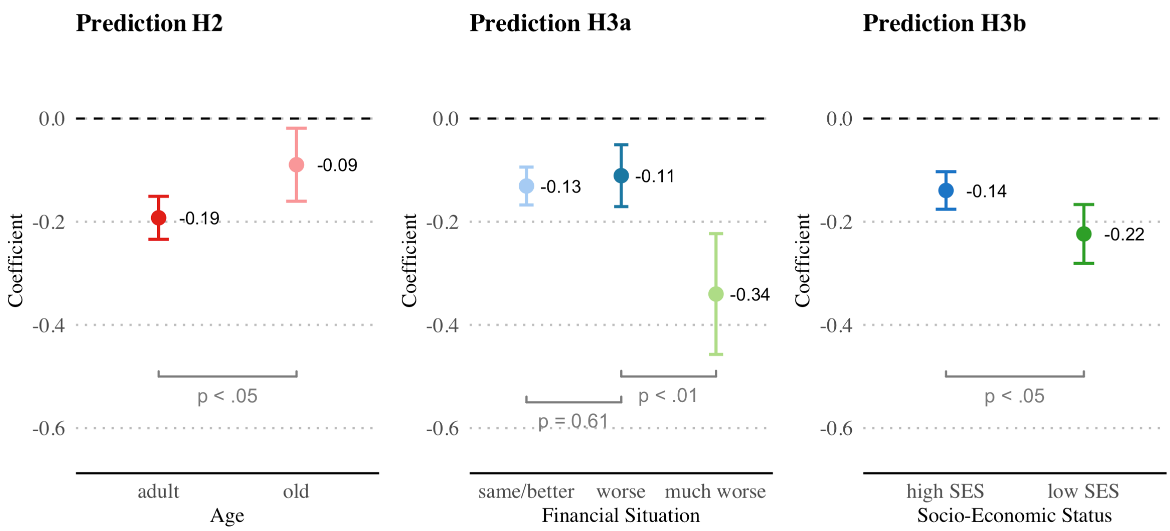


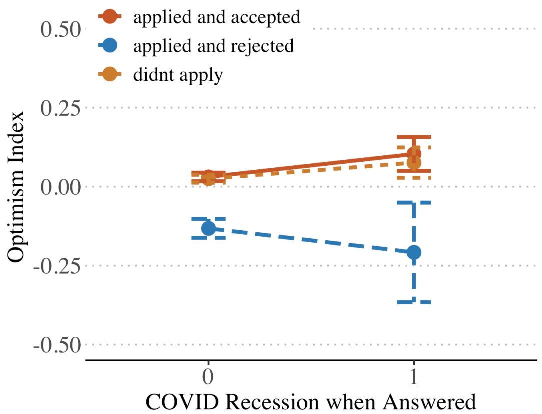
Figure 6: Test of Prediction H2 and H3: Age, Context and SES

Notes: Each panel plots estimated rejection coefficients with 95% confidence intervals from regressions that interact the rejection indicator with (i) age group (adult vs. old, left), (ii) perceived financial situation (same/better, worse, much worse, center), and (iii) socio-economic status (high vs. low SES, right): $OPTM_{it} = \sum_g \beta_r^g \text{ Rejected}_{it} \times \mathbb{1}\{G_i = g\} + \sum_g \nu^g \mathbb{1}\{G_i = g\} + \delta X_{it} + \chi_t + e_{it}$, where the coefficients β_r^g capture the rejection-acceptance gap within each subgroup. All specifications include controls and time fixed effects.

[18] While a larger rejection–acceptance gap for low-SES households or for those in worse financial situations is consistent with contextual retrieval, this heterogeneity cannot by itself disentangle whether the amplification comes from the rejection being more salient and costly (a direct-recall effect) or from a more negative baseline context in which these households live. I discuss this in Appendix D.

Prediction H4 implies that the rejection gap should be state-dependent: in bad times, past negative experiences are more similar to the prevailing macro state and thus more likely to be recalled, widening the gap. To test this, I interact past rejections with (i) an indicator for the COVID-19 recession of 2020 and (ii) the contemporaneous unemployment rate. Results are presented in Figure 7.

The left panel of Figure 7 shows that the rejection-acceptance gap in macroeconomic expectations nearly doubles when respondents are surveyed during the COVID recession. Importantly, the rejection experience occurred in the previous 12 months, while the COVID recession refers to the period in which they answer the survey. By contrast, beliefs of those who were accepted or did not apply move closely together across states, indicating that state dependence is concentrated among the previously rejected. The right panel shows a similar pattern for unemployment expectations: the rejection gap increases with the contemporaneous unemployment rate, consistent with the same cuing mechanism. These results imply that disagreement can disproportionately rise in bad times: downturns raise the retrievability of negative personal experiences, widening the cross-sectional wedge in expectations and potentially reinforcing contractions.



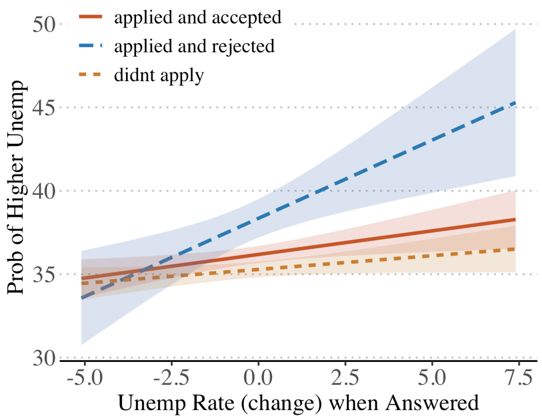


Figure 7: Test of Prediction H4: State Dependence in Beliefs

Notes: The figure plots interaction effects shown in Appendix Table D.9. 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.

Discussion and alternative explanations. Taken together, the evidence establishes a robust conditional pattern: recent credit rejection is associated with systematically more pessimistic macroeconomic expectations, even after controlling for rich observables, local time-varying shocks, and prior beliefs, and despite the limited informativeness of rejections for subsequent macro outcomes. The pattern is structured in ways that are hard to reconcile with confounding: the rejection gap displays a cross-domain gradient that aligns with independently measured perceived similarity, varies predictably with age and financial context, and strengthens in downturns. Within credit, the SCE recall module provides direct evidence consistent with a selective-memory channel. Online Appendix C shows that the memory-based framework coincides with Bayesian updating when recall is restricted to relevant macro transitions, and diverges precisely when personal experiences enter through perceived similarity, the case supported by the data.

While time-varying individual-level unobservables cannot be fully excluded in this setting, an alternative explanation would need to jointly account for these cross-domain gradients, comparative statics, and recall patterns. I therefore use the model to interpret the rejection gap through selective and associative recall, and to clarify why the mechanism can be macro-relevant. The next section studies the economic implications of these findings.

5 Implications for Economic Behaviour

Households rely on credit markets to smooth consumption over time, and rejections can directly impair this ability by tightening borrowing constraints. The evidence in this paper suggests a complementary margin: rejections are also systematically associated with more pessimistic beliefs about the macroeconomy. Because beliefs shape spending and saving decisions, differences in personal credit experiences can translate into differences in behaviour beyond what borrowing constraints alone would predict.

This section uses a parsimonious consumption–saving framework as an organising device to separate these two margins (a *constraint (budget) channel* and a *belief channel*) and then returns to the SCE survey data to assess whether household behaviour is consistent with the model's predictions.

5.1 A Parsimonious Framework: Constraints versus Beliefs

Consider households who choose consumption and borrowing over three periods $t = 0, 1, 2$. Households receive an endowment each period, and aggregate income risk is captured by a two-state Markov process $\theta \in \{H, L\}$ as in Section 4. Households can borrow subject to a credit limit, but at $t = 0$ a fraction λ_0 of credit applicants are rejected. Let $g \in \{A, R\}$ indicate whether a household is accepted or rejected at $t = 0$. Online Appendix D provides further details and derivations.

The key object for behaviour is the household's *subjective* belief about future income. Let $\hat{E}^g_t(y_2)$ denote the expectation of period-2 income. With quadratic utility and $\delta = 1/\mathcal{R}$, optimal choices imply consumption smoothing across $t = 1, 2$, so the desired borrowing at $t = 1$ takes the form

$$b^{g,i}_2 = \frac{1}{1+\mathcal{R}}\Big[\hat{E}^g_1(y_2) - y^i_1 + \mathcal{R} b^g_1\Big], \tag{7}$$

where $\mathcal{R}$ is the interest rate, b_1^g is the debt carried from $t = 0$ and $i \in \{H, L\}$ denotes the realised state at $t = 1$.

Benchmark (no imperfect memory). In a model without selective recall, the credit experience does not generate heterogeneity in beliefs: rejected and accepted applicants share the same conditional beliefs about future income, so $\hat{E}_t^A(y_2) = \hat{E}_t^R(y_2)$ for $t \in \{0, 1\}$. Equation (7) then implies that rejections affect behaviour only through the constraint term b_1^g: accepted households borrow at $t = 0$ and later repay, while rejected households do not. This is the standard budget/constraint channel.

Imperfect recall and an additional belief channel. Under selective recall as in Section 4, a rejection is a salient negative experience that shifts the recalled set toward adverse episodes. This implies that rejected households place a higher subjective probability on the low-income state at $t = 2$. The heterogeneity in beliefs is thus captured by:

$$\hat{E}_1^A(y_2) - \hat{E}_1^R(y_2) = (p_{iL}^R - p_{iL}^A)(y_2^H - y_2^L) \equiv \beta_r(y_2^H - y_2^L), \tag{8}$$

where $\beta_r > 0$ summarises the rejection–acceptance belief gap generated by selective recall.

Combining (7)–(8) yields a decomposition of the behavioural gap into a constraint term and a belief term:

$$b_2^{A,i} - b_2^{R,i} = \frac{1}{1 + \mathcal{R}} \Big[\underbrace{\mathcal{R} b_1^A}_{\text{constraint}} + \underbrace{\beta_r (y_2^H - y_2^L)}_{\text{belief}} \Big]. \tag{9}$$

Relative to the benchmark without imperfect memory, selective recall introduces a new margin: a rejection now enters behaviour twice — directly, by tightening today's budget constraint, and indirectly, by shifting expected future income through what comes to mind. Even holding observed constraints fixed, more pessimistic beliefs (lower $\hat{E}_1^R(y_2)$) reduce desired borrowing and, through smoothing, depress desired spending. The comparative statics of β_r from Section 4 carry over directly: the belief channel is stronger when the rejection is more salient (context) and when the memory pool is smaller (e.g., for younger households).

5.2 Behavioural Evidence

The model's central prediction is that credit rejections shape behaviour through two channels: a direct constraint channel and an indirect belief channel. To assess whether the belief channel is empirically present, I proceed in three steps. First, I document the basic association between rejections and spending and saving outcomes. Second, I quantify the share of these associations that is statistically absorbed by measured macro beliefs, and test whether this share is larger where the model predicts. Third, I examine households' stated saving motives, which provide a direct check on whether borrowing-related concerns enter the picture.

The belief margin in durable spending. Table 4 documents the basic behavioural association: rejected households are more likely to report no durable purchase in the past four months and report a lower probability of purchasing a durable in the next four months. These patterns are consistent with lower realised consumption and more cautious forward-looking spending plans among the rejected.

Table 4: Past and Planned Durable Consumption

	(1) No durable in past 4m	(2) Prob. durable next 4m (0–100)
Applied and rejected	0.049***	−1.997***
	(0.017)	(0.638)
Mean Dep.Var.	0.36	16.55
R^2	0.102	0.089
Observations	13996	13996

Notes: Coefficients from regressions of the specified outcome on a rejection indicator, demographic controls, and state-time fixed effects. Column 1 is a binary outcome equal to one if the respondent reports no durable purchase in the past four months. Column 2 is the reported probability of purchasing a durable in the next four months (average across appliances, electronics, furniture, and home repairs). $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

To connect these patterns to the belief channel in Equation (9), I implement a mediation decomposition using planned durable purchases. The exercise asks: of the total association between rejections and reduced durable spending, how much operates through the association between rejections and macro pessimism? I implement this using standard mediation tools (Imai et al., 2011; Tingley et al., 2014). The identifying assumptions and robustness are discussed in Online Appendix D.

Table 5 shows that rejection is associated with a lower probability of purchasing a durable (about two percentage points relative to a mean of 16.6%). Under the decomposition assumptions, the indirect component associated with beliefs accounts for about 8% of the total association. This share is modest but economically meaningful given that it reflects just one measure of macro expectations, and it is consistent with the model's implication that belief distortions can operate alongside borrowing constraints.

Table 5: Direct and Indirect Channel of Rejection on Durable Plans

	Indirect (IE)	Direct (DE)	Total	Prop. Mediated
Estimate	−0.158	−1.824	−1.982	0.081
p-value	< 0.001	0.002	< 0.001	< 0.001

Notes: Estimates from the R `mediation` package with 1,000 quasi-Bayesian simulations and robust covariance Tingley et al. (2014). The outcome is the reported probability (0-100) of a durable purchase in the next 4 months.

Heterogeneity in the belief margin. To test whether the belief margin is inline with the memory mechanism, I exploit the model's heterogeneity predictions: the belief margin should be larger when the memory pool is smaller (younger households) and when the rejection is more salient (lower-SES households). Both predictions are confirmed in Table 6: the indirect component is roughly three times larger for low-SES than for high-SES respondents, and substantially larger for younger than for older respondents. These patterns mirror the heterogeneity documented in beliefs in Section 4.3.

Table 6: Moderated Mediation: Indirect Channel by Age and SES

	High SES	Low SES	Older Age	Younger Age
Indirect (IE)	-0.16^{***}	-0.44^{***}	-0.10^{*}	-0.16^{***}
Direct (DE)	-3.41^{***}	-0.62	-2.23	-1.61^{**}
Proportion Mediated	0.04^{***}	0.26	0.03	0.09^{**}

Notes: Direct and indirect effects estimated using moderated mediation. SES is proxied by education and income; age split is above/below 60. Standard errors are robust. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Saving behaviour. The Finance Module of the SCE allows a complementary test through saving outcomes. If the belief channel operates as the model predicts, rejected households should not only spend less on durables but also save more, motivated by pessimistic expectations. Table 7 confirms this pattern: rejected households are less likely to expect their savings to gain in value (Column 1) and report higher saving flows over the past year (Column 2).

Most directly, rejected households are 27 percentage points more likely to cite "expected difficulty borrowing in the future" as an important saving motive (Column 3). This stated motive maps closely onto the belief channel: households are not just saving more, they are saving more *because* of pessimistic expectations about future credit access.

Table 7: Changes in Saving and Past Rejections

	Savings ↑ value	$\log(1 + \frac{savings}{income})$	Reason: difficult to borrow
Rejected	-0.176^{***}	0.151^{***}	0.269^{**}
	(0.055)	(0.074)	(0.115)
Mean Dep.Var.	0.857	0.115	0.209
R^2	0.114	0.289	0.209
Observations	3767	1815	1816

Notes: Each column reports the coefficient on a rejection indicator. All regressions include demographics, wealth and debt quantiles, changes in income, wealth and health in the last year, plus state and time fixed effects. Column 1: binary outcome equal to one if the respondent expects savings to gain value. Column 2: log of new savings over income. Column 3: binary outcome equal to one if the respondent cites expected borrowing difficulty as a very important reason for saving. Reported means of the dependent variables are shown in the row "Mean Dep. Var.". Robust standard errors in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

In sum, across consumption and saving outcomes, the data show systematic behavioural differences associated with credit rejection. A parsimonious model without imperfect memory would attribute these differences primarily to borrowing constraints. Allowing for selective recall introduces an additional belief margin, and the evidence is consistent with this margin being present and economically relevant, particularly among younger and lower-SES households.

5.3 Aggregate Overreaction: an Illustrative Aggregation

Can experience-linked beliefs translate into aggregate demand sensitivity? The evidence in this paper points to several features that make this plausible. Credit rejections are associated with broad-based pessimism that is concentrated among the rejected rather than offset by symmetric optimism among the accepted; this pessimism spills over to expectations about other macro outcomes, including unemployment and inflation; it co-moves with spending and saving plans; and it is stronger in downturns, consistent with negative experiences becoming more salient when aggregate conditions are weak.[19]

To illustrate the potential aggregate relevance of this mechanism, I conduct a stylised aggregation exercise. I combine (i) the share of households experiencing rejections with (ii) the estimated increase in the rejection–belief gap in downturns, and translate these moments into an implied additional decline in aggregate consumption in bad times.

State-Dependence in Beliefs and Aggregate Demand. Let λ_0 denote the share of households who experience a credit rejection over the relevant horizon. Let β_i denote the rejection–acceptance gap in the subjective probability of a Low aggregate state when the current state is $i \in \{H, L\}$. Let $G_y \equiv y_2^H - y_2^L > 0$ summarise the income gap between the High and Low states in the consumption–saving framework of Section 5.1.

Aggregating the model's consumption rule yields a decomposition of the change in aggregate consumption between states:

$$C_1^H - C_1^L = \underbrace{\left(C_1^{A,H} - C_1^{A,L}\right)}_{\text{benchmark (constraints and fundamentals)}} + \underbrace{\kappa\, G_y}_{\text{additional state-dependent belief component}}, \tag{10}$$

where the additional belief component is summarised by

$$\kappa \equiv \frac{\lambda_0}{1 + \mathcal{R}} \left(\beta_L - \beta_H\right).$$

If recall were absent ($\beta_H = \beta_L = 0$) or not state dependent ($\beta_H = \beta_L \neq 0$), the second term would be zero. With state-dependent recall ($\beta_L > \beta_H$), personal negative experiences are more likely to be recalled when the current macro state is also relatively negative, and thus beliefs

[19] The asymmetry between rejections and acceptances matters for average levels of pessimism, but the state dependence arises more generally from cue-dependent retrieval of negative experiences.

add an extra state-dependent wedge: the economy becomes more sensitive to a deterioration in fundamentals because the rejection–belief gap widens precisely in Low states.

To quantify the size of this belief component, I discipline κ using moments from the SCE. I set the rejection share to its sample average, $\lambda_0 = 0.18$. I define a Low state as an increase in unemployment by one standard deviation, and use the estimated state dependence in the rejection gap, $\beta_L - \beta_H = 1.669$ (Appendix Table D.9). These values imply $\kappa \approx 0.30/(1 + \mathcal{R})$. Intuitively, this means that state-dependent recall increases the sensitivity of aggregate consumption to the income gap G_y by roughly 30 basis points (scaled by $1/(1 + \mathcal{R})$).

While the exercise is stylised, it points to a potentially important margin: even a simple aggregation of micro evidence on personal rejections suggests a non-trivial additional sensitivity of aggregate consumption to downturns through belief formation. The estimate is best read as a lower bound. It focuses on a non-credit outcome (unemployment expectations) and abstracts from within-domain effects on credit-condition expectations, repeated participation in credit markets, and general equilibrium feedback, channels through which the memory mechanism could plausibly generate larger effects in richer settings.

6 Conclusion

This paper documents that idiosyncratic experiences can shape macroeconomic beliefs in structured and predictable ways. Households denied credit are systematically more pessimistic across macroeconomic outcomes, with a similarity-based ordering across domains and stronger effects among the young, the lower-SES, and in downturns. The evidence points to a memory-based mechanism, supported by direct measurement of perceived similarity in a complementary survey, and the resulting belief distortions show up in spending and saving decisions in ways consistent with the model's predictions.

Three broader implications follow. First, the paper shows that the cross-domain spillovers of personal experiences can be measured, ordered, and predicted, a step toward grounding "sentiment" in macroeconomic models in the documented experiences of individual households. Second, the evidence points to a belief margin that operates alongside borrowing constraints: even when credit access is held fixed, rejected households reduce durable spending and raise precautionary saving in ways consistent with their more pessimistic beliefs. Third, because the belief margin amplifies in downturns and concentrates among high-MPC households, it provides a mechanism by which idiosyncratic credit-market events can shape aggregate demand precisely when and among whom borrowing constraints already bind hardest. From a policy perspective, this implies that interventions altering the incidence or salience of credit rejections may operate not only through contemporaneous credit access but also through how households form expectations about the economy more broadly.

An important next step would be to integrate these belief dynamics into richer macroeconomic models. The evidence here suggests that household expectations are not well described by rational updating on common information, but instead reflect personal experiences, contextual cues, and selective recall in ways that are systematic and measurable. Building these features into heterogeneous-agent and business-cycle models would allow a quantitative assessment of how experience-driven belief heterogeneity shapes aggregate dynamics, particularly in downturns. The similarity-based ordering documented here also raises the question of whether other personal shocks (such as job loss, health events, housing shocks) generate comparably structured spillovers, and whether perceived similarity can be measured systematically enough to organise these patterns across domains.

Appendix

A Descriptive Statistics

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

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

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

B Regression Results

B.1 Main Results

Table B.2: Rejection Gap vs Income Gap

	Credit	INFL	UNEMP	StockP
Applied and Rejected	0.319^{***}	0.162^{***}	0.105^{***}	0.059^{**}
	(0.027)	(0.027)	(0.027)	(0.027)
Didn't Apply	-0.026^{*}	-0.039^{***}	-0.036^{***}	0.044^{***}
	(0.014)	(0.014)	(0.014)	(0.014)
Income Tercile: Mid	-0.111^{***}	-0.144^{***}	-0.056^{***}	-0.108^{***}
	(0.017)	(0.017)	(0.017)	(0.017)
Income Tercile: High	-0.113^{***}	-0.228^{***}	-0.027	-0.193^{***}
	(0.020)	(0.020)	(0.020)	(0.020)
Within R^2	0.035	0.038	0.012	0.056
Observations	25161	25091	25132	25135

Notes: The table presents regression coefficients of equation 1 with standardised outcomes. The reference category for credit experience is Accepted, while the reference category for income group is Low Tercile. The lowest tercile refers to those with household income below $40,000 approximately, while the highest tercile refers to those with household income above $100,000. All specifications include demographic and socioeconomic controls as well as state-month-year fixed effects. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

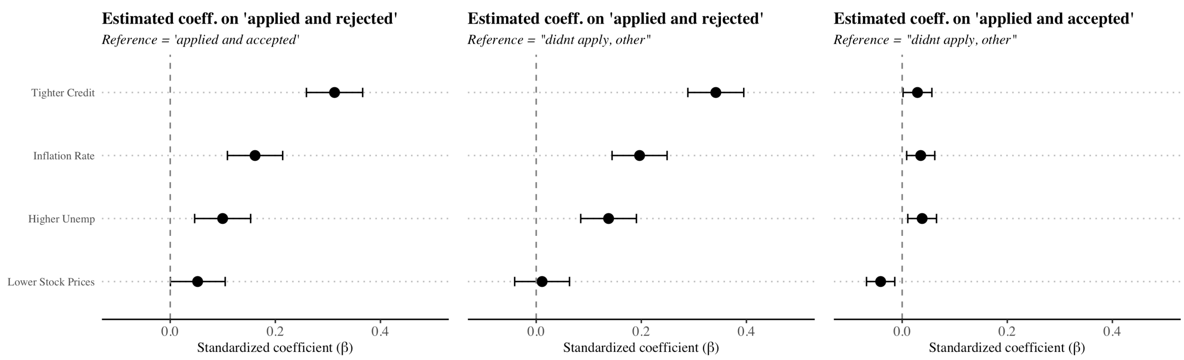


Figure B.1: The rejection gap in macro beliefs, for different reference categories

Notes: Each figure presents estimated standardised coefficients of a credit experience, for each macro outcome of interest. All specifications include baseline controls and state-month-year fixed effects. Standard errors are clustered at the respondent and date level.

B.2 Forecast Errors

For each survey outcome, I construct an objective 12-month-ahead realized counterpart and define a signed "forecast error" as realized minus forecast. Signs are normalised so that $FE_{it}^{k} < 0$ corresponds to an overly pessimistic forecast relative to what subsequently occurs.

- *Inflation rate (point forecast).* Let Y^{π}_{t+12} denote realized CPI inflation over $[t, t+12]$, measured as the 12-month percent change in the CPI from BLS.[20] Let F^{π}_{it} denote respondent i's point forecast of inflation over the next 12 months formed at time t. I define

$$FE^{\pi}_{it} = Y^{\pi}_{t+12} - F^{\pi}_{it}.$$

With this convention, $FE^{\pi}_{it} < 0$ means the respondent forecast inflation higher than realised (overly pessimistic).

- *Unemployment (probability of increase).* Respondents report the subjective probability that the unemployment rate will increase over the next 12 months. Let u_t denote the unemployment rate (UNRATE, seasonally adjusted, monthly) from FRED, and define the realised event

$$Y^{u}_{t+12} = \mathbf{1}\{u_{t+12} - u_t > 0\}.$$

Let p^{u}_{it} denote respondent i's stated probability (recorded in percentage points) that unemployment increases. To keep units consistent, I define the signed error in percentage points as

$$FE^{u}_{it} = 100 \cdot Y^{u}_{t+12} - p^{u}_{it}.$$

Then $FE^{u}_{it} < 0$ means the respondent assigns too high a probability to the adverse event (unemployment increases).

- *Stock prices (probability of decline).* The SCE elicits the subjective probability that stock prices will increase over the next 12 months. To maintain the sign convention that negative errors correspond to pessimism, I work with the adverse event (a decline). Let P_t denote the Shiller S&P Composite Stock Price Index level (monthly), and define the realised event

$$Y^{s}_{t+12} = \mathbf{1}\{P_{t+12} - P_t \leq 0\}.$$

Let $p^{s,up}_{it}$ denote respondent i's stated probability (in percentage points) that stock prices increase. Define $p^{s}_{it} = 100 - p^{s,up}_{it}$ as the implied probability of a decline, and set

$$FE^{s}_{it} = 100 \cdot Y^{s}_{t+12} - p^{s}_{it}.$$

Then $FE^{s}_{it} < 0$ corresponds to assigning too high a probability to a stock price decline (pessimism).

- *Credit conditions (categorical).* Respondents report a categorical forecast $C_{it} \in \{\text{tighten}, \text{unchanged}, \text{loosen}\}$ for credit conditions over the next 12 months. I proxy the realised credit-conditions category C_{t+12} using the SLOOS net percentage of banks reporting tighter standards, aggregated over the subsequent year and discretised into tighten/unchanged/loosen using a threshold rule. To put forecasts and realisations on a common signed scale, I map categories to an ordered "tightness" index: loosen $= -1$, unchanged $= 0$,

[20] Series: CPI for All items in U.S. city average, seasonally adjusted; units are 12-month percent change; monthly data.

tighten = 1, and define the signed credit error

$$FE^c_{it} = C^{ord}_{t+12} - C^{ord}_{it}.$$

This object equals 0 if the respondent predicts the correct category and takes values in $\{-2,-1,1,2\}$ otherwise. With this coding, $FE^c_{it} < 0$ means the respondent forecast tighter credit conditions than subsequently occur (a pessimistic directional error).

Table B.3: Predictability of Forecast Errors

	FE Unemp.	FE Credit	FE StockP	FE Infl.
Panel A: *Applied and Accepted* as reference				
Applied and rejected	-2.431^{***}	-0.229^{***}	-1.515^{**}	-1.730^{***}
	(0.647)	(0.019)	(0.607)	(0.298)
Panel B: *Didn't Apply* as reference				
Applied and rejected	-3.402^{***}	-0.247^{***}	-0.516	-2.191^{***}
	(0.644)	(0.019)	(0.604)	(0.296)
Within R^2	0.021	0.041	0.064	0.043
Observations	22949	25157	25131	22909
Mean Dep.Var.	−22.16	0.037	−43.7	−3.29

Notes: This table reports estimates from Equation $FE^k_{it} = \alpha_k + \delta_k r_{it} + \gamma_k X_{it} + \mu_t + e^k_{it}$, with *Applied and Accepted* as the reference group in Panel A and *Didn't Apply* in Panel B. Forecast errors (FE) are defined as realised minus expected outcomes. All regressions control for household characteristics, state-of-residence and month-year fixed effects. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

B.3 Selection and Prior Bias

Table B.4: Entry into and Exit from Rejection and Macro Expectations

Dep.Var.:	OPTM	UNEMP↑	FCredit	StockP↓	INFL
Entered Rejection	−0.087***	2.438**	0.115***	0.253	1.035**
	(0.024)	(1.015)	(0.030)	(0.987)	(0.436)
Exited Rejection	−0.033	0.756	0.037	−0.432	0.356
	(0.022)	(0.934)	(0.028)	(0.908)	(0.402)
Lagged OPTM	0.587***				
	(0.005)				
Lagged UNEMP		0.479***			
		(0.008)			
Lagged FCredit			0.475***		
			(0.007)		
Lagged StockP				0.537***	
				(0.007)	
Lagged INFL					0.307***
					(0.007)
Within R^2	0.397	0.246	0.269	0.333	0.185
Observations	23859	14252	14286	14256	14205

Notes: *Entered Rejection* indicates respondents moving from non-rejected to rejected between waves; *Exited Rejection* indicates the reverse; the omitted category is all other transitions. All models include the full control set (demographics, household and financial variables, numeracy, risk, loan type, and recent changes in residence, employment, and composition) and state-month-year fixed effects. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

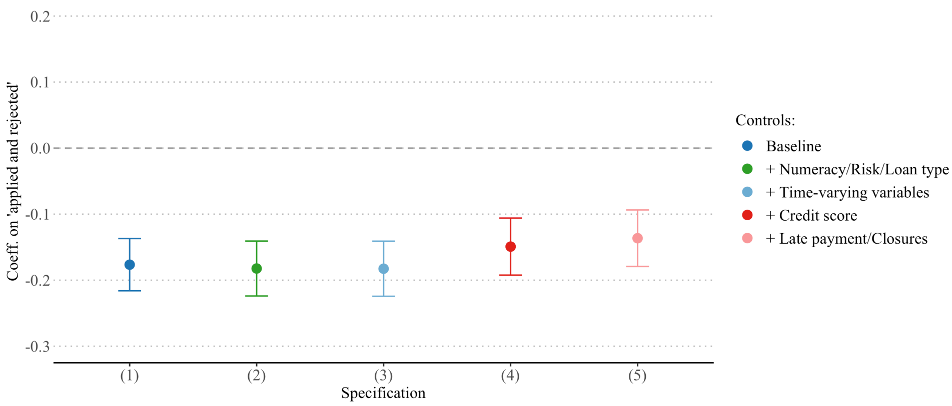


Figure B.2: Robustness of the Rejection Gap Across Specifications – Outcome: OPTM

Notes: Each point plots the coefficient on *applied & rejected* from panel OLS regressions as in Equation 1, estimated with month-year fixed effects and two-way clustered standard errors (by respondent and survey date). The omitted credit-application category is *applied and accepted*. Whiskers show 95% CIs. The x-axis reports five nested specifications: (1) baseline (age, female, married, college, race dummies, income category, partner employment, employment, unemployment duration); (2) + numeracy, risk preferences, and loan type; (3) + time-varying shocks (changes in residence, employment, and household composition); (4) + self-reported credit-score category; (5) + financial frictions in the past 12 months (30+/90+ day late payments, involuntary account closures). Each panel refers to a different outcome or macro expectation.

Individual Fixed Effects. Table B.5 reports estimates that add individual fixed effects to the baseline specification. While this estimator removes any time-invariant individual characteristics, it pools entries into and exits from rejection into a single within-person average. As Table 2 shows, these two transitions produce quantitatively different responses: entering rejection generates a sharp decline in optimism, while exiting rejection generates a smaller and statistically insignificant rebound. The lagged-optimism specification in the main text addresses this directly: by conditioning on each household's prior beliefs, it tests whether a change in credit status moves beliefs further than the household's existing level of pessimism would predict.

The FE point estimates are smaller in magnitude than the baseline but consistent in sign and statistically significant for OPTM, FCredit, UNEMP, and INFL, confirming that the rejection gap is not driven by stable individual heterogeneity.

Table B.5: Credit Market Rejection and Aggregate Pessimism within individuals

	OPTM	UNEMP↑	FCredit	StockP↓	INFL
Applied and Rejected	-0.057^{***}	1.267^{*}	0.059^{***}	0.435	0.907^{**}
	(0.018)	(0.764)	(0.023)	(0.715)	(0.383)
Didn't Apply	−0.006	−0.378	−0.019	1.341^{***}	−0.070
	(0.009)	(0.403)	(0.012)	(0.377)	(0.202)
Ind. Level Controls	Y	Y	Y	Y	Y
Month-Year FE + Ind. FE	Y	Y	Y	Y	Y
R^2	0.003	0.002	0.003	0.003	0.002
Num. obs.	27349	27304	27349	27306	27273

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

C Similarity Survey

This appendix describes the design and analysis of the similarity survey used to measure associative links between personal credit experiences and macroeconomic perceptions.

Objective and Hypotheses. The survey examines whether and how individuals perceive their personal credit market experiences as similar to broader macroeconomic outcomes. The central hypothesis is that personal experiences in credit markets shape the associative structure of beliefs about the economy. Specifically: (i) individuals who experienced a credit rejection perceive greater similarity between their own experience and adverse macroeconomic outcomes than those who were accepted; (ii) conditional on experience, perceived similarity follows a *domain gradient*: strongest for credit conditions and smaller, yet positive, for inflation, unemployment, and stock prices; (iii) memory attributes differ systematically across experiences, with rejections recalled as more vivid, less expected, less pleasant, and as having a stronger negative financial impact.

Sampling and Implementation. The survey is conducted online via Prolific, restricted to U.S.-based participants. Quotas are set to match the demographic composition of credit market participants in the New York Fed's Survey of Consumer Expectations (by age, race, and gender). Since roughly half of U.S. respondents are expected not to have applied for credit, I recruit about 2,000 individuals to obtain approximately 1,000 credit applicants. Based on SCE benchmarks, around 20% of applicants are expected to report a rejection.

The sample is restricted to participants who pass the attention check and complete the full survey, resulting in 970 respondents, among which 24% report being rejected in some loan application in the last 12 months, and 76% report having been accepted to all credit applications in the last 12 months.

Survey Design and Measures. The main dependent variable is a self-reported measure of perceived similarity. Respondents are first asked whether they applied for credit and, if so, what the outcome was (acceptance, rejection, or both). Those who did not apply are screened out. Participants who applied are then presented with four macroeconomic outcomes: credit conditions, unemployment, inflation, and stock prices, each described in both a positive and a negative version (e.g., "credit becomes easier" vs. "credit becomes tighter"). For each, they are asked:

> "Please think of your recent loan experience. How similar does it feel to the following economic scenarios?"

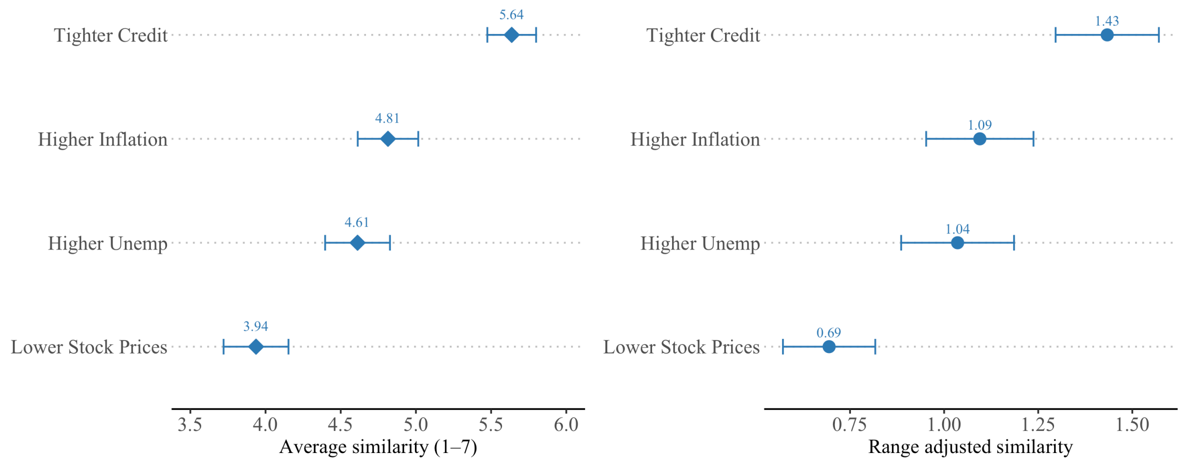
Responses are recorded on a 7-point Likert scale (1 = *Not similar at all*, 7 = *Extremely similar*). From these ratings, I construct: (i) average perceived similarity for each macro outcome and valence; (ii) a combined similarity measure across valences for each domain; and (iii) an overall similarity index averaged across all macro outcomes.

In addition, respondents evaluate four attributes of their credit experience: vividness, expectedness, pleasantness, and perceived financial impact, each measured on a 5-point scale (1 = lowest, 5 = highest). These serve to capture affective and cognitive features of recall.

To ensure understanding of the task, all participants first complete a "fruit task" in which they rate the similarity between an orange and several other items. This serves as both a practice exercise and a benchmark for scale usage. Since respondents can differ on their use of the scale (some use the full range 1-7, others only 4-6), I conduct robustness exercises in which I rescale the main-task responses using their idiosyncratic fruit-task ranges so that each person's answers are comparable, given their personal scale use.

Survey Results – Similarity Gradient. For respondents who experienced a credit rejection, I compute the average perceived similarity between their personal experience and four macroeconomic outcomes: tighter credit, higher inflation, higher unemployment, and lower stock prices. The left panel of Figure C.3 reports raw averages, while the right panel shows range-adjusted averages. In the latter, each respondent's ratings are first normalised by their individual response range in the "fruit task," ensuring comparability across participants who use different portions of the response scale. The resulting pattern is nearly identical across specifications: perceived similarity follows a clear domain gradient.

Figure C.3: Average perceived similarity between rejections and macro outcomes – Range-Adjusted



Notes: Each panel reports average perceived similarity between a respondent's personal credit rejection and the four macroeconomic outcomes, among those who experienced a rejection. The left panel (circles) shows unadjusted averages. The right panel (diamonds) shows range-adjusted averages, where each individual's responses are normalised by their personal range from the "fruit task": $x_{hj}^{adj} = (x_{hj} - \min_h)/(\max_h - \min_h)$, with $\min_h$ and $\max_h$ denoting the minimum and maximum values used by individual h in the fruit task.

Survey Results – Similarity Asymmetry. All respondents, both those whose credit applications were accepted and those who were rejected, were asked to rate how similar their personal experience felt to a range of macroeconomic outcomes, each presented in both positive and negative valences.

To compare how accepted and rejected applicants associate their personal experience with the macroeconomy, I construct two summary measures. First, for each experience group $m \in \{R, A\}$ (rejected or accepted) and for each valence $j \in \{L, H\}$ (low" or high" macro outcomes), I calculate an average similarity across the four domains $d \in \{$credit, unemployment, inflation, stock prices$\}$:

$$S(m, \theta_{ij}) = \frac{1}{4} \sum_d Sim(m, \theta_{i,j}^d), \quad \text{for each } m \in \{R, A\} \text{ and } j \in \{L, H\} \tag{C.1}$$

This captures how strongly individuals associate their experience with adverse (low) versus favorable (high) macroeconomic states.

Second, to obtain an overall similarity index that summarises how much each experience is associated with the macroeconomy as a whole, I average across both valences and domains:

$$S(m, \text{macro}) = \frac{1}{4} \sum_d \left(\frac{1}{2} \sum_j Sim(m, \theta_{i,j}^d) \right) \tag{C.2}$$

Table C.6 reports these average measures by experience group, both in raw and range-adjusted form, together with p-values for cross-group and within-group comparisons.

Table C.6: Average perceived similarity across experience groups

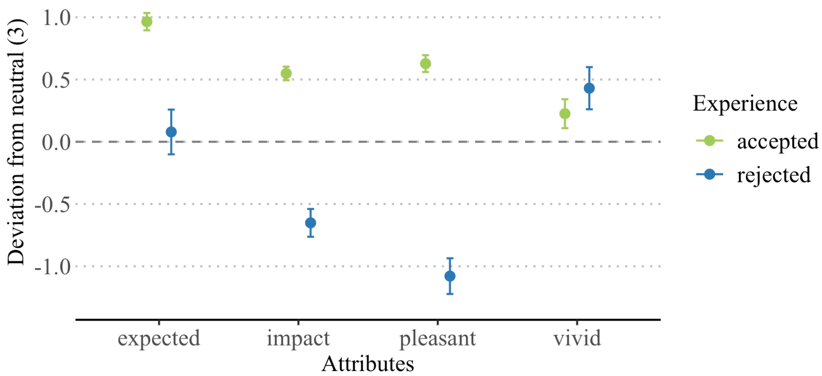
	$S(m, \theta_{iL})$	$S(m, \theta_{iH})$	$S(m, \text{macro})$
Unadjusted:			
Rejection ($m = R$)	4.75	2.65	3.7
Acceptance ($m = A$)	3.53	3.58	3.56
Range-Adjusted:			
Rejection ($m = R_{adj}$)	1.06	0.21	0.64
Acceptance ($m = A_{adj}$)	0.46	0.52	0.49
Difference in means across groups:			
$(R - A)$ p-value	0	0	0.035
$(R_{adj} - A_{adj})$ p-value	0	0	0.006
Difference in means within group:			
R: $(L - H)$ p-value			0
R_{adj}: $(L - H)$ p-value			0
A: $(L - H)$ p-value			0.47
A_{adj}: $(L - H)$ p-value			0.07

Comparing within experience groups and across valences, individuals who were rejected exhibit strong and polarised associations: they perceive their personal rejection as highly similar to adverse macroeconomic outcomes and dissimilar to favorable ones. In contrast, accepted individuals display neutral or mild associations: reporting slightly higher similarity with favorable macro conditions than with adverse ones, but both ratings hover around the midpoint of the scale. Comparing across groups, rejected respondents perceive their experiences as significantly more similar to "low" macroeconomic outcomes than accepted respondents do to "high" ones. On average, rejections are more strongly linked to macroeconomic perceptions than acceptances. These patterns, evident in both the raw and range-adjusted measures, point to a clear asymmetry in how individuals map personal credit experiences onto the macroeconomy.

Survey Results – Experience Attributes. Respondents evaluated key features of their credit-application experience along four dimensions. They reported how vividly the event came to mind (vivid: 1 = not vivid at all, 5 = extremely vivid), how pleasant or unpleasant it felt (pleasant: 1 = very unpleasant, 5 = very pleasant), how expected the outcome was at the time (expected: 1 = very unexpected, 5 = very expected), and how it affected their financial situation (impact: 1 = made things much worse, 5 = made things much better). All items were centered such that a value of 3 corresponds to a neutral evaluation. Hence, positive deviations indicate experiences recalled as more vivid, pleasant, expected, or financially beneficial, while negative deviations indicate less vivid, unpleasant, unexpected, or financially harmful memories. Figure C.4 plots mean responses for accepted versus rejected applicants, together with 95 percent confidence intervals.

Table C.7 tests for associations between perceived similarities and the attributes of the experience. Column 1 shows that the similarity between a personal rejection and tight credit markets in the economy increases when the rejection experience is recalled more vividly, when it is less expected, and when its financial impact is more harmful. Column 2 adds controls such as perceived financial situation, which absorbs the role of the perceived financial impact of the experience.

Figure C.4: Memory Attributes, by Experience Group



Notes: The figure shows average rating of experiences in terms of how vivid, pleasant, expected, and financially impactful the credit-application experience was (1-5 scale; 3 = neutral). Values shown are deviations from the neutral midpoint. Positive values indicate more vivid, pleasant, expected, and financially beneficial memories; negative values indicate the opposite. Error bars denote 95 percent confidence intervals.

Table C.7: Perceived Similarity and Memory Attributes

Dep.Var.: $S(R, Credit_{iL})$	(1)	(2)
(Intercept)	5.466^{***}	6.670^{***}
	(0.158)	(1.264)
vivid	0.304^{***}	0.326^{***}
	(0.091)	(0.097)
pleasant	−0.012	−0.083
	(0.108)	(0.109)
expected	-0.181^{**}	-0.221^{**}
	(0.083)	(0.089)
impact	-0.265^{*}	−0.000
	(0.141)	(0.158)
Financial Situation: Good		-0.552^{**}
		(0.273)
Fruit-Range		0.148^{**}
		(0.064)
Age		-0.017^{*}
		(0.009)
R^2	0.160	0.266
Observations	151	151

Notes: The table presents regression coefficients of individuals' perceived similarity between their personal rejection and credit markets getting tighter on the attributes of the experience (vividness, pleasant, expected, impact). Column (2) controls for reported financial situation (reference: "bad"), the range used in the fruit task, age, income category, and college, unemployment, sex, race indicators. Significance level: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table C.8: LSS: Asymmetry and Attributes

Dep.Var.: LSS	(1)	(2)	(3)
(Intercept)	0.49^{***}	0.55^{***}	0.52^{***}
	(0.00)	(0.01)	(0.01)
rejection	0.16^{***}		0.09^{***}
	(0.01)		(0.02)
vivid_dev		0.01	0.00
		(0.00)	(0.00)
expected_dev		-0.01^{*}	-0.01
		(0.00)	(0.00)
impact_dev		-0.02^{***}	-0.01
		(0.01)	(0.01)
pleasant_dev		-0.04^{***}	-0.03^{***}
		(0.00)	(0.00)
R^2	0.17	0.19	0.22
Observations	888	887	887

Notes: The table presents regression coefficients of individuals' Low-state Similarity Share (LSS) and a binary indicator for rejection (versus acceptance) and the attributes of the experience (vividness, pleasant, expected, impact) as deviation from the neutral (3). LSS is defined as the share of similarity weight assigned to adverse ("Low") rather than favorable ("High") macro outcomes, averaged across domains, $\text{LSS}(m) = \frac{S(m,\theta_{iL})}{S(m,\theta_{iL})+S(m,\theta_{iH})}$. Significance level: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

D Memory-Based Model

D.1 Model Expressions

The similarity function. Similarity is defined by a features based similarity function $S(x, y) \in [0, 1]$ which is increasing in shared features between x and y. The following standard functional form captures the dynamics described in the main text:

$$S(m, [\theta_{ij}, c]) = \exp\{-d(m, [\theta_{ij}, c])\}, \quad \text{where} \quad d(m, [\theta_{ij}, c]) = \alpha d(m, \theta_{ij}) + \beta d(m, c) \tag{D.3}$$

where $d(m, [\theta_{ij}, c])$ is the distance between the stored experience m and the cue $[\theta_{ij}, c]$, and $\alpha, \beta \geq 0$ weight how the event and the context shape recall. The term $d(m, \theta_{ij})$ captures how closely the experience matches the features of the event being forecasted. For instance, a macro transition θ_{LL} perfectly matches with itself (distance $d = 0$) but only partially aligns with a personal experience e_{LL} that shares "low" features but differs in type. The term $d(m, c)$ captures how well the experience aligns with the individual's current context: a negative context has a smaller distance from negative experiences, making them more easily retrievable.

Proof of Expression 4: beliefs as benchmark plus recall-driven deviation. The memory-based belief about a transition from i to L in context c is

$$p_{iL}^{M}(c) \;=\; p_{iL} + \Delta(c), \qquad \Delta(c) \;=\; \frac{1}{\omega(c)}\Big[(1 - p_{iL})\, s_{\cdot L}^{o}(c) - p_{iL}\, s_{\cdot H}^{o}(c)\Big], \tag{D.4}$$

where p_{iL} is the frequentist transition probability and $s_{\cdot L}^{o}(c)$ and $s_{\cdot H}^{o}(c)$ collect the recall weights on other (potentially uninformative) memories ending in L and H, respectively.

To see this, fix i and a context c. Let $N \;\equiv\; |\theta_{iL}| + |\theta_{iH}|$ be the total number of relevant macro transitions. The frequentist probability of transitioning from i to L is

$$p_{iL} \;=\; \frac{|\theta_{iL}|}{N}.$$

Let $s_{ij}^{o}(c) = S(o_{ij}, [\theta_{iL}, c])\,|o_{ij}|$ be the total recall weight on other experiences o_{ij} with valence (i, j) when evaluating θ_{iL} in context c, and define the aggregates

$$s_{\cdot L}^{o}(c) \;\equiv\; s_{LL}^{o}(c) + s_{HL}^{o}(c), \qquad s_{\cdot H}^{o}(c) \;\equiv\; s_{LH}^{o}(c) + s_{HH}^{o}(c). \tag{D.5}$$

For simplicity, I assume that past relevant macro transitions are perfectly recalled and used: they satisfy $S(\{i, j\}, \{i, j\}) \;=\; S(\{i, i\}, \{i, j\}) \;=\; \sigma(\{i, j\}, \{i, j\}) \;=\; \sigma(\{j, j\}, \{i, j\}) \;=\; 1$ and 0 otherwise. Although not necessary, this assumption simplifies the analysis and allows us to focus on deviations from the frequentist benchmark. Another way to interpret this is to think that households are informed and know about the frequentist probability, but they still recall other things with positive probability and use them to imagine the scenarios, thus shaping their probability estimates.

Total recall weight is then

$$\omega(c) \;=\; |\theta_{iL}| + |\theta_{iH}| + s_{\cdot L}^{o}(c) + s_{\cdot H}^{o}(c) \;=\; N + s_{\cdot L}^{o}(c) + s_{\cdot H}^{o}(c). \tag{D.6}$$

By the definition of memory–based beliefs (cf. equation (3)), only experiences ending in L are used to simulate θ_{iL}. Hence

$$p_{iL}^{M}(c) = = \frac{|\theta_{iL}| + s_{\cdot L}^{o}(c)}{\omega(c)}.$$

Use $|\theta_{iL}| = p_{iL} N$ and $N = \omega(c) - s_{\cdot L}^{o}(c) - s_{\cdot H}^{o}(c)$ to write

$$\begin{aligned} p_{iL}^{M}(c) &= \frac{p_{iL} N + s_{\cdot L}^{o}(c)}{\omega(c)} \\ &= \frac{p_{iL}\big(\omega(c) - s_{\cdot L}^{o}(c) - s_{\cdot H}^{o}(c)\big) + s_{\cdot L}^{o}(c)}{\omega(c)} \\ &= p_{iL} + \frac{s_{\cdot L}^{o}(c) - p_{iL}\big(s_{\cdot L}^{o}(c) + s_{\cdot H}^{o}(c)\big)}{\omega(c)} \end{aligned}$$

$$= p_{iL} + \frac{(1 - p_{iL})\, s^o_{\cdot L}(c) - p_{iL}\, s^o_{\cdot H}(c)}{\omega(c)}.$$

Identifying the second term with $\Delta(c)$ gives (D.4), i.e. beliefs equal the frequentist benchmark plus a recall–driven deviation. □

Proof of Implication (Context raises pessimism). From (4),

$$p^M_{iL}(c) = p_{iL} + \Delta(c),$$

so $p^M_{iL}(c_1) > p^M_{iL}(c_0)$ iff $\Delta(c_1) > \Delta(c_0)$. Assumption A1 (context monotonicity) implies that a more negative context increases the relative weight on L-ending memories and reduces the weight on H-ending memories, which raises $\Delta(c)$.[21] Hence $\Delta(c_1) > \Delta(c_0)$ and thus $p^M_{iL}(c_1) > p^M_{iL}(c_0)$. □

Proof of Corollary (Cross-sectional rejection gap). By the Implication (Context raises pessimism), $p^M_{iL}(c_1) > p^M_{iL}(c_0)$. Let $c \in \{c_0, c_1\}$ and write

$$\mathbb{E}[p^M_{iL} \mid g] = \sum_c p^M_{iL}(c)\ \Pr(c \mid g), \qquad g \in \{R, A\}.$$

Then

$$\begin{aligned}\mathbb{E}[p^M_{iL} \mid R] - \mathbb{E}[p^M_{iL} \mid A] &= \sum_c p^M_{iL}(c) \big[\Pr(c \mid R) - \Pr(c \mid A)\big] \\ &= \big(p^M_{iL}(c_1) - p^M_{iL}(c_0)\big)\big(\Pr(c_1 \mid R) - \Pr(c_1 \mid A)\big).\end{aligned}$$

Since $p^M_{iL}(c_1) > p^M_{iL}(c_0)$ and $\Pr(c_1 \mid R) > \Pr(c_1 \mid A)$ by assumption, the product is positive, so $\mathbb{E}[p^M_{iL} \mid R] - \mathbb{E}[p^M_{iL} \mid A] > 0$. □

Proof of Expression 5: the effect of personal rejections. Fix context c_1 and consider the evaluation of θ_{iL}. Let

$$\begin{aligned}W(c_1) &\equiv \sum_{m \in M} S\big(m, [\theta_{iL}, c_1]\big), \\ T(c_1) &\equiv \sum_{m \in M:\, j(m) = L} S\big(m, [\theta_{iL}, c_1]\big)\end{aligned}$$

denote, respectively, the total similarity weight of all memories in M and the total weight of L–ending memories in M. Then

$$p^M_{iL}(c_1) = \frac{T(c_1)}{W(c_1)}.$$

Now add the rejection $R \equiv e_{LL}$, an L–ending memory, to obtain $M^R = M \cup \{R\}$. Write

$$S_R(c_1) \equiv S\big(R, [\theta_{iL}, c_1]\big)$$

[21] Formally, $\Delta(c)$ is increasing in $s^o_{\cdot L}(c)$ and decreasing in $s^o_{\cdot H}(c)$ in (4).

for its similarity weight. The new total and L–ending weights are

$$W^R(c_1) = W(c_1) + S_R(c_1),$$
$$T^R(c_1) = T(c_1) + S_R(c_1),$$

so that

$$p_{iL}^{M^R}(c_1) = \frac{T^R(c_1)}{W^R(c_1)} = \frac{T(c_1) + S_R(c_1)}{W(c_1) + S_R(c_1)}.$$

We now rewrite this as an update around $p_{iL}^M(c_1)$. For brevity, let $W = W(c_1)$, $T = T(c_1)$, and $S_R = S_R(c_1)$. Then

$$\begin{aligned} p_{iL}^{M^R}(c_1) &= \frac{T + S_R}{W + S_R} \\ &= \frac{T}{W} + \frac{S_R}{W + S_R}\left(1 - \frac{T}{W}\right) \\ &= p_{iL}^M(c_1) + \frac{S_R}{W + S_R}\big(1 - p_{iL}^M(c_1)\big). \end{aligned}$$

By definition,

$$\frac{S_R}{W + S_R} = \frac{S\big(R, [\theta_{iL}, c_1]\big)}{\sum_{m \in M^R} S\big(m, [\theta_{iL}, c_1]\big)} \equiv r\big(R, [\theta_{iL}, c_1]\big)$$

so we obtain

$$p_{iL}^{M^R}(c_1) = p_{iL}^M(c_1) + r\big(R, [\theta_{iL}, c_1]\big)\big(1 - p_{iL}^M(c_1)\big),$$

□

Proof of Expression 6 in Proposition (Rejected vs. Accepted): the rejection-acceptance gap. By definition,

$$\hat{p}_{iL}^R \equiv p_{iL}^{M^R}(c_1), \qquad \hat{p}_{iL}^A \equiv p_{iL}^M(c_0).$$

Using the update formula at context c_1,

$$p_{iL}^{M^R}(c_1) = p_{iL}^M(c_1) + r\big(R, [\theta_{iL}, c_1]\big)\big(1 - p_{iL}^M(c_1)\big),$$

so

$$\begin{aligned} \hat{p}_{iL}^R - \hat{p}_{iL}^A &= p_{iL}^{M^R}(c_1) - p_{iL}^M(c_0) \\ &= \big[p_{iL}^M(c_1) - p_{iL}^M(c_0)\big] + r\big(R, [\theta_{iL}, c_1]\big)\big(1 - p_{iL}^M(c_1)\big). \end{aligned}$$

Identifying the first bracket as the context reweighting (CR) term and the second as the direct recall (DR) term yields

$$\begin{aligned}\hat{p}^R_{iL} - \hat{p}^A_{iL} &= \underbrace{\left[p^M_{iL}(c_1) - p^M_{iL}(c_0)\right]}_{\text{Context reweighting (CR)}} + \underbrace{r\big(R, [\theta_{iL}, c_1]\big)\big(1 - p^M_{iL}(c_1)\big)}_{\text{Direct recall (DR)}} \\ &\equiv \beta_r\end{aligned}$$

□

General rejection-acceptance gap with ex ante context differences. Let c^A_0 and c^R_0 denote the baseline contexts for accepted and rejected households, respectively, and let c_1 be the post–rejection context. Define

$$\hat{p}^A_{iL} \equiv p^M_{iL}(c^A_0), \qquad \hat{p}^R_{iL} \equiv p^{M^R}_{iL}(c_1),$$

where $M^R = M \cup \{R\}$ and $R \equiv e_{LL}$.

Using the rejection update formula at c_1,

$$p^{M^R}_{iL}(c_1) = p^M_{iL}(c_1) + r\big(R, [\theta_{iL}, c_1]\big)\big(1 - p^M_{iL}(c_1)\big),$$

we have

$$\begin{aligned}\hat{p}^R_{iL} - \hat{p}^A_{iL} &= p^{M^R}_{iL}(c_1) - p^M_{iL}(c^A_0) \\ &= \Big(p^M_{iL}(c_1) + r\big(R, [\theta_{iL}, c_1]\big)\big(1 - p^M_{iL}(c_1)\big)\Big) - p^M_{iL}(c^A_0) \\ &= \left[p^M_{iL}(c_1) - p^M_{iL}(c^R_0)\right] + \left[p^M_{iL}(c^R_0) - p^M_{iL}(c^A_0)\right] + r\big(R, [\theta_{iL}, c_1]\big)\big(1 - p^M_{iL}(c_1)\big),\end{aligned}$$

Then the general rejection-acceptance gap can be written as

$$\hat{p}^R_{iL} - \hat{p}^A_{iL} = \underbrace{\left[p^M_{iL}(c_1) - p^M_{iL}(c^R_0)\right]}_{\text{Context reweighting within rejected (CR}^R)} + \underbrace{r\big(R, [\theta_{iL}, c_1]\big)\big(1 - p^M_{iL}(c_1)\big)}_{\text{Direct recall (DR)}} + \underbrace{\left[p^M_{iL}(c^R_0) - p^M_{iL}(c^A_0)\right]}_{\text{Ex ante context gap } (B^{\text{ctx}})} \tag{D.7}$$

In the special case $c^R_0 = c^A_0 = c_0$, the ex ante context term B^{ctx} vanishes and (D.7) collapses to (6).

D.2 Model Testable Predictions

Proof of Prediction H1 (Domain gradient). Let the feature space be given by the type of experience, the valence, and the domain (d = credit, unemployment, inflation, stocks), so that sharing the same domain strictly increases the features-based similarity function.

Then the rejection–acceptance gap in domain d is

$$\beta^d_r = \left[p^{M,d}_{iL}(c_1) - p^{M,d}_{iL}(c_0)\right] + r\big(R, [\theta^d_{iL}, c_1]\big)\big(1 - p^{M,d}_{iL}(c_1)\big),$$

where θ^d_{iL} denotes a transition from i to L in domain d.

The rejection $R \equiv e_{LL}$ is a personal credit event with negative valence. When comparing the cue $[\theta^d_{iL}, c]$ across domains, forecasting "tighter credit markets" shares (i) the negative future state L and (ii) the credit domain feature with R, while the other domains share only the negative future state but not the domain. By the similarity structure, we thus have

$$S\big(R, [\theta^{\text{credit}}_{iL}, c]\big) > S\big(R, [\theta^d_{iL}, c]\big), \qquad d \in \{\text{unemployment, inflation, stocks}\}.$$

As in Prediction H3, recall probabilities are strictly increasing in similarity, so

$$S\big(R, [\theta^{\text{credit}}_{iL}, c]\big) > S\big(R, [\theta^d_{iL}, c]\big) \;\Rightarrow\; r\big(R, [\theta^{\text{credit}}_{iL}, c]\big) > r\big(R, [\theta^d_{iL}, c]\big),$$

holding the rest of M^R fixed. Since β^d_r is increasing in the recall weight on R for each domain (through the direct recall term and, via $p^{M,d}_{iL}(c)$, through context reweighting), it follows directly that

$$\beta^{\text{credit}}_r > \beta^d_r, \qquad d \in \{\text{unemployment, inflation, stocks}\},$$

establishing Prediction H1. □

Proof of Prediction H2 (Memory pool size). Recall that the rejection–acceptance gap is

$$\beta_r = \hat{p}^R_{iL} - \hat{p}^A_{iL} = \left[p^M_{iL}(c_1) - p^M_{iL}(c_0)\right] + r\big(R, [\theta_{iL}, c_1]\big)\big(1 - p^M_{iL}(c_1)\big),$$

where $p^M_{iL}(c)$ and $r(\cdot)$ are defined in (3) and in the rejection update formula, respectively.

Both $p^M_{iL}(c)$ and $r(m, [\theta_{iL}, c])$ are ratios of the form

$$r(m, [\theta_{iL}, c]) = \frac{S(m, [\theta_{iL}, c])}{\sum_{m' \in M} S(m', [\theta_{iL}, c])}.$$

Holding fixed the composition of M (and thus all numerators $S(m, [\theta_{iL}, c])$), increasing $|M|$ strictly raises the denominator and therefore strictly reduces $r(m, [\theta_{iL}, c])$ for every memory, including R. Since $p^M_{iL}(c)$ is a weighted average of indicators $\mathbb{1}\{j(m) = L\}$ with weights $r(m, [\theta_{iL}, c])$, the gap $p^M_{iL}(c_1) - p^M_{iL}(c_0)$ and the direct recall term $r(R, [\theta_{iL}, c_1])(1 - p^M_{iL}(c_1))$ both shrink in magnitude as $|M|$ grows. Hence

$$\frac{\partial \beta_r}{\partial |M|} < 0,$$

which proves Prediction H2. □

Proof of Prediction H3 (Context intensity). By the decomposition

$$p^M_{iL}(c) = p_{iL} + \Delta(c), \qquad \Delta(c) = \frac{1}{\omega(c)}\Big[(1 - p_{iL})\, s^o_{\cdot L}(c) - p_{iL}\, s^o_{\cdot H}(c)\Big],$$

a more negative context c affects $p^M_{iL}(c)$ only through $\Delta(c)$.

By Assumption A1 (context monotonicity) and Lemma 1, a more negative context raises the relative recall of L–ending memories and lowers the relative recall of H–ending memories, so that

$$s^o_{\cdot L}(c_1) > s^o_{\cdot L}(c_0), \qquad s^o_{\cdot H}(c_1) < s^o_{\cdot H}(c_0) \;\Rightarrow\; \Delta(c_1) > \Delta(c_0),$$

and hence $p^M_{iL}(c_1) > p^M_{iL}(c_0)$.

Since β_r can be written as

$$\beta_r = \underbrace{\left[p^M_{iL}(c_1) - p^M_{iL}(c_0)\right]}_{\text{CR}} + \underbrace{r\big(R,[\theta_{iL},c_1]\big)\big(1-p^M_{iL}(c_1)\big)}_{\text{DR}},$$

and both terms are increasing in the recall weight on negative memories under a more negative context, it follows directly that β_r is increasing in context negativity, proving Prediction 3. □

Proof of Prediction H4 (State dependence). Fix the context c and compare forecasting from H vs. from L. By the rejection update formula, for a given context c we have

$$\beta_r^{(iL)} = \left[p^{M,(i)}_{iL}(c_1) - p^{M,(i)}_{iL}(c_0)\right] + r\big(R,[\theta_{iL},c_1]\big)\big(1-p^{M,(i)}_{iL}(c_1)\big),$$

where the superscript (i) indicates the current macro state.

When the current state is L, the cue $[\theta_{LL},c]$ is closer to $R = e_{LL}$ in both domain and valence than $[\theta_{HL},c]$. By the properties of the similarity function,

$$S\big(R,[\theta_{LL},c]\big) > S\big(R,[\theta_{HL},c]\big).$$

By the definition of recall probabilities, r is strictly increasing in S holding fixed the other memories in M^R, so

$$S\big(R,[\theta_{LL},c]\big) > S\big(R,[\theta_{HL},c]\big) \;\Rightarrow\; r\big(R,[\theta_{LL},c]\big) > r\big(R,[\theta_{HL},c]\big).$$

Since $\beta_r^{(iL)}$ is increasing in $r(R,[\theta_{iL},c_1])$ (the direct recall term is $r(\cdot)(1-p^M_{iL}(c_1))$ with $1-p^M_{iL}(c_1) > 0$), we obtain

$$\beta_r^{(LL)} > \beta_r^{(HL)},$$

which establishes Prediction H4. □

D.3 Robustness Results

Table D.9: State Dependency in Beliefs across Macro Outcomes

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

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

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