Credit Market Experiences and Macroeconomic Expectations: Evidence and Theory *

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Abstract

Using the NY Fed Survey of Consumer Expectations, I show that people experiencing credit rejections are too pessimistic about US credit markets, inflation, unemployment, and stock prices. This finding challenges standard experience-effects, which are assumed to be domain specific, and has important economic implications. Using an associative memory model of belief formation I show, theoretically and empirically, that reliance on personal past rejections creates: i) systematic belief heterogeneity across age and other socio-economic groups, and ii) overreaction of average beliefs during recessions. Incorporating these findings into a consumption-saving model and using data on planned durable consumption, I show that 12% of the total negative impact of rejections on planned consumption results solely from the pessimism bias. Finally, I show that this effect is particularly pronounced among young and low socio-economic status individuals, and during economic downturns, leading to amplified contractions in aggregate demand.

Keywords: experiences, memory, expectations, disagreement, consumption

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

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1 Introduction

It is well known that expectations about an aggregate economic outcome are shaped by past personal experiences with that same outcome. People who lived through stock market crashes are more pessimistic about future stock market returns and less willing to invest in risky assets (Malmendier and Nagel, 2011; Ampudia and Ehrmann, 2017); inflation experiences shape inflation expectations and borrowing behaviour (Malmendier and Nagel, 2016; Cenzon and Szabo, 2023; Botsch and Malmendier, 2023). These experience effects are argued to be domain specific, as they do not affect beliefs outside the domain where they occur. For example, stock market experiences affect expectations about the stock market but not expectations about bond markets (Malmendier, 2021), or house price experiences affect expectations about house prices but not about inflation (Kuchler and Zafar, 2019).

This paper shows that experience effects are much broader, as they affect expectations about aggregate outcomes in several domains, even if the experience is wholly idiosyncratic. Using micro-level data from U.S. household surveys, I find that personal credit rejections lead to strong pessimism about US-level credit conditions but also about unemployment, stock prices, and inflation. This pessimism cannot be attributed to specific applicant characteristics, common shocks, or the informativeness of the experience.

To understand the origin of this pessimism, I develop a model of selective and associative memory, building on Bordalo et al. (2022). I use this framework to characterise conditions under which credit rejections lead to broad aggregate pessimism, and I show, theoretically and empirically, that such bias is stronger for young, low socio-economic-status individuals, and during economic recessions, leading to i) systematic belief heterogeneity across groups, and ii) overreaction of average beliefs during recessions.

Finally, I explore the economic implications of my findings by embedding memory-based beliefs into a standard consumption-saving model. In this framework, rejections have a direct effect on consumption via lower ability to spend, and an indirect effect via lower willingness to spend. Exploiting the availability of survey data on spending attitudes, I show that this indirect effect is sizeable, amplifying declines in planned durable consumption. In line with the model, I also document that this amplification is heterogenous across age and socio-economic groups. Moreover, combining the model with survey data estimates, I illustrate how the negative impact of an aggregate economic shock on consumption can be magnified due to the overreaction of those who have experienced credit rejections in the past.

Leveraging the comprehensive micro-level data from the New York Fed Survey of Consumer

Expectations (SCE), which is introduced in Section 2, I document the pessimism bias associated with personal credit rejections in Section 3. To do this, I augment the Core Module - which contains individuals' characteristics and expectations - with the Credit Access Module - which provides detailed insights into individuals' credit market experiences. Respondents are asked whether they have applied to any type of loan within the last 12 months and, if so, what was the outcome of such application - accepted or rejected. From this, I construct treatment and control groups: "applied and accepted", "applied and rejected", and "didn't apply". I show that individuals recently rejected for credit consistently exhibit greater pessimism about nation-wide credit market conditions, unemployment, stock prices and inflation. This pessimism is not driven by households' characteristics (age, gender, race, education, numeracy, income, employment), loan types (mortgage, credit card, student loan) or aggregate economic shocks, and it is economically large, as its size range from 17% to 100% of the pessimism induced by the COVID shock, depending on the outcome variable considered. To further validate the results, I take additional measures: (1) controlling for reported credit scores, (2) accounting for individual fixed effects, and (3) employing matching methods to ensure comparability between rejected and control groups (either accepted or didn't apply).[1] Taken together, results suggest that the observed pessimism is a robust phenomenon linked to the experience of rejection.

This rejection-pessimism cannot be explained by the information the rejection might provide, as I find that individuals who have experienced credit rejections make systematically larger forecast errors. Motivated by these facts, in Section 4 I build upon Bordalo et al. (2022) and provide a memory-based belief model to understand the origin of the bias and further characterise it. In the model, people form probabilities about future economic events by relying on memories of past personal experiences and statistical data. There are two key steps: first, what experiences are *recalled*, and second, how recalled experiences are *used*. The model builds on two well-established principles of the memory system. First, recall is selective and associative - personal experiences come to mind more easily when they are perceived as more *similar* to the outcome being evaluated (Kahana, 2012; Bordalo et al., 2023). Second, these experiences are used to construct similar scenarios - a process known as simulation (Kahneman and Tversky, 1981; Schacter et al., 2007, 2012; Bordalo et al., 2023).[2]

The model predicts over-estimation of economic downturns based on personal rejections en-

[1] This exercise also shows that rejections are associated with pessimism about the economy, but acceptances do not seem to be associated with optimism.

[2] The concept of simulation can be understood as a representation or construction of future scenarios based on experiences and memories that spontaneously come to mind (Kahneman and Tversky, 1981; Schacter et al., 2007, 2008, 2012; Bordalo et al., 2023). Kahneman and Tversky (1981) describes the simulation heuristic (the explicit construction of scenarios) as a procedure for the estimation of probabilities.

dogenously. Intuitively, when prompted to think about future credit conditions, individuals may recall not only official statistics but also their personal experiences of credit rejection and the subsequent financial difficulties they faced. This memory helps them picture others experiencing similar rejections and increases the likelihood they assign to bad aggregate scenarios. Likewise, while idiosyncratic rejections may not provide informative signals about future increases in unemployment or inflation rates, the recollection of financial struggles post-rejection can ease the imagination of other economic hardships, such as job loss or rising prices, thereby contributing to a pervasive pessimism across various economic domains.

According to the theory, the memory-based probability can be expressed as the sum of the bias originating from recalling a personal rejection and the probability based on all other experiences or data. The bias is determined by the perceived similarity between the experience and the outcome being forecasted. This yields three important predictions which are validated in the data. First, relying on memories of personal rejections induces pessimism across various markets, with a more pronounced effect when the forecast pertains to the same market as the personal experience. For instance, personal rejections increase pessimism about credit conditions by over 10 percentage points, while the impact on the less similar labor market pessimism is approximately 2 percentage points. Second, the effect of personal rejections is stronger for young individuals who have smaller databases of experiences, which allows experiences to be more easily remembered compared to older individuals. The reliance on rejections is also found to be stronger among those with lower socio-economic status (proxied by low income and no college attainment) - for whom rejections are potentially more costly and hence more helpful in imagining bad states - providing new insights into why low socio-economic individuals were found to be more pessimistic about the economy (Das et al., 2020). Third, the pessimism bias is stronger during recessions, as negative personal experiences are more likely remembered when current economic conditions are also "negative".[3] In particular, low economic states depress individuals' expectations but the effect is stronger for those who have personally experienced a rejection in the past, leading to strong overreaction in expectations.

In Section 5 I show that this mechanism of belief formation has important macroeconomic implications. First, I incorporate the model in a simple dynamic consumption-saving setting to isolate the mechanisms through which memory impacts behaviour. This framework shows that rejections can influence individual choices both directly, through credit constraints, and indirectly, by inducing pessimism about future macroeconomic states. This belief channel leads

[3] I test this by interacting past rejections with different measures about aggregate economic conditions and I find that people (1) extrapolate from current states (2) extrapolate from own personal rejections and (3) the extent of extrapolation depends on the interaction of the two.

to an increase in precautionary motives, as rejected individuals opt to reduce their borrowing and current consumption to prepare for negative future shocks that are now perceived as more likely.

Second, I quantify the amplification channel by using additional data on individuals' planned durable consumption. Using mediation analysis on the Spending Module of the SCE data, I find that the amplification channel is seizable: 12% of the total negative effect of rejections on intended durable consumption can be attributed solely to pessimism about the macroeconomy. In line with the predictions of the model, the belief channel is stronger for younger individuals, and for those with low income and no college education. Rejected individuals are also more likely to have increased their savings because they expect borrowing to be harder, and they are less likely to apply again for any credit because they think they wouldn't be approved.

Finally, I show that, since the pessimism from personal past rejections was found to be stronger during economic downturns, average expectations are characterised by overreaction to negative economic shocks leading to larger negative aggregate demand effects. Combining survey data with model equations, I demonstrate that an economic shock, proxied by a one-standard-deviation increase in unemployment rates, heightens overall pessimism and depresses aggregate demand. This effect is amplified by the overreaction of those previously rejected. A counterfactual analysis shows that if pessimism from past rejections remained constant across economic states, it would lead to a 0.8% decline in aggregate consumption. However, given the empirical finding that this pessimism bias is stronger during economic downturns, the drop in aggregate consumption is estimated to be 30 basis points higher, i.e. 1.1%. Thus, past personal rejections interact with a current aggregate shock in the labor market, and this interlinkage across markets can have relevant aggregate implications.

Related Literature. My work connects to several strands of literature. First, it contributes to the literature studying the determinants of individuals' expectations about the macroeconomy and the heterogeneity arising from their different experiences or personal circumstances (Das et al., 2020; D'Acunto et al., 2019, 2021b; Malmendier, 2021). In contrast to seminal papers by Malmendier and Nagel (2016, 2011) which study the effect of aggregate macro shocks on entire generations, I examine the impact of individual-level shocks, which may in turn be influenced by macroeconomic factors. While few other papers have explored the effects of idiosyncratic economic experiences, their focus is on within-domain effects in the labor market (Malmendier and Shen, 2018; Kuchler and Zafar, 2019) or the goods market (D'Acunto et al., 2021a; Cavallo et al., 2017, study effects of grocery prices), whereas my research focuses on the credit market, a highly relevant and relatively understudied domain of personal experiences. Moreover, the richness of the data set used allows me to employ different methodologies to identify the impact of experiences on beliefs and to go beyond previous research by directly estimating the influence of experiences on behaviour, considering both direct effects and the indirect influence through the belief channel.

While existing experience-effect models focus on domain-specific effects (Malmendier, 2021), I find that idiosyncratic experiences play a broad role unrelated to their informativeness, in line with theories of memory-based beliefs in which both relevant and irrelevant experiences affect probability judgements because of perceived similarity. This work thus relates to a growing literature exploring the relationship between memory and expectations in economics (Gennaioli and Shleifer, 2010; Enke et al., 2020; Malmendier and Wachter, 2021; Bordalo et al., 2021a; Nagel and Xu, 2022; Andre et al., 2022; Afrouzi et al., 2023; Bordalo et al., 2023). The model used builds on the theoretical framework introduced in Bordalo et al. (2022), which the authors use to understand how people form beliefs about new risks such as COVID mortality. Their model has already been applied in different contexts such as to understand beliefs about career choices (Conlon and Patel, 2022), beliefs about gender and pro-sociality (Exley et al., 2022), different role of stories and statistics (Graeber et al., 2023), and beliefs about stock returns (Jiang et al., 2023). I use the model to explore the role of idiosyncratic experiences on consumers' beliefs about the macroeconomy and further contribute by studying and quantifying the effect of memory distortions on consumers' behaviour and aggregate demand.

This paper is also related to a broad range of papers that use survey data to investigate deviations from the assumption of Full Information Rational Expectations (Coibion and Gorodnichenko, 2015; Bordalo et al., 2020; Broer and Kohlhas, 2022; Born et al., 2022; Kohlhas and Walther, 2021). As opposed to most of the literature that focuses on professional forecasters, this paper contributes by studying the predictability of forecast errors at the household level, but also by connecting the overreaction observed in the data to the associative nature of memory (Enke et al., 2020). Individuals react to the current economic state, but the extent to which they do it depends on the experiences that are cued by it.

More broadly, my findings contribute to the literature on demand-driven cycles and sentiment's role in shaping aggregate dynamics and business cycles (Bianchi et al., 2023; Angeletos and Lian, 2022; Maxted, 2023; Krishnamurthy and Li, 2020; Bordalo et al., 2021b; Angeletos and La'o, 2013; Benhabib et al., 2015; Lorenzoni, 2009). Some studies employ a rational expectations approach to model sentiment, while others use survey data to estimate beliefs and construct psychologically grounded models of sentiment. For instance, Bhandari et al. (2022) use survey data within a business cycle model to demonstrate that increased household pessimism can significantly reduce aggregate demand and impact macro outcomes. Bordalo et al. (2018a) model sentiment as an overreaction to current news or shocks through Diagnostic Expectations, drawing from Kahneman and Tversky (1972)'s representativeness heuristic, to explain credit cycles. My work contributes to this literature by (1) introducing a memory-based model to explain systematic biases and heterogeneity in households' macro beliefs, generating new testable predictions, and (2) integrating this memory model into the demand component of a macro model to explore its implications. My results capture overreaction and highlight that the extent of it depends on the personal memories triggered by shocks, which subsequently influence households' consumption choices. Moreover, I find that these effects are heterogeneous - rejected become pessimistic, and more so if they are young and less sophisticated. This heterogeneity in the amplification effect can interact with shocks and prolong their impacts, shedding light on phenomena like the prolonged drop in consumption following the Great Recession (Mian and Sufi, 2018), characterised by high rejection rates and significant consumption declines, especially among young, low-income, and less educated individuals who tend to overreact more due to their personal experiences.

2 Data

2.1 Main Data Source and Variable Definition

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

The SCE is composed of various special modules: the Credit Access Module, the Spending Module and the Annual Household Finance Module. As opposed to the core module, the special modules are not administered every month. The Credit Access Survey is conducted three times a year (February, June and October) and it covers October 2013 till October 2021. It spans 25 waves with approximately 1100 observations per wave (3330 per year), leading to a total of 28241 observations. There are 13053 unique individuals in the whole sample. Approximately 5518 individuals responded three times, 4101 twice and 3417 only once. This is a key module as it contains detailed information on households past experiences with the credit market and also personal expectations about future applications and their developments. I merge this module with the core module to obtain a final sample of 28241 person-month observations.

I also make use of the Spending Module to connect experiences, expectations and spending attitudes. This module is conducted three times a year and the data set spans from December 2014 till May 2021. I briefly use the Annual Household Finance survey which is only administered once a year (in August) and thus, it is a cross section of individuals. The survey covers 2014-2019 and contains 6809 observations. The advantage of this data set is that it has information about last year changes on individuals' savings which can be linked to changes in their experiences, and information about their net wealth.

Measure of experiences in the credit market. The key explanatory variable captures individuals' past experiences in the credit market. More specifically, respondents are asked whether they applied for credit over the last 12 months. They are presented with 7 different credit types: credit cards, credit card limit increases, mortgages or home based loans, auto loans, increases in the limit of an existing loan, mortgage refinances, and student loans. I classify as applicants those who answered "yes" to at least one of those categories. Within those who applied, respondents who had all their applications approved (either partially or fully) are categorised as "Applied and Accepted". If they report to have been rejected in any of those applications, they are classified as "Applied and Rejected". Those who didn't apply to any credit are further divided into two categories: those who did not apply because they thought they wouldn't be accepted ("Didn't Apply, Discouraged") and those who didn't apply for other reasons ("Didn't Apply, Other"). The latter distinction is particularly useful as it allows me to distinguish between those individuals who chose not to apply because they did not want credit and those who did not apply because they were pessimistic about their own prospects.

Since the main objective is to study the effect of rejections, the main experience variable does not distinguish between types of loan. I later allow for differential effects according to the type of rejection.

Measures of Expectations. I focus on four variables that measure individuals expectations about macroeconomic conditions 12 months into the future: (1) future credit market conditions for everyone (tightening (=1), no change (=0), loosening (-1)), (2) probability of higher US unemployment (scale from 0 to 100), (3) probability of higher stock prices in the US stock market (scale from 0 to 100), (4) inflation rate (continuous). To have a measure of aggregate macroeconomic optimism, I follow Das et al. (2020) and construct an Optimism Index. This index is an average of the standardised values of responses to the questions about credit, unemployment and stock prices. I also investigate the role of rejections for expectations about personal future prospects for which I use (1) subjective probability of rejection in next credit application, (2) subjective probability of loosing current job within the next 4 months (subject to being employed today).

Other variables. The SCE also contains detailed demographic and socioeconomic characteristics such as respondents' age, gender, race, college attainment, marital status, employment status, income category, income expectations and numeracy category. The latter is constructed based on respondents' answers to seven basic questions about probabilities and interest rates.

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

Other Data Sources. Through out the paper I use other several sources of data to either test for the external validity of the result or run additional exercises to further understand their implications. One important additional data source is the Survey of Consumer Finances (SCF). The SCF is a triennial survey conducted since 1989. As opposed to the SCE, this survey contains a cross section of households, and is conducted every three years. Although it has less focus on expectations, it has some advantages. First, it covers a much longer time series (1989-2021) and second, it provides more information about households balance sheet and credit experiences, including the type of information they use when borrowing, how much search they did and whether they have re-applied.

In Appendix A I report the SCE questions used to construct the credit market experience variables, respondents' expectations and respondents' planned spending in durables, and in Appendix B.3 I describe the SCF survey in detail.

2.2 Descriptive Statistics

Appendix Table A.9 reports summary statistics of respondents characteristics and their past experiences in the credit market. The average age is 51 years old, 50% are female and almost 50% have some college education. 28% of respondents lie on the highest category of the income distribution earning more than 100k a year, 30% between 100k and 50k and 41% less than 50k[4]. More than two thirds of the respondents are categorised within the high numeracy category, and almost three-quarters of the respondents own a home. Overall, almost 50% of the sample reports to have participated in the credit market during the last year and 7.2% claimed that they didn't participate because they thought they would not get accepted. Acceptances account for almost 40% of the total sample while rejections account for 7.6%. When concentrating among

[4]For the empirical analysis I use a more granular decomposition of income categories (instead of 3 categories, I use all 11 options).

participants, the rejection rate is on average 18%. The sample contains a panel component as well: there are 295 instances in which someone moved from acceptance to rejection within the sample and 318 instances in which someone transitioned from rejection to acceptance. Appendix Table A.8 shows the full transition matrix. Variation coming from these transitions will be exploited to further explore the effect of changes in credit market experiences on changes in beliefs within individuals.

The Credit Access Module asks individuals about their credit score. Around 55% of respondents report a credit score of above 720, 10.5% between 720 and 680, 20% below 680 and the rest are uncertain. The share of rejections among applicants within each credit score category varies considerably (see Appendix Table A.7). Although important for the analysis, this measure is also endogenous. Credit scores are a determinant of loan application approvals but they are also affected by the outcome of such application. I discuss how I make use of this information in the empirical analysis in the next section.

Table 1 presents summary statistics for respondents expectations about the economy.

Table 1: Summary Statistics of Expectations

	Mean	Standard Deviation	Min	Median	Max
Aggregate Expectations					
Optimism Index	-0.02	0.6	-2.23	-0.02	2.53
Unemployment	35.58	23.33	0	33	100
Stock Prices	40.03	23.35	0	48	100
Inflation (mean of distribution)	2.82	5.41	-25	3	36
Inflation (reported point estimate)	5.63	9.06	-25	3	50
Credit conditions					
tighten	0.32	0.46	0	0	1
no change	0.49	0.5	0	0	1
loosen	0.18	0.38	0	0	1

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

Respondents assign an average of 35.58% to the probability that US unemployment will increase in the next year, and an average of 40% to the probability that stock prices will increase in the next year. For inflation, I present summary statistics for the reported point estimates of expected inflation, but also for the mean expected inflation that emerges from a fitted distribution constructed based on their answers to a probabilistic question (see Armantier et al., 2017 for a complete description). The reported expected inflation has a considerable higher mean and higher dispersion than the one from the fitted distribution. Almost half percent of the US population expect credit conditions to stay the same, while more than 30 percent expect credit conditions to tighten.

3 Idiosyncratic Rejections and Macro Expectations

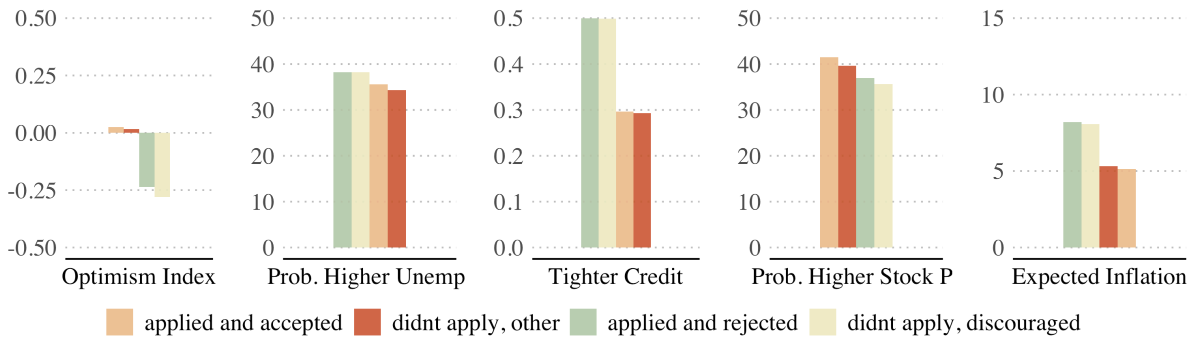
In this section, I explore the relationship between past experiences in the credit market and respondent's beliefs about future macroeconomic conditions. I start with a first look at the raw data, and then I move onto the main goal: identify the effect, if any, of individual rejections on macroeconomic expectations.

3.1 A First Look at the Data

Figure 1 shows there is considerable heterogeneity in macroeconomic expectations by credit experiences. Among those who have been rejected in their credit applications during the past year, pessimism seems to prevail. Almost 50% of rejected individuals expect tighter credit market conditions in the next year, while this percentage goes down to 30 or less for those who did not apply or got accepted. The heterogeneity is striking as well in other domains, such as labor market conditions, stock prices and inflation. The pattern observed for those rejected is very similar to the one observed for those who did not apply because they thought they would not be accepted. [5] Even in the raw data, individuals experiences within the credit market seem to correlate strongly with how they think about the economy as a whole.

[5] In Appendix Table B.11 I show that past rejections are highly predictive of discouragement.

Figure 1: Average Expectations by Credit Market Experience



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

The figure shows a clear pattern: rejected individuals tend to be more pessimistic about the macroeconomy. Is this macro-pessimism an effect of personal rejections?

3.2 Empirical Specification

To analyse the role of personal credit market experiences on respondent's expectations about the macroeconomy I run the following regression:

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

The unit of observation is a survey response by individual i in experience-group k and month-year t, where $k = 1, 2, 3$ is the number of categories or classifications of the key explanatory variable $T_{i,k,t}$. These dummy variables measure individual's i past experience in the credit market which is reported at time t. "Applied and Accepted" is the reference category, while $T_{i,1,t}$ equals 1 if "Applied and Rejected", $T_{i,2,t}$ equals 1 if "Didn't Apply, Other" and $T_{i,3,t}$ equals 1 if "Didn't Apply, Discouraged". The coefficient β_1 captures the heterogeneity in beliefs among those accepted and rejected in the credit market, β_2 differences among accepted and those who didn't apply because they didn't need or want, and β_3 differences among accepted and those discouraged. The dependent variable is the expectation of individual i in group k reported at time t about a future variable Y_{t+1}. $E_{i,k,t}(Y_{t+1})$ is either i's:

1. optimism index, OPTM
2. expected credit market conditions for *everyone*, FCredit

3. percent chance that unemployment will be higher 12 months from now, UNEMP
4. percent chance that stock prices will be higher 12 months from now, StockP
5. expected economy-wide inflation, INFL[6]

To highlight the importance of these idiosyncratic past experiences above the known determinants, in Equation 1 I include state-month-year fixed effects (i.e. χ_{st}) to absorb variation coming from time-varying shocks at the local level, and also a measure of lifetime experiences within domain a la Malmendier and Nagel. More specifically, for each respondent I calculate $\text{LifetimeExp}_{it}^{Y}$, a weighted average of individual i past lifetime experience of aggregate variable Y from birth until time t, with declining weights (Malmendier and Nagel, 2011, 2016).[7] $X_{i,k,t}$ is a vector of controls including age, income, employment status, gender, education status, numeracy, marital status and race. Equation 1 is estimated using OLS with robust standard errors clustered by date and respondent.

Identifying Assumptions. I start by exploring the relationship between past personal experiences on the credit market and individuals' macroeconomic expectations by relying on cross sectional estimates that control for covariates that are commonly thought of as affecting both experiences and beliefs. The identifying assumption is that rejections can be considered a random treatment conditional on the covariates, where the heterogeneity in such experiences comes from randomness in the supply side. Besides the controls already described above, I also run robustness with type of loan, and reported credit scores.

One of the main threats to such identification assumption is selection bias: households that are rejected might be different from those who aren't, and regression controls might not suffice (see Table A.10). The ideal experiment would consist of two individuals who are comparable - for example in age, income category, type of loan they applied to - but one gets randomly rejected while the other accepted. In Section 3.4 I aim to get closer to this ideal set up by using matching methods. Moreover, I also exploit the availability of a panel component in the SCE to explore whether individuals' expectations change when their experiences change.

[6] Throughout the main text I use respondents' point estimate, but results are robust to using the mean of the fitted distribution.

[7] Individual i lifetime experience of variable Y from birth year till time t is defined as $\text{LifetimeExp}_{it}^{Y} = \sum_{h=1}^{H_i} w_{i,t}(h) Y_{t-h}$, where $w_{i,t}(h)$ are linearly declining weights that assign higher value to recently experienced values of Y.

3.3 Pessimism associated with Rejections

Table 2 shows the estimation results of Equation 1. Each column refers to a different outcome variable, and all specifications include the full set of controls introduced before. For each variable presented, individuals who experienced a rejection in the credit market during the last year are significantly more pessimistic than those who were accepted in their applications. Rejected individuals expect tighter credit conditions for everyone, higher percentage chance of increasing U.S. unemployment, lower percentage chance of increasing stock prices, and higher inflation. The estimates imply substantial experience-driven heterogeneity in macroeconomic expectations. For example, a rejection is associated with an increase in expectations about credit tightening that is approximately 32% percent of its standard deviation, while for expectations about unemployment it represents 11% of its standard deviation.[8]

Although not rejected, individuals who chose not to apply because they thought they wouldn't be approved are also more pessimistic in all domains than those accepted. I exploit additional questions in the SCE to investigate the determinants of this discouragement and find that past rejections increase the likelihood of being discouraged from future credit applications by 48 percentage points (see Appendix B Table B.11). This suggests that current discouragement is highly related to rejections that occurred further in the past. Moreover, those who didn't apply because of other reasons are not statistically different than those accepted when looking at Optimism Index, which suggests that the difference between accepted and rejected might come from a rejection-pessimism rather than an acceptance-optimism, a pattern I explore more through matching in Section 3.4.

Lifetime experiences are also an important determinant of households' macro expectations. As previously found in the literature, individuals who experienced higher inflation throughout their lives expect higher inflation moving forward. The same holds when looking at credit conditions, unemployment and stock prices. The coefficient on rejections is robust to the inclusion of all these other experiences, demographic and socioeconomic variables, and state-month-year fixed effects. Results show that (1) own credit market related experiences drive beliefs about future credit conditions for my self and for others (extrapolation) (2) but also influence beliefs about future non-credit related variables (non-domain specific).

[8] A rejection is associated with an increase in expectations about inflation that is approximately 16% percent of its standard deviation and about stock prices that is approximately 6% of its standard deviation.

Table 2: Credit Market Experiences and Macroeconomic Expectations

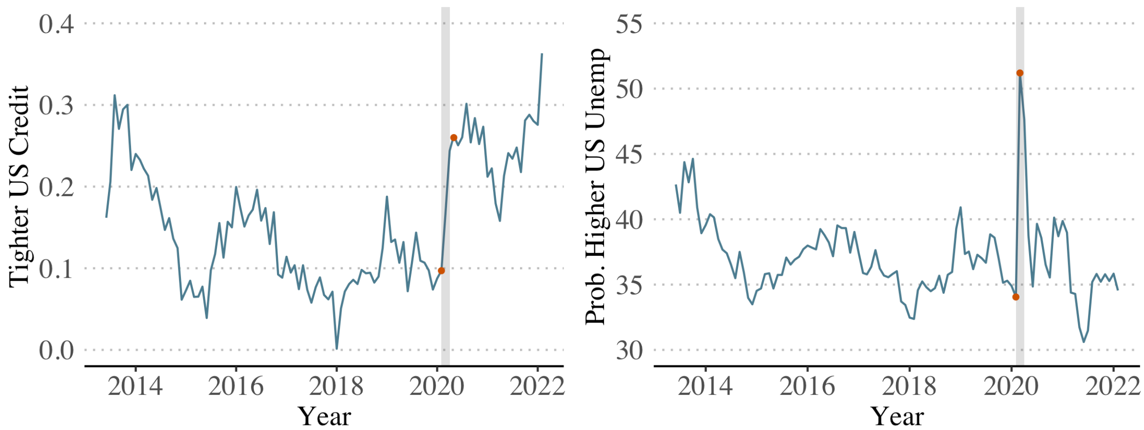
	OPTM	↑UNEMP	FCredit	↑StockP	INFL
Idiosyncratic Experiences					
Applied and Accepted			(omitted)		
Applied and Rejected	-0.175^{***}	2.480^{***}	0.223^{***}	-1.296^{*}	1.461^{***}
	(0.019)	(0.728)	(0.023)	(0.730)	(0.268)
Didn't apply, Discouraged	-0.172^{***}	1.680^{**}	0.249^{***}	-0.885	0.744^{**}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

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

In Appendix B Table B.15 I show that rejected individuals are also more pessimistic about their own future prospects: they believe their probability of future rejection is 30 percentage points higher compared to respondents who were accepted and, among employed individuals, experiencing a rejection in the near past is associated with a 4 percentage points higher expected probability of loosing their job (compared to accepted individuals).

To better understand the economic magnitude and significance of the estimates on rejection, I compare the estimated cross-sectional variation in expectations coming from a personal rejection with the average time-variation coming from an aggregate shock. The left panel in Figure 2 plots the time-series average households' expectations about credit markets, while the right panel repeats the plot but for expectations about unemployment. The shaded area represents the COVID Recession of 2020, which implied a jump in aggregate credit pessimism of approximately 16.5 percentage points and a jump in aggregate unemployment pessimism of approximately 17 percentage points. Comparing this time-variation with the cross-sectional variation estimated in Table 2, we see that being personally rejected is associated with a change in pessimism about general credit market conditions that is bigger in magnitude than the change implied by the COVID shock.[9] If we look at labor markets, which is arguably a different domain than credit markets, being personally rejected is associated with a change in pessimism about U.S. unemployment that is about 17% of the COVID shock.

Figure 2: Time Variation in Average Beliefs about the Macroeconomy



Notes: Figures plot the time variation in average beliefs about the macroeconomy, with credit conditions on the right figure and unemployment on the left figure. The shaded area corresponds to NBER recession period. Values account for the weights provided by SCE to make the sample representative of the US.

One important question is whether this pessimism from personal rejections is persistent or if it is undone after experiencing an acceptance. In the SCE, around 40% of respondents who were rejected in the previous year claim to have also been accepted to some loan application within

[9]Column 3 in Table 2 uses FCredit as the dependant variable and obtains an estimate of 0.22, which is bigger than the time variation in average credit market conditions which is 0.165.

that time frame. I test whether there is any difference in macro pessimism among individuals who have been only rejected versus those who experienced both. Table B.13 in Appendix presents the regression estimates. I find there is no statistically significant difference among them, suggesting that past experiences of rejections are persistent and not forgotten after experiencing an acceptance or finally obtaining the credit.[10]

3.4 Heterogeneity and Robustness

Individuals might apply for credit for different reasons: either buying a new house or refinancing a mortgage, asking for a credit card or extending current limits. Although all type of loan applications are discrete and noticeable choices, some loan types such as mortgages require a more extensive application process and are characterised by lower rejection rates post-application (see Appendix Table B.16 for summary statistics). Besides the loan type, applicants might also differ across important dimensions such as age, income and education. In Appendix B.2 I test the prevalence of the result for different loan types and applicant characteristics, and find that the rejection-pessimism is robust across all dimensions. In Appendix B.3 I further show that the result holds in the Survey of Consumer Finances (SCF), a cross-section of individuals from 1989 till 2019, and is independent of the amount of search individuals did or how informed they were when taking the loan.

Is the evidence suggestive of an effect of the rejection, or are rejected individuals intrinsically more pessimistic? I provide additional evidence in favour of a rejection-induced pessimism hypothesis by testing the robustness of the findings to (1) individual fixed effects and (2) matching methods.

3.4.1 Individual Fixed Effects

I exploit the panel component in the survey data to show that, for a given individual, when her experiences change her expectations also change. In particular, those who experience a rejection within sample become more pessimistic about the economy (see Appendix Table B.20).

[10]Alternatively, the SCF asks rejected individuals whether they have re-applied to the same loan and what was the outcome. I test if there is any difference in macro pessimism among individuals who were rejected and didn't re-apply, those that re-apply and got accepted and those that re-apply and got rejected the again. Table B.14 in Appendix presents the regression estimates. Once again, I find no statistically difference among individuals who have experienced a rejection in the past, irrespective of whether they were accepted later on or not.

Although helpful in addressing internal validity concerns, this estimation approach has limitations. Firstly, the survey's narrow resampling window, combined with the infrequency of loan applications, limits the number of transitions. Secondly, the within-individual estimation considers variations from both moving from acceptance to rejection and from rejection to acceptance. If experiencing acceptance doesn't fully offset the pessimism induced by prior rejections (as suggested earlier), individual fixed effects might bias the estimate of interest. Overall, the results presented in Appendix Table B.20 are consistent with a rejection-induced pessimism hypothesis, albeit coefficients are smaller and standard errors are higher. Next, I provide a detailed explanation of the second estimation strategy: matching

3.4.2 Estimates in a Matched Sample

I implement a preprocessing approach to adjust the data prior to the analysis, with the aim of increasing the comparability between those treated and those in the control group. Appendix B.5 describes the formal set up and identifying assumptions in detail.

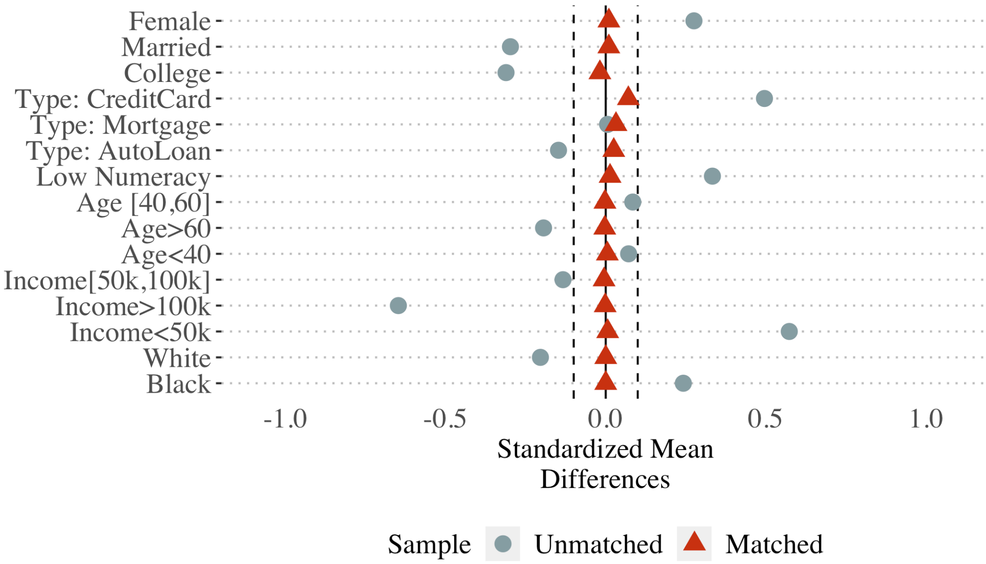
Set Up. I split the sample in three: (1) only participants in the credit market with accepted as control and rejected as treated, (2) non-participants as control and rejected as treated, (3) non-participants as control and accepted as treated. Through out the exercise, the category "non-participants" refers to those classified as "Didn't Apply, Other".

Design: Matching and Diagnostics. I start with a conservative selection of covariates to use in the matching procedure (gender, race, age category, income category, numeracy category, college attainment, type of credit application when applicable) and avoid including covariates that are potentially important but might have been influenced by rejection, such as reported credit scores. Given its critical role, I run robustness where I include it either in the matching step or in the outcome model as a control (Stuart, 2010).

Given the selection of covariates, within each of the three samples described above, I match each treated unit with the closest eligible control, resulting in three balanced matched samples.[11] Figure 3 shows standardised mean differences for the unmatched and the matched sample where the control is those accepted and the treatment is those rejected. Appendix Figures B.4 show the equivalent figures for the other two samples. Matching improves the covariate balance for all variables considerably, with all standardised mean differences below 0.1.

[11] I use $1:1$ nearest neighbour matching on Mahalanobis distance without replacement for samples (1) and (2) and exact matching for sample (3). Appendix B.5 describes the procedure in detail.

Figure 3: Standardised Mean Differences, Sample of Participants, Match and Unmatched



Analysis and Results. For each of the three matched samples, I run linear regressions of individuals' macro expectations on the treatment and the same set of covariates used for matching, since those can also directly influence beliefs. I control for state-month-year fixed effects. Cluster-robust standard errors account for pair membership.

The first two tables in Table 3 present the estimated average effect of rejection on the optimism index. Specification (1) uses the sample that only contains participants in the credit market and, thus, those accepted are the control group. Specification (2) uses the sample of non-participants and participants who were rejected - those who didn't apply are the control group. Irrespective of whether the control group refers to those who chose not to apply or those who were accepted in their application, rejections have a strong and negative effect on individuals' macroeconomic expectations. The size of the effect is almost identical to the estimates in Table 2 Column 1 .

I further exploit the availability of data on non-participants to explore the symmetry of the result. The evidence suggests that acceptances do not lead to optimism. Comparing individuals who did not participate (control group) with individuals who got accepted in their credit applications (treatment), we see that acceptances do not have an effect on macroeconomic expectations. Specification (3) in Table 3 presents the estimated average effect of acceptance on the optimism index which is approximately zero and insignificant.

Appendix Table B.21 shows the estimated effects for the full set of outcome variables (credit market conditions, unemployment, stock prices, inflation) and Appendix Figure B.6 summarises the results when credit score is used as control and also in the matching procedure. Additionally, Appendix Table B.27 presents a further robustness test, by focusing on a sub-sample of individuals for which matching can be performed based on covariates and level of pre-optimism. Overall, results are consistent.

Table 3: Credit Market Experiences and Macro Expectations - Matched Samples

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

Notes: The table presents OLS estimates from equation $E_{i,t}(Y_{t+1}) = \alpha + \beta \mathrm{T}_{i,t} + \delta X_{i,t} + \gamma_t + \gamma_s + e_{it}$ using the three different matched samples. Specifications (1) tests the effect of rejection on the optimism index where those accepted are the control. Specification (2) tests the effect of rejection on the optimism index where those who didn't apply are the control. Specification (3) tests the effect of acceptance on the optimism index where those who didn't apply are the control. All specifications include as individual-level controls the covariates used for the matching procedure plus state-month-year fixed effects. Cluster-robust standard errors account for pair membership. Significance level: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Although in this chapter I have primarily focused on credit rejections due to comprehensive data availability, additional exercises suggest that there might be a general pattern worth exploring: individual-level economic adversities —such as unemployment, negative net wealth shocks, and bankruptcy— are also associated with pessimism about the economy in the SCE data (see Appendix Table B.28).

3.5 Over-Pessimism Bias

Is this rejection-pessimism justified by the informativeness of the experience, or are individuals assigning too much weight to the rejection experience? To investigate this, I rely on standard tests in the literature, and find evidence of an over-pessimism bias:

1. Individuals' forecast errors are predictable from their personal past rejections.
2. Individuals do not use their experiences in line with their informativeness: while rejec-

tion rates among non-college-educated and low-income applicants are acyclical, these individuals are the ones who rely the most on their rejections when forecasting economic outcomes.

Appendix C provides a complete description of the tests, while here I provide the main intuition and findings. A description of the data used for the construction of the individual-level forecast errors can be found in Appendix Table C.29.

Predictability of Individuals' Forecast Errors. I construct individuals' forecast errors $F_{it}Y_{t+1} \equiv Y_{t+1} - \hat{E}(Y_{t+1}|I_{it})$ and test whether such errors in expectations can be predicted by their personal rejections. Under this definition, a household who is too pessimistic about credit markets, unemployment or inflation has a negative error while a household who is too pessimistic about stock prices has a positive error.

Figure 4 illustrates the average forecast errors across different experience groups and economic indicators. Individuals are on average pessimistic about the economy, although there is considerably heterogeneity depending on credit market experiences. While individuals who do not apply to loans tend to have similar errors to those accepted, the mean forecast error of those who experienced a rejection is always higher (and significantly different). Can we systematically predict their individual error based on their experiences?

Figure 4: Average Forecast Errors by Credit Market Experience

Notes: The figure shows average mean forecast errors for each outcome variable within each experience group, constructed as the difference between ex post realised outcomes and individuals' expectations about that outcome. The credit panel refers to credit conditions, which can be either loosen -1, unchanged 0 or tighten 1. Unemployment panel refers to the probability that US unemployment goes up and the Inflation panel is the expected rate of inflation. The Stock Prices panel refer to the probability that stock prices go up.

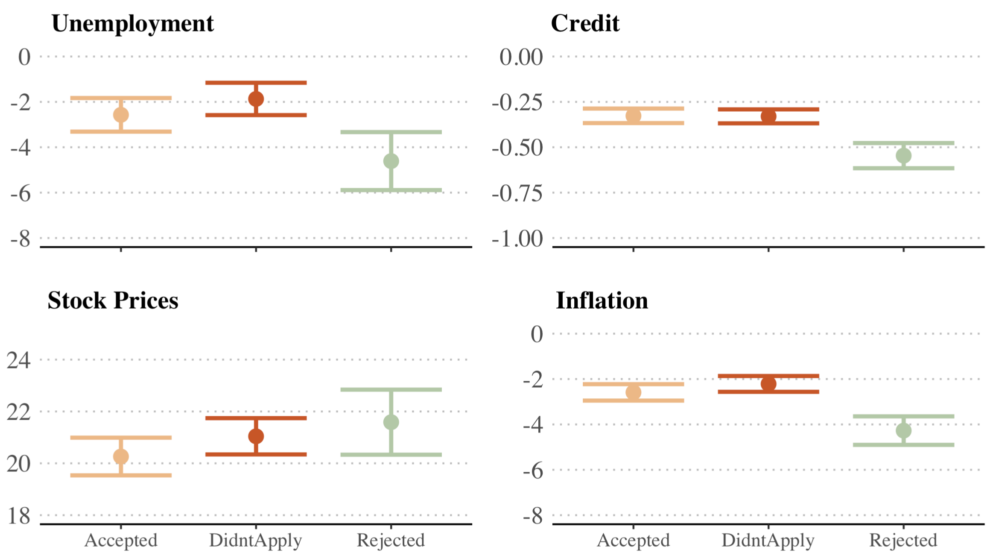
Since households with different experiences also differ across other characteristics, I run the following OLS regression:

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

where the outcome variable is individuals' i forecast error at time t, X_i are the individual level controls described in Section 3.2, r_{it} is a dummy that takes value 1 if the individual experienced a rejection in the past year and d_{it} is a dummy that takes value 1 if she chose not to apply. Figure 5 shows the forecast error by credit market experience predicted by the OLS regression when all other regressors are at their sample mean (coefficients from Table C.30). Even after including the full set of controls, rejected individuals have consistently higher forecast errors than accepted individuals and non-participants.

The fact that their errors can be systematically forecasted based on their rejections suggests that they are not using their experiences in line with their informativeness. Since individuals' own rejection is in their information set when making the forecast, optimal use of information predicts $\delta = 0$, whereas the estimated coefficient is significantly different from zero for all variables. The findings thus suggests that people rely too much on their own rejection experience when forming beliefs about the economy, leading to over-pessimism.

Figure 5: Predicted Forecast Errors by Credit Experience



Notes: The figure shows predicted forecast errors based on regression results from Table C.30. Column 1 refers to the panel on Unemployment, Column 2 to the panel on Credit, Column 3 to the panel on Stock Prices and Column 4 to the panel on Inflation. Predicted values are computed while holding all other explanatory variables at their sample mean.

Several other papers have found that individuals' FE are predictable (Bordalo et al., 2020; Broer and Kohlhas, 2022; Born et al., 2022; Kohlhas and Walther, 2021, for example). While most of the literature has focused on the predictability coming from news or aggregate outcomes, I focus on the role of personal experiences. An advantage of my set up is that I do not need to make assumptions about individuals information sets, as respondents' report their own experience when interviewed at time t. $r_{it} \in I_{it}$ is enough to test whether $(Y_{t+1} - F_{it}Y_{t+1}|I_{it}) \perp I_{it}$. Appendix C.3 provides robustness using the matched sample and individual fixed effects.

Informativeness by Types. In examining the correlation between rejection shares across different groups and aggregate economic conditions, I find that during the study period only rejection shares among "high" types - characterised by high income and college attendance - are strongly correlated with macroeconomic conditions (see Figure C.7 and Tables C.34, C.35 in the Appendix). If individuals are using their experiences in accordance with the information they provide, one would expect "high" types to rely more on their rejection when thinking about the economy. Contrary to this, my findings reveal that individuals with lower income and no college attendance exhibit a *greater* reliance on their personal rejections, even though rejection shares among them are acyclical (see Appendix Table B.19).

Overall, I find that rejected individuals are more pessimistic about the macroeconomy than those who weren't, and this is irrespective of their demographics, loan type and informativeness of the experience. The evidence suggests that to understand individuals' belief formation process, a departure from models in which experiences are no different than information is needed.

4 Modelling the Mechanism: Memory-Based Beliefs

My findings contribute to the literature on experience-effects, which established that experiences have a strong influence on individuals' beliefs (see Malmendier (2021); Malmendier and Wachter (2021) for reviews), but they represent challenges for existing theories, which are domain specific and directly assume the existence of experience-effects. Why is that experiences are used in the first place? Why personal experiences in the credit market affect expectations not only about credit conditions but also about unemployment? What determines the magnitude of the effect?

In this section I present a belief formation process based on selective memory that can generate the documented effects, and allows for a thorough exploration into the psychological underpinnings of why past experiences matter and how people use them. I argue that personal experiences affect expectations about the economy not because they provide information but because they are perceived as similar and help to imagine those economic outcomes. The model formalises this idea through two key mechanisms: (1) similarity-based recall: each piece of information or past experience can be recalled when thinking about a future event, and the probability of recalling each experience increases in the similarity between it and the event; (2) simulation: if these recalled experiences ease simulation of the future event, they are used for the formation of probabilities thus leading to deviations from statistical probabilities. In other words, similarity is the process by which elements of the memory database come to mind in a selective and associative way, whereas simulation is the process whereby an uninformative yet similar experience is used for the estimation of probabilities. In Section 4.1 I introduce the model which builds closely on Bordalo et al. (2022, 2023). In Section 4.2 I show how it can shed light on the empirical findings while also deriving new predictions that I validate in the data.

4.1 The Model

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

Households have a database of memories denoted by $M = \{\Theta, E\}$, where Θ denotes the set of historical macro transitions from state i to state j for all i, j, while E contains other macro data and past personal experiences. Each element of the database is characterised by a set of attributes. In principle, these attributes or features can include time, location, context, emotion and so on. For simplicity, I assume that each experience $m \in M$ can be fully characterised by a small vector of 3 features. The first one refers to the type, either a relevant macro transition or other experience. The other two refer to the effect of the experience, either positive or negative and to its persistence. Formally, each $m \in M$ is defined by (f_0, f_1, f_2) where $f_0 \in \{\theta, e\}$ captures the type, $f_1 \in \{L, H\}$ the "current" state and $f_2 \in \{L, H\}$ the "future" state. For example, a macro transition from state L to state L is denoted as $\theta_{LL} \in \Theta \cup M$ and has features (θ, L, L) whereas $e_{LL} \in E \cup M$ is a personal experience that had a persistent negative effect and is characterised by (e, L, L). Thus the memory database can be expressed as $M = \{\Theta, E\}$ where $\{\Theta\} = \{|\theta_{HL}|, |\theta_{HH}|, |\theta_{LH}|, |\theta_{LL}|\}$, $\{E\} = \{|e_{HL}|, |e_{HH}|, |e_{LH}|, |e_{LL}|\}$, and $|x_{ij}|$ is the number of transitions from state i to j stored in memory for either macro transitions $x = \theta$ or other experiences $x = e$.

Recall and Simulation. Sampling from the database M is shaped by similarity and interference: experiences that are relatively more similar to the event being forecasted (compared to other experiences) are more likely to be retrieved. How individuals make these associations between experiences is formally described by a similarity function: $S(x, y) : M \times M \to [0, 1]$ measures similarity between experience x and y in M. This function is increasing in shared features and it is maximal when $x = y$. For example, a macro transition from a L state to a L state (i.e. θ_{LL}) has maximal similarity with itself, but also positive similarity with personal experience e_{LL} because of shared features $\{L, L\}$ (i.e. $S(e_{LL}, \theta_{LL}) > 0$).

Thinking about a transition from i to j acts as a cue that induces the recall of elements of the memory database. Formally, *Cued-Recall* states that when thinking about moving from i to j, the probability that the agent recalls experience $m \in M$ is proportional to its similarity to the event:

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

An experience m is more likely to be recalled if it is similar to the event θ_{ij}. For example, when thinking about the probability of transitioning to a future low state with tight credit markets, we are likely to remember own negative experiences that we perceive as similar because of shared features, such as personal rejections in the credit market. While the numerator of Equation 3 is increasing in similarity, the denominator is increasing in the total number of experiences with positive similarity in the database. Overall, the probability that any given experience is recalled depends on how similar such experience is relative to all other experiences in the database, implying that people with larger databases have a lower probability of recalling any given experience.

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

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

This depends on a process called *simulation*: the household remembers experience m when thinking about a transition from i to j with probability $r(m, \theta_{ij})$, and then she uses it to simulate the transition to state j with probability $\sigma(m, \theta_{ij}) \in [0, 1]$ which satisfies $\sigma(x, \theta_{ij}) \geq \sigma(y, \theta_{ij})$ if and only if $S(x, \theta_{ij}) \geq S(y, \theta_{ij})$. Simulation regulates how experiences are used for probability judgements once they are recalled. This process is a form of reasoning by analogy which gets easier when experiences are similar to the event, even if they are from different domains (Kahneman and Tversky, 1981).

Examples. Whether beliefs are distorted from statistical probabilities or not depends on the role of non-domain specific and potentially uninformative experiences - whether they are recalled and how they are used thereafter. The following examples illustrate the properties of memory-based beliefs (derivations and proofs are relegated to Appendix D).

Example 1: Frequentist Estimate. If only historical macro transitions from state i are retrieved and only transitions to j are used to simulate the event - namely, only type θ memories are recalled and used with $S(\{i,j\},\{i,j\}) = S(\{i,i\},\{i,j\}) = \sigma(\{i,j\},\{i,j\}\}) = \sigma(\{j,j\}\},\{i,j\}\}) =$ 1 and 0 otherwise - then probabilities are unbiased and given by the frequentist estimate:

$$p_{ij} = \frac{|\theta_{ij}|}{|\theta_{ij}| + |\theta_{ii}|} \tag{5}$$

In this case, both similarity and simulation are "narrow": only macro transitions from current state i are recalled, as this are the relevant pieces of information to evaluate transitions from such a state. From those recalled datapoints, only the ones that reflect transitions to the state of interest j will be helpful to imagine such event.

Example 2: Memory Distortions when Similarity is Broad - Only Information. Suppose that simulation is still narrow but recall is broader: macro transitions from i are recalled with maximum similarity but, since we are thinking about transitions to j, macro transitions that share that feature will also come to mind. Among the recalled ones, only those related to a transition to j are used for simulation and thus:

$$\tilde{p}_{ij} = \frac{|\theta_{ij}| + s^{\theta}_{jj}}{|\theta_{ii}| + |\theta_{ij}| + s^{\theta}_{jj}} > p_{ij} \tag{6}$$

where $s^{\theta}_{jj} = S(\theta_{jj},\theta_{ij})|\theta_{jj}|$. Remembering a piece of information that is similar and helps to imagine event j increases households' perceived probability of a transition to such event j, leading to an over-estimation compared to the frequentist estimate.

Example 3: Memory Distortions when Similarity is Broad - Information and Experiences. Examples 1 and 2 assume that people only recall relevant data (i.e. macro transitions $\theta \in \Theta$), but personal experiences also share features with macroeconomic conditions, and thus come to mind even if not statistically relevant. Once recalled, they are used if they help imagine state j

- namely, share feature $f_2 = j$. The probability estimate is now given by:

$$p_{ij}^e = \frac{|\theta_{ij}| + s_{jj}^\theta + s_j^e}{|\theta_{ii}| + |\theta_{ij}| + s_{jj}^\theta + s_j^e} > \tilde{p}_{ij} > p_{ij} \tag{7}$$

where $s_{jj}^\theta = S(\theta_{jj}, \theta_{ij})|\theta_{jj}|$ and $s_j^e = S(e_{jj}, \theta_{ij})|e_{jj}| + S(e_{ij}, \theta_{ij})|e_{ij}|$. To see the effect that recalling one extra experience has on probability estimates, let $|e_{jj}| = 1$ and $|e_{ij}| = 0$. Probability estimates can be expressed as a function of $\tilde{p}_{ij}$ in Equation 6 and the distortion induced by recalling the experience e_{jj}:

$$p_{ij}^e = \tilde{p}_{ij} + \underbrace{r(e_{jj}, \theta_{ij})\,[1 - \tilde{p}_{ij}]}_{\text{bias from recalling } e_{jj} \,>\, 0} \tag{8}$$

Therefore, because of similarity-based recall and simulation, personal experiences can lead to over-estimation of macroeconomic outcomes even if uninformative.

Note that whether people think about transitions to low or high states is key, since the state tomorrow j acts like a focal point: when thinking about a transition from i to j, personal experiences with i and j features are recalled because of similarity but only those with j help to simulate a j event tomorrow. Thus e_{hj} experiences impact p_{ij} while e_{ki} experiences are discarded, for all h, k and $i \neq j$.

Assumptions and Roadmap. Based on this framework, Section 4.2 focuses on the role of one particular experience, the rejection, and presents novel implications about the magnitude of the effect. The following two clarifications are in place.

First, although simulation can vary between 0 and 1, I assume that once recalled, experiences that share feature $f_2 = j$ are used perfectly for simulation, $\sigma(m_{hj}, \theta_{kj}) = 1$ for all h, k, while others are discarded (as in the examples above). This simplifying assumption disciplines the model and suffices to explain my empirical findings, but can be easily relaxed.[12] In Appendix D I present model equations and results for the general case, which are in line with Bordalo et al. (2022).

Second, I focus on the case where individuals are trying to estimate the probability of transitioning from state i to a future low state L (i.e. $\hat{p}_{iL}$), and thus negative experiences are more likely recalled than positive ones. Given their focal point L, they estimate $\hat{p}_{iL}$ and assign $1 - \hat{p}_{iL}$

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

to the alternative H state. This is motivated by the empirical evidence: (1) personal rejections have a strong statistically significant effect on expectations while acceptances do not (Table 3), (2) individuals who experience both a rejection and an acceptance are as pessimistic as those only rejected (Table B.13). More generally, reading the empirical results from the lenses of the memory model open the scope for interesting questions. For example, is it that the survey questions induce the recall of specific experiences or do people generally focus on "worst case scenario" which then lead to the recall of negative experiences? I now proceed to interpret the empirical findings and explore the model's predictions through the lenses of the assumption described above.

4.2 Effect of Personal Rejections

The database of a rejected individual can be expressed as $M^R = M \cup R$, where $R = e_{LL}$ represents a prior rejection experience, and M includes the history of transitions and other experiences. Based on M^R, individuals estimate the probability of transitioning to state L through memory-based recall and simulation, expressed as:

$$\hat{p}^R_{iL} = \hat{p}_{iL} + \underbrace{r(R, \theta_{iL}) \times (1 - \hat{p}_{iL})}_{\text{bias from recalling } R \,\equiv\, \beta_r} \tag{9}$$

where $r(R, \theta_{iL}) = \frac{S(R,\theta_{iL})}{S(R,\theta_{iL}) + \sum_M S(m,\theta_{iL})} \equiv \omega_{iL}$ is the recall probability and $\hat{p}_{iL} = \frac{\sum_{m \in M} S(m,\theta_{iL})\sigma(m,\theta_{iL})}{\sum_{m \in M} S(m,\theta_{iL})}$ is the estimated probability without using the rejection. Expression 9 is akin to Bayesian updating, where $\hat{p}_{iL}$ serves as the prior belief, ω_{iL} as the weight assigned to new information, and $(1 - \hat{p}_{iL})$ as the adjustment in beliefs compared to the prior. However, it is essential to note that the interpretation differs. In this setup, there is no explicit prior probability, and no updating of such a prior. Instead, individuals recall a set of experiences based on cues and use them to simulate future events. $\hat{p}^R_{iL}$ is the resulting mean probability, and Equation 9 breaks it down into the effects of the rejection experience and other recalled experiences.

This memory-based belief model can capture over-estimation of low economic states based on personal and relatively uninformative rejections through similarity and simulation. The next proposition summarises this result:

Proposition 1. *(Over-Estimation)* A rejection experience $R = e_{LL}$ induces over-estimation of Low macroeconomic states if such an experience is perceived as similar to the state and helps imagine a transition to it: if $S(R, \theta_{iL}) > 0$ and $1 > 1 - \hat{p}_{iL} > 0$ then $\hat{p}^R_{iL} > \hat{p}_{iL}$. The size of the bias that results from recalling such an experience - β_r - is increasing in similarity and decreasing in

$\hat{p}_{iL}$: $\frac{\partial \beta_r}{\partial S(R,\theta_{iL})} > 0$, $\frac{\partial \beta_r}{\partial \hat{p}_{iL}} < 0$.

Experience-driven heterogeneity emerges endogenously. Given that people have different experiences in their databases, any given cue tends to trigger the recall of individuals' specific experiences. Notably, the empirical findings presented in Section 3.4 reveal an asymmetric effect: while rejections lead to pessimistic beliefs, acceptances do not yield a corresponding sense of optimism. The model provides insights into this phenomenon through three key mechanisms. First, the L-cue or focal point, as mentioned earlier. If the focal point is a future negative state, acceptances, while potentially recalled when the current state is good, are typically discarded as they don't contribute to simulating negative future scenarios. Second, even if the focal point involves high states, acceptances are predicted to play a less significant role compared to rejections. This is because (1) they face greater interference from other positive experiences, making them less salient than rejections, and (2) the likelihood of transitioning to a high state is higher than a low state, so recalling a positive experience doesn't significantly increase its perceived probability (Proposition 1). Furthermore, the model yields several new predictions:

Prediction 1. *(Unlikely Events)* Recalling a personal experience has a stronger effect on expectations about a given outcome when such outcome is relatively unlikely (either objectively or perceived as such), i.e. $\frac{\partial \beta_r}{\partial \hat{p}_{iL}} < 0$.

If individuals are already pessimistic to start with, recalling an additional negative experience won't increase pessimism as much as when the perceived likelihood of a future L state is low.

Prediction 2. *(Heterogeneity in Perceived Similarity Across Domains)* Heterogeneity in similarity functions results in different associations between a given experience and event, and thus heterogeneity in beliefs.

Let experiences and events be also characterised by the domain they pertain to (credit markets, labor markets, inflation and so on). The model then predicts $S(R, Credit_{LL}) > S(R, Unemp_{LL})$ and thus

$$\beta_r^{cr} \equiv |\hat{p}_{iL}^{cr} - \hat{p}_{iL}^{cr,R}| > |\hat{p}_{iL}^{unemp} - \hat{p}_{iL}^{unemp,R}| \equiv \beta_r^{unemp}$$

The effect of rejections should be stronger when the event being forecasted pertains to the same domain as the experience (credit markets).

Prediction 3. *(Heterogeneity in Databases)* Increasing the size of the original database M reduces the probability of recalling any given experience $\frac{\partial r(.)}{\partial |M|} < 0$. Therefore, the effect of a rejection on beliefs will be smaller for bigger databases. This suggests that the effect of rejections should be stronger for younger individuals with less interfering experiences.

Prediction 4. *(State Dependency)* The probability of recalling a rejection is higher when the current state is low, as the similarity between the two is higher: $S(R,\theta_{LL}) > S(R,\theta_{HL})$ which implies $r(R,\theta_{LL}) > r(R,\theta_{HL})$. Low current macro states induce recall of past negative experiences.

4.3 Test of Model Predictions

I test the predictions sequentially using the SCE survey data. First, to test Prediction 1 and Prediction 2, I use the coefficients estimated in the survey data and the memory model equations to calculate individuals' implied similarity function across domains. In particular, the memory-model implies that the probability of recalling a personal rejection is given by:

$$r(R,\theta_{iL}) = \beta_r/(1-\hat{p}_{iL}) \tag{10}$$

I calculate this implied recall probability across the different domains where rejections are recalled: probability of tighter credit markets, probability of higher unemployment, probability of higher inflation. For the latter I use the probabilistic questions included in the SCE and analyse the effect of rejection on individuals' perceived probability of inflation higher than 4% and probability of inflation higher than 8%. These measures allow me to evaluate differences across more or less likely events. To have a measure of $\hat{p}_{iL}$ I calculate average probabilities for the whole sample who has not experienced a rejection. Table 4 presents the results.

Table 4: Implied Similarity Across Domains and Ranking

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

Notes: The second column reports the weighted average response in the sample, excluding rejected individuals. The third column reports the estimated coefficient on rejection for each of the outcome variables, for which regression results are shown in Appendix Table D.36. The last column presents the implied similarity function and the suggested ranking, when simulation equals 1. Lower values of simulation increase the value of the implied recall, but the ranking prevails. The results in this table thus provide a lower bound for implied recall.

As predicted by the model, personal credit rejections play a much stronger role on expectations about credit markets, and this can be explained by a higher perceived similarity between the two (Column 4). Personal rejections are also associated with high unemployment and high inflation, which translates into pessimism across the board, although the effect is smaller because of lower perceived similarity. Note that the average probabilities in sample do not differ much, but estimates of the effect of rejection do because of differences in implied recall.

When it comes to inflation, the average probability assigned to inflation being higher than 4% is almost double than the one assigned to inflation being higher than 8%, which suggests that the latter is perceived as a less likely scenario. As can be observed from Columns 3 and 4, the estimated coefficient of rejection on the unlikely scenario of an 8% increase is higher than on the 4% event, but the implied similarities are almost identical. Thus, in line with Prediction 1, rejections play a stronger role when thinking about the more unlikely inflation scenario, not because the similarity between inflation and rejection differs, but because the recalled rejection is used to imagine an event that does not occur often.

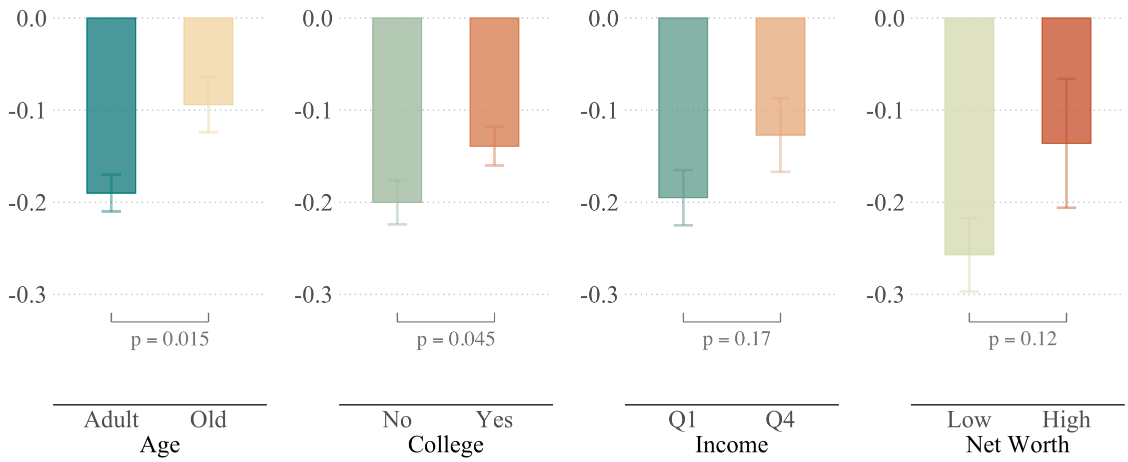
The model also suggests that other economic outcomes that are further away in terms of similarity from personal rejections would not be influenced by such an experience. One example of this could be individuals' reported probability of increases in "the level of U.S. government debt". Although related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

The role of personal rejections is not only heterogeneous across domains but also across individuals. As Prediction 3 highlights, the particular role that an experience plays when forming beliefs depends on the database that it is incorporated. To test this in the data, I take age as a proxy for the size of the database and test whether young people who have smaller databases indeed rely more on their rejection experience.

Previous literature has also emphasised that people with lower socio-economic status - proxied by college attainment, income levels and net wealth - are more pessimistic about the economy (Das et al., 2020). I thus investigate whether these people rely more on their own rejection experience when thinking about the future economy. Reading this through the lenses of the model, for individuals with low socio-economic status, being denied credit can be much more costly, leading to stronger associations of this negative experiences with negative aggregate outcomes. Note that given the evidence in Section 3.5, this is the opposite of what a theory based on partial information would predict: since rejections among individuals with low income and no education are not correlated with the aggregate economy, they should assign less weight to such experiences compared to those with high income or no education.

The data supports the predictions of the memory-based belief model, summarised in Figure 6. Individuals who are younger, or have no college attainment, or lower income, or lower net wealth rely more on their own experiences of rejections when thinking about the future economic state.

Figure 6: Heterogeneity in Estimated Coefficient on Personal Rejection



Notes: The figure shows the estimated coefficient on rejection that results from regressing personal past rejections interacted by an individual characteristic on optimism index. Each panel includes, in grey colour, the p-value from a test of statistical difference between the two categories. Table B.19 shows the regression results in detail.

People disagree about the future state of the economy not only because they have different experiences, but also because these experiences are perceived differently by different groups. This can lead to great dispersion and heterogeneity which, according to the model, could be even more prevalent in low economic states.

Prediction 4 on State Dependency suggests that the extent to which an experience is remembered co-moves with the aggregate state. To test this, I interact past personal rejections with a binary variable that takes value 1 if the individual answered the survey during the COVID induced recession of 2020, and regress this onto individuals' Optimism Index. The left table in Table 5 presents the results. Being rejected in the last year is associated with a strong macro pessimism about the future, and the effect is almost doubled when respondents' expectations are elicited during the recession period.

The right table in Table 5 looks at state dependency when the outcome variable is unemployment, and in Appendix Table D.37 I present equivalent regression results but using other outcome variables such as credit markets and inflation. The cuing effect is robust. Results show that people extrapolate from current economic states into future states, that their personal rejections further impact these expectations, and that the effect of the latter is more pronounced when the current state is relatively low.

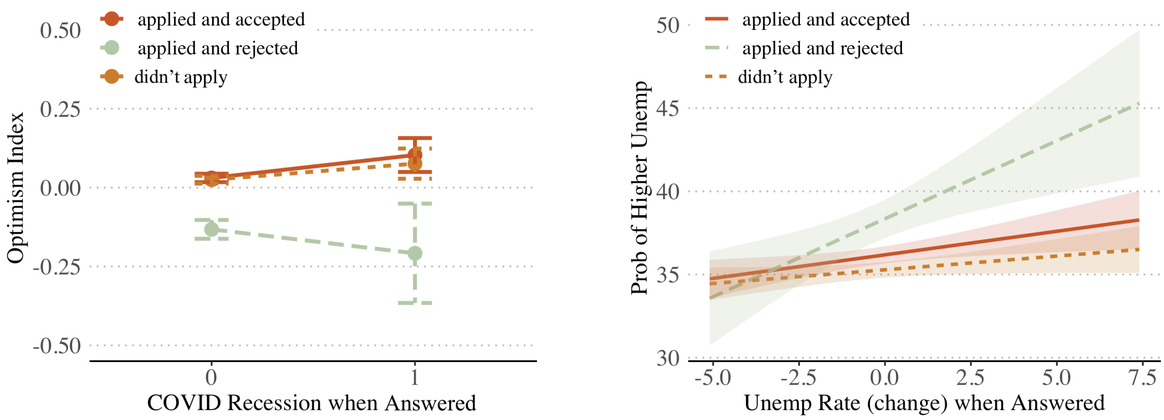
Table 5: State Dependency in Beliefs - Optimism Index and Probability of Higher Unemployment

	OPTM		↑UNEMP
Applied and Accepted	(omitted)	Applied and Accepted	(omitted)
Applied and Rejected	-0.155^{***}	Applied and Rejected	2.173^{***}
	(0.016)		(0.626)
Didn't Apply	-0.011	Didn't Apply	-0.935^{***}
	(0.008)		(0.310)
Recession	0.065^{**}	USunemp	0.276^{**}
	(0.028)		(0.110)
Applied and Rejected × Recession	-0.150^{*}	Applied and Rejected×USunemp	0.672^{**}
	(0.086)		(0.300)
Didn't Apply × Recession	-0.023	Didn't Apply× USunemp	-0.107
	(0.037)		(0.141)
Controls	Y	Controls	Y
R^2	0.103	R^2	0.018
Observations	25146	Observations	25132

Notes: The left table presents regression estimates from equation 1 where individual rejection is interacted with a binary variable that takes value 1 if individual was interviewed during the Covid recession of 2020. The dependant variable is the Optimism Index. The right table presents regression estimates from equation 1 where individual rejection is interacted with a measure of aggregate unemployment. This variable refers to unemployment rates from FRED (change from year ago, percent). The dependent variable is respondent's subjective probability of US unemployment increasing in the next 12 months. All specifications control for demographics and socioeconomic characteristics such as age, gender, race, employment status, married, college, income, income expectations and fixed effects for the state where respondents live. Standard errors are clustered at the respondent and date level. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Interestingly, individuals who answered the survey during the COVID recession are on average more optimistic about the future economic state, but if they personally experienced a rejection in the past year, they are much more pessimistic. This result suggests that the overreaction to negative economic states could be explained through the recall of negative experiences that such states induce. Figure 7 provides a graphical illustration of these interaction effects shown in Table 5. Beliefs of those who were accepted move closely to beliefs of those who chose not to apply, irrespective of the economic state. The figure illustrates that the recall of idiosyncratic negative experiences such as rejections leads to further disagreement in beliefs during bad times.

Figure 7: State Dependency in Beliefs - Optimism Index and Probability of Higher Unemployment



Notes: The figure plots interaction effects shown in Table 5. 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

Recalling personal rejections is associated with pessimism about the economy, and such effect is even stronger when current economic conditions are tight. When looking at individuals' subjective probabilities of higher unemployment, a 1 standard deviation increase in aggregate unemployment rates lead to an increase in individuals' probability judgements of around 0.68 pp. The marginal effect of personal past rejections on individuals' subjective probabilities of higher unemployment depends on the current state of unemployment: for average rates of unemployment, the marginal effect of rejection is approximately 2 pp but it goes up to 4.5 pp when unemployment increases by 1 standard deviation (see Table 6). This once again shows that people extrapolate from current states, but the extent of extrapolation depends on their own experiences.

Similarly as before, using the model equations and the estimated coefficients, one can calculate the implied probability of recalling a personal rejection in times when unemployment rates are average as opposed to times when unemployment rates are 1 standard deviation higher than average. The last column of Table 6 presents the results. As predicted by the model, the probability of recalling personal negative experiences is much higher when the current economic conditions are also relatively negative.

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

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

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

Extrapolation and overreaction to aggregate states, as formalised in models like diagnostic expectations (Bordalo et al., 2020), have been widely documented. Negative news about the current state tend to make negative future states more prominent in individuals' minds, leading to their over-estimation. These models have proven valuable in studying overreactions to aggregate shocks and their economic consequences. For instance, Bianchi et al. (2023) demonstrate how diagnostic beliefs can lead to boom-bust cycles following a monetary policy shock. However, the findings in this paper suggest that overreaction is not solely tied to recent news; rather, its extent depends on the experiences triggered by the news. Therefore, the observed bias in beliefs can be broken down into a systematic component (overreaction to current states) and an idiosyncratic component (individuals' personal experiences cued by the current state).

While existing theories of belief formation can partially explain some of these phenomena in isolation, they struggle to account for the full spectrum of evidence presented. In Appendix D.4, I provide a detailed comparison between the memory model and its predictions, and other potential explanations frequently studied in macroeconomics and finance.

Now, I delve into the economic implications of the documented over-estimation and heterogeneity, and the overreaction to economic downturns.

5 Implications for Economic Behavior

In this section I embed the memory-based beliefs into a simple three period consumption-saving model to explore its economic implications. The theoretical framework allows me to isolate the mechanisms through which memory can impact household behaviour and the aggregate economy. First, using this theoretical framework, I show that memory leads to amplification. Second, I quantify the importance of this amplification channel in the data and provide evidence that it is heterogenous, in line with the predictions from the memory model. Finally, I argue that this amplification channel can have important aggregate implications which interact with the aggregate state of the economy.

5.1 Theoretical Framework

The economy is populated by a continuum of ex-ante identical households who live for three periods, $t = 0, 1, 2$. As before, there are two states of nature that determine the aggregate state of the economy, either High or Low. They evolve as a 2-state Markov process with transition probability matrix P. States are known and households can use both information and experiences to form beliefs about the transition probabilities.

Income. At the start of each period, each agent receives an endowment. In periods $t = 1$ and $t = 2$, the endowment moves with the macroeconomic state: $y_t = y^H$ if $\theta_t = \theta_H$ and $y_t = y^L$ if $\theta_t = \theta_L$. During the first period $t = 0$ the endowment is deterministic and satisfies $y_0 < E(y_1 + y_2)/2$ for all agents, irrespective of the state. The intuition is that, when households enter the economy, they are young and lack resources, but they expect their income stream to improve in the next periods.

The main elements from the credit market block of the model are now described while a formal description is left for Appendix E.1.

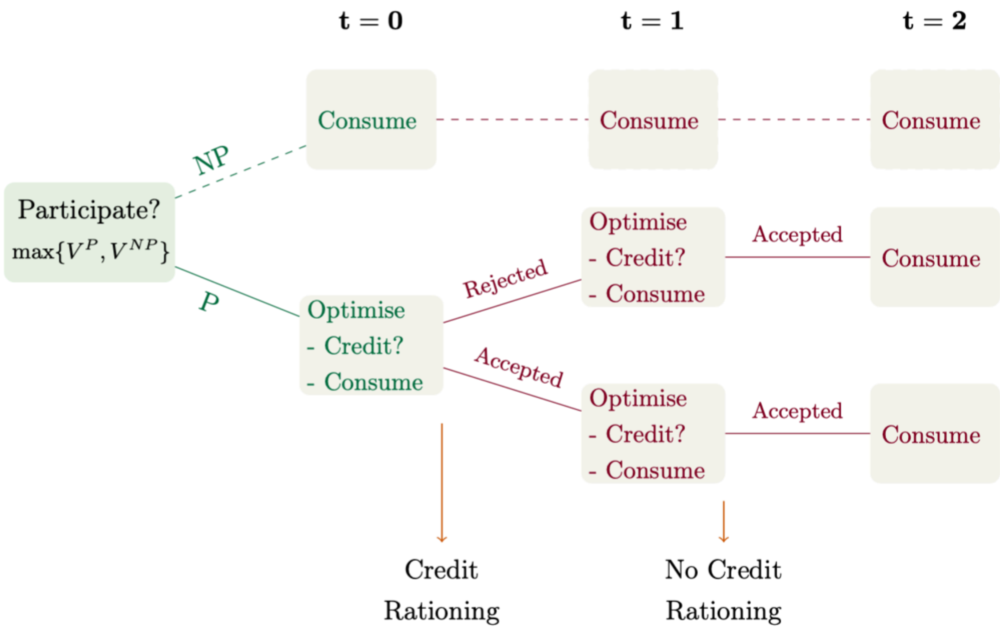
Credit Market. Households can transfer resources across states by saving or borrowing from a credit market. Before $t = 0$, they choose whether to participate in this credit market or not. It is assumed that this choice is made only once and, if they choose not to participate, they have no other means to transfer resources across periods.[13] At time $t = 0$, young adults who choose to participate in the credit market have an incentive to borrow because they expect their income to increase. They first solve for their optimal level of borrowing b_{t+1} and then apply for a loan.

The supply side of the market is characterised by a bank that provides loans at a given interest rate R. To generate random rejections as in the empirical investigation, I introduce credit rationing by limiting the total amount of credit that banks can provide (Calomiris et al., 2008). More specifically, the total amount of credit that can be provided in the economy is capped by

[13]Households participate in the credit market if $V^P > V^{NP}$, which occurs so long as they assign a relatively high probability to future increasing income - such that their V^P if accepted is higher than their V^{NP} - and their perceived probability of rejection is lower than a threshold (see Appendix E.1 for its derivation).

an exogenous limit $\bar{B}_t$. If the total demand for credit is lower or equal than this supply limit, everyone can obtain their desired credit at the given R. If the total demand surpasses the exogenous limit, banks can reject a share $\lambda_t > 0$ of the applicants to make the constraint slack once again. To stress the role of past rejections, I assume that the limit $\bar{B}_0$ is tight and thus $\lambda_0 > 0$, whereas the limit at the second period is such that $\lambda_1 = 0$. Figure 8 illustrates the timeline.

Figure 8: Timeline for Households Decision Problem



I focus on the problem of households who choose to participate in the credit market[14]. Given the described set up and their expectations about future endowment, households solve

$$\max_{\{c_0,c_1,c_2\}} \sum_{t=0}^{2} \beta^t \hat{E}_0(u(c_t)) \tag{11}$$

subject to the budget constraints $c_0 = y_0 + b_1$, $c_1 = y_1 - Rb_1 + b_2$ and $c_2 = y_2 - Rb_2$ and the borrowing constraints

$$b_1 \begin{cases} \leq R^{-1}(y_1^L + R^{-1}y_2^L) & \text{if accepted} \\ = 0 & \text{if rejected} \end{cases} \tag{12}$$

[14]Since I have assumed households are initially homogenous, either all of them choose to participate or no-one does. I focus on the case where $V^P > V^{NP}$.

$$b_2 \leq R^{-1} y_2^L \tag{13}$$

Households can borrow at most the lowest realisation of the present discounted value of their future income. Following the description of the credit market, all households who wish to borrow in the second period can do it ($\lambda_1 = 0$), subject to the borrowing constraint. On the other hand, in the first period, a fraction $1 - \lambda_0$ of households can borrow until the limit while others are randomly rejected and get $b_1 = 0$. For clarity of exposition, I further assume that $\beta = 1/R$ and utility is quadratic $u(c) = bc - 0.5c^2$ with $b > 0$ and $b < c$.

The model is solved by backwards induction.[15] In the second period $t = 1$, households receive their endowment and learn about the aggregate state of the economy. Everyone has access to the credit market and thus, everyone optimises. Subject to their endowment, their past savings/borrowings and their beliefs, households choose b_2 that solves their Euler Equation $c_1 = \hat{E}_1^h(c_2)$:

$$b_2^{h,i} = \frac{1}{1+R}\left[\hat{E}_1^h(y_2) - y_1^i + Rb_1^h\right] \tag{14}$$

where h refers to the type of household, either accepted $h = a$ or rejected $h = r$ last period and i refers to the economic state, either H or L; the expectation of household type h is given by $\hat{E}_1(y_2) = \hat{p}_{iL} y_2^L + (1 - \hat{p}_{iL}) y_2^H$.

At time 0, all households get a fixed endowment y_0 and observe the current state. A share $\lambda_0 > 0$ of them gets rejected from the credit market and become constrained: $b_1^r = 0$ and $c_0^r = y_0$. Those accepted optimise and get:

$$b_1^a = \frac{1}{1+R(1+R)}\left[\hat{E}_0^a(y_2 + Ry_1) - y_0(1+R)\right] > 0 \tag{15}$$

Households' perceived probabilities about future aggregate conditions are key determinants of their choices, as they determine their expectations about future income. How are these formed? If these probabilities are unbiased (only historical transitions are recalled and receive positive weight), then there is no heterogeneity in beliefs and the only difference among households comes from the direct effect that rejections have on their ability to smooth consumption. In particular, when first rejected in $t = 0$, individuals can consume less than what they would

[15] Under quadratic utility, Inada Conditions are not satisfied and hence individuals might choose to borrow up to the limit. I start by solving for interior solutions of the Euler Equations and then check that they satisfy the borrowing constraints. In the main text, I work under the assumption that parameters are such that borrowing constraints are slack. In appendix I derive the parametric assumptions needed for this.

desire. In period $t = 1$, because they do not carry past debt, they have lower desire to borrow than accepted individuals. The direct channel can be summarised as:

Result. Being rejected from the credit market has a direct effect on individuals consumption and saving decisions.

a. Being rejected in the past reduces the desire to borrow again.

b. Average lifetime realised consumption for rejected individuals is lower than the average lifetime realised consumption for accepted ones.[16]

On the other hand, if beliefs are formed based on memories of very personal and even uninformative experiences, heterogeneity in credit market experiences will induce systematic heterogeneity in expectations which can in turn amplify heterogeneity in choices. Households memory-based beliefs about transitioning to a low state are given by:

$$\hat{p}_{iL} = \sum_{m \in M} r(m, \theta_{iL}) \sigma(m, \theta_{iL}) = \sum_{m \in M} \frac{S(m, \theta_{iL}) \sigma(m, \theta_{iL})}{\sum_{m \in M} S(m, \theta_{iL})} \tag{16}$$

where $\sigma(m, \theta_{iL}) = 1$ for all $m \in M$ with $f_2 = L$ and 0 otherwise. All households start with homogenous databases and experiences, but through their interaction in the credit market, they gain a new experience that differentiates them. I focus on the difference in expectations that emerges from those rejected recalling their own past experiences, and how this affects their choices.

Guided by the empirical evidence presented in Section 3.3 and the model description in Section 4, I focus on the case where people are trying to forecast future low states, and therefore acceptances do not come to mind, neither induce over-optimism.[17] Moreover, since my interest is on the role of credit market experiences, I assume that the only difference between individuals comes from their different experiences in that domain and recall of them. Introducing heterogeneity in endowments or preferences would capture more differences among individuals but wouldn't alter the role of rejections. The probability estimates of individuals who have been rejected in the past can thus be expressed as $\hat{p}^R_{iL} = \hat{p}_{iL} + \omega_{iL} \times [1 - \hat{p}_{iL}]$ where $\omega_{iL} \equiv r(R, \theta_{iL})$ and $\hat{p}_{iL}$ is the subjective probability formed using all other recalled experiences except for the

[16] $AvgRejC \equiv (c^r_0 + c^r_1 + c^r_2)/3 < (c^a_0 + c^a_1 + c^a_2)/3 \equiv AvgAccC$ and $b^r_2 < b^a_1 + b^a_2$

[17] This assumption implies that beliefs of those accepted stay constant across periods, simplifying the analysis considerably without affecting the results. More generally, when individuals are affected by their personal memories their choices might exhibit time inconsistencies due to the failure of the law of iterated expectations. Under the current assumptions, accepted individuals have constant beliefs, so there are no time inconsistencies. Whereas rejected individuals do not make choices in the first period and only choose in the second period under their distorted beliefs. The analysis can be easily generalised, although that would induce further distortions and heterogeneity.

rejection. Given the assumptions, $\hat{p}_{iL} = \hat{p}^a_{iL}$ also reflects the memory-based probability of those accepted.

5.2 The Amplifying Effect and Implications for Household Finance

Rejected individuals will not only be affected directly by the rejections, but also indirectly through the belief channel. Plugging in Equation 9 into rejected individuals' optimal choice at time 1,

$$b_2^{r,i} = \frac{1}{1+R}\left[\hat{E}_1(y_2) - y_1^i - \underbrace{\omega_{iL}(1-\hat{p}_{iL})(y_2^H - y_2^L)}_{\equiv \text{ Memory Distortion}}\right] \tag{17}$$

where i refers to the economic state, $\hat{E}_1(y_2) = \hat{p}_{iL}y_2^L + (1-\hat{p}_{iL})y_2^H$ and $\omega_{iL}(1-\hat{p}_{iL})(y_2^H - y_2^L)$ captures the bias coming from the memory of personal past rejection. This bias has the properties of memory-based beliefs described in Section 4, and it leads to an increase in precautionary motives, as individuals wish to decline their borrowing and their current consumption to prepare for negative future shocks.

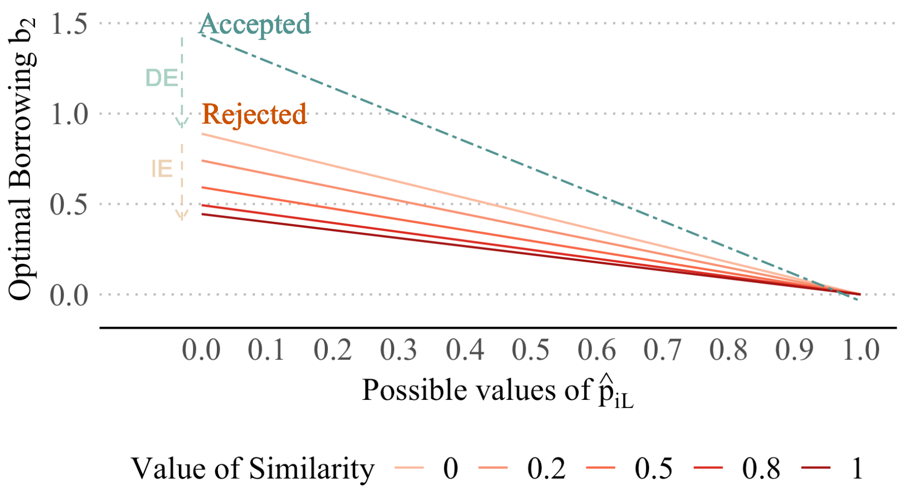
Proposition. Being rejected from the credit market has both a direct effect (DE) and an indirect effect (IE) through beliefs on individuals' consumption and savings choices. Relative to a model with rational expectations, memory-based beliefs lead to lower borrowing and lower average consumption:

$$b_2^a - b_{2,\omega>0}^r = \frac{1}{1+R}\left[\underbrace{Rb_1^a}_{DE} + \underbrace{\omega_{iL}(1-\hat{p}_{iL})(y_2^H - y_2^L)}_{IE}\right] > 0 \tag{18}$$

$$AvgC^r_{\omega>0} \underbrace{<}_{IE} AvgC^r_{\omega=0} \underbrace{<}_{DE} AvgC^a \tag{19}$$

The size of the belief channel or indirect effect depends on $(1-\hat{p}_{iL})$ and the value of $S(R, \theta_{iL})$ which impacts the probability of recall ω_{iL}. Figure 9 illustrates the direct and indirect effect on optimal borrowing choices when we let $\hat{p}_{iL}$ and similarity vary. The green dashed line depicts the optimal borrowing choice for those accepted for different values of the probability. The direct effect is captured by the jump from the green dashed line to the light red line, when similarity equals 0 and thus the bias from rejection is 0. As soon as the similarity between personal rejections and macro low states increases (darker red lines), the indirect effect pushes the optimal borrowing decision of those rejected down, for all values of $\hat{p}_{iL}$. The figure also emphasises the role of heterogeneity in similarity functions: households who rely more on their personal experiences reduce their desired borrowing even more, leading to lower consumption through the belief channel.

Figure 9: Optimal Borrowing at second period, for different $\hat{p}_{iL}$ and similarity values



Notes: The figure plots optimal borrowing b_2 for accepted and rejected, with and without memory based beliefs, for different probabilities and similarity values. The model was simulated under $\beta = 1/R$, $R = 1.25$, $y^L = 1$, $y^H = 3$.

In sum, the total effect of rejection on behaviour can be decomposed into a (1) direct effect: rejection → behaviour and an (2) indirect effect: rejection → beliefs → behaviour, and this amplifying indirect effect affects people differently.

Direct and Indirect Effect in the Data. To test whether there is evidence of the direct and indirect channel of personal rejections in the data, I return to the SCE survey data and implement the causal model of mediation analysis (Baron and Kenny, 1986; Rucker et al., 2011; Imai et al., 2011; Tingley et al., 2014; Pearl, 2014, 2022; Das et al., 2020), which allows not only to estimate the effect of the treatment (i.e. rejection) but also the mechanism through which the treatment affects the outcome (i.e. consumption).

I start by combining the data on expectations and experiences with the Spending Module present in the SCE. To measure individuals' consumption, I use their reported percent chance of buying durables within the next four months.[18]

The first step consists of a regression of individuals' macroeconomic beliefs on their experiences of rejections (as done in Section 3):

$$\text{OptimismIndex}_{it} = \beta_0 + \beta_1 \text{Rejection}_{i,t-1} + \delta X_{it} + \gamma_{st} + v_{it} \tag{20}$$

The second step of the estimation consists of a multivariate regression of rejections and beliefs on individuals' spending attitudes, while also controlling for a broad set of variables and fixed effects:

$$\text{Spending}_{it,t+1} = \alpha_0 + \alpha_1 \text{Rejection}_{i,t-1} + \alpha_2 \text{OptimismIndex}_{it} + \delta X_{it} + \gamma_{st} + u_{it} \tag{21}$$

The direct effect measures the portion of the total effect that would be transmitted to spending absent belief's ability to respond to the rejection treatment and is measured by α_1. The indirect effect measures the portion transmitted absent spending's ability to respond to changes in rejection, except those transmitted through beliefs and is defined as $\beta_1 \times \alpha_2$. For the estimation of the effects I rely on the estimation strategy proposed in Imai et al. (2011) and Tingley et al. (2014).

Table 7 provides the results. Rejections have a total negative effect on households' spending attitudes, and 12% of that negative effect can be attributed solely to their rejection-induced pessimism about the macroeconomy. For a person whose probability of spending in durables is the average probability in sample (i.e. 16.55%), experiencing a rejection directly reduces this probability to 13.33% and the pessimism bias induces an extra reduction of 0.455, leading to a final probability of spending of 12.87%. Appendix E.2 provides robustness through other estimation strategies.

[18] The SCE questions states: "Now looking ahead, what do you think is the percent chance that a member of your household (including you) will make any of the following large purchases within the next 4 months?". I construct an average percentage chance using households responses to home appliances, electronics/computers/cell phones, furniture, home repairs/improvements/innovations. Therefore, the outcome variable in this exercise refers to spending *attitudes* or intentions. Although I cannot test whether these intentions are then translated into actual consumption choices for each individual, I construct an aggregate measure of these spending intentions and corroborate that it is highly correlated with realised durable demand during those 4 months (corr= 0.57, p-value= 0.02). The source for aggregate contemporaneous monthly demand for durable goods is the FRED database of the Federal Reserve Bank of St. Louis.

Table 7: Direct and Indirect Effect of Rejection

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

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

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

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

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

The pessimism bias from personal rejections was shown to be stronger for younger individuals and for those with no college attendance and lower levels of income.[19] The model thus predicts that the belief channel should also be relatively stronger for them. I test this hypothesis by allowing for the indirect effect to be moderated by age and socio-economic status (SES), and present results in Table 8. I find that the belief channel for young, no college educated and low income individuals is always strong and statistically significant, and it accounts for a higher proportion of the total effect compared to older and high SES individuals, as predicted in the model.

The amplifying effect from the pessimism bias can have broad implications for households finances. Using the SCE and SCF data sets I find that rejections are also associated with lower likelihood of applying again even if desired (Appendix Table B.12), increases in savings due to fear of tighter credit conditions (Appendix Table E.39), and lower holdings of risky assets (Appendix Table E.40).

5.3 Overreaction and Further Implications

Apart from their amplifying effect, an excessive reliance on memories of rejections can induce overreactions to negative economic shocks. People typically adjust their probability judgments in response to such shocks and changes in the economic environment. However, an additional idiosyncratic component comes into play through the recall of past experiences triggered by the shock itself. As detailed in Section 4.3, past rejections foster pessimism, especially in the context of already unfavourable economic conditions. Therefore, the recall of negative experiences intensifies overall pessimism, resulting in greater belief dispersion and instability. This begs the question: How does this memory channel impact aggregate consumption?

In this section, I investigate the aggregate implications of the identified memory channel by integrating the survey data's identified moments with the model equations. This framework enables the examination of two aspects: (1) the influence of past rejections on aggregate demand, and (2) how a transition to a low economic state interacts with the memory of rejections, affecting aggregate demand.

Parameters. I use the empirical estimates from Section 4.3 to define the model's key parameters, as shown in Table 9. For the rejection rate (i.e. λ_0), I use the average rejection rate observed in the SCE data. Given that the aggregate state in the model affects individuals' income, I define a low state as one where unemployment rates increase by one standard deviation, and I

[19]The model also predicts differences in terms of wealth, but data limitations restrict such analysis.

focus on individuals' expectations about higher U.S. unemployment in the upcoming year. As outlined in Section 4.3, the average probability assigned to rising unemployment increases as the state worsens (i.e. $p_{HL} < p_{LL}$). Additionally, the likelihood of recalling a personal rejection experience is higher during low states compared to high states (i.e. $\omega_{LL} > \omega_{HL}$).

Table 9: Parameters and their estimated value based on SCE

	λ_0	p_{HL}	p_{LL}	ω_{HL}	ω_{LL}
Value SCE	0.18	0.355	0.363	0.03	0.07

Notes: The first row refers to the average share of rejections across the sample in the SCE data. Probabilities are based on individuals' responses to the question on the SCE that refers to the probability of higher US unemployment in the next 12 months. The parameter values were estimated using the survey data and described in Section 4.3.

Amplification in Aggregate Demand across States. Aggregate consumption at time 1 depends on the optimal consumption of those accepted and rejected in the previous period such that $C_1^i = (1 - \lambda_0)c_1^{a,i} + \lambda_0 c_1^{r,i}$ where $i \in \{H, L\}$. Thus the direct and indirect effect of rejection impacts aggregate demand, and their relevance its regulated by the share of rejections λ_0:

$$C_1^i = c_1^{a,i} + (1+R)^{-1}\,\lambda_0 \left[\underbrace{Rb_1^a}_{DE} \underbrace{- \omega_{iL}(1 - \hat{p}_{iL})\Delta y_2}_{IE} \right] \tag{22}$$

In any given economic state i, the reliance on personal rejection experiences affects aggregate consumption. Even in a favourable state, there is a share of individuals who got rejected in the past and still believes the economy might transition to a low state with a relatively high probability. This is because their personal past experiences allow them to easily imagine such state, which induces over-estimation in their probability judgements. This increase in their precautionary motives translates into slightly lower aggregate consumption (as shown in Column 1). This mechanism also holds in a low economic state, but its impact is more pronounced. Adverse economic conditions increase the likelihood of recalling personal rejections, as their similarity is stronger (ω_{LL} is higher than ω_{HL}). This heightened recall of personal rejections leads to over-reaction and further diminishes aggregate demand through the memory channel (as seen in Column 2). Table 10 provides estimates of these reductions in aggregate consumption caused by the indirect belief channel in both high and low states.

Table 10: Effect of Belief Channel on Aggregate Consumption, given the Economic State

Effect of Memory Channel or IE	
(1) High State	(2) Low State
-0.22%	-0.52%

Notes: The table presents estimated percentage change in aggregate consumption at period 1 when memory matters: $(C_1^{i,\omega=0} - C_1^i)/C_1^i = ((1+R)^{-1}\lambda_0\omega_{iL}(1-p_{iL})\Delta y_2)/C_1^{i,\omega=0}$. Parameter values are defined in Table 9 and $R = 1.25$, $y_2^H = 3y_2^L$, $y_2^L = 1$.

Due to the asymmetry of the estimated experience-effect, the pessimism arising from personal rejections does not dissipate when aggregated. Rejected individuals are consistently more pessimistic whereas accepted individuals do not compensate through higher optimism, leading to aggregate pessimism and amplified contractions in aggregate demand.

In sum, compared to an alternative scenario in which memories do not affect expectations, aggregate consumption is depressed and even more during low economic states. This state-dependency of the pessimism bias leads to average overreaction to aggregate negative shocks. Is this state-dependency relevant for aggregate consumption?

Overreaction to Bad News. I explore this by comparing households' optimal choices and resulting aggregate demand in two scenarios: one with a continuous favourable economic environment, and another where after a good state the economy transitions to a low state.

In the initial period, both economies are homogeneous. A fraction $\lambda_0 > 0$ of the population faces credit rejection, while the rest can optimise their consumption. In the second period, one economy experiences a recession, reducing everyone's income to y^L, and shifting beliefs since now the relevant transition probability is $\hat{p}_{LL}$. This affects everyone equally, but there is a share λ_0 who was rejected in the past, and now their past rejection experiences are more likely to be remembered ($\omega_{HH} \rightarrow \omega_{LL}$). Equation 23 shows the difference in aggregate consumption at time 1 between high and low states, and emphasises the existence of the three described forces that shape households' decisions:

$$\Delta C_1^{H\to L} = \underbrace{(y_1^H - y_1^L)}_{\substack{\text{(1) Income} \\ \text{Channel} >0}} + \frac{1}{1+R}\left(\overbrace{\underbrace{E_1^H(y_2) - E_1^L(y_2)}_{\substack{\text{(2) Probability} \\ \text{Channel} >0}} \underbrace{- [\omega_{HL}(1-p_{HL}) - \omega_{LL}(1-p_{LL})]}_{\text{(3) Memory Channel } >0}}^{\text{Belief Channel}} \lambda_0 \Delta y_2\right) \tag{23}$$

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

When the economy transitions from a high to a low state, people adjust their probabilities accordingly and make their choices based on the transition probability $\hat{p}_{LL}$ instead of $\hat{p}_{HL}$. If rejections were equally likely to be recalled in bad and good times, a negative shock would decline aggregate consumption through those changes in probabilities only. In such a case, memory does not interact with the economic state in significant ways, and thus it is not relevant for changes in aggregate consumption (Columns 1 and 2 in Table 11). However, my empirical findings in Section 4.3 reveal that past rejections are more likely remembered during bad times, and this translates into overreaction in average expectations. This interaction of past rejections and current negative shocks results into a decline in consumption that is 30 basis points higher than the benchmark scenario of constant pessimism bias (Column 3 in Table 11). Thus, past personal rejections interact with a current aggregate shock in the labor market, and this interlinkage across markets can have relevant aggregate implications.

Table 11: Over-Reaction through Memory and Lower Aggregate Demand

Decline in C_1 through Belief Channel (%)		
No Recall	Constant Recall	State-Dependent Recall
$\omega_{HL} = \omega_{LL} = 0$	$\omega_{HL} = \omega_{LL}$	$\omega_{HL} < \omega_{LL}$
-0.813%	-0.811%	-1.11%

Notes: The table presents estimated percentage change in aggregate consumption that results from changes in beliefs, calculated based on Equation 23 and parameters in defined in Table 9 plus $y_2^H = 3y_2^L$, $y_2^L = 1$.

While the model is stylised, it offers insights into the potential impact of the memory channel and can inform the demand component of larger macro models. The estimates presented here represent a conservative lower bound, as they focus on unemployment expectations (non-domain specific) and do not consider the impact of expectations about future credit market tightening (within-domain experiences), which can be more pronounced in models involving long-lived agents participating in the credit market multiple times.

Furthermore, the relevance of rejection-induced pessimism depends on the aggregate rejection rate. If a higher proportion of the population has experienced rejection in the past, a greater portion of the population will exhibit an overreaction to the low state due to their memories of rejection, i.e., $\partial \Delta C_1^{H \to L} / \partial \lambda_0 > 0$. For example, if the initial rejection rate were to increase by 30% (equivalent to the rise observed during the Great Recession), compared to the average rate of 18% from SCE data, aggregate consumption in low states would decrease by an additional 40 basis points, resulting in a total decline of 1.2% due to the pessimism effect.

These findings underscore that credit crises or policies leading to a higher share of households facing rejections can have unintended consequences through the belief channel, with significant effects. Even households inattentive to policy changes can exhibit excessive reactions due to changes in their experiences, and these effects can vary across the population.

6 Conclusion

This paper uncovers a pessimism bias about future economic conditions associated to past personal credit market rejections. Using both micro level data from the SCE from 2013-2022 and from the SCF from 1989- 2019, I find that rejected individuals - irrespective of their demographics, what type of loan they apply to or how well informed they are - are significantly more pessimistic about the macroeconomy than those who weren't rejected. They expect tighter credit market conditions for everyone, higher unemployment, lower stock prices and higher inflation. I find that these past rejections influence households' macroeconomic expectations excessively, and that the estimated pessimism goes beyond the potential informative content embedded in the rejection.

Building upon Bordalo et al. (2022), I provide a memory-based belief model to interpret the empirical findings and further characterise the bias. The model predicts that the effect of personal rejections on pessimism about the macroeconomy is stronger for younger and low socio-economic individuals, and during recessions, contributing to cross sectional heterogeneity in beliefs but also to overreaction in average beliefs to negative shocks. I find support for these predictions in the data.

Although I have primarily focused on credit rejections due to comprehensive data availability, there is suggestive evidence that there might be a general pattern worth exploring: individual-level economic adversities - such as unemployment, negative net wealth shocks, and bankruptcy - are also associated with pessimism about the economy in the SCE data.

My findings highlight that models of human memory can be useful to understand how people's idiosyncratic experiences within the economy affect their macroeconomic expectations and behaviour, but they also open up important questions for future research. The model is built on a key assumption: individuals make associations between their own experiences and the aggregate economy and then use those experiences to form expectations. Despite robust evidence in psychology and neuroscience that this is the case, its application within the realms of economics and household-finance remains relatively nascent. An interesting next step is to directly assess this modelling assumption by designing and conducting an online survey experiment to investigate what type of information and experiences come to people's mind when asked about the future state of the economy.

Gaining a better understanding of how households think about the economy and what type of associations they make before taking financial decisions can have important implications both for household finance and the economy as a whole. By incorporating the model of memory-based beliefs into a simple dynamic consumption-saving model I show that rejections can influence individual choices both directly, through credit constraints, and indirectly, by inducing pessimism about future macro states. This pessimism increases individuals' precautionary motives, leading to amplified contractions in consumption and lower desire to borrow once again. Using the SCE data I estimate the importance of this belief channel on households' planned durable consumption, and using both the SCE and SCF I find that past rejections are also associated with increases in savings, discouragement from participating in credit markets again and low holdings of risky assets. Moreover, since the documented pessimism bias is stronger during recessions, a counterfactual exercise shows that it can amplify contractions in aggregate consumption. A further exploration into the macroeconomic implications of the documented household-level bias and the interlinkage across markets represents a crucial avenue for future research.

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Appendix

A Data Appendix

A.1 Variable Definition and Construction of Measures

Panel A: Application. During the last twelve months, did you ...?		
During the last twelve months, did you ...?	Yes (1)	No (0)
Apply for a credit card (1)	○	○
Apply for a mortgage or home-based loan (2)	○	○
Apply for an auto loan (3)	○	○
Request an increase in the credit limit of a credit card (4)	○	○
Request an increase in the limit of an existing loan (5)	○	○
Request to refinance your mortgage (6)	○	○
Apply for a student loan (7)	○	○

Panel B: Outcome. Was your request for [X] granted?
Yes, my request was fully granted (1)
Yes, but my request was only partly granted (2)
No, my request was rejected (3)

Panel C: Did not apply for any loans/extensions. What is the reason for that?
I was satisfied with my fin. situation, and had no additional need (1)
Too time consuming, and not worth the benefits (2)
Borrowing rates were too high (3)
I do not know how to go about doing any of these (4)
I did not think I would get approved (5)

Table A.1: Credit Market Experience: SCE Questions

Table A.2: Construction of Credit Market Experience Measure

Variable	*Description*	*Questions Used*
Applied and Rejected	Dummy variable that takes value 1 if respondents applied to any type of loan within the last 12 months and got rejected in that application.	Panel A and B
Applied and Accepted	Dummy variable that takes value 1 if respondents applied to loans within the last 12 months and got approved either partially or fully in all applications.	Panel A and B
Didn't apply, Other	Dummy variable that takes value 1 if respondent didn't apply to any type of loan within the past 12 months because of reasons (1) to (4).	Panel A and C
Didn't Apply, Disc.	Dummy variable that takes value 1 if respondent didn't apply to any type of loan within the past 12 months because of reason (5).	Panel A and C

Table A.3: Probabilities Assigned to Different Inflation Scenarios

Now we would like you to think about the different things that may happen to inflation over the next 12 months. We realize that this question may take a little more effort. In your view, what would you say is the percent chance that, over the next 12 months ...	
the rate of inflation will be 12% or higher (bin 1)	___ percent chance
the rate of inflation will be between 8% and 12% (bin 2)	___ percent chance
the rate of inflation will be between 4% and 8% (bin 3)	___ percent chance
the rate of inflation will be between 2% and 4% (bin 4)	___ percent chance
the rate of inflation will be between 0% and 2% (bin 5)	___ percent chance
the rate of deflation (opposite of inflation) will be between 0% and 2% (bin 6)	___ percent chance
the rate of deflation (opposite of inflation) will be between 2% and 4% (bin 7)	___ percent chance
the rate of deflation (opposite of inflation) will be between 4% and 8% (bin 8)	___ percent chance
the rate of deflation (opposite of inflation) will be between 8% and 12% (bin 9)	___ percent chance
the rate of deflation (opposite of inflation) will be between 12% or higher (bin 10)	___ percent chance
TOTAL 100	

Table A.4: Individuals' Macroeconomic Expectations

Name	*Description*	*Question Used*	*Possible Answers*
UNEMP	Probabilistic question about rising unemployment	"What do you think is the percent chance that 12 months from now the unemployment rate in the U.S. will be higher than it is now?"	[0,100]
StockP	Probabilistic question about rising stock prices	"What do you think is the percent chance that 12 months from now, on average, stock prices in the U.S. stock market will be higher than they are now?"	[0,100]
INFL	Point estimate about expected inflation	"What do you expect the rate of [inflation/deflation] to be over the next 12 months? Please give your best guess."	Unbounded
Fcredit	Categorical variable assessing perceived credit market conditions	"Compared to 12 months ago, do you think it is generally harder or easier these days for people to obtain credit or loans (including credit and retail cards, auto loans, student loans, and mortgages)?"	(1) much harder [1] (2) somewhat harder [1] (3) equally easy/hard [0] (4) somewhat easier [-1] (5) much easier [-1]

Table A.5: Probabilities Assigned to Spending in Different Durable Goods

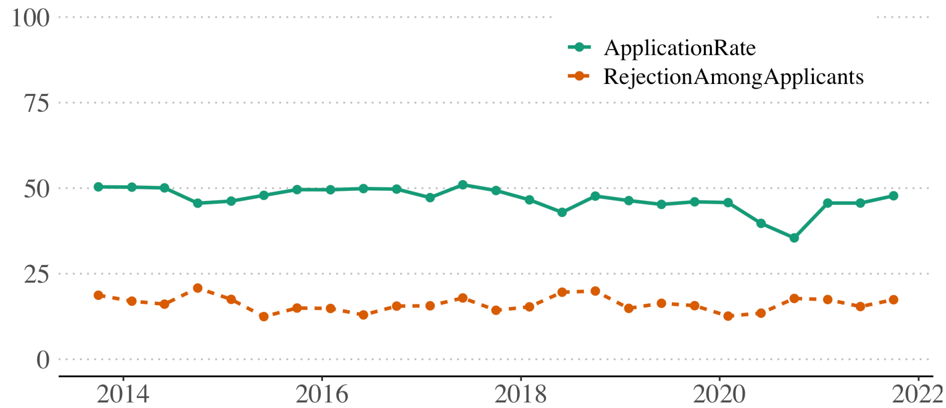
Now looking ahead, what do you think is the percent chance that a member of your household (including you) will make any of the following large purchases within the next 4 months? Please enter separately the percent chance of purchasing each item below.	
Home appliances (1)	______ percent chance (1)
Electronics, computers or cell phones (2)	______ percent chance (2)
Furniture (3)	______ percent chance (3)
Home repairs, improvements or renovations (4)	______ percent chance (4)
Car or other vehicles (5)	______ percent chance (5)
Trips and vacations (6)	______ percent chance (6)
A house or apartment (7)	______ percent chance (7)

Table A.6: SCE Question on past spending in durables

And thinking about the more recent past, did any members of your household (including you) make any of the following large purchases during the last 4 months? Please select all that apply.
◯ Home appliances (1)
◯ Electronics, computers or cell phones (2)
◯ Furniture (3)
◯ Home repairs, improvements or renovations (4)
◯ Car or other vehicles (5)
◯ Trips and vacations (6)
◯ Other (please specify) (7)
◯ A house or apartment (9) [added August 2016]
◯ None of the above (8)

A.2 Descriptive Statistics

Figure A.1: Application Rate and Rejection Rate among Applicants



Notes: The figure plots the average application rate and rejection rate among participants for each data in sample. Values account for the weights provided by SCE to make the sample representative of the US.

Credit Score Category	Share of Population	Application Rate	Rejection Rate among Applicants
< 680	0.1992	0.534	0.44
>= 680& < 720	0.104	0.573	0.13
>= 720	0.549	0.465	0.042
DK	0.147	0.32	0.19

Table A.7: Application and Rejection Rate by Credit Score

Table A.8: Transition Matrix

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

Table A.9: Summary Statistics of Experiences and Controls

	Mean	Standard Deviation	Min	Median	Max
Experiences in the Credit Market					
Applied and Accepted	0.39	0.63	0	0	1
Applied and Rejected	0.076	0.27	0	0	1
Didn't Apply, Other	0.46	0.68	0	0	1
Didn't Apply, Discouraged	0.072	0.27	0	0	1
Demographics					
Age	51	7.12	17	51	85
Female	0.5	0.7	0	0	1
White	0.84	0.92	0	1	1
Black	0.09	0.3	0	0	1
Married	0.64	0.8	0	1	1
College	0.49	0.7	0	1	1
Employment Status					
Employed	0.65	0.81	0	1	1
Looking for a job	0.03	0.17	0	0	1
Retired	0.21	0.46	0	0	1
Out of labor force	0.08	0.28	0	0	1
Income Category					
Below 50k	0.41	0.64	0	0	1
Between 50k and 100k	0.3	0.55	0	0	1
Above 100k	0.28	0.53	0	1	1
Home Owner	0.72	0.85			
Numeracy Category					
Low	0.34	0.81	0	0	1
High	0.65	0.59	0	1	1

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

Table A.10: Summary Statistics for Credit Market Participants, by Experience

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

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

B Additional Regression Results

B.1 Rejection and Macroeconomic Expectations

Past Rejections Predict Discouragement. Households are asked how likely they are to apply to each of the seven categories of credit in the near future. Those that answer "very unlikely" to all options, are then asked to report the reason.

You just said that it is very unlikely that you will apply for any new loans/limit extensions/refinance. What is the reason for that?
◯ I am satisfied with my financial situation, and see no additional needs (1)
◯ Too time consuming to apply, and not worth the benefits (2)
◯ I do not know how to go about doing any of these (3)
◯ Current borrowing rates are too high (4)
◯ I do not think I would get approved (5)

From the answers I construct I variable called "discouraged" which takes value one if the individual selected option (5) and zero otherwise. To understand whether past rejections predict discouragement from applying again, I regress individuals' past credit market experiences onto this measure of discouragement.

Table B.11 shows that those rejected in the past year are, on average, almost 48 percentage points more likely to answer that they are unlikely to apply because "they think they would not be approved".

Table B.11: Past Credit Market Rejections and Future Discouragement - SCE 2013-2021

	Discouraged
Applied and rejected	0.477^{***}
	(0.013)
Didn't apply	-0.039^{***}
	(0.005)
Individual Level Controls	Y
State×Month×Year FE	Y
R^2	0.531
Observations	8790
Mean Dep. Var.	12.8

Notes: The table presents the results from regressing respondents' past personal rejections in the credit market against a binary variable that takes value one if individuals reported that they are unlikely to apply to any credit because of fear of rejection. The data source is the Survey of Consumer Expectations from 2013 till 2021, and the coefficients were estimated using a probability linear model. Controls include state-month-year fixed effects, income category, income expectations, gender, age, race, employment status, college attendance, marital status. Statistical Significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

I also corroborate this results using the Survey of Consumer Finances, which asks "Was there any time in the past twelve months that you thought of applying for credit at a particular place, but changed your mind because you thought you might be turned down?". I again construct a variable called "discouraged" if they answered "yes" to the question and regress it on their past experiences.

Table B.12: Past Credit Market Rejections and Discouragement - SCF 1999-2019

	Discouraged
Applied and rejected	0.317***
	(0.008)
Didn't apply	0.020***
	(0.004)
Individual Level Controls	Y
Year FE	Y
R^2	0.217
Observations	42205
Mean Dep. Var.	12.5

Notes: The table presents the results from regressing respondents' past personal rejections in the credit market against a binary variable that takes value one if individuals reported to have desired credit but didn't apply because of fear of rejection. The data source is the Survey of Consumer Finances from 1999 till 2019, and the coefficients were estimated using a probability linear model that account for survey weights. Controls include year fixed effects, income category, income expectations and income perceptions, gender, age, race, a binary variable that measures whether the individual recently became unemployed, home-ownership, college attendance, marital status. Statistical Significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Evidence on Persistence of the Effect. Some respondents report to have experienced both acceptance and rejection within the last 12 months. I test whether those that were only rejected are any different in terms of macro pessimism from those who were both accepted and rejected. Table B.13 presents the results.

Table B.13: Rejected versus Rejected & Accepted

	OPTM	FCredit	UNEMP	StockP	INFL
rejected			(omitted)		
rejected & accepted	0.04	0.64	−0.06	0.89	0.11
	(0.04)	(1.56)	(0.05)	(1.50)	(0.74)
Demographics	Y	Y	Y	Y	Y
State-month-year FE	Y	Y	Y	Y	Y
R^2	0.05	0.03	0.05	0.06	0.10
Observations	1669	1666	1669	1665	1608

Notes: The dependant variable is specified in the title of each Column. All specifications control for state-month-year fixed effects and demographics - age, gender, race, employment status, married, college, income, income expectations. Standard errors are clustered at the respondent and date level. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

The SCF asks rejected individuals whether they reapplied to that loan after their rejection. I therefore distinguish them between: (1) rejected and didn't re-apply, (2) rejected, re-apply and rejected, (3) rejected, re-apply and granted. I test whether there is any difference among them in terms of macro pessimism and report the results in Table B.14.

Table B.14: Rejected, Rejected & Granted, Rejected & Rejected

Dep.Var.: EconState	(1)
Didn't Re-Apply	(omitted)
Re-Apply & Granted	0.088
	(0.086)
Re-Apply & Rejected	−0.091
	(0.085)
Demographics	Y
Year FE	Y
R^2	0.033
Observations	5692
stat-diff	$p > 0.1$

Notes: The dependant variable is households' expectations about the future state of the economy: better, same (= 1) or worse (= 0). All specifications control for year fixed effects and demographics - age, gender, race, employment status, married, college, income, income expectations, income perceptions. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Past Rejections and Expectations about Personal Future Prospects. The following table presents regression estimates from equation 1. The tittle of each column specifies the dependent variable used. All columns control for demographics, month-year fixed effects and commuting zone fixed effects. The reference category for the employment status is employed. Income includes 11 categories where the reference one refers to income lower than 10k. The table only shows comparisons of those in the highest category with those in the lowest. Standard errors are clustered at the respondent and date level.

Table B.15: Credit Market Experiences and Personal Expectations

	Prob. Personal Rejection	Prob. Job Loss
Applied and rejected	30.039^{***}	3.636^{***}
	(0.898)	(0.678)
Didn't apply, discouraged	35.074^{***}	4.543^{***}
	(0.975)	(1.019)
Didn't apply, other	-1.470^{***}	-0.665^{*}
	(0.414)	(0.371)
age	0.280^{***}	-0.210^{*}
	(0.105)	(0.118)
E(income)	-3.131^{***}	-11.402^{***}
	(0.568)	(0.974)
Female =1	0.349	-1.183^{***}
	(0.432)	(0.374)
Married =1	2.132^{***}	−0.209
	(0.499)	(0.490)
College =1	-3.372^{***}	1.582^{***}
	(0.629)	(0.480)
Low Numeracy =1	7.838^{***}	−0.262
	(0.599)	(0.514)
White =1	-5.702^{***}	−0.043
	(1.087)	(0.660)
Black = 1	0.503	−0.454
	(1.252)	(0.929)
Unemployed	1.745	
	(1.506)	
Out of Labor Force	3.135^{***}	
	(1.016)	
Retired	-4.757^{***}	
	(0.808)	
Student	-6.861^{***}	
	(2.583)	
Income >= $200k$	-31.981^{***}	-11.266^{***}
	(2.260)	(2.884)
Month-Year FE	Y	Y
Commuting Zone FE	Y	Y
Observations	17011	14799
R^2	0.398	0.111

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

B.2 Robustness to Credit Type and Individual Characteristics

Individuals might apply for credit for different reasons: either buying a new house or refinancing a mortgage, asking for a credit card or extending current limits. Although all type of loan applications are discrete and noticeable choices, mortgage and student loans are less frequent than credit card loans or auto loans. Moreover, the rejection rate among applicants in each type of credit market differs. Table B.16 shows that almost 30% of the sample reports to have applied to a new credit card within the last year. Among the total sample of participants in the credit market, 60% apply for credit cards alone and the rejection rate among them is higher than in any other market.

Table B.16: Share of applications and rejections by credit type

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

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

Besides the differences in application and rejection rates, the process of applying to a mortgage or a credit card are considerably different. When applying to a mortgage, the incentives to search for good terms and gather information are relatively stronger. I test whether the type of credit market rejection matters for the estimated effect of rejections on expectations. I construct different samples that only contain individuals who applied to the same type of loan and re-run Equation 1 in each sample. Table B.17 presents results for such estimation where column (1) refers to credit card loans, column (2) to mortgage or home-based loans, column (3) to auto loans and column (4) to student loans. The dependent variable refers to the Optimism Index, which serves as a summary of individuals' macro expectations. Irrespective of the type of credit application, rejected individuals are consistently more pessimistic about the aggregate economy.

Table B.17: Credit Market Rejection and Aggregate Pessimism by loan type - New Loans

Dep.Var: Optimism Index	(1)	(2)	(3)	(4)
Applied and Accepted	(omitted)			
Applied and Rejected	-0.209^{***}	-0.169^{***}	-0.163^{***}	-0.229^{***}
	(0.027)	(0.044)	(0.036)	(0.046)
Sample	CreditCard	Mortgage	Auto Loan	Student Loan
Demographics	Y	Y	Y	Y
State-Month-Year FE	Y	Y	Y	Y
R^2	0.162	0.279	0.224	0.368
Observations	6686	2012	3605	854

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

Table B.18: Credit Market Rejection and Aggregate Pessimism by loan type - Existing Loans

Dep.Var: Optimism Index	(1)	(2)	(3)
Applied and rejected	-0.069^{*}	-0.148	-0.107^{**}
	(0.036)	(0.091)	(0.051)
Sample	Limit CreditCard	Limit Loan	Refinance Mortg
Individual level Controls	Y	Y	Y
Month-Year FE	Y	Y	Y
Commuting Zone FE	Y	Y	Y
Observations	2205	405	1625
R^2	0.289	0.633	0.290

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

In Table B.18, I present results considering only individuals who applied for an extension in the limit of an existing credit card, existing loan or refinance of an existing mortgage. Results are consistent with the rejection induced pessimism hypothesis, although the size of the effect is smaller. Moreover, in Table

B.19 I test the heterogeneity of the effect by households' characteristics. I find that the rejection-induced pessimism holds across the income distribution, college attainment, and age.

Table B.19: Individuals' Past Rejection on their Optimism Index - by Respondent Characteristics

	(1)	(2)	(3)	(4)
Applied and Rejected * Young	-0.151^{***}			
	(0.030)			
Applied and Rejected * Adult	-0.187^{***}			
	(0.023)			
Applied and Rejected * Old	-0.083^{*}			
	(0.045)			
Applied and Rejected * High Num		-0.138^{***}		
		(0.023)		
Applied and Rejected * Low Num		-0.196^{***}		
		(0.028)		
Applied and Rejected * College			-0.127^{***}	
			(0.023)	
Applied and Rejected * No College			-0.204^{***}	
			(0.029)	
Applied and Rejected * High Income				-0.142^{***}
				(0.025)
Applied and Rejected * Low Income				-0.173^{***}
				(0.028)
Didn't apply	−0.010	−0.011	−0.010	−0.011
	(0.010)	(0.010)	(0.010)	(0.010)
Individual level Controls	Y	Y	Y	Y
State-Month-Year FE	Y	Y	Y	Y
Stat. Diff.	$p = 0.01$	$p = 0.01$	$p = 0.04$	$p = 0.17$
Observations	25146	25146	25147	25146
R^2	0.105	0.103	0.105	0.105

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

B.3 Results using the Survey of Consumer Finances

The Survey of Consumer Finances (SCF) is a triennial survey conducted since 1989. As opposed to the SCE, this survey contains a cross section of households, conducted every three years and, although it has less focus on expectations, it has some advantages. First, it covers a much longer time series (1989-2021) and second, it provides more information about households balance sheet and credit experiences, including the type of information they use when borrowing, how much search they did and whether they have re-applied. Similarly to before, I construct an indicator variable that measures whether households were rejected in their past credit applications. Then, I use the following question to measure expectations about the aggregate: *"Over the next five years, do you expect the U.S. economy as a whole to perform better (=1), worse (=0), or about the same (=1) as it has over the past five years?"*.

To have a measure of how informed households were when they asked for credit, I use the following two questions:

1. *Amount of search done in the pursuit of better credit terms (0 no searching-10 great deal).*
2. *Sources of information used for credit decisions.*

The most used sources of information are "friends and/or material from work/business contacts" with 41.4% respondents choosing it and "financial advisors such as bankers, brokers, real state broker, builder, dealer and/or insurance agent" with 40%. I define households as "financially informed" if they report using financial services/advice from bankers, brokers, real state broker, builder, dealer and/or insurance agent on top of their list. I define households as "financially informed" if they report using financial services/advice from bankers, brokers, real state broker, builder, dealer and/or insurance agent on top of their list[20].

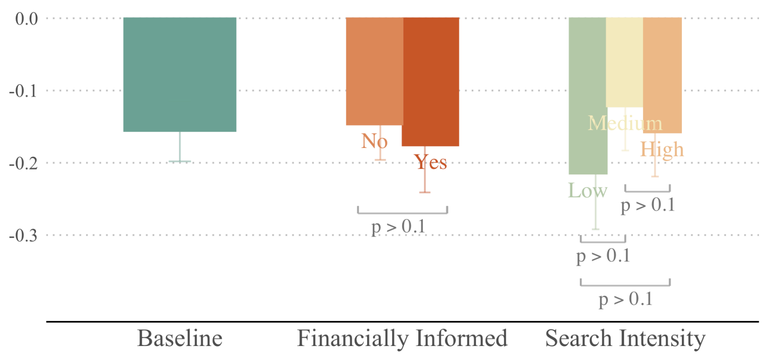
I classify rejected individuals according to (1) their intensity of searching (low, medium, high), (2) whether they were financially informed before asking for credit or not. The hypothesis is that individuals who search a lot for good terms and/or receive professional financial advice before applying for credit are more informed about credit market conditions and thus, react less to their own experience. I test this by running logit regressions of experience on expectations. All specifications control for individuals' characteristics and time fixed effects which absorb any aggregate variation. Figure B.2 illustrates the estimated coefficients.

The baseline estimate refers to the estimated coefficient that results after regressing past rejections on expectations about the state of the economy, which corroborates previous findings: rejected individuals are more pessimistic about future macroeconomic conditions than accepted individuals, even

[20]For the analysis presented, I classify as "financially informed" those who chose option "financial advisors such as bankers, brokers, real state broker, builder, dealer and/or insurance agent" within the first 5 main used sources of information. Results are robust to expanding this classification both in terms of where in the list they chose such option and also considering other type of info used. For example, I also include financial planners, accountants and lawyers in an extended version of the definition.

after controlling for several other experiences, own expected income and time fixed effects. The odds of being pessimistic about the economy are 15% higher if you were rejected compared to someone accepted. The two following bars refer to the estimates obtained when regressing own rejection on macro expectations conditional on being financially informed (or not). The last three bars repeat the analysis but distinguishing among levels of search intensity. As can be observed, although coefficients differ in magnitude, there is no statistically significant difference among them. Being more informed about the macro/credit conditions does not affect the reliance on own experience, and such reliance is not in line with the informativeness of the rejection.

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



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

B.4 Robustness to Individual Fixed Effects

An alternative interpretation of the documented relation is that it captures individuals' fixed characteristics that systematically affect both general macro pessimism and rejections in the credit market (rejected individuals might be naturally more pessimistic). To address such concern, I exploit the panel structure of the SCE data and add individual fixed effects to Equation 1. Such specification focuses only on individuals who have answered the survey at least two times and, among those, it partial-outs the effect of only experiencing rejection. Table B.20 shows results from this two-way fixed effect model.

The results show that when an individual goes from acceptance to rejection (or vice-versa), her beliefs also become more pessimistic across domains. Comparing the size of the effect in the cross section and within individuals, we can conclude that those individuals who are consistently rejected are more pessimistic than those who have experienced both acceptance and rejection. Overall, results are robust, although standard errors increase, specially for expectations about stock prices and inflation. This is not surprising, as the panel component used contains at most three responses per individual, 4-months apart. Given that applying to a loan is a discrete and unfrequent choice, the tight re-sampling window of the survey does not allow for many transitions: there are only 295 instances in which an individual moved from an acceptance to a rejection and 318 in which someone transitioned from acceptance to rejection.

Table B.20: Credit Market Rejection and Aggregate Pessimism within individuals

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

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

Another caveat of this exercise is that, although it helps to alleviate concerns of internal validity, it also partials out the persistent effect that rejections might induce on individuals beliefs. Moreover, the within estimation exploits variation from transitioning from acceptance to rejection but also from rejection to acceptance. The smaller coefficients might suggest that experiencing an acceptance does not undo the pessimism of a past rejection, inline with the estimates presented in Tables B.13 and B.14 .

B.5 Results in a Matched Sample

Set Up and Assumption. I split the sample in three: (1) only participants in the credit market with accepted as control and rejected as treated, (2) non-participants ("didn't apply, other") as control and rejected as treated, (3) non-participants ("didn't apply, other") as control and accepted as treated.

Each of the subsamples is composed of a group exposed to the treatment S_T and a group exposed to the control S_C. Covariate data on pre-treatment covariates is available for both groups. For each individual i who participates in the survey at date t we have covariates denoted by X_{it}, treatment assignment T_i ($T_i = 1$ if treated or $T_i = 0$ if not) and the observed outcome of interest, in this case, beliefs denoted as $Y_{it} \equiv E_{it}(Y_{t+1})$.

The object of interest is the difference in potential outcomes or marginal effect defined as

$$\tau = E(Y_{it}(1)|X_{it} = x) - E(Y_{it}(0)|X_{it} = x) \tag{24}$$

To efficiently estimate this object, groups must be comparable and the treatment should be random conditional on those covariates. In non-experimental studies, this requires a key assumption: strongly ignorable treatment assignment (Rosenbaum and Rubin, 1983). This implies (a) unconfoundedness: treatment assignment (T_i) is independent of the potential outcomes ($Y_{it}(0), Y_{it}(1)$) given the covariates X_{it}; and (b) overlap: there is a positive probability of receiving the treatment for all values of the covariates X_{it}: $0 < P(T_i = 1|X_{it} = x) < 1$ for all X (Stuart (2010)).

Design: Matching and Diagnostics. Covariates need to be related to both treatment assignment (rejection) and the outcome (beliefs) but they should not be affected by the treatment itself. This represents a challenge for the survey data at hand, since all data is collected at a certain point in time while the treatment assignment occurred in the year before the data collection. As described in the text, I start with a conservative selection of covariates to use in the matching procedure (gender, race, age category, income category, numeracy category, college attainment, type of credit application (when applicable)) and avoid including covariates that are potentially important but might have been influenced by rejection. An important example of such variable is the reported credit score. I initially exclude such variable from the matching procedure and analysis but I run robustness where I include it either in the matching step or in the analysis model for the outcome as a control (Stuart, 2010). Results are robust.

Given the selection of covariates, I use $1:1$ nearest neighbour matching on Mahalanobis distance without replacement.[21] For the sample of accepted vs didn't apply, such matching method results in poor balance. Given that there are several treatment and control units in this sample, I use exact matching.

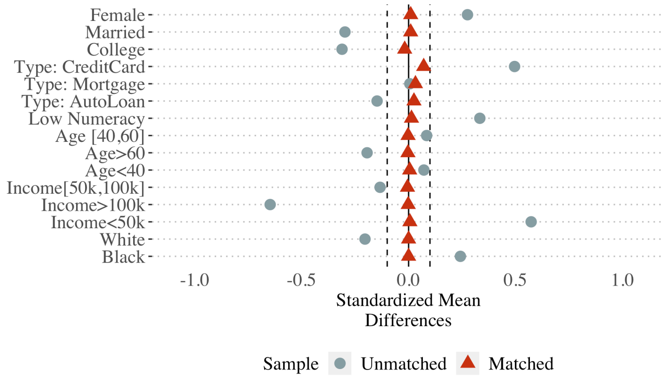
I obtain three balanced matched samples. Figure B.3 shows standardised mean differences for the unmatched and matched sample among the sample of participants. Table B.4 shows the equivalent figure when the treatment group is composed of those accepted and the control group of those who didn't apply, while Table B.5 does the same when the treatment group is composed of those rejected and the control group of those who didn't apply. Matching improves the covariate balance for all variables considerably, with all standardised mean differences below 0.1.

[21] The distance metric for a treated unit i and a control unit j is defined as:

$$\delta(\mathbf{X}_i, \mathbf{X}_j) = \sqrt{(\mathbf{X}_i - \mathbf{X}_j)' S^{-1} (\mathbf{X}_i - \mathbf{X}_j)} \tag{25}$$

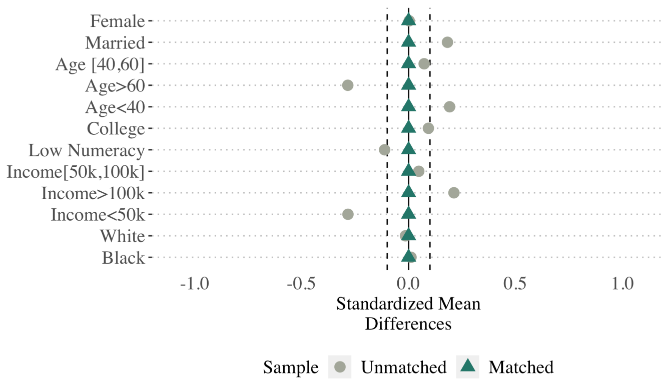
where $\mathbf{X}$ is a $p \times 1$ vector containing the value of each of the p included covariates for that unit, S is a scaling matrix and S^{-1} is the generalised inverse of S. For Mahalanobis distance matching, S is the pooled covariance matrix of covariates (Rubin 1980).

Figure B.3: Standardised Mean Differences in Match and Unmatched Sample of Credit Market Participants



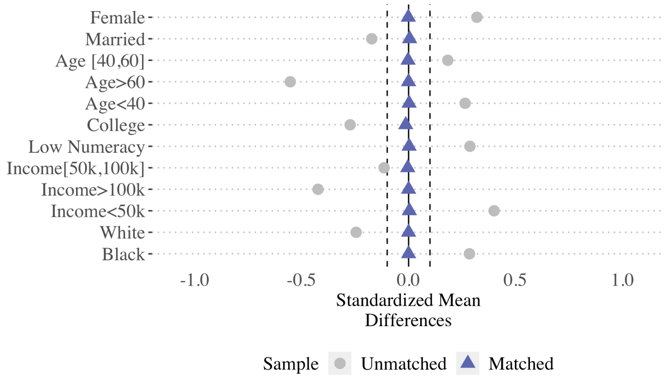
Notes: Matching method is 1 : 1 nearest neighbour matching on Mahalanobis distance without replacement. Covariates are expressed on the y-axis. The x-axis shows the standardised mean differences, for the unmatched sample in grey dots and for the matched sample in dark red triangles.

Figure B.4: Standardised Mean Differences in Match and Unmatched Sample - Accepted vs Didn't Apply



Notes: Matching method is exact matching. Covariates are expressed on the y-axis. The x-axis shows the standardised mean differences, for the unmatched sample in grey dots and for the matched sample in dark green triangles.

Figure B.5: Standardised Mean Differences in Match and Unmatched Sample - Rejected vs Didn't Apply



Notes: Matching method is 1 : 1 nearest neighbour matching on Mahalanobis distance without replacement. Covariates are expressed on the y-axis. The x-axis shows the standardised mean differences, for the unmatched sample in grey dots and for the matched sample in dark blue triangles.

Additional Regression Results in the Matched Samples. Table B.21 shows the regression coefficients on the treatment for each outcome variable using the matched sample of credit market participants. Table B.22 repeats the analysis using the second sample and Table B.23 uses the third sample to highlight the asymmetric effect.

Table B.21: Rejections and Macroeconomic Expectations - Matched Sample of Rejected and Accepted

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

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

Table B.22: Rejections and Macroeconomic Expectations - Matched Sample of Rejected and Non-Participants

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

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

Table B.23: Rejections and Macroeconomic Expectations - Matched Sample Accepted and Non-Participants

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

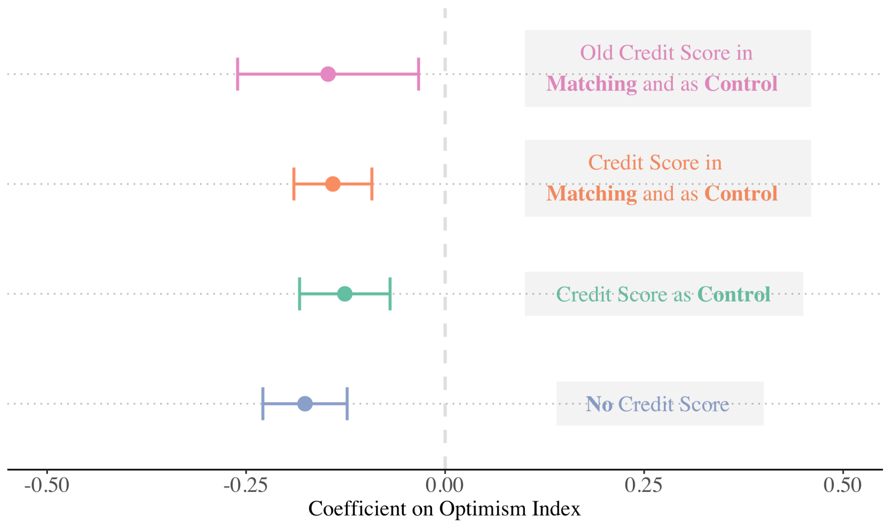
Notes: The table presents OLS estimates from equation $E_{i,t}(Y_{t+1}) = \alpha + \beta \mathrm{T}_{i,t} + \delta X_{i,t} + \gamma_{st} + e_{it}$. The title of each column specifies the dependent variable used. All columns control for state-month-year fixed effects and individual-level covariates (employment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

B.6 Robustness to the Inclusion of Credit Score

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

With this in mind, I run different exercises that highlight the robustness of the result even to the inclusion of the reported credit scores either as control variables or as a covariate in the matching procedure. Figure summarises the findings when using Optimism Index as the outcome variable and "accepted" individuals as the control. The blue bar (closest to the x-axis) shows the estimated coefficient when the variable *credit score* is not included as a control (first column in Table B.21) while the green bar shows the coefficient after including *credit score* as control (first column in Table B.24).

Figure B.6: Robustness of the Rejection-Induced Pessimism to including Reported Credit Score



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

In the last two exercises, I want to asses the robustness of the result to including information about individuals' credit score in the matching procedure. First, I choose a "naive" approach where I include individuals' reported credit score in the matching procedure and also as a control. The orange bar shows the coefficient on the treatment that results from this analysis (first column Table B.25). This specification can be problematic, as covariates used for matching have to be pre-treatment. To alleviate such concern, in the fourth exercise I only match individuals for which I know that they haven't checked their credit score in the last year. Within those, I match accepted and rejected based on the covariates mentioned before and a new binary variable - *Old Credit Score* - that takes value 1 if their credit score is above 680 and 0 otherwise. This leads to a smaller matched sample of approximately 550 individuals. The pink bar in the graph shows the estimated coefficient on the treatment using such sample and the covariates as controls (first column Table B.26).

Table B.24: Rejections and Macroeconomic Expectations controlling for Credit Score - Matched Sample of Rejected and Accepted

	OPTM	UNEMP	FCredit	StockP	INFL
Rejected	-0.126^{***}	2.151^{*}	0.180^{***}	0.916	0.782
	(0.029)	(1.147)	(0.034)	(1.112)	(0.671)
Individual level Controls	Y	Y	Y	Y	Y
Reported Credit Score	Y	Y	Y	Y	Y
State-Month-Year FE	Y	Y	Y	Y	Y
R^2	0.330	0.292	0.311	0.324	0.286
Observations	3320	3315	3320	3313	3315

Notes: The table presents OLS estimates from equation $E_{i,t}(Y_{t+1}) = \alpha + \beta T_{i,t} + \delta X_{i,t} + \gamma_{st} + e_{it}$. The title of each column specifies the dependent variable used. All columns control for state-month-year fixed effects and individual-level covariates (employment status, gender, race, age, marital status, college attainment, type of loan, income category, numeracy category and credit score binary variable - either >= 680 or below). The matching method is 1 : 1 nearest neighbour matching on Mahalanobis distance without replacement on the covariates described above. Cluster-robust standard errors account for pair membership. Standard errors are reportes in parenthesis. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table B.25: Rejections and Macroeconomic Expectations controlling for Credit Score - Matched Sample of Rejected and Accepted based on Credit Score

	OPTM	UNEMP	FCredit	StockP	INFL
Rejected	-0.141^{***}	1.083	0.203^{***}	-1.042	1.166^{*}
	(0.025)	(0.998)	(0.030)	(1.000)	(0.642)
Individual level Controls	Y	Y	Y	Y	Y
Reported Credit Score	Y	Y	Y	Y	Y
State-Month-Year FE	Y	Y	Y	Y	Y
R^2	0.320	0.287	0.304	0.326	0.282
Num. obs.	3320	3314	3320	3313	3315

Notes: The table presents OLS estimates from equation $E_{i,t}(Y_{t+1}) = \alpha + \beta T_{i,t} + \delta X_{i,t} + \gamma_{st} + e_{it}$. The title of each column specifies the dependent variable used. All columns control for state-month-year fixed effects and individual-level covariates (employment status, gender, race, age, marital status, college attainment, type of loan, income category, numeracy category and credit score binary variable - either >= 680 or below). The matching method is exact matching on 'Credit Score' and $1:1$ nearest neighbour matching on Mahalanobis distance without replacement on the other covariates. Cluster-robust standard errors account for pair membership. Standard errors are reportes in parenthesis. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table B.26: Rejections and Macroeconomic Expectations controlling for Past Credit Score - Matched Sample of Rejected and Accepted Based on Past Credit Score

	OPTM	UNEMP	FCredit	StockP	INFL
Rejected	-0.147^{**}	2.396	0.264^{***}	1.560	2.745^{*}
	(0.058)	(2.321)	(0.071)	(2.139)	(1.470)
Individual level Controls	Y	Y	Y	Y	Y
Reported Credit Score > 12months	Y	Y	Y	Y	Y
State and Year FE	Y	Y	Y	Y	Y
R^2	0.137	0.152	0.158	0.182	0.148
Observations	528	527	528	527	527

Notes: The table presents OLS estimates from equation $E_{i,t}(Y_{t+1}) = \alpha + \beta T_{i,t} + \delta X_{i,t} + \gamma_{st} + e_{it}$. The title of each column specifies the dependent variable used. All columns control for state and year fixed effects and individual-level covariates (employment status, gender, race, age, marital status, college attainment, type of loan, high income binary variable, numeracy category and credit score binary variable - either >= 680 or below). Sample contains only individuals who report to have checked their credit score for the last time more than 12 months ago. The matching method is exact matching on 'Past Credit Score' and $1:1$ nearest neighbour matching on Mahalanobis distance without replacement on the other covariates. Cluster-robust standard errors account for pair membership. Standard errors are reportes in parenthesis. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

B.7 Robustness to Matching based on Covariates and Optimism

Individuals can be different in their covariates but also on their level of optimism before being rejected. To corroborate that different levels of initial optimism are not driving the results, I focus on the sub-sample of people who started the sample by not being rejected and then at some point within the sample experienced such a rejection. These people can then be matched to other individuals who never experienced a rejection and are similar to them both in terms of covariates and their level of optimism when they started the sample. Table B.27 presents the results of running the OLS regression on such a matched sample.

Table B.27: Rejection and Macroeconomic Expectations - Matched Sample (covariates & pre-optimism level)

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

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

B.7.1 Pessimism from Experiences as a General Pattern

Being recently unemployed, recently rejected, thinking about bankruptcy, going through a negative wealth shock is associated to pessimism about the macro.

	OPTM
Accepted	0.009
	(0.008)
Rejected	-0.156^{***}
	(0.016)
Unemp.>= 12m	-0.051
	(0.036)
Unemp.< 12m	-0.091^{***}
	(0.032)
R^2	0.048
Obs.	24937

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

(a) Full Sample SCE

	OPTM
Accepted	0.022
	(0.022)
Rejected	-0.129^{***}
	(0.043)
Consider Bankruptcy?	-0.122^{**}
	(0.058)
Large Net Wealth ↓	-0.178^{***}
	(0.049)
Large Net Wealth ↑	0.032
	(0.043)
Large Income ↓	0.041
	(0.039)
Large Income ↑	0.060^{*}
	(0.035)
Unemployed	-0.116^{*}
	(0.064)
R^2	0.133
Num. obs.	3252

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

(b) Finance Module SCE

Table B.28: Personal Experiences and Optimism Index

The table presents regression estimates using the full SCE sample in Panel (a) and only the finance module in the SCE in Panel (b). Panel (a) considers credit market experiences (reference didn't apply) and employment situation –unemployed for more or less than twelve months (reference employed). Panel (b) considers credit experiences, whether the person considered filling for bankruptcy in the last 12 months, recents shocks to net wealth and income, and employment status.

C Households' Belief Formation - Details and Data

If people were to know all relevant public information and weight it correctly (including their own information), their personal rejections should have no predictive power for their beliefs about the macroeconomy. This is the prediction of the Full Information Rational Expectations (FIRE) assumption, and is inconsistent with the findings in Section 3. An alternative hypothesis is that individuals lack information about the macro outcomes that they are trying to forecast and thus use their own personal experiences of rejection to forecast. The aim now is to understand whether these experiences are used optimally in line with their informativeness (lack of FI but RE), or if a further deviation from rational updating is needed to understand the results (lack of RE).

C.1 Optimal Use of Limited Information?

I start by outlying basic assumptions on data generating process (DGP) and belief formation of individuals, similarly to Kuchler and Zafar (2019).

Assumptions on DGP. Suppose the aggregate outcome Y_{t+1} depends on the past share of rejected individuals between time t and $t-1$, other known variables at time t and a random error term. I further assume that each term enters additively:

$$Y_{t+1} = \beta R_t + \gamma B_t + v_{t+1} \tag{26}$$

The share of rejections at t is defined as the number of rejections over the number of applications: $R_t = \frac{\#\text{rejections}}{\#\text{applicants}} = \sum_i \frac{r_{it}}{\sum_i a_{it}}$ where $a_{it} = 1$ if applied to a loan and $r_{it} = 1$ if rejected in the application.

Full Information. Under FIRE, the best predictor of the aggregate variable is given by

$$\mathbb{E}(Y_{t+1}|I_{it}) = \beta R_t + \gamma B_t \tag{27}$$

The regression coefficient β captures the relationship between the share of rejected individuals and the macro outcome, or how much they move together. If R_t and B_t belong to individuals data set I_{it}, Equation 27 does not vary in the cross section and it is thus absorbed by time fixed effects. Under the null hypothesis of FIRE, individuals know all relevant information and weight it correctly, thus their own experience should have no predictive power after including time fixed effects. Previous findings are inconsistent with such hypothesis.

Limited Information. Individuals might be uninformed about the aggregate share of rejections, but they do know their own experience in the credit market r_{it}. The best predictor using only their own experience is given by

$$\mathbb{E}^*(Y_{t+1}|I_{it}) = \eta\, r_{it} + \gamma B_t \tag{28}$$

Individuals *believe* the best predictor to be

$$\hat{E}(Y_{t+1}|I_{it}) = \hat{\eta}\, r_{it} + \hat{\gamma} B_t \tag{29}$$

where $\hat{\eta}$ is individuals perceived co-movement of their own rejection with the aggregate outcome next period.

If individuals are using their own information optimally, then their own experiences should be weighted optimally: $\eta = \hat{\eta}$ or $\eta - \hat{\eta} = 0$. In other words, the perceived co-movement of their experiences with the aggregate economy should equal the true co-movement between the two. Ideally one would test this hypothesis by estimating the true informativeness of personal experiences η by regressing them on aggregate outcomes Y_{t+1} and the perceived co-movement $\hat{\eta}$ by regressing them on reported beliefs about those outcomes $\hat{E}(Y_{t+1}|I_{it})$. Directly testing such hypothesis goes beyond the scope of the data at hand, since it would require running both regressions for each individual and thus a much longer panel than the one contained in the SCE. Despite this limitation, there are alternative hypothesis that build on this simple framework and can be tested to assess whether individuals are using their own information in line with its informativeness. I find evidence that:

1. Individuals' forecast errors are predictable from their personal past rejections.
2. Individuals are not using their experiences according to their informativeness: rejections rates among "high income, college attendant" applicants correlate more strongly with macroeconomic conditions, but the effect of personal rejections on expectations about macroeconomic conditions is stronger among "low income, no college attendance" applicants.

C.2 Construction of Forecast Errors

Table C.29: Description of Variables used for constructing Forecast Errors

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

C.3 Regression Results

Predictability of Individuals' Forecast Errors. Table C.30 presents the OLS regression results plotted in Figure 5 in main text.

Table C.30: Idiosyncratic Rejections on Individuals' Forecast Error

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

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

Robustness. The following tables provide robustness checks for the finding on Section 3.5.

An important consideration is whether the regressor is endogenous as, in such cases, the estimates might suffer from small sample bias. In particular, for the OLS estimator to be unbiased, the zero conditional mean independence assumption must be satisfied. If controls are available, a weaker assumption suffices: conditional on the controls, the regressor can be considered as if randomly assigned, so that r_{it} is uncorrelated with the error term. As argued in Section 3.3, SCE provides sufficient controls under which this assumption can be plausibly met.

Table C.32 and Table C.33 repeat the analysis using the matched samples.

Hjalmarsson (2008) further showed that panel regressions with pooled estimates do not suffer from small sample bias even if the regressor is persistent and endogenous. Thus, I do not include individual fixed effects in the main text but results hold if I do as can be seen in Table C.31.

The result is overall robust: individuals' forecast errors are predictable by their own rejection experience.

Table C.31: Individuals' Forecast Errors - With Individuals' Fixed Effects

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

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

Table C.32: Individuals' Forecast Errors - Matched Sample of Participants

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

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

Table C.33: Individuals' Forecast Errors - Matched Sample of Rejected and Non-Participants

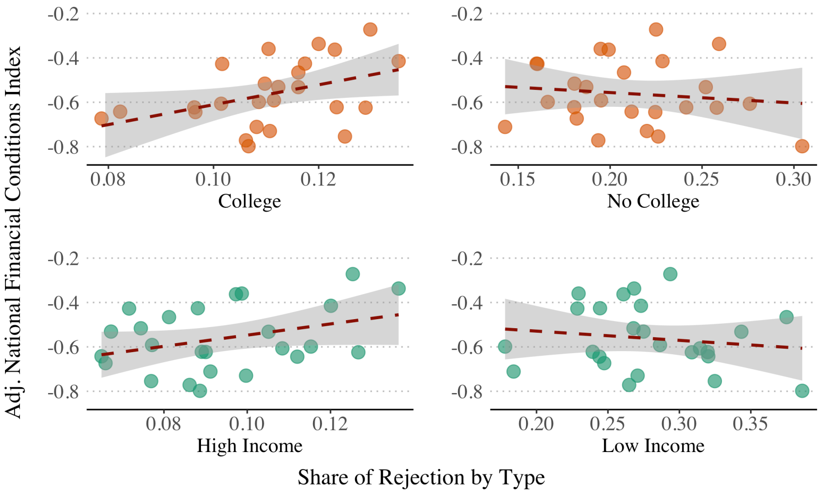
	FE Unemp	FE Credit	FE Stock	FE Infl
(Intercept)	-22.579	-0.610^{*}	20.305	-9.272^{**}
	(14.309)	(0.335)	(13.124)	(4.010)
Didn't Apply		(omitted)		
Rejected	-3.723^{**}	-0.126^{**}	-1.650	-1.824^{*}
	(1.460)	(0.061)	(1.489)	(1.051)
R^2	0.05	0.35	0.10	0.06
Observations	3317	3054	3315	3048

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

Personal Rejections and Macroeconomic Expectations - by Informativeness. The next figure and tables investigate the correlation between the share of rejections and different macroeconomic outcomes. I am interested in understanding whether rejections rates among different types of applicants correlate differently with the economy.

Using the SCE data, I calculate the share of rejections at each point in time by income category and college attainment. To have a summary of economic conditions, I use an adjusted index of national financial conditions (ANFCI) from the Chicago Fed. Figure C.7 shows scatter plots relating these measures. The y-axis reflects the ANFCI while the x-axis refers to the rejections rates. Rejection rates among applicants with college attainment and high income correlate positively with tightness in financial conditions, while rejection rates among those with no college attainment or low income have no statistically significant correlation.

Figure C.7: Share Of Rejections by Individuals' Type and Financial Conditions



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

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

Table C.34: Share of rejection by Education and Macro Outcomes

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

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

Table C.35: Share of rejection by Income and Macro Outcomes

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

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

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

D Memory-Based Model

D.1 Model Expressions

Over-estimation when simulation varies. If only macro transitions from i to j are recalled with similarity 1 when thinking about transitions from i to j and only transitions to j can perfectly simulate the transition to j, then the memory-based probability equals the statistical probability p_{ij}. On the other hand, if transitions from j might also be recalled according to similarity S, and experiences other than macro transitions might be recalled with similarity $\hat{S}$ and used to simulate a future j state by factor $\hat{\sigma}$, then the memory based probability can be expressed as

$$\hat{p}_{ij} = \frac{|\theta_{ij}| + S|\theta_{jj}| + \hat{S}\hat{\sigma}|E|}{|\theta_{ij}| + |\theta_{ii}| + S|\theta_{jj}| + \hat{S}|E|} \tag{30}$$

this probability judgement is higher than the statistical estimate if and only if the latter is sufficiently low

$$\frac{|\theta_{ij}|}{|\theta_{ij}| + |\theta_{ii}|} = p_{ij} < p^{*} \equiv \frac{\hat{S}\hat{\sigma}|E| + S|\theta_{jj}|}{\hat{S}|E| + S|\theta_{jj}|} \tag{31}$$

Proof of Expression 9. To derive the expression for probability of rejected, one can multiply and divide by the sum of similarities across the database and re-arrange:

$$\hat{p}^B_{iL} = \frac{S(R)}{S(R) + \sum_{m\in M} S(m)}\sigma(R) + \frac{\sum_{m\in M} S(m)\sigma(m)}{S(R) + \sum_{m\in M} S(m)} \tag{32}$$

$$= \frac{S(R)}{S(R) + \sum_{m\in M} S(m)}\sigma(R) + \frac{\sum_{m\in M} S(m)\sigma(m)}{S(R) + \sum_{m\in M} S(m)} \times \frac{\sum_{m\in M} S(m)}{\sum_{m\in M} S(m)} \tag{33}$$

$$= \frac{S(R)}{S(R) + \sum_{m\in M} S(m)}\sigma(R) + \left(1 - \frac{S(R)}{S(R) + \sum_{m\in M} S(m)}\right)\frac{\sum_{m\in M} S(m)\sigma(m)}{\sum_{m\in M} S(m)} \tag{34}$$

$$= \omega_{iL}\sigma(R) + (1 - \omega_{iL})\hat{p}_{iL} \tag{35}$$

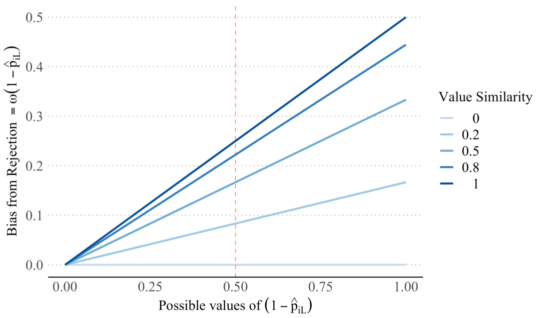
where $\omega_{iL} \equiv r(R, \theta_{iL}) = \frac{S(R)}{S(R)+\sum_{m\in M} S(m)}$ and $\hat{p}_{iL} = \frac{\sum_{m\in M} S(m)\sigma(m)}{\sum_{m\in M} S(m)}$.

D.2 Simulation of the Rejection Effect

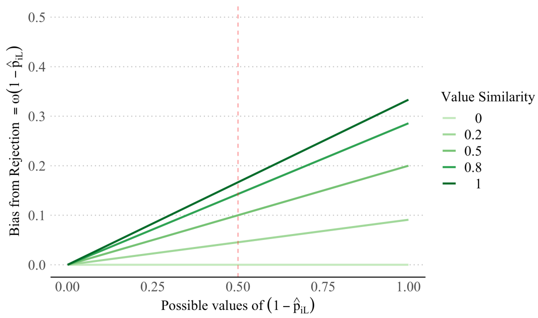
The effect of rejection is defined as $|\hat{p}_{iL} - \hat{p}^R_{iL}| = \omega \times (1 - \hat{p}_{iL})$. For a given size of the database, Figure D.8 shows how the bias changes when both similarity (and thus probability of recall ω) and $\hat{p}_{iL}$ change[22]. Darker colours represent higher similarity between personal rejection and macro negative states, which translates into higher biases for any value of $\hat{p}_{iL}$. For a given value of the similarity function (fixing one color), more unlikely events are going to be characterised by higher bias. On the other hand, if people were already pessimistic to start with (low values of $1 - \hat{p}_{iL}$), irrespective of how similar the rejection might be perceived, the bias will be relatively small. In terms of the memory model, the value of $\hat{p}_{iL}$ depends on how many other experiences in line with hypothesis L are remembered when thinking about L. The size of the database also influences the results, as it limits the maximum size that the bias can take. Figure D.8 panel (a) shows how the bias change as similarity and $\hat{p}_{iL}$ change when the database has a size x while panel (b) repeats the analysis for a database that has double the size.

[22] Lower values of simulation ($\sigma() < 1$) would accelerate the decline of the bias that we observe in the x-axis.

Figure D.8: Dynamics of the Bias from Rejection



(a) database of size x



(b) database of size $2x$

Notes: Figures plot the bias from rejection $\omega(1-\hat{p}_{iL})$ on the y-axis and $(1-\hat{p}_{iL})$ on the x-axis. Different coloured lines refer to the bias under different values of the similarity function, which directly impact the probability of recall or weight ω. This also depends on the size of the database with positive similarity or $\sum_M S(m,\theta_{iL})$. Panel (a) normalises $\sum_M S(m,\theta_{iL})$ in the denominator of ω to be equal to 1. Panel (b) duplicates the size of the database and thus has $\sum_M S(m,\theta_{iL}) = 2$.

D.3 Predictions of Memory Model

Table D.36: Rejections and Expectations about the Macro - Implied Similarity Exercise

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

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

Table D.37: State Dependency in Beliefs across Macro Outcomes

	OPTM	↑UNEMP	FCredit	↑StockP	E(INFL)
(Intercept)	0.207**	43.054***	−0.367***	47.269***	4.575***
	(0.103)	(3.992)	(0.123)	(4.359)	(1.342)
Applied and rejected	−0.163***	2.173***	0.349***	−1.473**	0.624*
	(0.016)	(0.626)	(0.044)	(0.658)	(0.348)
Didn't apply	−0.005	−0.935***	0.026	−0.914***	−0.129
	(0.008)	(0.310)	(0.022)	(0.332)	(0.172)
Recession	0.069**				
	(0.028)				
Applied and rejected×recession	−0.148*				
	(0.086)				
Didn't apply×recession	−0.018				
	(0.037)				
UNEMPrate		0.276**			
		(0.110)			
Applied and rejected×UNEMPrate		0.672**			
		(0.300)			
Didn't apply×UNEMPrate		−0.107			
		(0.141)			
CrCond			−0.109***		
			(0.016)		
Applied and rejected×CrCond			0.140***		
			(0.041)		
Didnt apply×CrCond			0.018		
			(0.021)		
STCKPgrowth				0.012***	
				(0.003)	
Applied and rejected×STCKPgrowth				−0.001	
				(0.009)	
Didn't apply×STCKPgrowth				0.002	
				(0.005)	
INFLrate					0.647***
					(0.054)
Applied and rejected×INFLrate					0.318**
					(0.143)
Didn't apply×INFLrate					−0.032
					(0.072)
Individuals' Controls	Y	Y	Y	Y	Y
R^2	0.053	0.018	0.036	0.065	0.086
Observations	25161	25132	25161	25135	24744

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

D.4 Alternative Theories of Beliefs

The analysis can be summarised in a set of empirical facts relating own past experiences of rejections to beliefs about the macroeconomy: (1) experience-driven-heterogeneity: rejected are more pessimistic about the macro than accepted and/or those who do not apply; (2) not-domain specificity: credit-related experiences affect beliefs about non-credit related variables; (3) asymmetry: rejection induces pessimism but acceptances do not induce optimism; (4) over-pessimism unrelated to the informativeness of the experience; (5) heterogeneity: stronger association for young, low numeracy, low SES; (6) cued recall: negative states today induce recall of past negative experiences, increasing future pessimism.

I have presented a model of memory-based beliefs that explains facts (1)-(4) and yields new predictions (5)-(6) that I validated in the data. Existing theories of belief formation can rationalise some of the facts separately, but struggle to explain all of them together. I now discuss some of such theories. This is not meant to be an exhaustive exploration of all possible theories, but rather a discussion of a set of alternative explanations that are widely studied in macro and finance and that can capture some of the main documented facts. The proposed model of memory based belief nests these alternatives, while also allowing for a through exploration of the psychological underpinnings.

Partial Information Models. Models that only deviate from the assumption of full information predict that individuals use their own experiences to forecast macro outcomes precisely because of limited information about those macro outcomes. These hypothesis rely on the assumption that experiences are informative about such macro outcomes and that individuals use their own experiences according to their informativeness. Such models could provide an explanation as to why own experiences are used to forecast macro outcomes (Fact 1) but, as discussed in Section 3.5, there is no support for such hypothesis in the data. Moreover, such model struggles to explain all of the remaining empirical facts. The evidence thus suggest that to understand individuals belief formation process, we need to depart from the assumption of optimal use of limited information.

Diagnostic Expectations. Building on the representativeness heuristic, Bordalo et al. (2018b) introduce Diagnostic Expectations, a model of belief formation that overweights future outcomes that become more likely in light of new data. Bordalo et al. (2020) combine diagnostic expectations with a noisy information model and show that it rationalises the widely documented fact of over-reaction in expectations. Such a model can potentially explain why individuals' assign such a high weight to their own past rejections (Fact 4). Nevertheless, Diagnostic Expectations have some specific features that limit its applicability to the current set up. First of all, diagnostic expectations could explain over-reaction to own rejections as long as we assume that own experiences are an informative signal of the variable being forecasted. In other words, it cannot explain why irrelevant experiences are used for belief formation neither the documented heterogeneity in the reliance on own rejections. Moreover, the over-reaction to signals is symmetric: individuals are expected to be over-pessimistic after rejections and over-optimistic after acceptances. I do not find support for this in the data. Finally, diagnostic expectations predicts only temporal effects: individuals' over-react when a signal arrives but have rational expectations the next period. It thus struggles to explain the persistent effect of past rejections.

Bordalo et al. (2023) shows that Diagnostic Expectations can be micro-founded and generalised by a memory-based model in the spirit of the one used in this paper.

Experienced-Based Learning. My findings contribute to the literature on experience effects and its psychological underpinnings. Nevertheless, the existing models of experience-based learning struggle to capture all the results presented.

Models of experienced based learning build on adaptive learning by assuming individuals form expectations from historical data, but they depart from such literature in two important ways: (1) individuals form beliefs using a "biased" database, as it is only composed of data they have personally lived through, instead of all historical data; (2) they are subject to a recency bias: recent experiences receive a higher weight. If there is no recency bias, individuals behave as Bayesian "within-life". Such models predict heterogeneity across individuals with different lifetime experiences and, in particular, they imply stronger reaction of younger cohorts to past macro experiences as opposed to older cohorts. Such models can explain the rejection-driven heterogeneity and the differences among young and old individuals (Fact 1 and Fact 5).

A key difference among models of experience-effects and my results is the idea of domain-specificity, for which I do not find support in the data. Since current models of experienced-based learning reflect this domain-specificity, they struggle to capture the findings.

When studying the role of past experiences on beliefs and behaviour, Malmendier (2021) and Malmendier and Wachter (2021) highlight the importance of (1) moving from theories of over-extrapolation based on information and focus on theories that emphasise encoding in memory and retrieval, (2) studying truly personal experiences. The empirical findings and the presented theory of memory based beliefs move into this direction.

E Economic Implications

E.1 Model - Credit Market Block

Households can transfer resources across states by saving or borrowing from a credit market. Before $t = 0$, they need to choose whether to participate in this credit market or not and this choice is made only once. If they choose not to participate, they have no other means to transfer resources across periods.

Choice to Participate. Agents start their life (beginning of period 0) with an endowment y_0 and expectations about the evolution of the economy (and thus their income) and their possibilities of obtaining credit. The maximisation problem of those who do not participate in the credit market is:

$$V^{NP}(\theta) = \max_{\{c_0,c_1,c_2\}} \sum_{t=0}^{2} \beta^t \hat{E}_0(u(c_t)) \tag{36}$$

subject to the stochastic income process, $y_t = y^H$ if $\theta_t = \theta_H$ and $y_t = y^L$ if $\theta_t = \theta_L$; the budget constraints, $c_0 = y_0 + b_1$, $c_1 = y_1 - Rb_1 + b_2$ and $c_2 = y_2 - Rb_2$; and the borrowing constraints, $b_1 = b_2 = 0$. Non-participants then consume their endowment each period, which varies according to the state of the economy: $c_t = y_t$ where $y_t = y^H$ if $\theta_t = \theta_H$ and $y_t = y^L$ if $\theta_t = \theta_L$.

The maximisation problem of those who do participate in the credit market is:

$$V^{P}(\theta, \lambda_0) = \max_{\{c_0,c_1,c_2\}} \sum_{t=0}^{2} \beta^t \hat{E}_0(u(c_t)) \tag{37}$$

subject to the stochastic income process, $y_t = y^H$ if $\theta_t = \theta_H$ and $y_t = y^L$ if $\theta_t = \theta_L$; the budget constraints, $c_0 = y_0 + b_1$, $c_1 = y_1 - Rb_1 + b_2$ and $c_2 = y_2 - Rb_2$; and the borrowing constraints,

$$b_1 \leq \phi_0 \left[R^{-1}(y_1^L + R^{-1}y_2^L) \right] \tag{38}$$

$$b_2 \leq R^{-1}y_2^L \tag{39}$$

$$\phi_0 = \begin{cases} 0 \text{ with prob } \lambda_0 \\ 1 \text{ with prob } 1 - \lambda_0 \end{cases} \tag{40}$$

Alternatively, the value function from participation can be rewritten as

$$V^P(\theta, \lambda_0) = \lambda_0 V^{P,R} + (1 - \lambda_0) V^{P,A} \tag{41}$$

where $V^{P,A}$ is the value function V^P when accepted $\phi_0 = 1$ and $V^{P,R}$ is when rejected $\phi_0 = 0$.

Agents participate in the credit market whenever

$$\begin{aligned} V^P = \lambda_0 V^{P,R} + (1 - \lambda_0) V^{P,A} > V^{NP} \\ \lambda_0 < \left| \frac{V^{NP} - V^{P,A}}{V^{P,R} - V^{P,A}} \right| \equiv \bar{\lambda} \end{aligned} \tag{42}$$

Households participate in the credit market if so long as they assign a relatively high probability to future increasing income - such that their $V^{P,A}$ is higher than their V^{NP} - and their perceived probability of rejection is lower than the threshold $\bar{\lambda}$.

I have assumed households are homogenous, thus either everyone participates in the credit market or no-one does. Allowing for heterogeneity in preferences, income or beliefs would induce heterogeneity in participation and could also capture the distinctions between participants and non-participants observed in the data. For example, households who have previously been rejected and are pessimistic about their probabilities of getting credit (i.e. discouraged) might not find it optimal to participate because $\lambda_0 > \bar{\lambda}$. Since the goal is to study credit market experiences, the focus is on cases where participation is optimal.

Credit Market Participants. Conditional on participating, individuals ask the bank for their desired level of borrowing. The supply side of the market is characterised by a bank that provides loans at a given interest rate R. The total amount of credit that can be provided in the economy is capped by an exogenous limit $\bar{B}_t$. The bank is thus willing to lend $\min\{Rb_{t+1}, NPV(\theta_L)\}$ to each accepted applicant subject to the total amount of credit they can provide $(1-\lambda_t)b_{t+1} \leq \bar{B}_t$, where λ_t refers to the share of households that are rationed or rejected from the credit market. As long as the constraint is slack, the supply of loans will meet the demand at the given R such that markets clear. If the total demand surpasses the exogenous limit, banks can set $\lambda_t > 0$ to make the constraint slack once again. To stress the role of past rejections, I assume the limit $\bar{B}_0$ is tight and thus $\lambda_0 > 0$, whereas the limit at the second period is such that $\lambda_1 = 0$.

Period 1. The banker takes as given R and the total amount of credit available $\bar{B}_1$. She is willing to lend

$$B_1 = \min\{\ b_2,\ R^{-1}y_2^L\ \}$$

to each accepted applicant and she will be able to lend to all applicants as long as

$$\lambda_1 B_1\ \leq\ \bar{B}_1$$

Households solve

$$\max_{\{c_0,c_1,c_2\}} u(c_1) + \beta E_1^h(u(c_2)) \tag{43}$$

subject to $c_1 = y_1 - Rb_1 + b_2$, $c_2 = y_2 - Rb_2$ and the borrowing constraint $b_2 \leq R^{-1}y_2^L$. h refers to the type of household, either accepted $h = a$ or rejected $h = r$. Individuals who were accepted in their past credit application demand an optimal level of borrowing b_2^a while those who were rejected demand b_2^r.

Banks are willing and able to lend to all individuals in this period, since the supply side of the credit market is high enough to meet all the demand. Market clearing implies:

$$\underbrace{(1-\lambda_1)}_{=1}[(1-\lambda_0)b_2^a + \lambda_0 b_2^r] = \bar{B}_1 \tag{44}$$

Period 0. The banker takes as given R and the total amount of credit available $\bar{B}_0$. She is willing to lend

$$B_0 = \min\{\ b_1,\ R^{-1}(y_1^L + R^{-1}y_2^L)\ \}$$

to each accepted applicant and she will be able to lend to all applicants as long as

$$\lambda_0 B_0 \;\leq\; \bar{B}_0$$

Households take as given their b_2^h and solve

$$\max_{\{c_0,c_1,c_2\}} \sum_{t=0}^{2} \beta^t \hat{E}_0(u(c_t)) \tag{45}$$

subject to the budget constraints $c_0 = y_0 + b_1$, $c_1 = y_1 - Rb_1 + b_2^h$ and $c_2 = y_2 - Rb_2^h$ and the borrowing constraints

$$b_1 \leq \phi_0 \left[R^{-1}(y_1^L + R^{-1} y_2^L)\right] \tag{46}$$

Banks are willing but not able to lend to all individuals in the first period, as the aggregate supply of credit is limited. Thus for the credit market to clear, the bank rations credit by setting $\lambda_0 > 0$ such that

$$\lambda_0 b_1^a = \bar{B}_0 \tag{47}$$

The rest of the model is described in the main text in Section 5.1.

E.2 Additional Regression Results

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

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

$$\text{OptimismIndex}_{it} = \beta_0 + \beta_1 \text{Rejection}_{i,t-1} + \delta X_{it} + \gamma_{st} + v_{it} \tag{48}$$

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

$$\text{Spending}_{it,t+1} = \alpha_0 + \alpha_1 \text{Rejection}_{i,t-1} + \alpha_2 \text{OptimismIndex}_{it} + \delta X_{it} + \gamma_{st} + u_{it} \tag{49}$$

The indirect effect is then calculated as the multiplication of the estimated effect of rejections on beliefs (β_1) and the estimated effect of beliefs on spending attitudes (α_2). Table E.38 presents results from regression 48 in Column (1) and regression 49 in Column (2). The direct effect of a rejection reduces the percent chance of buying durables in the near future by approximately 2.8 percentage points. The indirect effect or belief-channel is calculated as $-0.161 \times 2.968 = -0.478$. Thus, the total effect of a rejection on spending attitudes is a reduction of 3.3 points on the percent chance. The importance of the indirect effect can be measured as the ratio of the indirect effect over the total effect: the rejection induced pessimism accounts for almost 15% of the reduction in spending attitudes.

Table E.38: Direct and Indirect Effect of Rejections on Spending Attitudes

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

Notes: Column (1) reports estimated coefficients of Equation 48 relating past personal rejections to Optimism Index, while Column (2) presents estimated coefficients of Equation 49 relating both past rejections and beliefs to spending attitudes. Individuals' beliefs are instrumented by their first-ever reported belief (Weak Instrument statistic 1563.168 with p-value$< 2e-16$, Wu-Hausman statistic 4.398 with p-value$= 0.036$). Both specifications control for age, age squared, gender, race, marital status, employment status, college attainment, expected income, income, numeracy, type of credit application (either credit card, mortgage or auto loan) and state-month-year fixed effects. Standard errors are clustered at the respondent-time level. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

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

Assumptions for Identification of the Effect. First, the rejection should be random conditional on the covariates, an assumption that was discussed in Section 3. Here as well I include the full set of controls and run robustness with the matched sample. We can also rule out concerns about reverse causality, since spending attitudes were measured after beliefs (different modules in SCE) and beliefs were measured after rejections occurred. It may be further argued that macroeconomic beliefs and spending attitudes are both influenced by a third variable related to individuals' own assessment about their future income. To alleviate such concerns, I include expected income as control. Finally, there should be no measurement error in the mediator variable. Unfortunately, expectations tend to be a hard object to measure and can be subject to mood fluctuations and error. I follow Das et al. (2020) and instrument individuals' current beliefs about the macroeconomy with their first-ever reported belief.[23]

Rejections and Changes in Savings. Using the SCE, I test whether individuals who were rejected in the past year also increased their savings during that period and, if they did, why they did it. For this, I use the cross sectional data on households' balance sheet. More specifically, the Finance Module asks "During the last 12 months, about how much more did you add to your investments or savings than you withdrew from them?".

Table E.39 reports the results. Individuals who became rejected during the last year report higher increases in their savings rates, both in levels and as a share of their income. Is this effect coming from beliefs or other changes in households situation? Do respondents who go through rejection become more cautious? Given that they have added money to their account, respondents are asked about the reason for their increase in savings during the last year. I am particularly interested on their answer to the following question: "Is "I expect it will be more difficult to borrow in the future" an important reason?". Higher values reflect higher importance. Results go in line with the rejection-induced pessimism: individuals who became rejected during the last year are 30 percentage points more likely to report that fear of tighter credit conditions was an important reason.

Table E.39: Past Rejections and Increases in Savings

	$log(1 + Added)$	$log(1 + Added/Income)$	Why? Harder to borrow
(Intercept)	5.897^{***}	0.115	0.564^{*}
	(1.486)	(0.111)	(0.325)
Become Rejected	1.179^{**}	0.077^{*}	0.277^{**}
	(0.532)	(0.040)	(0.115)
Individual level Controls	Y	Y	Y
State-Month-Year FE	Y	Y	Y
R^2	0.393	0.319	0.206
Observations	1749	1749	1831
Mean Dep Var	8.26	0.10	0.21

Notes: All specifications control for age, gender, race, marital status, employment status, income, college attainment, quintiles of debt holdings, quintiles of net worth, reported credit score and state-month-year fixed effects. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Rejections and Risky Holdings. Using the SCF, I investigate whether past credit market experiences correlate with their holdings of stocks, bonds, saving and share of savings in risky assets.

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

Table E.40: Households' Rejections and their Balance Sheet - SCF Data

	Has Stocks?	Has Bonds?	Has Savings?	% Savings in Stocks
Fully Granted		(omitted)		
Partially granted	-0.218^{**}	-0.060	-0.021	-19.931
	(0.107)	(0.111)	(0.020)	(17.144)
Rejected	-0.497^{***}	-0.331^{***}	-0.079^{***}	-19.271^{**}
	(0.059)	(0.058)	(0.010)	(8.114)
Didn't apply	-0.112^{***}	-0.152^{***}	-0.074^{***}	-0.083
	(0.039)	(0.044)	(0.007)	(6.478)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
R^2	0.221	0.057	0.085	0.014
Observations	42205	42205	33458	28939
Mean Dep Var	0.168	0.162	0.546	36.63

Notes: Outcome variables refer to (1) binary variable that takes value 1 if respondent holds stocks, (2) binary variable that takes value 1 if respondent holds bonds, (3) binary variable that takes value 1 if respondent has savings, (4) among those with savings, percent of savings in stocks. All specifications control for year FE and individuals' characteristics - age, education, gender, race, marital status, employment status, income category, expected income, wealth category and reported risk aversion. Statistical significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$