Discouragement in Consumer Credit Markets

Carlos Eduardo Ladeira

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Abstract

This paper uses survey data from the U.S. to study discouragement in consumer credit markets, defined as households abstaining from applying for credit because they expect a rejection. Discouragement is mainly explained by creditworthiness as perceived by households. Low-credit-score individuals are significantly more likely to expect a credit denial. However, my estimates indicate that about 25% of discouraged borrowers would have been approved for a credit card had they applied, suggesting that discouragement leads to a shortage in credit demand. This outcome is explained by the fact that discouraged borrowers, who lack financial sophistication, use outdated information about their credit risk when forming beliefs about their prospects in credit markets. I show that these information frictions significantly declined due to a new credit reporting policy that facilitated the acquisition of information by non-sophisticated households.

Carlos Eduardo Ladeira: Department of Applied Economics, HEC Montréal, cealadeira@gmail.com. I am grateful to my advisors, Hafedh Bouakez and Nora Traum, for their guidance through every stage of this project. I thank participants to seminars at CEEA, CIREQ, and HEC Montreal for helpful comments, and Tatyana Deryugina for valuable suggestions to the first versio of this paper. All errors are my own.

1. Introduction

Differences in access to credit markets are often highlighted as a primary driver of the heterogeneous consumption behavior across households (e.g., Sullivan 2008; Baker and Yannelis 2017; Braxton et al. 2020). The sources of the unequal access to credit have been heavily studied and debated, with proposed explanations ranging from credit rationing due to information asymmetries (e.g., Stiglitz and Weiss (1981)) or imperfect competition (e.g., Parlour and Rajan (2001)) to discrimination against minorities (e.g, Berkovec et al. 1998; Bhutta and Hizmo 2021).

Research, however, has largely overlooked that consumers often self-select out of the loan application process. These consumers demand credit but decide not to apply for a loan because they expect a rejection. These discouraged borrowers account for an important share of actual credit-constrained households in the U.S. (Figure 1). For example, 13 to 18 percent of U.S. households were discouraged in 2019, while 11 to 23 percent were rejected in the same year. Which factors drive households into discouragement? Would discouraged borrowers have been approved for credit had they applied? If yes, which policies can be effective in encouraging their application?

These questions are relevant for various reasons. Households' misbeliefs about their borrowing ability might distort their consumption and savings decisions. For example, if households are overly-pessimistic about their credit access, they may over-accumulate precautionary assets and consume less on average.[1] Unjustified discouragement can also have self-fulfilling effects on consumers' ability to borrow in the future, as the length of a borrower's credit history predicts binding credit constraints. Furthermore, consumers' over-pessimism about their prospects in credit markets is likely to play an important role in the transmission of monetary policy, as these consumers may believe that changes in monetary policy do not extrapolate to their credit terms.

To investigate these issues, I use the New York Fed's Survey of Consumer Expectations (SCE), a nationally representative survey of about 1,300 U.S. household heads. The SCE elicits respondents' reasons for not applying for credit, the most common being – among potential borrowers – the expectation of credit denial. The SCE also collects a rich array of demographic and financial information about the respondents, such as their perceived credit scores and when they last checked/learned about their credit scores or requested a copy of their credit reports. My sample consists of roughly 12,000 household heads and spans from 2014 to 2021, which allows me to investigate the incidence of discouragement over several years, including during the economic crisis in the early stage of the COVID-19 pandemic.

[1] Fulford (2015) shows that households became more precautionary after the financial crisis of 2008, partly because credit conditions became significantly tighter afterwards.

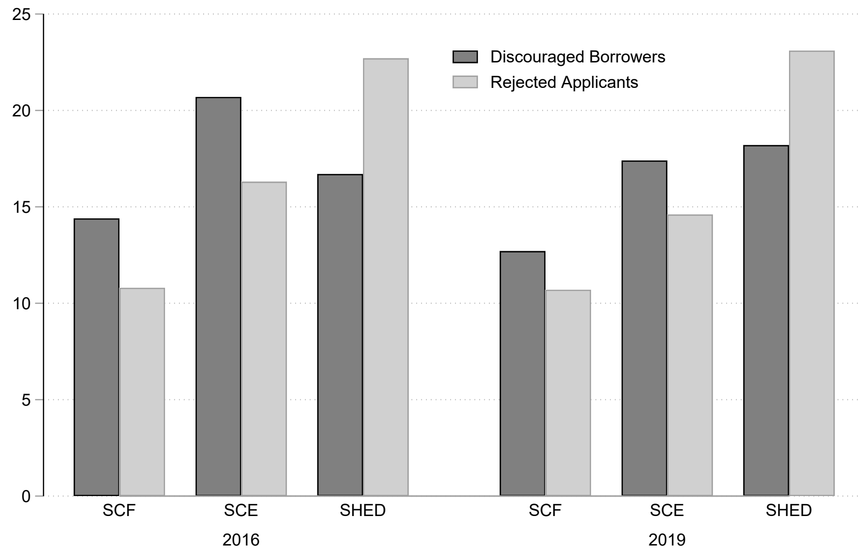

FIGURE 1. Discouragement and rejection in the U.S.

Notes: The figure reports discouragement and rejection rates in 2016 and 2019, computed by different surveys: NY Fed's Survey of Consumer Expectations (SCE), Survey of Consumer Finances (SCF), and Survey of Household Economics and Decisionmaking (SHED). Discouragement and rejection rates refer to the past 12 months.

The paper starts out by studying the determinants of discouragement in the cross-section. The results show that households' perceived creditworthiness – measured by the guess about their credit scores – is the primary driver of discouragement. Individuals who believe they have low credit scores are, all else equal, about 27% more likely to expect a credit rejection and opt out of the loan application process. After controlling for perceived credit scores, other determinants of discouragement are less precisely estimated and, more importantly, smaller in magnitude. For instance, I no longer find differences in discouragement by gender or race once I include perceived credit scores. My results also indicate that households with higher debt-to-income ratios are more likely to expect a credit denial and abstain from applying. Exploiting cross-sectional and within-household variation, I find that both sophisticated and non-sophisticated consumers believe that their prospects in credit markets improve on their credit scores. This result suggest that credits scores are, perhaps because of their salience, a piece of information whose effects on credit access are relatively easy to grasp.

Next, I ask whether discouraged borrowers would have been approved for a credit card had they applied. I focus on credit cards because of its importance for consumption smoothing (e.g., Sullivan 2008; Herkenhoff 2019; Horvath et al. 2021). To that end, I first restrict my sample to 2014-2019, that is, prior to the COVID-19 outbreak and the adoption of new policy that facilitated the acquisition of information by households. Next, I estimate a model of credit access using the sample of applying households. The model includes various demographic characteristics and strong predictors of binding borrowing constraints such as debt-to-income ratio and housing tenure status. After the out-of-sample validation of the model, I use its estimated parameters to obtain the predicted approval likelihood of discouraged borrowers. Comparing their predicted values to those of applying-and-approved consumers, I quantify that 25% of the discouraged borrowers would have (most likely) obtained credit had they applied.

This finding has two important implications. First, it indicates that households' imperfect consumption smoothing through unsecured revolving credit is partially due to a misjudgment about their borrowing ability rather than actual constraints from lenders. Second, it suggests a novel mechanism – in addition to, for example, asymmetric information that arises in bank-borrower interactions (Agarwal et al. (2018)) – through which the pass-through of credit expansion policies to household borrowing and hence aggregate demand might be incomplete.

I investigate the potential reasons behind this result. In my sample, a large proportion of households have outdated information about their creditworthiness. Specifically, in the restricted sample in 2014-2019, 17% of the respondents learned about their credit scores or requested a copy of their credit reports more than two years (or never) before the survey interview. This means that discouraged borrowers, who thought about applying for credit in the past twelve months, might have used information outdated by at least a year when forming beliefs about their prospects in the credit markets.

To formally test this information friction explanation, I study the correlates of household information acquisition in a regression framework – also using the restricted sample. Conditional on covariates, discouraged borrowers are significantly more likely to have outdated information about their credit scores/reports than applicants. The differences are economically large. For example, according to my estimates, discouraged borrowers are about 6 percentage points more likely to have obtained that information more than two years (or never) before the survey interview. This result is at odds with models of endogenous information acquisition (e.g., Reis 2006; Mackowiak and Wiederholt 2009; Maćkowiak and Wiederholt 2015) and cannot be explained by *actual* monetary costs.

Instead, this paper shows that the lack of financial sophistication likely explains discouraged borrowers' outdated information set despite the benefits of acquiring information before applying for credit. Because of their low levels of sophistication, discouraged borrowers are more likely to mistakenly believe that checking their credit scores or requesting a copy of their credit reports in advance hurts their current and future ability to borrow. Since they also tend to self-perceive as low-credit-score consumers, they are slower in updating their information set and learning about their actual type. According to my estimates, likely approved discouraged borrowers are about 8 percentage points less likely to have high numeracy skills than similar approved households.

Next, I exploit a policy change implemented by credit bureaus early in 2020 facilitating the acquisition of information by non-sophisticated households. In April 2020, Equifax, TransUnion and Experian announced a significant change to their credit reporting policy. People could now request up to three free credit reports every week rather than every twelve months. In a less coordinated manner, the credit bureaus also facilitated the acquisition of credit scores. Using a difference-in-difference and event study designs, I show that the new policy significantly increased the probability of non-sophisticated households update their information set for the first time. My estimates indicate an average reduction in the degree of information rigidity of roughly 8 percentage points, or 50% relative to the sample mean of the pre-policy period. This result remains virtually unchanged after accounting for COVID-19, which may have prompted households to seek information. Finally, I show that during the post-policy/pandemic period, discouraged borrowers opted out of the loan application process using new information.

Literature and Contribution. My findings contribute, first and foremost, to the empirical literature on discouragement in credit markets. Most of this literature investigates the discouragement of firms. Han et al. (2009) find that improvements in information quality, measured by longer bank-borrower relationships, encourage less risky borrowers to apply, which they interpret as an increase in the efficiency of discouragement. Anastasiou et al. (2022) show that higher economic uncertainty increases the probability of a firm being discouraged. The results in Ferrando and Mulier (2022) are similar to mine. They also show that a significant fraction of discouraged borrowers would have been approved for credit had they applied. Exploiting a legal change in Belgium that reduced firms' loan application costs, they find a significant reduction in firms' probability of discouragement and an increase in firm-level employment growth and sales.[2] In my work, I show that a change in the credit bureaus' credit reporting policy facilitated the acquisition of information by non-sophisticated households.

My paper is related to a growing literature that builds on experimental designs to test several predictions of models of endogenous information acquisition (e.g., Mikosch et al. 2021; Fuster et al. 2022; Roth et al. 2022). Relative to these studies, I find that households differ in the costs of acquiring information, but not in how they process information. While non-sophisticated consumers obtain information about their credit scores or reports less frequently, they understand the effect of creditworthiness on credit access as sophisticated consumers do. Similar to these

[2] For example, by requiring banks to provide the main details of loan contracts clearly and concisely, potential borrowers in-kind costs became significantly lower.

papers, I provide evidence that information frictions are better modeled as endogenous rather than exogenous. Taken together, my results can help calibrate models of imperfect information.

This article also contributes to a research agenda that uses survey data to better understand how households form expectations and their effect on economic behavior (e.g., Hyytinen and Putkuri 2018; Massenot and Pettinicchi 2019; Cocco et al. 2020). These studies often find an association between optimistic beliefs (e.g., about income streams) and overindebtedness. My results suggest that pessimistic beliefs can also exacerbate financial distress. Specifically, discouraged borrowers might turn to financial services outside the banking system, which facilitate impulsive spending and are higher-cost products (e.g., payday loans).

My results are also contribute to a growing literature on the importance of financial literacy/sophistication in explaining differential outcomes in household finance (e.g., Bucks and Pence 2008; Keys et al. 2016; Bhutta et al. 2021). I find that less financially savvy households are more likely to make financial mistakes because they have higher (perceived) costs in acquiring useful information.

The remainder of the paper is organized as follows. Section 2 presents a simple conceptual framework that guides my empirical analysis. Section 3 describes the data. Section 4 studies the determinants of discouragement and the extent to which they vary by household sophistication. Section 5 quantifies the share of likely approved discouraged borrowers and investigates the role of information frictions in explaining discouragement. In Section 6, I present and discuss the effect of the credit bureaus' new policy on information demand. Section 7 studies discouragement during the COVID-19 pandemic. Section 8 concludes.

2. Conceptual Framework

Following most empirical research on discouragement in credit markets (e.g., Han et al. 2009; Ferrando and Mulier 2022), I structure my empirical analysis on the theoretical framework by Kon and Storey (2003). In their model, discouraged borrowers would be approved for a bank loan, but they do not apply because they expect a rejection. Two arguments rationalize discouragement in their baseline framework. First, as banks are only partially informed about borrowers' types, their screening device is imperfect. Second, banks' screening errors, combined with positive and sunk application costs, result in creditworthy borrowers – assumed to be perfectly informed about their type – being discouraged from applying for credit. Applications costs can be in-kind (e.g., time spent in the application process), financial (e.g., money spent in acquiring information required by banks), and psychological (e.g., discomfort experienced in sharing personal information).

Two testable predictions arise from Kon and Storey (2003). First, given banks' screening errors, a reduction in the application costs encourages potential borrowers to apply. When deciding whether to apply for credit, they trade off the benefits and costs of applying. By improving the terms of the trade off, a decline in the application costs leads to a higher number of applications from all borrowers, reducing discouragement. Second, given the application costs, less risky borrowers are more likely to apply when banks' screening device improves, implying less discouragement. The empirical evidence in Han et al. (2009) and Ferrando and Mulier (2022) supports these two theoretical predictions. Using households' perceived rather than actual application costs, I also find support for the first prediction in Kon and Storey (2003).

I closely follow Kon and Storey (2003) extended model, where borrowers are imperfectly informed about themselves, while banks' screening errors are assumed to be zero. In their model, truly creditworthy borrowers believe they are creditworthy only with an exogenous probability $1-fb_G$. Since this is the best information available to them ex-ante, they assume that banks will consider them creditworthy with the same probability. Therefore, in this setup, borrowers self-screen into the loan application process, rather than banks. Borrowers' effective application costs are given by $K/(1-fb_G)$, with $K > 0$ being paid irrespective of the loan request outcome. In the context of consumer credit markets, K also includes a "hard" credit inquiry, defined as a lender's request to review the applicant's credit report when making a lending decision. This inquiry results in a marginal decline in the applicant's credit scores and may stay on her credit report for up to 36 months.

In this modified framework, if $K = 0$, then even the pessimistic borrowers (i.e., ex-post approved) would apply for credit. However, with $K > 0$, creditworthy borrowers might be discouraged from applying. In this case, they would benefit from information acquisition, as it implies a reduction in the effective application costs, $K/(1-fb_G)$. For example, when a truly creditworthy consumer acquires information about herself and learns that she is creditworthy, the psychological cost associated with a credit rejection becomes zero. Similarly, optimistic borrowers (i.e., ex-post rejected) also benefit from acquiring information in advance, as they would avoid paying the positive and sunk application costs associated with the request for credit.

Despite the benefits of information acquisition, in my sample, a significant proportion of discouraged borrowers had outdated information about their credit risk when they were thinking about applying for credit. In this paper, I show that this result is consistent with information frictions. Potential borrowers might believe that checking their credit scores or requesting a copy of their credit reports before applying for a loan – i.e., a "soft" credit inquiry – negatively and persistently impact their credit scores, especially if scores are perceived to be initially low. Thus, while acquiring information reduces the effective application costs, $K/(1-fb_G)$, borrowers' misconception about the effects of soft credit inquires works to maintain their outdated information set and initially low *perceived* credit scores (i.e., high/persistent fb_G). To further investigate this explanation, I study the impact of a policy that made it easier for people to acquire information about their credit scores and reports.

3. Data

The empirical analysis uses data from the New York Fed's Survey of Consumer Expectations (SCE). The SCE is a monthly, nationally representative survey of about 1,300 household heads with a rotating panel structure.[3] Demographic and financial characteristics of survey participants align well with corresponding characteristics of the U.S. population of household heads. The survey contains a core monthly module and various supplementary modules on specific topics. This paper uses data from the core and credit access modules. The credit access module is fielded in February, June, and October.

I identify discouraged borrowers using questions in the credit access module, as discussed below. From this module, I also obtain information on consumer debt and the outcome of credit and loan applications. Specifically, households report their best guesses of the current amount/balances of their: (a) credit card debt, (b) mortgage debt, (c) student loan debt, (d) home-based loans, (e) auto loans, and (f) other personal loans. Households also inform the outcome of previous applications for these loans and lines of credit. I consider a partly granted request as rejected, as only a small number of these requests list the amount granted. About 80 percent of the credit requests in my sample are approved. The survey elicits households' beliefs about their credit scores and what was the last time they checked/learned about their credit score or requested a copy of their credit report.[4] The answers to the first of these two questions report households' perceptions of their creditworthiness, while those to the second question indicate to what extent their perceptions are updated.

I gather detailed demographic characteristics for each respondent from the core module. Demographic information includes gender, marital status, age, race, labor force status, education, numeracy skills, willingness to take financial risk, homeownership status, and nominal pre-tax income. I also obtain households' subjective expectations of credit conditions for people in general.

[3] Respondents participate in the survey for up to twelve months.

[4] In the U.S., FICO and three credit bureaus (Equifax, Transunion, and Experian) issue credit scores: FICO Score and VantageScore, respectively. To sort households by their creditworthiness, I closely follow credit bureaus' classification.

Analysis sample. Combining the core and the credit access modules results in 25,752 observations spanning from February 2014 to June 2021. The analysis sample thus consists of 23 survey waves and contains roughly 12,000 household heads. I report selected demographic and financial characteristics of my sample in Table 1, along with their population counterparts (column (4)). Most of the reported characteristics are stable over time, as shown by columns (2) and (4). The Appendix provides the definitions of all variables.

TABLE 1. Sample characteristics

	SCE(All)	SCE(2014)	SCE(2020)	U.S. Pop.
Demographics				
Female	49.8%	50.2%	52.5%	50.8%
Age	51.11	50.67	51.50	51.06
White/non-Hispanic	78.4%	78.2%	78.5%	69.0%
College +	34.1%	32.2%	35.9%	31.0%
Homeowner	70.4%	70.1%	71.4%	59.0%
Financial characteristics				
Credit score	680-760	680-760	680-760	682
Household income $\leq$ 50k	35.5%	38.1%	32.5%	37.0%
Household income 50k-100k	35.9%	35.6%	36.9%	30.0%
Household income > 100k	28.6%	26.4%	30.6%	31.0%
Sample size	25752	3389	3225	

Notes: For the SCE sample, all statistics use survey weights. Comparison is with the 2015 ACS (demographics) and Experian's 2019 State of Credit Report (credit score).

3.1. Identifying discouraged borrowers

Each wave of the credit access module asks households why they (1) did not apply for new loans or credit over the past 12 months and (2) do not expect to apply for new loans or credit over the next 12 months. To these questions there are multiple possible answers: (a) the household does not need a loan, (b) application procedures are too time-consuming, (c) borrowing rates are too high, (d) the household does not know how to apply, or (e) the household believes the application would be rejected.

Discouraged borrowers are consumers who do not apply for (at least one type of) credit because they expect a rejection. They account for most non-applicants who have a demand for credit. Note that the first and second questions identify past and currently (as in the current survey wave) discouraged borrowers, respectively. I use both definitions in my empirical analysis. Consumers also do not apply for credit because they expect adverse credit terms, that is, "borrowing rates are too high". While these consumers can also be characterized as discouraged, I do not consider them in my analysis.[5] Non-discouraged borrowers apply for at least one type of credit and when they do not apply for one type, it is because they do not need it.

Figure 2 plots the evolution of discouragement and rejection rates over the sample period. It shows that discouragement is consistently higher than actual credit constraints, especially in the first half of the sample. We also note an increase in discouragement and rejection rates after the COVID-19 outbreak followed by a decline in both. Finally, discouragement and rejection rates are highly correlated over time.

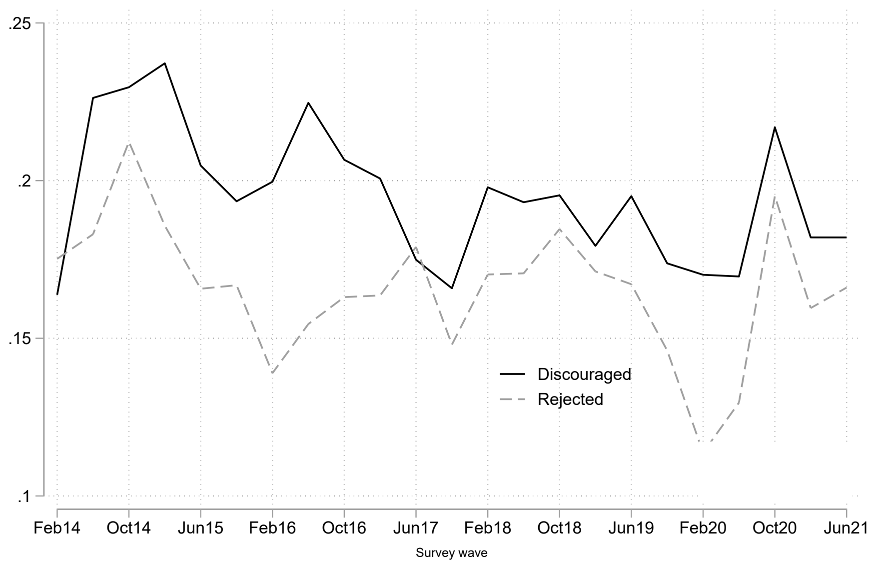

FIGURE 2. Discouragement and rejection

Notes: The figure shows discouragement and rejection rates in the 12 months prior to each survey wave. Student loans are not included.

[5] These consumers account for about 25% of the non-applicants who have a demand for credit.

4. The Determinants of Discouragement

In this section, I investigate what drives consumers who need credit to either apply for a loan or to be discouraged from applying. Next, I discuss whether the results suggest that discouragement is an efficient self-rationing mechanism. In this case, riskier and more indebted potential borrowers are more likely to be discouraged.

My choice of explanatory variables falls into four broad categories. First, I include a wide range of demographic regressors. My analysis focuses on gender and racial differences in discouragement. Previous studies document pronounced gaps in access to business credit along those dimensions, either due to actual (e.g., Blanchflower et al. 2003; Morazzoni and Sy 2022) or self-imposed credit constraints (e.g., Ongena and Popov 2016). I ask whether those (self-imposed) gaps are also present in consumer credit markets. Second, I add households' assessment of application costs – for example, whether they think the application process is too time-consuming. In theory, a reduction in application costs increases the likelihood that potential borrowers apply, as long as their subjective expectations of approval are not zero.[6] Third, I account for households' debt positions since previous research (e.g., Johnson and Li (2010)) underscores their relevance as a predictor of actual borrowing constraints. Finally, to investigate whether households extrapolate from macroeconomic to personal expectations (e.g., Roth and Wohlfart (2020)), I consider their expectations of credit conditions for people in general.

$$\begin{aligned}\Pr(\mathrm{DB}^i_{t,t+12} = 1) = \mathrm{F}(\beta'\mathrm{SES}_{i,t} + \theta\mathrm{AppCosts}_{i,t} + \delta'\mathrm{BS}_{i,t} + \gamma'\mathrm{Scores}_{\mathrm{i,t}} \\ + \phi\mathrm{EasierCredit}^i_{t,t+12} + \lambda_t + \lambda_{s(i)})\end{aligned} \tag{1}$$

The likelihood of being discouraged is thus estimated by running the probit regression:

where $\mathrm{DB}^i_{t,t+12}$ is a dummy variable equal to 1 if household i reports, in survey wave t, that she is discouraged from applying for credit over the next twelve months. The vector $\mathrm{SES}_{i,t}$ contains socioeconomic characteristics, including dummy variables for being female and non-Hispanic white.[7] $\mathrm{AppCosts}_{i,t}$ is a dummy variable equal to 1 when the household reports that the application process it too burdensome – either too time-consuming or too difficult to understand. The vector $\mathrm{BS}_{i,t}$ includes a measure of the household debt position (debt-to-income) and a dummy variable equal to 1 if the household is a homeowner. Perceived credit scores are included in $\mathrm{Scores}_{\mathrm{i,t}}$. $\mathrm{EasierCredit}^i_{t,t+12}$ is a dummy variable equal to 1 if the household expects easier

[6] Differently from Han et al. (2009) and Ferrando and Mulier (2022), I rely on households' reported perceptions of their costs, rather than proxies for application costs (e.g., firm size and distance from their primary lender).

[7] Demographic covariates also include income and age bins, dummy variables for being employed, married or living as a partner with someone, and having children in the household.

credit conditions for people in general over the next twelve months. The regression includes survey-wave (λ_t) and state ($\lambda_{s(i)}$) fixed effects. Standard errors are clustered at the household level.

Table 2 reports the empirical results. Women and non-white/Hispanic have a higher probability of being discouraged even after controlling for other demographic characteristics, application costs, and debt-to-income ratio (columns (2) and (3)). Specifically, women are 3% more likely to be discouraged and non-white/Hispanic are 2% more likely. However, when I account for households' perceived creditworthiness (columns (4) and (5)), the estimated effects of gender and race are smaller and statistically indistinguishable from zero. In contrast to female and black entrepreneurs (e.g., Blanchflower et al. 2003; Ongena and Popov 2016), women and non-white/Hispanic are not more likely than their similar counterparts to self-select out of the loan application process based on the belief of a rejection.

Consumers who self-perceive as risky borrowers and report higher debt levels are significantly more likely to opt out of the loan application process. For instance, low-credit-score individuals are roughly 28% more likely (column (4)) to be discouraged than those with "fair" credit scores. These findings indicate that households' perceptions about their creditworthiness are the most important determinant of discouragement.

My results also indicate that households' assessment of application costs is significantly and positively associated with discouragement. Therefore, policies aiming at reducing these costs would likely contribute to a decrease in discouragement. Interestingly, this conclusion is in the spirit of Ferrando and Mulier (2022). They find a decline in the proportion of discouraged firms after the introduction of a law (in Belgium) that reduced firms' loan application costs. Finally, households are less likely to be discouraged when they expect easier credit conditions for people in general (column (5)). For example, households may believe that changes in monetary policy are transmitted to their credit terms.

4.1. Heterogeneity

Do the determinants of discouragement vary with household sophistication? This question has important implications for our understanding of household expectation formation and the transmission of economic policy. Recent empirical research documents that households' understanding of (un)conventional measures of fiscal and monetary policy vary systematically with sophistication (e.g., D'Acunto et al. 2019; D'Acunto, Hoang, Paloviita and Weber 2021; D'Acunto et al. 2022). I examine this issue in Table 3.

Exploiting cross-sectional variation and accounting for various characteristics of the households (columns (1) and (3)), I find that high-and low-numeracy households form beliefs about

TABLE 2. Determinants of household discouragement

	(1)	(2)	(3)	(4)	(5)
Female	0.029***	0.030***	0.027***	0.005	0.003
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
White/Non-Hispanic	-0.023***	-0.021**	-0.019**	0.007	0.007
	(0.009)	(0.009)	(0.009)	(0.007)	(0.007)
High application costs		0.070***	0.065***	0.046***	0.045***
		(0.013)	(0.013)	(0.012)	(0.012)
Debt-to-income (rank)			0.143***	0.090***	0.088***
			(0.014)	(0.011)	(0.011)
High credit scores (> 760)				-0.222***	-0.220***
				(0.013)	(0.013)
Good credit scores (680-760)				-0.176***	-0.173***
				(0.014)	(0.013)
Low credit scores (< 620)				0.280***	0.274***
				(0.022)	(0.022)
Expect easier credit					-0.037***
					(0.007)
Individual controls	✓	✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓
Survey-Wave FEs	✓	✓	✓	✓	✓
Observations	19724	19724	19724	19724	19724
Pseudo-R^2	0.153	0.157	0.176	0.378	0.381

Notes: Estimates are average marginal effects. Survey weights are used. The dependent variable is a binary indicator equal to 1 if the household is discouraged from applying for credit over the next twelve months, and 0 if the household is an applicant. Individual controls are dummy variables for being female, married, homeowner, college educated (or more), and for having children in the household. They also include household nominal income and age categories. Omitted category for for credit scores is *Fair credit scores (620-679)*. Standard errors clustered at the household level in parentheses. $^{***}\, p < 0.01$, $^{**}\, p < 0.05$, $^{*}\, p < 0.10$.

their ability to borrow in credit markets remarkably similarly. When I control for unobserved time-varying heterogeneity across households (columns (2) and (4)), one result remains consistent: both high-and low-numeracy households believe that their prospects of obtaining consumer credit improve on their (perceived) creditworthiness. This finding suggests that credit scores

TABLE 3. Discouragement: heterogeneity by sophistication

	High Numeracy		Low Numeracy	
	(1)	(2)	(3)	(4)
High application costs	0.055***	0.032	0.045**	-0.004
	(0.008)	(0.021)	(0.022)	(0.004)
Debt-to-income (rank)	0.096***	0.056***	0.125***	0.007
	(0.009)	(0.017)	(0.023)	(0.045)
Good/High credit scores (> 720)	-0.139***	-0.039***	-0.280***	-0.061***
	(0.005)	(0.011)	(0.013)	(0.020)
Expect easier credit	-0.034***	0.003	-0.085***	-0.026*
	(0.006)	(0.005)	(0.015)	(0.015)
Individual Controls	✓	✓	✓	✓
State FEs	✓		✓	
Survey-Wave FEs	✓	✓	✓	✓
Household FEs		✓		✓
Observations	14618	12310	5034	4099
(Pseudo-)R^2	0.343	0.770	0.282	0.745

Notes: This table reports average marginal estimates (columns (1) and (3)) and OLS estimates (columns (2) and (4)). The dependent variable is a binary indicator equal to 1 if the household is discouraged from applying for credit over the next twelve months, and 0 if the household is an applicant. Individual controls are dummy variables for being female, married, homeowner, college educated (or more), and for having children in the household. They also include household nominal income and age categories. In columns (2) and (4) only time-varying individual controls are estimated. Standard errors clustered at the household level in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

are, perhaps because of their salience, a piece of information that both sophisticated and non-sophisticated consumers value when forming their expectations of credit approval.

5. Would Discouraged Borrowers be Approved for Credit?

This section shows that discouragement leads to a shortage in credit demand, as a significant proportion of the discouraged borrowers would have (most likely) obtained credit had they applied. Next, it investigates what may explain this result.

5.1. Discouraged borrowers and counterfactual outcomes

To study whether discouraged borrowers would have obtained credit had they applied, I proceed as follows. First, I restrict the sample to unsecured revolving (non-mortgage) credit: applications for a new credit card or an increase in the credit limit of a credit card. The credit card market is of particular interest because credit cards are the marginal source of credit for many U.S. households.[8]

Second, I use a probit specification to estimate the likelihood of applying households to obtain credit. The specification is similar to equation 1. It includes various demographic and financial characteristics such as household nominal income, age, loan delinquency, and debt-to-income ratio. Differently from equation 1, however, the credit access regression equation excludes households' perceived credit scores, application costs, and expectations of credit conditions for people in general. Since (actual) credit scores are often regarded as key determinants of loan approval, a household's age, income, credit history (e.g., loan delinquency), and debt-to-income ratio help approximate a borrower's credit score/risk.

Table A3 and Figure A.1 in the Appendix report the regression results and the model in-sample discriminatory power, respectively. To formally test the overall classification ability of my model, I plot (Figure A.1) the receiver operating characteristics curve (ROC curve) and compute the area under this curve (AUC). Let $A_i \in \{0, 1\}$ denote the actual loan outcome of borrower i, with 1 denoting a credit approval and 0 a rejection. Let Y_i denote the probability prediction about A_i, computed by the loan approval model. Y_i and the threshold c define a binary prediction approval whenever $Y_i \geq c$, and a rejection whenever $Y_i < c$. We can define the following conditional probabilities:

$$TPR(c) = Pr[Y_i \geq c | A_i = 1]$$
$$FPR(c) = Pr[Y_i \geq c | A_i = 0]$$

If we set c close to 1, we predict credit approval for relatively few borrowers. Conversely, as c decreases, we obtain a higher number of correctly predicted approvals – i.e., a high true positive rate (TPR). By reducing the threshold, however, the proportion of incorrectly predicted approvals also increases – i.e., a higher false positive rate (FPR). The ROC curve illustrates this trade-off by plotting the TPR on the y axis against the FPR in the x axis. The AUC ranges from 50% (pure random prediction) to 100% (perfect prediction) and summarizes the model's overall

[8] In my sample, slightly more than half of the households apply for a new credit card and higher limit of an existing credit card.

classification ability. As reported in Figure A.1, I obtain an AUC of 76.5%, above the targets of 60% and 70% in information-scarce or information-rich environments, respectively (e.g., Iyer et al. 2016; Berg et al. 2020).[9]

Third, I conduct an out-of-sample validation of the loan approval model. Since the results reported in Table A3 are estimated in-sample, a concern is that we overstate the model discriminatory power due to overfitting. For the out-of-sample test, I closely follow Berg et al. (2020). Specifically, I also use Nx2-fold cross-validation, a standard method to evaluate an estimator's out-of-sample performance. The algorithm initiates by randomly dividing the sample into half samples, A and B. Next, it estimates a predictive probit regression using sample A, whose coefficients are used to create predictive values for the observations in sample B. Similarly, it estimates a predictive probit regression using sample B, whose coefficients are used to create predictive values for the observations in sample A. It then determines the AUC for the full sample of observations, using all predictive values estimated out-of-sample. I repeat this procedure $N = 100$ times and report the mean and confidence interval out-of-sample AUCs. I obtain an average AUC of 72.9%, and a 95% confidence interval of [71.2 , 74.6]. These results strongly support the high discriminatory power of my loan approval model.

Having validated the model, I use its parameters to predict the approval likelihood of the discouraged borrowers. I compare their predicted values with those of the approved applicants. Specifically, I calculate the distribution of the predicted values for the approved applicants and locate discouraged borrowers' predicted values in this distribution. Discouraged borrowers whose predicted values are in the highest percentiles of that distribution would have (most likely) obtained credit had they applied. Figure 3 plots the cumulative distribution function of the predictive approval likelihood of discouraged borrowers relative to that of approved applicants. The figure shows that about 25% of the discouraged borrowers would have been approved for credit had they applied. They have a predicted approval likelihood higher than the first quartile of the approved households.

Interestingly, my findings echo those in Ferrando and Mulier (2022). They also find a large proportion of discouraged borrowers with a high approval likelihood – i.e., above the first quartile of the applying-and-approved firms. My results thus suggest that a considerable share of households are unable to smooth consumption even though they do not face actual binding borrowing constraints. To put this into perspective, approved applicants report an average credit/borrowing limit request of \$ 7625, which corresponds to about 10% of their average annual income. Unconstrained discouraged borrowers would thus be likely to obtain a similar credit-to-income ratio. This credit utilization amount is strikingly similar to that in the literature.

[9] Table A3 reports the AUC's 95% confidence interval in the range [74.9 , 78.1].

For example, Sullivan (2008)) show that low-asset households replace 11% of their lost income (due to unemployment) through unsecured borrowing.

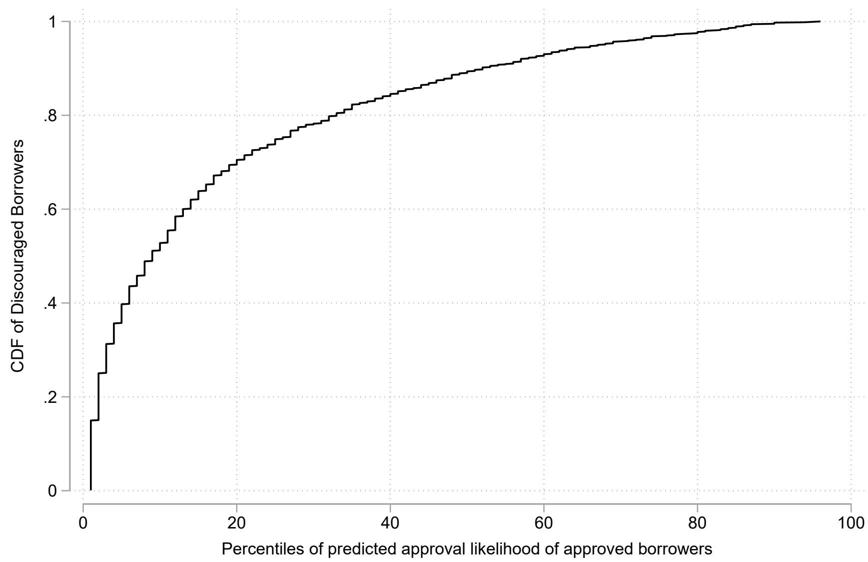

FIGURE 3. Predicted approval likelihood of discouraged borrowers

Notes: The figure shows the cumulative distribution function of the predicted approval likelihood of discouraged borrowers relative to that of approved households.

A concern with my approach is that my loan approval model is misspecified, as I do not observe the actual screening model of financial institutions. It is thus possible that my credit access model does not capture all relevant dimensions of consumer risk. While these caveats apply when interpreting my findings, my empirical model: 1) includes strong predictors of binding borrowing constraints – i.e., debt-to-income ratio (e.g., Johnson et al. (2006)) and housing tenure status (e.g., Cloyne et al. 2020; D'Acunto, Hoang and Weber 2021) –, and 2) performs well out-of-sample. Furthermore, my conclusions should be the same if the unobserved determinants of credit approval are correlated with the observed determinants in my model.

5.2. Inspecting the mechanism: information frictions

In Section 4, we document the relevance of households' perceived creditworthiness in explaining discouragement. In my sample, however, a sizable proportion of households have outdated information about their credit scores or credit reports.[10] Specifically, 28% of the respondents learned about their scores or requested a copy of their reports more than a year before the

[10] Credit bureaus advise consumers to check their credit scores/reports at least once a year. A credit report is a summary of a consumer's credit history. It includes information about her existing credit (e.g., outstanding debt),

survey interview, and 17% more than two years before (or never). Discouraged borrowers having outdated information about their "type" is thus a potential candidate to explain their "mistake".

To test this hypothesis, Table 4 shows the correlates of information acquisition. I use two indicators that measure the degree to which households have outdated information about themselves, *Info (more than a year ago)* and *Info (more than two years ago)*. The former is a dummy variable which equals one if the household obtained the information about her credit score or report more than a year before the survey interview, and the latter is a dummy for having acquired that information more than two years before the interview (or never).

I investigate differences in information acquisition between discouraged borrowers, applicants, and non-applicants. My preferred specifications use *Info (more than two years ago)* as the dependent variable (columns (5)-(8)). They imply that discouraged borrowers, who thought about applying for credit in the past twelve months, used information outdated by at least a year when forming their beliefs of credit denial. Furthermore, I restrict the estimating sample to the pre-COVID period (i.e., before March 2020), when consumers could obtain one free credit report every twelve months from each of the three credit bureaus. This fact, combined with the definitions of the dependent variables, implies that *actual* monetary costs associated with information acquisition are unlikely to explain the results of Table 4.

As shown in columns (1) and (5), discouraged borrowers and non-applicants are significantly more likely to have outdated information than applicants. The estimated effects are economically large. For example, according to my estimates, a discouraged borrower is about 11 and 7 percentage points more likely to have outdated information than an applicant, all else being equal (unconditional averages of 28% and 17%). Non-applicants' information set being more outdated than that of applicants and discouraged borrowers is expected, as non-applicants report no need for additional credit.

In light of macroeconomic models of endogenous information acquisition (e.g., Reis 2006; Mackowiak and Wiederholt 2009; Maćkowiak and Wiederholt 2015), however, the information set of discouraged borrowers and applicants should be similarly likely to be updated, as both consumers demand credit. A basic prediction of these models is that the demand for information depends on its expected benefits. Potential borrowers would benefit from a "soft" credit inquiry, i.e., learning or checking their scores/reports before applying for credit. First, optimistic applicants (i.e., ex-post rejected) would avoid incurring a "hard" credit inquiry, which results in a decline in credit scores, especially when multiple "hard" inquires occur in a relatively

public records (e.g., whether the consumer has filed for bankruptcy), and credit inquiries (e.g., from an employer). Credit bureaus use these characteristics to calculate credit scores.

short period.[11] Second, pessimistic discouraged borrowers would satisfy their demand for credit. Interestingly, I find that applicants with updated information about their credit scores/reports are significantly more likely to be approved for credit. This result is reported in Appendix Table A4. Although it is difficult to establish causality, this result holds after controlling for several characteristics of the applicant, including debt-to-income ratio.[12]

These results remain virtually unchanged when I include dummy variables for being sophisticated (columns (2) and (6)) and in charge of the financial decisions in the household (columns (3) and (7)).[13] There are two possible, non-exclusive interpretations of the latter variable: respondents in charge of financial decisions are more likely to be financially sophisticated and exposed to financial information in general. I find that the information set of non-sophisticated/unexposed respondents is significantly more likely to be outdated. This result is also consistent with models of endogenous information acquisition, as they predict that consumers' demand for information decreases in the cognitive costs of information acquisition and processing. The estimated effects are economically significant as well. For example, compared to a sophisticated consumer, a non-sophisticated respondent is 5 percentage points (columns (6)) more likely to have acquired information more than two years before the survey interview, all else being equal.

Finally, I restrict the comparison to approved applicants and discouraged borrowers who would have (most likely) obtained credit had they applied, as discussed in subsection 5.1. I focus the analysis on credit cards. Since the estimation includes approval likelihood fixed effects, identification comes from comparing discouraged borrowers and similar approved applicants. The results reported in columns (4) and (8) of Table 4 support the argument that discouraged borrowers' mistakes are partly explained by the outdated information – at the time they are thinking about applying for credit – about their actual credit risk.

[11] A lender's request to review the applicant's credit report when making a lending decision is a "hard" credit inquiry. This inquiry may stay on the applicant's credit report for up to 36 months. When a consumer applies for credit several times in a short period, that typically signals higher credit risk, resulting in a reduction of credit scores.

[12] Establishing causality in this setting is difficult for two main reasons. First, I cannot fully control for self-selection. Second, the nature of the data is such that is not possible to rule out reverse causation. It is possible that consumers learn their scores/reports after applying for credit. To reject this alternative explanation, we would need to know exactly when a consumer applied for credit and obtained information about her score/report.

[13] A respondent is in charge of financial decisions in the household if she makes all financial decisions herself, as reported by the answers to question Q46 in the SCE's core module.

TABLE 4. Correlates of information acquisition

	Info (more than a year ago)				Info (more than two years ago)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Discouraged	0.114***	0.113***	0.103***	0.082***	0.066***	0.064***	0.064***	0.051**
	(0.016)	(0.017)	(0.018)	(0.031)	(0.015)	(0.015)	(0.017)	(0.024)
Non-applicant	0.245***	0.245***	0.241***		0.158***	0.157***	0.147***	
	(0.010)	(0.010)	(0.011)		(0.009)	(0.009)	(0.009)	
Sophisticated		-0.037***				-0.052***		
		(0.015)				(0.014)		
Make fin decisions			-0.063***				-0.051***	
			(0.013)				(0.011)	
Individual Controls	✓	✓	✓	✓	✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
Survey-Wave FEs	✓	✓	✓	✓	✓	✓	✓	✓
Approval Likelihood FEs				✓				✓
Observations	19299	19299	14855	3276	19299	19299	14855	3276
R^2	0.117	0.119	0.122	0.005	0.100	0.100	0.095	0.003

Notes: This table reports OLS estimates. Estimating sample excludes COVID-19 period. Survey weights are used. The dependent variables are binary indicators for whether the household's information is older than a year (columns (1) to (4)) or two years (columns (5) to (8)). *Discouraged* is a dummy equal to one if the respondent did not apply for credit in the past 12 months because she expected a rejection. In columns (4) and (8), discouraged borrowers are only those who would have been approved for credit had they applied. *Non-applicant* is a dummy equal to one if the respondent did not apply for credit in the past 12 months because she did not need it. The omitted group for *Discouraged* and *Non-applicant* is *Applicant*, a binary indicator equal to one 1 if the respondent applied for credit in the past 12 months. *Sophisticated* is a dummy variable equal to one if the respondent has either a college degree (or more) or high numeracy. *Make fin decisions* is a binary variable equal to one if the respondent is the person in charge of financial decisions in the household. Individual controls include dummy variables for being female, employed, homeowner, white/non-Hispanic, married, and household nominal income, and age bins. Approval likelihood fixed effects consists of deciles of the approval likelihood. Standard errors clustered at the household level in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

What may explain discouraged borrowers' outdated information set, given the benefits of acquiring information in advance? Two facts sustain my proposed answer to this question. First, discouraged borrowers tend to believe they are low-credit-score individuals (see Table 2). Second, as the first column of Table 5 reports, the subset of discouraged borrowers who would have most likely obtained credit had they applied are less likely to be sophisticated than similar approved applicants. The insignificant association between discouragement and college degree (column (2)) reflects the inclusion of formal education in the loan approval model (see subsection 5.1). Discouraged borrowers are about 8 percentage points less likely to have high numeracy skills (column (3)). This result suggests that financial literacy is to a large extent unexplained by formal education.[14] The lack of financial sophistication arguably causes discouraged borrowers to mistakenly believe that a soft credit inquiry has a negative and persistent impact on their already low (perceived) credit scores. Since households could have obtained a copy of their credit scores/reports for free, it is possible that *perceived* monetary costs also explain their outdated information. While I cannot evaluate which friction is more relevant, Appendix Figures A.2 and A.3 provide anecdotal evidence supporting the former explanation. These figures suggest that a confusion about soft and hard credit inquiries is a common information friction among potential borrowers. However, as reported in Table 3, once non-sophisticated consumers obtain new information about their type, they correctly update their beliefs of credit approval.

My proposed explanation for information frictions in consumer credit markets – lack of financial sophistication – aligns well with the evidence that government assistance programs may not benefit the individuals who would take advantage of them. Allen et al. (2022) find limited enrollment in debt-relief programs (e.g., credit card deferral) implemented in Canada in response to the COVID-19 crisis, partly because households may have believed that a deferral would damage their credit scores and thus their ability to borrow in the future. Building on a field experiment in the U.S., Bhargava and Manoli (2015) show that a lack of understanding of earned income tax credit benefits helps explain the puzzle of its low take-up. Similarly, Humphries et al. (2020) find differential access to the Paycheck Protection Program resources between smaller and larger businesses in the U.S., one of the reasons being that smaller firms are less sophisticated and thus have greater difficulties in acquiring and processing information.

[14] Interestingly, Lusardi and Mitchell (2007) and Bachmann et al. (2021) find that financial literacy is more important than schooling for explaining differences in wealth and pension contributions across households.

TABLE 5. Explaining information frictions

	Sophisticated (1)	College (2)	High numeracy (3)
Discouraged	-0.035*	-0.032	-0.076**
	(0.017)	(0.034)	(0.032)
Individual Controls	✓	✓	✓
State FEs	✓	✓	✓
Survey-Wave FEs	✓	✓	✓
Approval Likelihood FEs	✓	✓	✓
Observations	3276	3276	3276
R^2	0.092	0.129	0.038

Notes: This table reports OLS estimates. Estimating sample excludes COVID-19 period. The dependent variables are binary indicators for whether the household is sophisticated (column (1)), has a college degree or more (column (2)), and high numeracy skills (column (3)). Discouraged borrowers includes only those who would have been approved for a credit card had they applied. Approval likelihood fixed effects consists of deciles of the approval likelihood. Robust standard errors in parenthesis. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

6. Credit Reporting Policy and Information Frictions

Next, I study the effect of a new policy that facilitated the acquisition of information by households. If information frictions explain their outdated information sets, we expect the policy to reduce the degree of information rigidity. To estimate its effect on information demand, we need to consider that the policy was implemented in response to the economic hardship and uncertainty caused by the COVID-19 pandemic. The unprecedented nature of the crisis might have prompted households to seek information. Failing to account for this shock may bias the estimates of the effect of the policy.

6.1. The policy change

In the U.S., until March 2020, individuals could request, by law, one free credit report every twelve months from each of the three credit reporting agencies: Equifax, Experian, and TransUnion. A credit report is a summary of a consumer's credit history. It includes information about a consumer's existing credit (e.g., outstanding debt), public records (e.g., bankruptcy), and credit inquiries (e.g., from a lender or employer). Credit bureaus use this information to compute credit scores.[15] By law, credit bureaus can charge up to $13.50 for a credit report.

In April 2020, the credit bureaus announced a significant change to their credit reporting policy. People could now request up to three credit reports every week rather than every twelve months. Initially set to expire in one year, the new policy was first extended through April 2022 and then December 2022.[16] In a joint statement, the credit bureaus' CEOs justified the adoption/extension of the policy: "The combined pressures of job changes, inflation, market uncertainty and health anxiety continue to present consumers with enormous challenges. Our industry's hope is to support consumers as they make decisions – big and small – by making it easier to regularly track their financial health." The credit bureaus also facilitated the acquisition of credit scores, but in a less coordinated manner.

Therefore, we expect the policy to mitigate information frictions if sufficiently publicized. These frictions are defined as impediments to acquiring credit scores or reports, including awareness of the differences between hard and soft credit inquiries and misconceived monetary costs.

6.2. Empirical strategy

I use a difference-in-differences design to assess the effect of the policy on information demand. To construct the treatment and control groups, I leverage a basic prediction of models of endogenous information acquisition: an economic agent's demand for a specific piece of information decreases in the cognitive costs of information acquisition and processing.

The treatment group thus consists of non-sophisticated households who have never checked their credit scores nor requested a copy of their credit reports. Sophisticated households who also lack such information form the control group. Intuitively, a policy facilitating information acquisition should not affect financially sophisticated households who have never acquired information about their creditworthiness. I estimate the following event study specification:

$$y_{i,t} = \alpha + \sum_{\substack{\tau=-7 \\ \tau\neq-1}}^{2} \delta_\tau \mathbb{1}(t - t^* = \tau) \times \mathrm{Unsoph_i} + \lambda_t + \lambda_{s(i)} + \epsilon_{i,t} \tag{2}$$

$y_{i,t}$ is an indicator variable equal to 1 if individual i has never acquired information about her credit score/report and 0 otherwise. $\mathrm{Unsoph_i}$ is a dummy for being unsophisticated. Indicator

[15] Credit reports from the credit bureaus do not usually contain credit scores.

[16] The first extension was announced in March 2021, and the second in June 2021.

variables $\mathbb{1}(t - t^* = \tau)$ measure the time relative to the implementation of the policy, t^*. Since the new policy was in place in April 2020, I set t^* to June 2020, the first survey wave after the policy adoption. The omitted category is $\tau = -1$, the survey wave prior to the policy change (i.e., February 2020). The δ_τ are the coefficients of interest. Each estimate of δ_τ provides the change in outcomes for unsophisticated households relative to sophisticated households in wave τ, as measured from the period immediately prior to the policy change. In this equation, λ_t denotes calendar time fixed effects and $\lambda_{s(i)}$ state fixed effects. Standard errors are clustered at the household level.

Three key assumptions underlie the estimation of equation (2). First, individuals did not anticipate the policy change and therefore did not time their demand for information. This is plausible as the enactment of the policy occurred immediately after the unexpected COVID-19 outbreak in the second half of March 2020. Second, in the absence of policy change, the outcome variable would have evolved similarly in treated and control groups. The coefficients $(\delta_{-7},\ldots,\delta_{-2})$ test the plausibility of this parallel trends assumption. Third, there are no compositional changes between sophisticated and non-sophisticated households. This assumption is required because of the (mostly) cross-sectional nature of the data. Table 1 suggests that compositional changes in my sample are relatively small.

In addition to the event study analysis, I present a standard difference-in-differences (DD) estimates as a summary of the effect across all post-policy period. These are estimated using the same equation except that the event study indicators are replaced with $Post_t$. This indicator turns on starting in June 2020 for all households.

6.3. The impact of the policy on information demand

6.3.1. Main results

The results are presented in Figure 4 and in the first column of Table 6. The figure shows no change in the differential probability of being uninformed between non-sophisticated and sophisticated households before the policy. This supports the credibility of the identifying assumption that, in the absence of policy, the evolution of the outcome variable would be similar in treatment and control units. Under this assumption, I interpret the coefficients for the post-policy period as the causal effect of the policy.

I find an immediate effect of the policy on information demand of about 10 percentage points. This represents a reduction in the degree of information rigidity of about 62.5% relative to the sample mean. In addition, I observe a gradual decline in the effect of the policy on information acquisition. However, the point estimates are still economically large. The top panel of Table

6 reports (column (1)) the DD estimate that pools all post-policy period together. This model estimates an average reduction in the degree of information rigidity of roughly 8 percentage points, or 50% relative to the sample mean. Taken together, my findings show that the new policy was largely effective in facilitating the acquisition of information by households who lack financial literacy/sophistication.

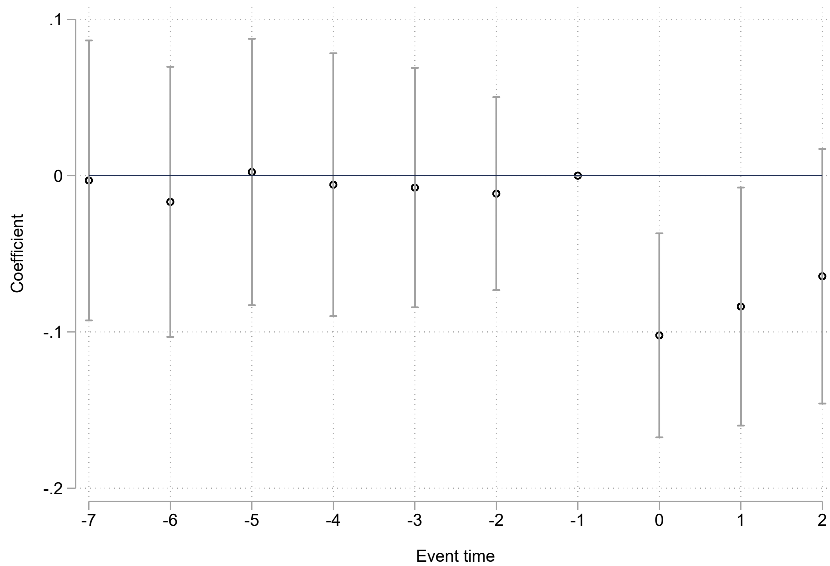

FIGURE 4. Effect of credit bureaus' policy on information demand

Notes: The figure reports coefficients from the estimation of equation (2). Error bars represent 95 percent confidence intervals from standard errors clustered at the household level.

6.3.2. COVID-19 as a threat to identification

Models of endogenous information acquisition also predict that an agent's demand for a piece of information responds to economic conditions. Several papers provide causal evidence for this prediction using experimental designs (e.g., Link et al. 2021; Roth et al. 2022) or natural experiments (e.g., Baker et al. (2020)). Given the unprecedented nature of the COVID-19 pandemic, it is likely that households adjusted the resources devoted to collecting information. What is more, non-sophisticated households could have been more affected by the crisis. These considerations suggest that the COVID-19 shock threatens the identification of the effect of the policy, although, *a priori*, the sign of the bias is ambiguous. I address this challenge in two complementary ways.

I first examine the sensitivity of my results to time-varying individual-specific shocks by interacting households' demographic characteristics with $Post_t$. For example, non-sophisticated

TABLE 6. Effect of credit bureaus' policy on information demand

	(1)	(2)	(3)
Difference-in-differences model			
$\text{Unsoph}_i \times \text{Post}_t$	-0.077^{***}	-0.093^{***}	-0.091^{***}
	(0.025)	(0.026)	(0.026)
Event study model			
Wave 2	−0.064		
	(0.042)		
Wave 1	-0.084^{**}		
	(0.039)		
Wave 0	-0.102^{***}		
	(0.033)		
Wave −2	−0.011		
	(0.031)		
Wave −3	−0.008		
	(0.040)		
Wave −4	−0.006		
	(0.043)		
Wave −5	0.002		
	(0.043)		
Wave −6	−0.017		
	(0.044)		
Wave −7	−0.003		
	(0.046)		
$\text{X}_i \times \text{Post}_t$		✓	✓
$\text{State} \times \text{Post}_t$			✓
Observations	11186	11186	11186

Notes: This table displays the event study estimates of equation (2). X_i are individual controls. Standard errors clustered at the household level in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

households are more likely to be women, whose labor market outcomes disproportionately deteriorated during the pandemic (e.g., Alon et al. 2020; Albanesi and Kim 2021; Fuchs-

Schündeln et al. 2022).[17] The differential exposure to unemployment risk could lead non-sophisticated consumers to acquire more or less information. Recently unemployed households may have a higher demand for credit than employed households and thus more incentives to acquire information before applying for credit. Alternatively, they may think that access to credit is more restricted to the unemployed and thus abstain from seeking information.

Second, I assess the sensitivity of my findings to time-varying local shocks by including state dummies interacted with $Post_t$. These terms control for the severity of the pandemic in each state and states' restrictions on economic activity (i.e., non-pharmaceutical interventions). Non-sophisticated households are more likely to live in Midwest and South states, which adopted less stringent policy restrictions on economic activity in response to the pandemic. Relative to sophisticated households, their credit demand could be higher, encouraging the acquisition of information. Conversely, if the credit supply is relatively abundant for non-sophisticated households – because of the lower negative impact of policy restrictions on the local economy – they could be less prone to seek information.

The results of these tests are reported in columns (2) and (3) of Table 6. I continue to find a large and statistically significant decrease in the probability non-sophisticated households are uninformed about their credit reports or scores. Since the point estimates remain consistent across the specifications, I am more confident that potential confounding explanations are not driving my main results.

[17] Several factors explain the pandemic's disproportionate impact on women's labor market outcomes. In particular, they are more likely to work in contact-intensive sectors and carry a higher childcare burden when schools are closed.

7. Discouragement during COVID-19

The previous section shows that households have acquired information about their credit scores or reports. Next, I test whether discouraged borrowers, who differ from the average household, also updated their information sets. Although the effect of information acquisition on discouragement is not clear *a priori*, I can still evaluate whether households' beliefs about credit rejection and, ultimately, decisions to abstain from applying for credit are based on new information. To answer this question, I estimate the following probit model, restricted to the COVID-19/post-policy period:

$$\Pr(\text{UpdatedInfo}_{i,t} = 1) = F(\alpha + \beta \text{DB}^{i}_{t,t+12} + \theta' X_{i,t} + \lambda_t + \lambda_{s(i)}) \tag{3}$$

where $\text{UpdatedInfo}_{i,t}$ is a dummy variable equal to 1 if the household has acquired information about her credit scores or reports in the last month, and $\text{DB}^{i}_{t,t+12}$ is a dummy variable equal to 1 if the household is discouraged from applying for credit over the next twelve months. The vector $X_{i,t}$ contains demographic characteristics and households' perceived application costs. The regression includes survey-wave (λ_t) and state ($\lambda_{s(i)}$) fixed effects. Standard errors are clustered at the household level.

In contrast to my previous findings (see Table 4), the results reported in Table 7 show that, during the COVID-19 pandemic (and post-policy period) and relative to other potential applicants, discouraged borrowers are similarly likely to be well informed when deciding whether to apply for credit. The first column estimates the association between discouragement and information updating for all households, whereas column (2) restricts the sample to households that were discouraged in the past 12 months. This restriction mitigates concerns that households applied in the past 12 months and obtained information about their credit scores or reports. My findings thus suggest that discouraged borrowers opt out of the loan application process using new information about their credit risk.

TABLE 7. Discouragement and information acquisition during COVID-19

	(1)	(2)
Discouraged (next 12 months)	0.027	0.043
	(0.033)	(0.054)
Estimating Sample	All Households	Discouraged (past 12 months)
Individual Controls	✓	✓
State FEs	✓	✓
Survey-Wave FEs	✓	✓
Observations	3701	364
Pseudo-R^2	0.035	0.114

Notes: Estimates are average marginal effects. The estimating sample consists of the COVID-19 period. The dependent variables is a dummy for having acquired information in the past month. *Discouraged (next 12 months)* is a dummy variable for whether the household is discouraged from applying for credit over the next 12 months. Individual controls are gender, employment status, homeownership, race, household income groups, marital status, education, age categories, and debt-to-income Standard errors clustered at the household level in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

8. Conclusion

Using household survey data from the U.S., this paper finds that discouragement leads to a shortage in credit demand. This result is primarily explained by information frictions due to the lack of financial sophistication. Non-sophisticated discouraged borrowers mistakenly believe that checking their credit scores/reports before applying for credit negatively affects their current and future ability to borrow. Had they been informed about this mistake, they would have learned their actual credit risk and revised their expectations of credit approval upwards. My article also finds a significant reduction in the degree of information rigidity after the credit bureaus approved a policy facilitating the acquisition of information by non-sophisticated households. My results also suggest a role for financial literacy education in mitigating financial mistakes.

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Appendix A. Appendix

A.1. Variables: Definitions

TABLE A1. Description of Variables

Variable Name	Definition
Discouraged	Dummy = 1 if the household head did (will) not apply for credit in the past (next) 12 months because expected (expects) a rejection
Female	Dummy = 1 if the household head is a female
Household Income	Total income of all members of the household, from all sources before taxes and deductions
Age	Age of the household head

Variable Name	Definition
Currently working	Dummy = 1 if the household head is currently working, for someone or self-employed,full-time or part-time, or on sick leave
Married	Dummy = 1 if the household head is married or lives as a partner with someone
College	Dummy = 1 if the household head has a college degree or more
Children in the household	Dummy = 1 if the household head has a children under 18 years in the household
Whine/non-Hispanic	Dummy = 1 if the household head is white and non-Hispanic
Homeowner	Dummy = 1 if the household head is owns a house
Low-aversion to financial risk	Dummy = 1 if the household head is not averse to risk in a Likert scale from 1 (not willing at all to take risks regarding financial matters) to 7 (very willing to take risks regarding financial matters)
High numeracy skills	Dummy = 1 if the household head correctly answers at least 4 out of 5 financial literacy questions
Sophisticated	Dummy = 1 if the household head has (at least) a college degree or high numeracy skills
High Application Costs	Dummy = 1 if the household head did not apply for credit because she thought it was too time consuming and/or did not know how to apply
Loan delinquency	Dummy = 1 if the household head reports a loan delinquency (more than 30 days) in the past 12 months
Debt-to-income (rank)	Percentiles of consumer debt within each income category and survey interview and divide by 100. Consumer debt consists of credit card debt, mortgage debt, home-based loans, auto loans, and other personal loans.
Perceived credit scores	Household head guess about credit scores, in the ranges: less than 620, 620-679, 680-719, 720-760, more than 760

A.2. Summary statistics: discouraged and non-discouraged borrowers

Table A2 presents summary statistics on discouraged and non-discouraged borrowers. Specifically, the table shows average characteristics and their differences based on whether the household states she did not apply for credit in the past 12 months because she believed the application would be rejected. This designation implies that the same household may be represented in the second and third columns, although in different waves.

TABLE A2. Summary characteristics of discouraged and non-discouraged borrowers

	Discouraged	Non-Discouraged	Difference
Panel A: Demographics			
College +	0.38	0.59	−0.21***
Currently working	0.62	0.70	−0.08***
Female	0.62	0.47	0.15***
Married	0.52	0.68	−0.16***
White/non-Hispanic	0.69	0.79	0.10***
Age	47.74	48.29	0.55*
Household income (+ 50k)	0.40	0.72	−0.32***
Homeownership	0.49	0.74	−0.25***
Panel B: Perceptions and Expectations			
Discouraged over next 12 months	0.61	0.07	0.55***
Credit scores (> 680)	0.30	0.85	0.55***
Aggregate credit conditions will be easier	0.12	0.23	−0.11***
Panel C: Borrower Behavior/Type			
Loan delinquency	0.30	0.04	0.26***
Debt-to-income (rank)	0.58	0.54	0.04***
Panel D: Behavioral Traits			
High numeracy score	0.57	0.75	−0.18***
Low financial risk aversion	0.24	0.31	0.07***
Panel E: Survey specifics			
Number of interviews (credit access module)	2.44	2.49	−0.05

Notes: This table presents average characteristics on both discouraged and non-discouraged households and their differences. Discouraged households did not apply for credit in the 12 months prior to the current survey wave.

A.3. The determinants of credit approval and model validation

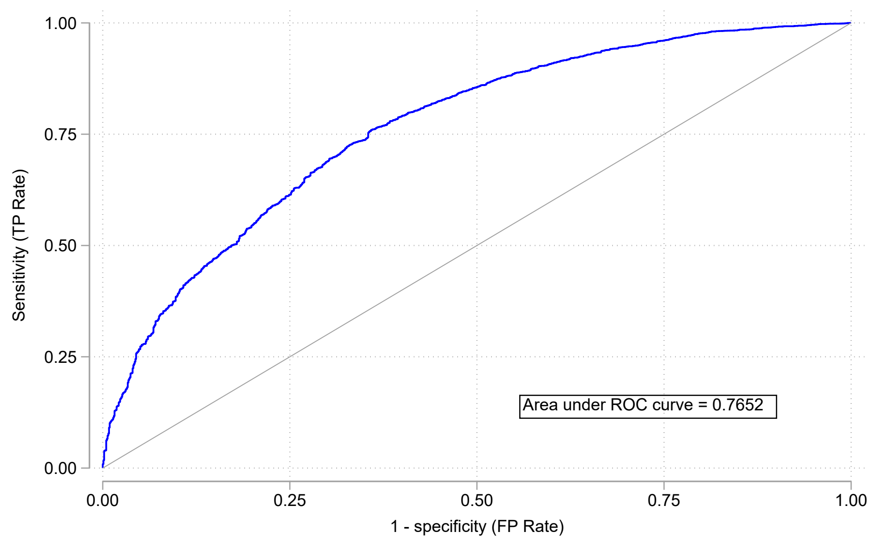


FIGURE A.1. ROC Curve

Notes: The figure illustrates the in-sample discriminatory power of the loan approval model by providing the receiver operating characteristics curve (ROC curve) and the area under the curve (AUC). The ROC curve is estimated using a probit regression of the approval dummy on a credit card application. The explanatory variables are reported in Table A3.

TABLE A3. The determimants of credit approval

	(1)
Female	-0.017
	(0.010)
White/non-Hispanic	0.027**
	(0.012)
Currently working	0.021
	(0.013)
Age (- 40)	-0.014
	(0.016)
Age (40-59)	-0.051***
	(0.015)
Homeowner	0.129***
	(0.013)
Debt-to-income (rank)	-0.129***
	(0.020)
Loan delinquency (+30 days)	-0.192***
	(0.016)
Individual Controls	✓
State FEs	✓
Survey-Wave FEs	✓
Observations	6069
AUC	0.765
	[0.749 , 0.781]
Pseudo-R^2	0.155

Notes: Estimates are average marginal effects. The dependent variables is a dummy variable for whether the household's application for a credit card was approved. The omitted group for age is *Age (+60)*, a binary indicator equal to one if the household is older than 60 years. Individual controls are household income, marital status, education. Confidence interval for the area under the receiver operator characteristics curve (AUC) in brackets. Standard errors clustered at the household level in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

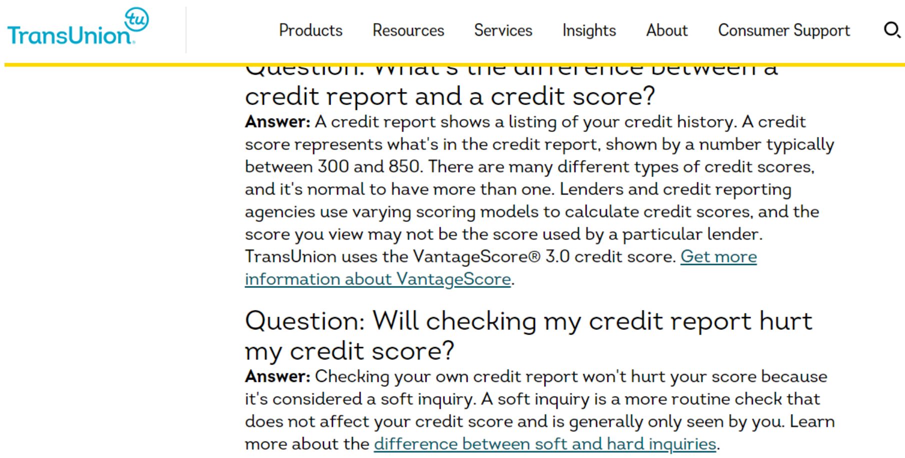
A.4. Updated information and credit approval

TABLE A4. Effect of updated information on credit approval

	Credit card (1)	Personal loans (2)	Home-based loan (3)
Updated info.	0.031**	0.031*	0.088*
	(0.016)	(0.018)	(0.052)
Individual Controls	✓	✓	✓
State FEs	✓	✓	✓
Survey-Wave FEs	✓	✓	✓
Observations	5792	3466	1708
R^2	0.178	0.197	0.259

Notes: This table reports OLS estimates. The dependent variables are binary indicators for whether the household's credit or loan application was approved. *Updated info* is a dummy equal to one if the household acquired information between one and twelve months before the survey interview. The omitted group for *Updated info.* is *Updated info. (+1 year ago)*, a binary indicator equal to one if the household obtained information more than one year before the survey interview. Personal loans refer to auto loan and request of an increase in the limit of an existing loan. Individual controls are gender, employment status, homeownership, race, household income groups, marital status, education, age categories, and debt-to-income. Standard errors clustered at the household level in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.5. Soft and hard credit inquiries



TransUnion

Products Resources Services Insights About Consumer Support

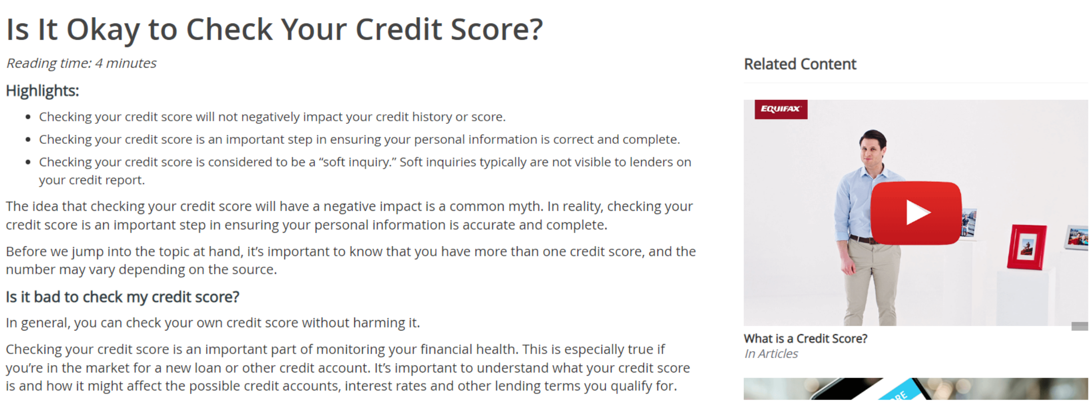
Question: What's the difference between a credit report and a credit score?

Answer: A credit report shows a listing of your credit history. A credit score represents what's in the credit report, shown by a number typically between 300 and 850. There are many different types of credit scores, and it's normal to have more than one. Lenders and credit reporting agencies use varying scoring models to calculate credit scores, and the score you view may not be the score used by a particular lender. TransUnion uses the VantageScore® 3.0 credit score. Get more information about VantageScore.

Question: Will checking my credit report hurt my credit score?

Answer: Checking your own credit report won't hurt your score because it's considered a soft inquiry. A soft inquiry is a more routine check that does not affect your credit score and is generally only seen by you. Learn more about the difference between soft and hard inquiries.

FIGURE A.2. Soft credit inquiry, TransUnion



Is It Okay to Check Your Credit Score?

Reading time: 4 minutes

Highlights:

- Checking your credit score will not negatively impact your credit history or score.
- Checking your credit score is an important step in ensuring your personal information is correct and complete.
- Checking your credit score is considered to be a "soft inquiry." Soft inquiries typically are not visible to lenders on your credit report.

The idea that checking your credit score will have a negative impact is a common myth. In reality, checking your credit score is an important step in ensuring your personal information is accurate and complete.

Before we jump into the topic at hand, it's important to know that you have more than one credit score, and the number may vary depending on the source.

Is it bad to check my credit score?

In general, you can check your own credit score without harming it.

Checking your credit score is an important part of monitoring your financial health. This is especially true if you're in the market for a new loan or other credit account. It's important to understand what your credit score is and how it might affect the possible credit accounts, interest rates and other lending terms you qualify for.

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What is a Credit Score?

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FIGURE A.3. Soft credit inquiry, Equifax