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 44 percent of discouraged borrowers would have been approved for a credit card had they applied. A back-of-the-envelope calculation that builds on this counterfactual estimate shows that discouragement leads to a shortage in aggregate credit demand of about 2.7 percent of total U.S. credit card debt. This outcome is explained by the fact that discouraged borrowers, who lack financial sophistication and face larger information frictions, use outdated information about their credit risk when forming beliefs about their prospects in the credit markets. Using a difference-in-differences design, I find a significant decline in the degree of information rigidity due to a new credit reporting policy that facilitated information acquisition 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 Nicolas Vincent and participants to seminars at CEEA, CIREQ, and HEC Montreal for valuable comments, and Tatyana Deryugina for helpful suggestions to the first version 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; Agarwal et al. 2018) 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 many consumers self-select out of the loan application process despite their demand for credit. These potential borrowers decide not apply for a loan because they expect a rejection and hence are defined as discouraged. 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, what does explain their failure to obtain otherwise available credit?

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 access credit in the future, as a borrower's short credit history makes it harder for banks to verify their type. 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

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

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.

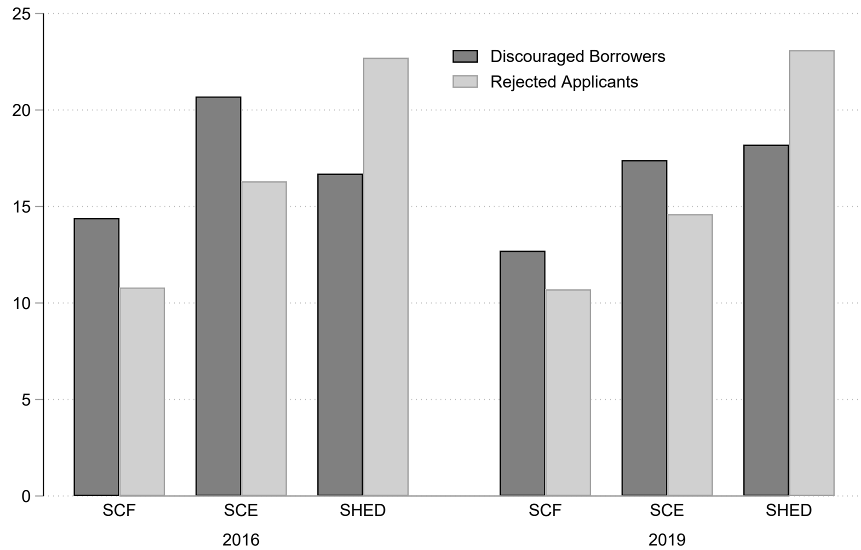

FIGURE 1. Discouragement and rejection in the U.S.

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 suggests 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 find that this is the case for 44% of discouraged borrowers. I focus on credit cards because of its importance for consumption smoothing (e.g., Sullivan 2008; Herkenhoff

2019). I also restrict my sample to between 2014 and February 2020, that is, prior to the COVID-19 outbreak and the adoption of a new policy that facilitated the acquisition of information by households. I then 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 loan delinquency. After the out-of-sample validation of the model, I use its estimated parameters to obtain discouraged borrowers' predicted approval likelihood. I classify discouraged borrowers as unconstrained when their predicted probability of approval is above that of the "marginally" approved consumer. Since the unconditional probability of rejection in my sample is 20%, the marginally approved consumer is at the 20th percentile of the predicted probability of approval distribution.

This finding has two important implications. First, it indicates that differences in access to unsecured revolving credit across households – e.g., for consumption smoothing purposes – are partly due to a misjudgment that some households have about their borrowing ability rather than actual constraints from lenders. Second, it suggests a novel mechanism through which the pass-through of credit expansion policies to household borrowing and aggregate demand might be incomplete – in addition to, for example, the rigidity of mortgage contracts (e.g., Di Maggio et al. (2017) and employment documentation requirements to mortgage refinancing (e.g., DeFusco and Mondragon (2020)). A simple back-of-the-envelope calculation that builds on the counterfactual estimate that 44% of discouraged borrowers are unconstrained suggests that discouragement leads to a shortage in aggregate credit demand of about 2.7% of total U.S. credit card debt.

I investigate the potential reasons behind discouraged borrowers' failure to obtain otherwise available credit. In my sample, a significant portion of households have outdated information about their creditworthiness. Specifically, in the restricted sample, 17% of respondents checked their credit scores or requested a copy of their credit reports more than two years before the survey interview or never. This means that discouraged borrowers, who thought about applying for credit in the previous twelve months, used information outdated by at least a year when forming beliefs about their prospects in the credit markets. Discouraged borrowers' outdated information about their "type" is thus a candidate to explain their financial mistake.

To formally test this explanation, I study the correlates of information acquisition in a regression framework. My first set of results show that discouraged borrowers are, on average and all else being equal, significantly more likely to have outdated information about their credit scores or reports than applicants. I then show that even unconstrained discouraged borrowers, who would benefit from accessing new information, tend to have older/inaccurate information about their credit scores compared to similar approved applicants. The differences are economically large. According to my estimates, discouraged borrowers are about 6 percentage points more likely to have checked their scores/reports more than two years before the survey interview or never. This finding supports my hypothesis that unconstrained discouraged borrowers fail to obtain credit because they use outdated information about their credit risk.

Next, I investigate the potential reasons for the infrequent updating of information by potential borrowers – discouraged or not. I start by arguing that *real* monetary costs associated with acquiring a credit report and an "unchanged financial conditions" story are unlikely to rationalize potential borrowers' infrequent updating. These considerations, combined with the result that unsophisticated households' information sets are more likely to be outdated than those of their sophisticated peers, hint at a role for information frictions in explaining discouraged borrowers' outdated information. Indeed, models of endogenous information acquisition (e.g., rational inattention) predict that an economic agent's demand for a piece of information decreases in the *perceived* cognitive costs of obtaining and processing that information. Consistent with this view, my results show that even creditworthy discouraged borrowers are less sophisticated than similar approved applicants.

Because discouraged borrowers do not expect to be approved for credit, their beliefs, not information frictions, could explain their outdated information. Indeed, their net benefit of acquiring a credit score/report is less likely to be positive, even if they do not face information frictions. However, the quantitative expectations of approval reported by a subset of discouraged borrowers show that many of them are not fully convinced that they would be rejected for credit. This indicates that information frictions likely play a role in explaining their outdated information. I propose the following scenario for a negative net benefit associated with information acquisition. 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 reduces their current and future ability to borrow. Since they self-evaluate as low-credit-score individuals, this misperceived non-monetary cost can bind. As a result, discouraged borrowers are slower in updating their information sets and learning about their type. I provide some anecdotal evidence from credit bureaus supporting this interpretation.

Next, I study the effect of a policy change implemented by credit bureaus in early 2020 on information demand. 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. Using difference-in-differences and event study designs, I show that unsophisticated households (the treated group) were significantly more likely than their sophisticated peers (the control group) to update their information set for the first time after years. My estimates indicate an average reduction in the degree of information rigidity of

10 percentage points, or 54.2% relative to the unconditional mean of the pre-policy period. Since sophisticated households' outdated information cannot be explained by information frictions, I interpret this result as the policy mitigating unsophisticated households' misperceptions about the costs of obtaining credit scores/reports.

I show that this result holds after taking into account non-sophisticated households' differential exposure to the unemployment/income risk associated with the COVID-19 shock. I also compare the updating behavior of sophisticated households who were more or less exposed to the pandemic shock to assess whether a change in the value of information can explain my findings. Specifically, households that perceive their financial conditions to be more uncertain should track their finances more frequently – e.g., by checking their credit scores or reports. However, my regression results do not support this prediction of models of endogenous information acquisition. Collectively, my results suggest that the new credit reporting policy facilitated the acquisition of information by non-sophisticated households. Nevertheless, they should be interpreted with caution, as the measure of exposure to unemployment/income risk – gender, race, and age – might not capture all relevant risk dimensions.

Contribution to the literature. My findings contribute, first and foremost, to the empirical literature on discouragement in credit markets. Most of this literature identifies key determinants of discouragement among firms, whereas my work investigates discouragement among consumers. The former finds that firms are more likely to be discouraged when their *actual* credit quality is poor (e.g., Han et al. (2009)), loan *actual* application costs are large (e.g., Ferrando and Mulier (2022)), and economic uncertainty is high (e.g., Anastasiou et al. (2022)). Relative to these studies, I show that borrowers' *perceptions* of their creditworthiness largely explain their discouragement. Furthermore, my results indicate that discouraged borrowers' misperceptions about application costs (e.g., the impact of soft credit inquiries on credit scores) impede them from acquiring relevant information. The infrequent updating of their creditworthiness results in some discouraged borrowers missing otherwise available credit. Similar to Cole and Sokolyk (2016) and Ferrando and Mulier (2022), I also quantify that a considerable fraction of discouraged borrowers would have been approved for credit had they applied. Closer to my paper is the work of Jappelli (1990). Using data from the 1983 SCF, he documents that discouraged borrowers account for a large share of credit-constrained households. However, he finds that most discouraged borrowers would be rejected for credit.

My paper also adds to a large body of research on the importance of financial literacy or sophistication for households' economic outcomes. The extant literature finds that financially sophisticated individuals are more likely to be aware of – and thus prepared for – the interest rate risk embedded in their adjustable-rate mortgages (e.g., Bucks and Pence (2008)), avoid overpayment for their mortgage (e.g., Bhutta et al. (2021)), and plan for retirement (e.g., Lusardi and Mitchell (2007)). I find that less financially savvy households are more likely to make financial mistakes – e.g., failure to obtain consumer credit – because they use outdated information about their creditworthiness when thinking about applying for credit. In addition, my result that many discouraged borrowers fail to obtain consumer credit contributes to a growing literature that studies the implications of households' financial mistakes for the effectiveness of macroeconomic policies (e.g., Keys et al. 2016; D'Acunto et al. 2022).

Finally, this article contributes to a research agenda that uses survey data to understand how households form expectations and the effect of expectations on economic behaviors. These studies often find substantial heterogeneity in expectations by socioeconomic status (e.g., Das et al. (2020)). Heterogeneous expectations across households might be explained by differences in their information set – e.g., due to variation in the updating of information (e.g.,Coibion and Gorodnichenko (2012)). Another reason might be that different persons process the same pieces of information differently (e.g., Andre et al. 2022). My results are consistent with the first explanation. While non-sophisticated borrowers are more likely to have outdated information about their credit risk than sophisticated borrowers, both types of borrowers think similarly about the effect of credit risk on their ability to borrow.

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 reporting policy on information demand. Section 7 concludes.

2. Conceptual Framework

Following most empirical research on discouragement in credit markets (e.g., Han et al. 2009; Cole and Sokolyk 2016; Ferrando and Mulier 2022), I structure my analysis on the theoretical framework of 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, potential borrowers face positive sunk application costs. 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). Banks' screening errors, combined with positive sunk application costs, result in creditworthy borrowers – assumed to be perfectly informed about their type – being discouraged from applying for credit.

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, creditworthy potential 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) – although my definition of discouraged borrowers encompasses risky borrowers.

I closely follow Kon and Storey (2003) extended model, where borrowers are imperfectly informed about themselves, while banks' screening errors are assumed to be null. I follow their modified model for two reasons. First, in my sample, many discouraged borrowers have outdated information about their credit scores/reports. Second, my empirical analysis abstracts from supply-side frictions. In their model, truly creditworthy borrowers believe they are creditworthy with an exogenous probability $1-fb_G$. Since this is their best information available ex ante, they assume that banks will consider them creditworthy with the same probability. Therefore, in this setup, potential 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 regardless of the loan request outcome.

In this modified framework, if $K=0$, then even pessimistic borrowers (i.e., ex post approved) would apply for credit. However, with $K>0$, creditworthy borrowers might be discouraged if they perceive K to be too high and/or they are fully convinced that they would be rejected for credit (i.e., $1-fb_G$ is too low). What is more, they would not have incentives to acquire information about their credit risk.

In consumer credit markets, K also includes a "hard" credit inquiry, defined as a lender's request to review the applicant's credit reports when making a lending decision. This inquiry often results in a marginal decline in the applicant's credit scores and may stay on her credit reports for up to 36 months. In contrast, a "soft" credit inquiry – i.e., checking scores/reports before applying for credit – has no such effects on scores or reports. However, if potential borrowers believe that a soft inquiry also negatively affects their scores and perceive themselves as low-credit-score individuals, they will have less incentive to apply and update their information.

In contrast to Kon and Storey (2003), K might be perceived (by consumers) to be endogenous, not exogenous, with respect to $1-fb_g$.

In my sample, a significant portion of discouraged borrowers had outdated information about their credit scores when they were thinking about applying for credit. I show that this result is consistent with information frictions, defined as misperceptions of the costs of information acquisition. To further investigate this interpretation, 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.[2] 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.[3] 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

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

[3] 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.

income. I also obtain households' subjective expectations of credit conditions for people in general.

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. Selected 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, they are excluded from the analysis since I can not quantify their misperceptions.[4] 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.

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. 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.[5]

[4] These consumers account for about 25% of non-applicants who have a demand for credit. Since the SCE does not ask respondents about actual and expected borrowing rates, one can not quantify their misperceptions.

[5] 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).

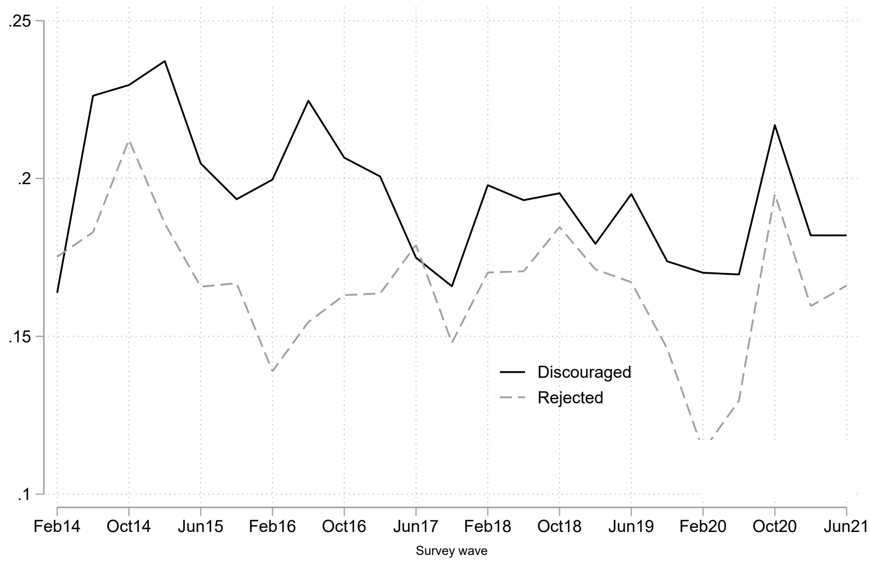

FIGURE 2. Discouragement and rejection

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

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

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

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.[6] $\mathrm{AppCosts}_{i,t}$ 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 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

[6] 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.

$\text{Scores}_{i,t}$. $\text{EasierCredit}^{i}_{t,t+12}$ is a dummy variable equal to 1 if the household expects easier 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.[7] Finally, households are less likely to be discouraged when they expect easier credit conditions for people in general (column (5)).

4.1. Heterogeneity

Do the determinants of discouragement vary with household sophistication, as measured by their numeracy skills? Recent empirical research documents that sophistication on economic matters is a relevant source of households' heterogeneous expectations and economic outcomes, with implications for the transmission of economic policy (D'Acunto et al. 2019, 2022; Bachmann et al. 2021). I examine this question in Table 3.

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

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. $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.10$.

Exploiting cross-sectional variation and accounting for various households' characteristics (columns (1) and (3)), I find that high-and low-numeracy households form beliefs about their ability to borrow remarkably similarly. For example, both types of households appear to think that they are more likely to obtain a loan when the overall credit supply is larger. One possibility

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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

is that they expect easier lending standards from banks following an expansionary (conventional) monetary policy.

When I include household fixed effects to absorb unobserved time-invariant heterogeneity across households (columns (2) and (4)), one result remains consistent: both high-and low-numeracy consumers believe that their likelihood of obtaining credit improves on their (perceived) credit scores. This finding suggests that credit scores are, perhaps because of their salience, a piece of information whose effect on credit access are somewhat easier to understand.

5. Would Discouraged Borrowers be Approved for Credit?

This section shows that a significant portion of discouraged borrowers would have (most likely) obtained credit had they applied. A simple back-of-the-envelope calculation then quantifies the aggregate effect of discouragement. Next, I delve into the potential reasons for discouraged borrowers' failure to obtain otherwise available credit.

5.1. Discouraged borrowers and counterfactual outcomes

To study whether discouraged borrowers would have obtained credit had they applied, I proceed as follows. I start by restricting my sample in two ways. First, I only consider unsecured revolving (non-mortgage) credit: applications for a new credit card or an increase in the credit limit of an existing 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 focus on the period before the COVID-19 outbreak and adoption of a new policy (by credit bureaus) that facilitated acquiring credit reports/scores – i.e., from 2014 to February 2020.

Next, I use a probit specification to estimate the likelihood of applying borrowers to obtain credit. The specification is similar to equation (1). It thus includes various demographic and financial characteristics such as household nominal annual income, age, loan delinquency, and homeownership status. 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, I approximate them using a borrower's age and payment history as measured by having a 30-day (or more) loan delinquency within the past twelve months. A borrower's age serves as a proxy for the length of her credit history.

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).[9] 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:

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

[9] Berge and Jordà (2011) use this method to evaluate the NBER's Business Cycle Dating Committee accuracy in classifying economic activity into expansions and recessions.

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

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 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).[10]

Third, I conduct an out-of-sample validation of the loan approval model. Since the results reported in Table A3 are estimated in-sample, one 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 can use it to answer the counterfactual question of whether discouraged borrowers would have been approved for credit had they applied. In my sample, about 20% of the credit card applications were rejected. Using the estimated parameters of the model, I search for the approved consumer at the 20th percentile of the predicted probability of approval. The probability of this "marginally" approved borrower (71%) defines the threshold above which discouraged borrowers would have obtained credit had they applied. I find that 44% of discouraged borrowers have predicted probabilities of approval above that threshold.

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

This result suggests that many discouraged households fail to obtain consumer credit, which can have important implications for their financial well-being. Using similar approved consumers as a benchmark, unconstrained discouraged borrowers would have obtained credit corresponding to about 10% of their annual income. To put this foregone credit amount into context, Sullivan (2008)) shows that low-asset households replace 11% of their earnings lost due to unemployment through unsecured debt.

My result differs from Jappelli (1990), who finds that most discouraged consumers in the U.S. are credit-constrained. Interestingly, Cole and Sokolyk (2016) and Ferrando and Mulier (2022) also quantify that a large share of discouraged borrowers (firms) are most likely unconstrained, while Keys et al. (2016) find that about 20% of U.S. households fail to refinance their mortgages.

Since I do not observe financial institutions' actual screening model(s), one concern is that my loan approval model is misspecified. To some extent, the focus on the market for credit cards mitigates this problem. Because credit cards are unsecured and do not require contemporaneous underwriting, it is conceivable that banks' use simpler and more homogeneous screening models when evaluating the demand for a credit card. An omitted variable bias is a related concern. Even if I knew a bank's model, it could be unfeasible to estimate it because of unobserved inputs. In particular, a borrower's age and loan delinquency may not perfectly predict her actual credit scores. While these caveats apply when interpreting my findings, my empirical model includes strong predictors of credit scores and binding borrowing constraints. For example, Keys et al. (2016) find that mortgage payment history – which I add to my model – is a high-quality proxy for creditworthiness in the absence of credit score data.[11]

Back-of-the-envelope calculation. To get an idea of the aggregate effect of discouragement, I perform a simple back-of-the-envelope calculation. I use the SCE's February 2019 wave to estimate the aggregate effect of discouragement in 2018. In that wave, about 11% of households with a demand for a credit card did not apply for it in the previous 12 months because they expected a rejection. According to the Consumer Financial Protection Bureau's Consumer Credit Panel (CFPB CCP), there were about 67.7 million credit card origination in 2018.[12] Thus, in the aggregate, about 8.4 million applications were not carried through because potential borrowers expected a rejection. In my sample, approved borrowers obtained $6,240 on average.

[11] Similarly, Kowalik et al. (2021) show that variation in credit card utilization since the onset of the pandemic is the main driver of the differences in credit scores across households. Adding an indicator for whether a household has reached the limit on her credit card does not alter the results of the paper. In particular, roughly 40% of discouraged borrowers would be classified as unconstrained. I leave this indicator out of my model because I would have a much smaller sample.

[12] The CFPB CCP is an anonymized 1-in-48 sample of credit records from one of the three national credit reporting agencies. The sample is statistically representative of the population of consumers with credit records.

Together, this means approximately \$52.4 billion in that year. The \$52.4 billion represents 6.0% of total U.S. credit card debt as estimated by the New York Fed/Equifax Consumer Credit Panel (FRBNY/Equifax CCP) in the fourth quarter of 2018.[13] Under the assumption that 44% of the discouraged borrowers are unconstrained, households' failure to obtain credit amounts to roughly 2.7% of total U.S. credit card debt. Thus, my back-of-the-envelope calculation suggests that discouragement leads to a particularly large shortage in aggregate credit demand.

5.2. Inspecting the mechanism: information frictions

In Section 4, I document the relevance of households' perceived creditworthiness in explaining discouragement. In my sample, however, a sizable portion of households have outdated information about their credit scores or credit reports.[14] Specifically, 28% of respondents learned about their scores and/or requested a copy of their reports more than a year before the survey interview, and 17% did so more than two years before the survey or never. Discouraged borrowers using outdated information about their "type" is thus a candidate to explain their financial mistake.

To test this hypothesis, Table 4 studies the correlates of information acquisition. I use two indicators that measure the degree to which households have outdated information about their credit quality, *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 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. Furthermore, I restrict the sample to between 2014 and February 2020.

The results reported in columns (1) and (5) show that discouraged borrowers are significantly more likely to have outdated information about their credit scores/reports than applicants. The estimated effects are economically large. According to my estimates, discouraged borrowers are about 11 and 7 percentage points more likely to have outdated information than applicants, all else being equal. This result is sensible because discouraged borrowers, in line with their beliefs of being approved for credit, may perceive smaller benefits in acquiring information. Non-applicants' information set being more outdated relative to those of applicants and discouraged borrowers appears plausible because non-applicants report no need for additional credit. My findings then show (columns (2) and (6)) that even creditworthy/unconstrained discouraged

[13] The FRBNY/Equifax CCP panel contains quarterly observations of a nationally representative, randomly drawn sample of 5% of all U.S. individuals with a credit report.

[14] 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), 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.

borrowers are much more likely to use outdated information than similar approved applicants when assessing their prospects in the credit markets.[15] The fact that unconstrained discouraged borrowers have outdated information, not only their constrained peers, about their credit scores supports my explanation for discouraged borrowers' financial mistake.

Next, I investigate the potential reasons for the infrequent updating of information by potential borrowers – discouraged or not. My analysis starts by ruling out two explanations. First, *real* monetary costs associated with acquiring a credit report might exceed the benefits, especially for those who have low expectations of being approved for credit. During my sample period, however, people could obtain up to three free credit reports every twelve months from the three U.S. credit bureaus: Equifax, TransUnion, and Experian. This fact, combined with the definitions of both dependent variables, implies that *real* monetary costs cannot explain potential borrowers infrequent updating. Second, using *Info (more than two years ago)* as the main outcome variable likely excludes the "unchanged financial conditions" story as a reason for not updating information. The definition of this variable means that discouraged borrowers, who thought about applying for credit in the previous twelve months, used information outdated by at least a year when forming their beliefs of credit approval. It is conceivable that their financial circumstances have changed in meaningful ways after a year or more.

After ruling out the *real* monetary cost and "unchanged financial conditions" reasons, I examine the relationship between information acquisition and proxies for cognitive ability. Models of endogenous information acquisition (e.g., Reis 2006; Mackowiak and Wiederholt 2009; Maćkowiak and Wiederholt 2015) predict that an economic agent's demand for a piece of information decreases in the *perceived* cognitive costs of obtaining and processing that information. Columns (3) and (7) include a dummy variable for whether the respondent is financially sophisticated, and columns (4) and (8) add a dummy which equals one if the respondent is in charge of the financial decisions in the household.[16] There are two possible interpretations of the latter variable. First, respondents are in charge of financial decisions because they are financially sophisticated and/or exposed to financial information. Second, respondents make financial decisions because they are sophisticated and/or exposed to financial information compared only to the other members of the household. For this reason, the sophistication dummy appears to be a cleaner indicator of literacy and/or exposure to financial matters.

[15] Creditworthy or unconstrained discouraged borrowers would have been approved for a credit card had they applied, as discussed in subsection 5.1. By including approval likelihood fixed effects, identification comes from comparing unconstrained discouraged borrowers to similar approved applicants.

[16] A respondent is in charge of the 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.

Consistent with models of endogenous information acquisition (e.g., rational inattention), I find that unsophisticated/unexposed respondents' information sets are significantly more likely to be outdated than those of their peers. The estimated effects are economically large. For example, all else being equal and compared to a sophisticated peer, a non-sophisticated respondent is about 5 percentage points (column (7)) more likely to have acquired information about her score/report more than two years before the survey interview or never.

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***	0.101***			0.066***	0.059***		
	(0.016)	(0.027)			(0.015)	(0.022)		
Non-applicant	0.245***				0.158***			
	(0.010)				(0.009)			
Sophisticated			−0.038***				−0.052***	
			(0.016)				(0.014)	
Make fin decisions				−0.070***				−0.055***
				(0.014)				(0.012)
Individual Controls	✓	✓	✓	✓	✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
Survey-Wave FEs	✓	✓	✓	✓	✓	✓	✓	✓
Approval Likelihood FEs		✓				✓		
Observations	19299	3464	19299	14855	19299	3464	19299	14855
R^2	0.117	0.017	0.059	0.063	0.100	0.018	0.064	0.062

Notes: This table reports OLS estimates. Estimating sample is restricted to between 2014 and February 2020. 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 (2) and (6), 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Collectively, these results indicate that information frictions might play a role in explaining discouraged borrowers' outdated information sets. I define information frictions as *misperceptions* of the net benefit of acquiring a credit score or report before applying for credit, i.e., the net benefit of a "soft" credit inquiry. Table 5 provides evidence that even unconstrained discouraged borrowers are more likely to face larger information frictions. The first column shows that they 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 roughly 9 percentage points less likely to have high numeracy skills (column (3)) compared to approved applicants.[17]

TABLE 5. Explaining information frictions

	Sophisticated (1)	College (2)	High numeracy (3)
Discouraged	-0.050^{**}	-0.028	-0.087^{***}
	(0.025)	(0.030)	(0.029)
Individual Controls	✓	✓	✓
State FEs	✓	✓	✓
Survey-Wave FEs	✓	✓	✓
Approval Likelihood FEs	✓	✓	✓
Observations	3464	3464	3464
R^2	0.060	0.074	0.048

Notes: This table reports OLS estimates. Estimating sample excludes 2020-2021. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

I propose the following scenarios of misperceptions that could rationalize discouraged borrowers' use of outdated information when assessing their chances of being approved for credit. First, they may have misperceptions about the monetary cost of acquiring a credit report.

[17] This result suggests that financial literacy is to a large extent unexplained by formal education. Interestingly, Lusardi and Mitchell (2007) and Behrman et al. (2012) find that financial literacy is more important than schooling for explaining differences in wealth and pension contributions across households.

Second, discouraged borrowers might confuse the non-monetary costs of a soft credit inquiry with those of a "hard" credit inquiry. A hard credit inquiry occurs when a lender requests to review the applicant's credit reports when making the lending decision, and it is visible to other prospective creditors. In contrast to a soft inquiry, a hard credit inquiry can stay on the applicant's credit reports for up to 36 months and might negatively impact her credit scores, regardless of the application outcome.[18] It is thus conceivable that discouraged borrowers believe that a soft credit inquiry has a negative and persistent impact on their credit scores. Appendix Figures A.2 and A.3 provide some anecdotal plausibility to my interpretation. The figures suggest that a lack of understanding of the differences between a soft and hard credit inquiry is a common friction among potential borrowers. Since discouraged borrowers, by definition, see themselves as low-credit-score individuals, the (mis)perceived costs of a soft credit inquiry are more likely to bind for them, adding to the actual costs of a hard credit inquiry to hinder the updating of their credit scores.

Because discouraged borrowers do not expect to be approved for credit, one might argue that their beliefs, not information frictions, explain their outdated information. If a discouraged borrower is fully convinced that she would be rejected for credit, then she will perceive no net benefit in updating her information set, even if she has no misperception about a soft credit inquiry.[19] In a second scenario, if her subjective beliefs of approval are low but non-negligible, and if she understands what a soft credit inquiry means, then it is more likely that she perceives positive net benefit – justifying the update of information. Lastly, if a discouraged borrower's beliefs of approval are non-negligible but she misperceives the cost of a softy inquiry, then it is more likely that the net benefit is negative .

A small subset of discouraged borrowers provide their quantitative (percent chance) subjective beliefs of approval, which I use to investigate my interpretation. At the 10th percentile of the distribution, individuals report a subjective chance of approval of 0 percent, while at the median, they report 10 percent. For these discouraged borrowers, their beliefs alone could rationalize their outdated information – although it is conceivable that information frictions also play a role for the borrowers at the median of the distribution. However, at the 75th and 90th percentiles, discouraged borrowers report chances of approval of 25 and 50 percent, respectively. For these borrowers, information frictions – i.e., misperceptions about a soft credit inquiry – are a more probable reason for their decision not to update their information sets.

[18] According to Equifax, "the hard inquiry may be the leading indicator, the first sign of financial distress that appears on the credit file." Furthermore, the number of inquiries into a credit file may account to about 10% of credit scores. See https://www.consumer.equifax.ca/personal/education/credit-score/how-are-credit-scores-calculated.

[19] This is because there might be other non-monetary costs (e.g, time) involved.

My proposed explanation for information frictions in consumer credit markets – lack of financial sophistication – aligns well with existing evidence that government assistance programs may not benefit the individuals and firms who would take most advantage of them. Allen et al. (2022) find limited enrollment in debt-relief programs (credit card and mortgage deferrals) implemented in Canada in response to the COVID-19 crisis. Their results show a higher enrollment in the credit card debt-relief program at neighborhoods with higher levels of education. As a potential explanation for the low take-up rates, they suggest that households may have perceived that a deferral would damage their credit scores and thus their ability to borrow in the future.[20] 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) attribute part of the differential access to the Paycheck Protection Program resources across smaller and larges firms in the U.S. to the fact that the former are less sophisticated and thus have more difficulty with obtaining and processing information.

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 these types of information to compute credit scores.[21]

[20] Their paper does not find evidence that customers' credit scores – or credit limits – declined following enrollment, at least not compared to those of non-deferrers.

[21] Credit reports from the credit bureaus do not usually contain credit scores. Individuals can obtain their credit scores in different ways, for example, by purchasing them directly from credit bureaus.

In April 2020, the credit bureaus announced/implemented 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 until April 2022 and then December 2022.[22] 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.

The policy might have reduced the degree of information frictions if sufficiently publicized. First, non-sophisticated individuals might have learned – or remembered – they could obtain a free copy of their credit reports. Second, they might also have learned that a soft credit inquiry does not affect their credit scores. Unfortunately, I cannot isolate or quantify a precise mechanism for how the policy might have affected households' misperceptions.

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 central prediction of models of endogenous information acquisition: an economic agent's demand for a specific piece of information decreases in the *perceived* cognitive costs of collecting and processing information.

The treatment group thus consists of non-sophisticated households who have checked their credit scores/reports more than two years ago or never. 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 not recently (or never) checked that information. I estimate the following event study specification:

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

where $y_{i,t}$ is an indicator variable that equals 1 if individual i, in survey wave t, reports that either she has never checked her credit scores/reports or done so more than two years ago, and 0 if she has checked them within the past six months. Unsoph_i is a dummy for being

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

unsophisticated.[23] Indicator 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 wave after the policy adoption. The omitted category is $\tau = -1$, the wave prior to the policy change (i.e., February 2020). The δ_τ are the coefficients of interest. Each estimate of δ_τ measures the change in the outcome of interest for non-sophisticated households compared to their sophisticated peers in wave τ relative to the period immediately prior to the policy change. In this equation, λ_t is a vector of fixed effects for each survey wave and $\lambda_{s(i)}$ is a vector of fixed effects for each state. I estimate equation (2) with a linear probability model and report standard errors clustered at the household level.

The estimation of equation (2) requires three key assumptions. The first assumption is that unsophisticated individuals did not anticipate the policy change and hence did not time their demand for information.[24] This is plausible for two reasons. Unsophisticated individuals are arguably unlikely to anticipate the adoption of policies in general. In addition, the enactment of the policy occurred immediately after the unexpected COVID-19 outbreak in the second half of March 2020. The second assumption states that, absent the treatment, 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. The third assumption posits that the composition of treated and control groups is stable over time. This is required because of the (mostly) cross-sectional nature of the data. Table A4 in the Appendix suggests that while unsophisticated households are significantly more likely to be female, non-white/Hispanic, renters, and below-median-income individuals, these differential probabilities hold both before and after February 2020, when $Post_t$ equals one.

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 3 and in the first column of Table 6. The figure shows that trends in the probability of being uninformed between non-sophisticated and sophisticated

[23] The results are the same if I define unsophisticated households as those with low numeracy skills.

[24] Intuitively, if an unsophisticated household learns that she will be able to request up to three free credit reports every week rather than every twelve months, it is probable that she will also learn that she can request one for free immediately, before the new policy is in place. This reasoning does not apply for sophisticated households.

households evolved in parallel prior to the policy change. The graphical evidence thus supports the credibility of the parallel trends assumption.

Immediately after the policy change, non-sophisticated households were 11.6 percentage points more likely than their sophisticated peers to have obtained information about their scores/reports for the first in years. This represents a reduction in the degree of information rigidity of about 61.1% relative to the unconditional mean of the pre-policy period. In addition, I observe a gradual decline in the effect of the policy on information acquisition. As of February 2021, however, the point estimate remains economically large. The top panel of Table 6 reports, in column (1), the DD estimate that pools all post-policy periods together. This model estimates an average reduction in the degree of information rigidity of 10 percentage points, or 54.2% relative to the unconditional pre-policy mean.

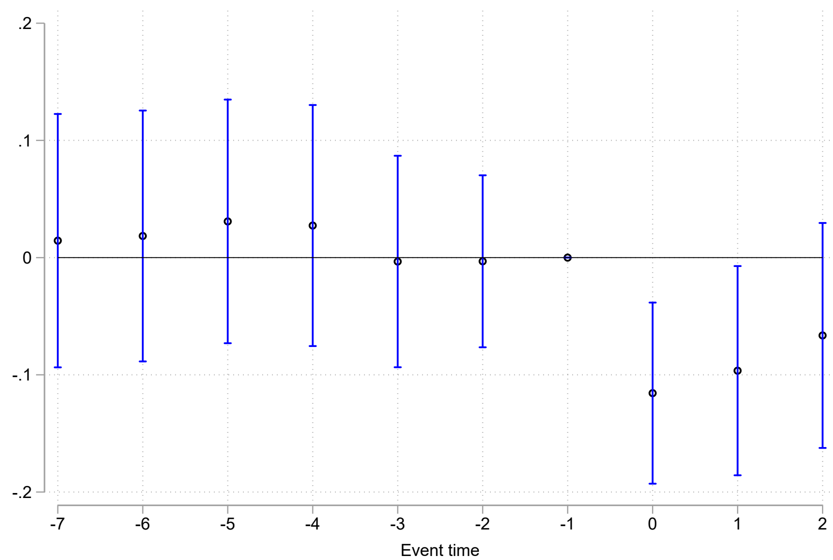

FIGURE 3. Effect of credit bureaus' policy on information demand

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.

Taken together, my findings suggest that the policy change was largely effective in facilitating information acquisition by non-sophisticated households. The results speak to previous papers that study the role of information disclosure in altering various types of behavior. For instance, Bertrand and Morse (2011) show that consumers reduce payday borrowing after receiving additional information disclosure about the product, which suggests that a subset of payday borrowers do not make an informed, utility-maximizing choice.

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 increases in response to a higher uncertainty about this variable. Several papers provide causal evidence for this prediction using experimental designs (e.g., Link et al. 2021; Roth et al. 2022) and natural experiments (e.g., Baker et al. (2020)).

Given the large effect of the COVID-19 shock on income risk as perceived by U.S. households (e.g., Dietrich et al. (2022)), it is thus conceivable that they adjusted the resources devoted to collecting information about their finances – e.g., by checking their credit reports or scores. The increased value associated with learning or tracking their finances more regularly could by itself rationalize a higher information demand by households. What is more, the value of this information might have increased disproportionately for non-sophisticated households compared to their sophisticated peers. These considerations suggest that the COVID-19 shock threatens the identification of the effect of the policy on information acquisition through a resolution to misperceptions.

I first examine whether differential exposure to the pandemic could be an important confounding factor. I explore this possibility by adding time-invariant individual controls (e.g., for race, gender, and aversion to financial risk) and their interactions with the $Post_t$ dummy. This allows for each borrower characteristic to have a separate and time-varying effect on the likelihood of information updating. I continue to find that non-sophisticated households were significantly more likely to have updated their information set compared to their sophisticated counterparts. This result is reported in the second column (in the first row) of Table 6.

Next, I compare changes in updating behavior before and after the policy change across sophisticated households that were more or less likely to be unemployed during the COVID-19 crisis – especially early in the crisis. Since sophisticated households do not face information frictions, this comparison informs us of the effect of the change in information value on information acquisition. More formally, I estimate the following linear specification:

$$y_{i,t} = \alpha + \beta \mathrm{Post_t} + \theta \mathrm{HighExposure_i} + \delta(\mathrm{HighExposure_i} \times \mathrm{Post_t}) + \gamma X_i + \lambda_t + \lambda_{s(i)} + \epsilon_{i,t} \quad (3)$$

where $\mathrm{HighExposure_i}$ is a dummy denoting whether household i was more exposed to unemployment risk during the pandemic. Several studies document disproportionate impacts of the pandemic on the labor market outcomes of women, minority groups, and young workers (e.g., Alon et al. 2020; Couch et al. 2020; Albanesi and Kim 2021).[25] Therefore, $\mathrm{HighExposure_i}$ equals one for non-white/Hispanic women, women ages 18 to 40, and non-white/Hispanic households ages 18 to 40; and 0 for white men, men ages 40 or older, and white households ages 40 or older. In this specification, $\mathrm{X_i}$ includes dummy variables for marital status, having children in the household, housing tenure status, and financial risk aversion. The coefficient of interest is δ. In line with models of endogenous information acquisition, I expect to find $\delta < 0$. Furthermore, λ_t is a vector of fixed effects for the month of the survey and $\lambda_{s(i)}$ for the state of residence.

The third column of Table 6 reports, in the second row, the result of this test. I do not find evidence on the importance of the exposure to unemployment/income risk for the updating behavior of sophisticated households. Under the assumption that $\mathrm{HighExposure_i}$ is a high-quality proxy for risk exposure, then it is conceivable to expect a similar result for non-sophisticated households. Although it is difficult to establish causality, my findings, taken together, support the interpretation that the new credit reporting policy played an important role in explaining the higher information acquisition by non-sophisticated households.

[25] Many factors explain the pandemic's larger impacts on the labor market outcomes those groups. For instance, women were more likely to carry a higher childcare burden when schools were closed, and Latinx tended to work in contact-intensive sectors.

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

	(1)	(2)	(3)
DD estimates			
$\mathrm{Unsoph_i} \times \mathrm{Post_t}$	-0.103^{***}	-0.117^{**}	
	(0.030)	(0.030)	
$\mathrm{HighExposure_i} \times \mathrm{Post_t}$			0.003
			(0.026)
Event study estimates			
Wave 2	−0.066		
	(0.049)		
Wave 1	-0.096^{**}		
	(0.046)		
Wave 0	-0.116^{***}		
	(0.039)		
Wave −2	−0.003		
	(0.037)		
Wave −3	−0.003		
	(0.046)		
Wave −4	0.027		
	(0.052)		
Wave −5	0.031		
	(0.053)		
Wave −6	0.018		
	(0.055)		
Wave −7	0.014		
	(0.055)		
Survey-wave FEs	✓	✓	✓
State FEs	✓	✓	✓
$\mathrm{Post_t} \times \mathrm{X_i}$		✓	
Observations	8885	8885	7293

Notes: The first column displays the event study estimates of equation (2) and the corresponding DD estimate in the first row. The second column reports, in the first row, the DD estimate with additional controls, interacted with $Post_t$. The last column reports the DD estimate for equation (3)Standard errors clustered at the household level in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7. Discussion and Conclusion

This paper uses survey data from the U.S. and quantifies that 44% of discouraged borrowers who appeared unconstrained to meet their demand for a credit card failed to do so. A simple back-of-the-envelope calculation based on this counterfactual estimate shows that discouragement leads to a particularly large shortage in aggregate credit demand. This result thus indicates that discouragement might have implications for the power of the credit channel of monetary policy transmission.

My empirical findings provide evidence that discouraged borrowers use of outdated information about their creditworthiness when forming beliefs about their ability to borrow is a sensible explanation for their mistake. Because these borrowers are financially unsophisticated, they are more likely to face information frictions, which makes them slower in updating their information set. One possibility is that non-sophisticated discouraged borrowers mistakenly believe that checking their credit scores/reports negatively affects their current and future ability to borrow. Consistent with non-sophisticated households facing larger information frictions, I show, in a difference-in-differences framework, that a change in credit bureaus' credit reporting policy in early 2020 contributed to a significant decline in the degree of information rigidity by facilitating information acquisition.

While I find that discouraged borrowers would have obtained credit amounting to 10% of their annual income had they applied, I remain agnostic as to rendering judgment on the welfare consequences of discouragement or desirability of credit for those borrowers. Credit access can exacerbate financial distress among financially illiterate/unsophisticated individuals, as they might also have self-control problems (e.g., Gathergood 2012; Benjamin et al. 2013). However, it is also possible that unjustified discouragement exacerbates financial hardship. If households are pessimistic about their access to bank credit, they might turn to financial services outside the banking system (e.g., payday loans), which are readily available but are higher-cost products. In such a scenario, access to a bankcard is arguably a better alternative to discouraged borrowers, even if the desirability of credit itself is ambiguous. Interestingly, data from the National Survey of Unbanked and Underbanked Households maintained by the Federal Deposit Insurance Corporation provide suggestive evidence on a substitution toward higher-cost, alternative financial products because of discouragement. For example, part of the decline in the share of households with unmet demand for mainstream credit in 2017 relative to 2015 is followed by a reduction in the proportion of borrowers that were discouraged about applying for bank credit or used alternative sources of credit. I leave for future research a careful examination of the real cost of borrower discouragement through this substitution channel.

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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

Variable Name	Definition
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
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

Variable Name	Definition
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

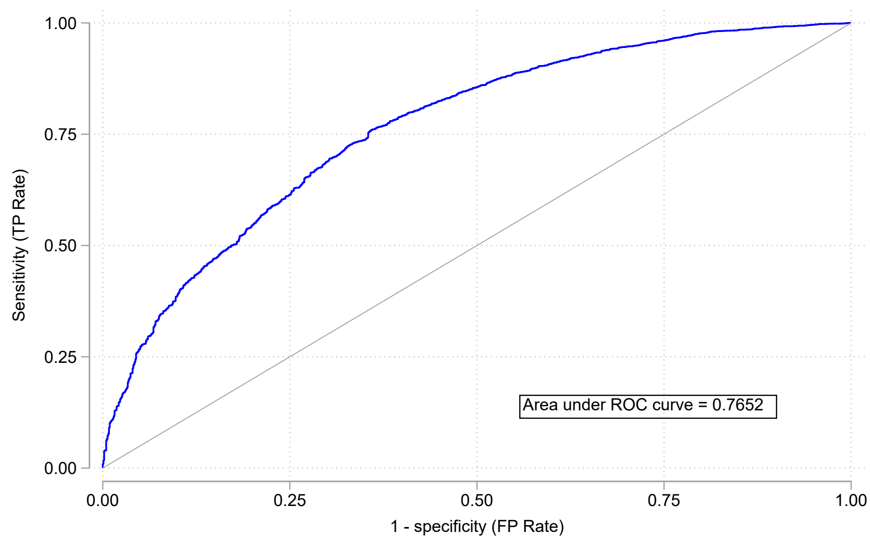


FIGURE A.1. ROC Curve

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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

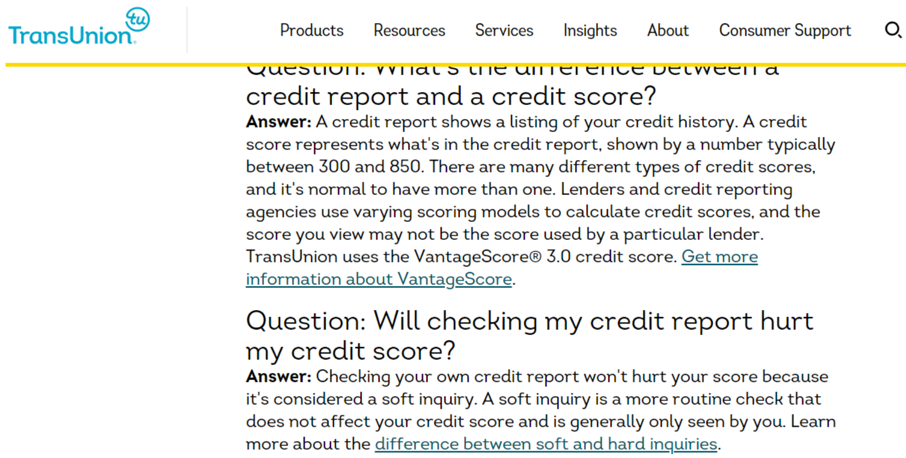
A.4. Compositional changes before and after February 2020

TABLE A4. Probability of being unsophisticated

	(1)
Female	0.070***
	(0.013)
Female × Post	−0.004
	(0.043)
White/non-Hispanic	−0.106***
	(0.018)
White/non-Hispanic × Post	−0.005
	(0.030)
HH income < $70k$	−0.194***
	(0.014)
HH income < $70k$ × Post	0.007
	(0.024)
Homeowner	-0.066***
	(0.017)
Homeowner × Post	−0.010
	(0.027)
Observations	11179
R^2	0.123

Notes: The dependent variables is a dummy variable for whether the household is unsophisticated. The model is estimated by OLS. $Post_t$ equals 1 from June 2020 to February 2021, and 0 from February 2018 to February 2020. 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

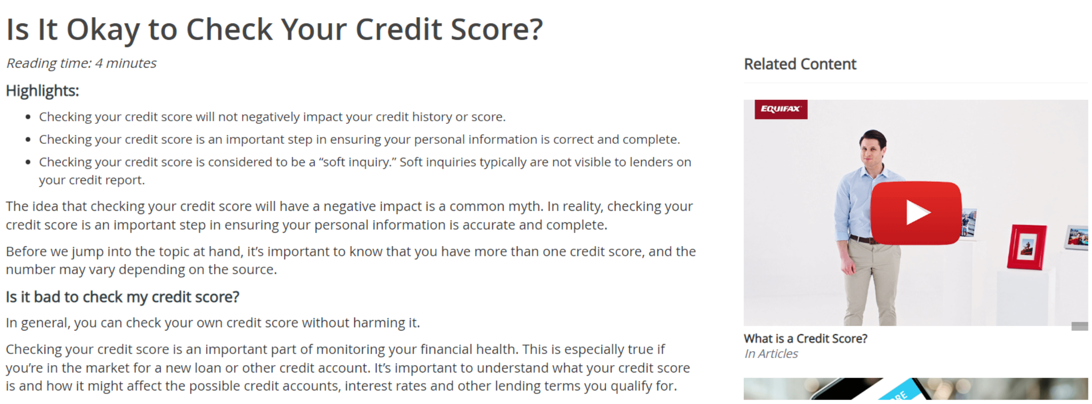
Question: What's the difference between a credit report and a credit score?

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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FIGURE A.3. Soft credit inquiry, Equifax