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LEARNING HOW TO BORROW IN A FINTECH WORLD: CONSUMER BEHAVIOR WHEN SEARCH COSTS ARE (NEAR) ZERO

Alex Günsberg
Camelia M. Kuhnen

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ABSTRACT

Online loan marketplaces are changing consumer lending. Here we investigate consumer behavior in these markets with near-zero search costs. Using administrative data on 730,000 applications, 750,000 offers, and 200,000 individuals, together with credit registry records, we document four facts. First, substantial within-applicant dispersion in offered terms makes search highly valuable. Second, marketplace nudges mitigate choice complexity. Third, applicants search significantly, applying repeatedly, asking for different terms, and rejecting offers, in ways consistent with their creditworthiness. Fourth, dynamic adverse selection constrains search, as lenders penalize repeat applicants. Our findings highlight trade-offs between informational gains from search, and reputational and cognitive costs.

Alex Günsberg
Hanken School of Economics
alex.gunsberg@hanken.fi

Camelia M. Kuhnen
University of North Carolina at Chapel Hill
Kenan-Flagler Business School
and NBER
camelia_kuhnen@kenan-flagler.unc.edu

1 Introduction

Consumer lending is an area of active fintech innovation. Prior work has shown that loan approval decisions can now be made faster or using better data than before, thanks to innovation in this space. In this paper we focus on a less studied fintech development in consumer lending, namely, the significant growth in online loan marketplaces. These marketplaces, where loan applicants obtain almost instantaneously offers from many lenders, minimize one of the main frictions we typically think as determining a borrower's strategy, namely, search costs. Here we investigate how consumers search, learn, and make borrowing choices in this new environment characterized by almost zero search costs.

In the absence of online marketplaces for consumer finance products, individuals needing a loan – whether a mortgage, a car loan, or unsecured credit – would have to incur significant costs to sample from the distribution of loan offers and terms available to them. This could be due to significant travel or interaction time needed to sample multiple lenders, or barriers in observing the relevant terms of the products offered, which would make it difficult to compare them. Hence the prior literature studying consumer borrowing-related questions generally has relied on standard models of costly search, and documented evidence consistent with their predictions (Honka, Hortaçsu, and Wildenbeest (2019)). For example, most such models yield a reservation price equilibrium, where consumers stop searching once they see a price better than their reservation value, and price dispersion is obtained as an outcome.[1]

But how do people behave in a world where due to fintech innovations, they can find information about the supply side of credit almost instantaneously and can repeatedly sample customized loan offers with zero search cost? This is the question we address in this paper. Briefly, we find that in such a setting, potential borrowers search extensively – more so if they are credit constrained – due to high variability in loan offers received and thus high benefit from searching more, but the extent of search is dampened by two main forces: the complexity

[1] See, for example, Stigler (1961) and Reinganum (1979). Reservation price equilibria may not exist in settings where the distribution of prices is not known by consumers, who learn about this distribution as they search (Rothschild (1974), Janssen, Parakhonyak, and Parakhonyak (2017)).

of having to choose among many options, and the reputational cost of being a repeat loan applicant. Overall, our evidence highlights the importance of costs previously not central in the literature on consumer borrowing choices, namely, costs driven by dynamic adverse selection concerns, and cognitive capacity, which are features of the novel marketplaces for consumer loans that we see nowadays.

Our data come from the largest online loan marketplace in Finland, Sortter.fi, where consumers can apply for loans and receive within one or two minutes personalized offers from about 20 financial institutions present on the platform at any given time. The dataset covers about 730,000 loan applications made during 2019-2024 by more than 200,000 unique individuals, and about 750,000 resulting loan offers. We complement this dataset of loan applications, offers, and disbursements with credit registry information regarding applicants' credit score as well as any type of defaults post-loan application, whether or not they received a loan.

Lenders on this platform use proprietary machine-learning algorithms to determine if an offer will be made to an applicant, and if so, what loan amount, interest rate and maturity to offer. These decisions are based on information provided at the time of application, as well as on data obtained by lenders on the spot from the Finnish credit registry and other databases containing personal information. Lenders' offers are binding subject to income verification. Lenders are able to infer generally how competitive their loan offers are in each segment of the applicant pool, as they are provided with segment-specific summary statistics by the platform. Although loan applications involve verifiable information, including via lenders' access to the applicant's credit record, this is a marketplace with significant asymmetric information regarding an individual's type, i.e., their ability or willingness to repay the loan.

Applicants may choose to take one of the offers, if any is made, or not. They can also reapply immediately or later on, without restrictions, and can change the terms of the loans they are seeking. Applying repeatedly has no impact on the information recorded about the individual in the credit registry.[2] Hence this is a setting where loan applicants are able to learn with minimal cost information about the supply of credit available to them.

Empirically, we document four main results. First, there are significant benefits to individuals from learning about the credit supply side, and hence high benefits to searching, as there exists high dispersion in terms offered by lenders to the same applicant. Second, in this environment where consumers have many options to consider, cognitive costs matter, but certain marketplace features can mitigate those. Specifically, soft nudges – here, automatically tagging the best loan offer among those received by an applicant – can help people select loans in this complex setting, with lower income individuals being most impacted by the information provided by the platform. That being said, we also find that very strong nudges – here, the platform auto-selecting the best offer on behalf of the applicant – have the unintended consequence of reducing loan offer take-up rates. Third, loan applicants search significantly, by applying multiple times, and asking for loans with different terms, while rejecting many of the offers. Search intensity and offer rejection probability vary with the applicant's credit score in ways that suggest that individuals understand their own creditworthiness. Fourth, as evidence that this is a dynamic adverse selection setting, we find that lenders are less likely to offer loans to, scrutinize more intensely, and offer higher APRs to repeat applicants, which are inferred to be worse types. Hence, in this paper we show the existence of important trade-offs for consumers between informational gains from search, and reputational and cognitive costs. We believe that documenting these trade-offs is informative for future work focused on the optimal design of marketplaces for consumer finance products, as well as on lenders' optimal strategy in these types of markets.

Our results relate to two broad strands of the literature, namely, fintech lending, and borrower search. Prior work on fintech lending has shown that technology can increase ef-

[2]Prior to May 2024 (close to the end of our sample period) Finland only had a negative credit registry, which recorded delinquent behavior, such a missing bill or debt payments. In mid-2024 the Finnish government created a positive credit registry, which keeps track of behaviors such a taking out a new loan or making loan payments on time, much like the positive information that typically is recorded by U.S. credit bureaus.

ficiency in lending decisions. This is be done by increasing decision speed (Fuster, Plosser, Schnabl, and Vickery (2019)), using digital footprints to better predict default (Berg, Burg, Gombovic, and Puri (2020), Chioda, Gertler, Higgins, and Medina (2024)), or by better processing hard information about borrowers (Balyuk, Berger, and Hackney (2025)). Moreover, fintech has also been shown to reduce biases in lending (Erel and Liebersohn (2022), Bartlett, Morse, Stanton, and Wallace (2022), D'Acunto, Ghosh, Jain, and Rossi (2022) and Howell, Kuchler, Snitkof, Stroebel, and Wong (2024)), and improve financial inclusion (Babina, Bahaj, Buchak, De Marco, Foulis, Gornall, Mazzola, and Yu (2025)). To this literature we add the insight that fintech can also reduce to almost zero the search costs faces by potential borrowers, which therefore can change consumers' strategies and borrowing outcomes.

The fintech literature has also examined the extent to which lenders face asymmetric information, and has documented evidence that fintech lenders face lower quality borrowers and actively attempt to address this issue. Chava, Ganduri, Paradkar, and Zhang (2021) show that consumers who borrow from marketplace lending platforms have lower credit scores and higher default rates in the long run relative to observably similar applicants for bank loans, and Di Maggio and Yao (2021) provide evidence that U.S. fintech lenders making unsecured personal loans tend to lend to individuals with lower credit scores, who have higher likelihood of subsequent default, and charge higher interest rates on these loans. Approaches to address asymmetric information include the use of alternative data (Buchak, Matvos, Piskorski, and Seru (2018) and Di Maggio, Ratnadiwakara, and Carmichael (2022)), specialization in subpopulations of borrowers (Johnson (2021)), or screening based on contract terms (Hertzberg, Liberman, and Paravisini (2018)). [3]

Turning now to the literature on borrower search, a long line of theoretical work in en-

[3]Theoretically, lender competition has been found to impact screening intensity and equilibrium interest rates. Yannelis and Zhang (2023) show that generally, in more competitive markets, borrowers receive lower rates. However, when borrowers are high risk, more competition means each lender has a smaller share of the market and thus weaker incentives to acquire costly signals about loan applicants. As a result, in settings with high risk borrowers, more competition can lead to higher interest rates offered to applicants. The effect of financial innovation on lenders' ability to obtain signals about borrower type and on resulting contracts offered to loan applicants has been examined in Livshits, Mac Gee, and Tertilt (2016), who find that better technology leads to increased lending, more defaults, and higher dispersion in APRs.

vironments with search costs has shown that consumers' search outcomes depend on these individuals' types in terms of credit risk and their resulting reservation prices (e.g., Stigler (1961), Reinganum (1979), Rothschild (1974), Janssen, Parakhonyak, and Parakhonyak (2017)). These predictions have been confirmed in empirical work focused on describing search strategies. In the context of credit card offers, Ausubel (1999) finds that lower types are more likely to take higher rate offers. In the context of mortgage origination, Agarwal, Grigsby, Hortacsu, Matvos, Seru, and Yao (2024) find evidence that lower type borrowers strategically incorporate information about their chance of being rejected by the next lender sampled when deciding whether to take a current offer.

Existing empirical work has also shown that borrower search costs impact consumer lending outcomes, as there exists significant dispersion in rates offered to similar individuals seeking credit. Bhutta, Fuster, and Hizmo (2021) and Coen, Kashyap, and Rostom (2023) examine mortgage loans in the US and UK, respectively. Using data from the U.S., Bhutta, Fuster, and Hizmo (2021) find that identical borrowers obtain different interest rates from the same lender. Borrowers likely to be less financially savvy are more likely to obtain a mortgage with a rate higher than the lowest rate the lender could have offered to that type of borrower at the time. Using data from the U.K., Coen, Kashyap, and Rostom (2023) construct menus of mortgages that theoretically could have been on offer by any bank at the time when an individual obtained a specific mortgage, and find that mortgage terms that could have been offered to similar borrowers by the same lender exhibit significant dispersion, with inexperienced borrowers getting more expensive loans. Cota and Sterc (2025) emphasize the potential of financial literacy to improve consumer borrowing choices by reducing cognitive search costs. Borrower search costs related to barriers in reaching potential lenders can also lead to differences in loan terms across borrowers with identical credit risk, across a variety of consumer credit markets. For example, this is shown by Argyle, Nadauld, and Palmer (2023) in the context of auto loans, or Butler, Cornaggia, and Gurun (2017) in the context of consumer loans on peer-to-peer platforms.

So far there is little empirical evidence regarding whether or not consumers know or learn the distribution of prices of interest when searching, how quickly they learn, or how firms can influence this learning process (Honka, Hortaçsu, and Wildenbeest (2019)). In recent work, Alexandrov and Koulayev (2017) and Berwart, Higgins, Kulkarni, and Truffa (2024) document evidence from U.S. and Chile, respectively, that a large fraction of individuals looking for mortgages or other consumer loans are unaware of the extent of price dispersion that exists in the markets for those products. This underscores the need for fintech products, such as the online marketplace that we study here, that can provide valuable information to consumers regarding all options available to them. Survey evidence from King, Medina, Radoc, and Umanan (2025) suggests that standardized presentation of product-related information, product rankings, or changes in attribute salience can help direct consumers to specific products in the credit market. At the same time, nudges to attend to specific types of financial transactions may have detrimental side effects by detracting consumers' attention from other outcomes. For example, Medina (2021) shows that reminders about upcoming credit card payments reduce households' credit card late payment fees, but increase overdraft fees in their checking accounts.

The empirical setting we study here also relates to those studied in recent papers belonging to the theoretical literature on search and dynamic adverse selection. For example, Zhu (2012) examines sequential search in opaque over-the-counter markets, while Kaya and Kim (2018) focus on the relationship between the duration of an asset on the market and trade. These models imply that repeat searches might lead to having one's type inferred to be low. This suggests the existence of a reputational cost that customers might face if they sample repeatedly from the set of choices potentially available to them – here, by repeatedly making inquiries to learn the supply side of credit, in terms of interest rates, loan amounts available, and loan maturity.

The type of setting we study here, with what appear to be near-zero search costs, will likely become even more prevalent, due to fintech advances. Already there exist multiple platforms similar to the one we study – for example, Credible is a U.S.-based marketplace for consumer loans, as well as auto and home insurance products, and Lending Tree (also in the U.S.) focuses on consumer loans. In the future there will probably be more such online marketplaces, where lenders or providers of various other financial products (e.g., insurance policies) post offers that can be immediately seen, side by side, by consumers.[4] Given the growing presence of these platforms [5], it is important to study how financial intermediaries and consumers behave in such settings with negligible search costs. Hence, the contribution of this paper is to provide novel evidence about consumers' search strategy and borrowing outcomes in this new but increasingly important ecosystem of marketplaces for financial products. The main insight we provide, which can help with the design of these new markets, as well as with understanding lender strategies in such environments, is that consumers face important trade-offs between informational gains from expansive search when search is free, and the resulting reputational and cognitive costs of this behavior.

2 Data

We use three data sources: Sortter.fi, which is the largest online loan marketplace in Finland, Suomen Asiakastieto, which is the Finnish credit registry provider, and Statistics Finland, which provides local level demographics and economic measures. From Sortter we observe who applies for loans, when, and what terms they ask for (i.e., loan amount requested and preferred loan maturity); which lenders make offers and at which terms (APR, amount approved, loan maturity); which offers people select; and which loans are disbursed and when. From Statistics Finland we obtain socio-demographic information about the population in

[4] An interesting question is what type of marketplace might be most successful in the future. It may be that the type of fintech platforms or online marketplaces that will succeed in this space will be those providing standardized products, and not products requiring significant customization. Moreover, given that some early versions of online marketplaces, such as LendingClub, based on peer-to-peer lending, do not appear to be growing (Berg and Fuster (2022)), it is likely that models involving retail investors rather than financial institutions might not work well either.

[5] According to the Federal Reserve Bank of New York, fintech players in the U.S. have been the key drivers of the large increase ($86 billion) in unsecured consumer lending from 2021 to 2023 (Nair and Beiseitov (2023)).

the postal code of each applicant we see on Sortter. From Suomen Asiakastieto we obtain the credit risk score and credit rating of each individual who has used the Sortter platform at the time of each of their applications, as well as the time of their first default in terms of paying debt or bills after each loan application, and the amount in default.

We observe 736,802 loan applications from 208,932 unique individuals in Finland, from the introduction of the Sortter online marketplace in early April 2019 until mid-June 2024. A total of 211,954 loan applications from 113,228 unique individuals received at least one offer from one of the lenders on the platform. That is, 54% of individuals using this marketplace get at least one offer, and 29% of applications result in at least on loan offer. In total there are 747,855 loan offers made on the platform.[6]

During 2019-2024 there were 37 unique financial institutions participating on this online platform. These lenders can be either banks with a branch network, online banks, other credit providers that accept deposits, and non-deposit taking institutions. They are headquartered or supervised in Finland, Sweden, Norway, Estonia, Lithuania, or Malta. Not all lenders are present on the platform at the same time; some join early and either remain active throughout the sample period or stop participating for a while, while others join the marketplace later during the sample period. There are between 15-20 lenders on the platform on any given day.

Offers are generally made within minutes by the lenders on the platform, via algorithm-based lending decisions automatically implemented by each lender. Sortter submits the loan application to all lenders as soon as the applicant clicks on a "submit" button. Lenders then do an automatic credit record check, and issue a decision – namely, each lender specifies an approved amount for a loan, an interest rate expressed as an APR with monthly compunding, and a loan term. The most common terms are 60 months (20% of loan offers), 120 months (14% of offers), 36, 48 or 72 months (each around 10% of offers). Very long maturity loans

[6]To get to this sample from the raw data received from the platform, we drop observations where applicants income or expenses or outstanding debt are higher than the 99.5% of their respective distributions, as it is likely that some of these observations contain typos.

are not common – for example, 180-month loan offers make up only 5% of the sample of offers, and loans of maturities longer than that account for only 0.25% of the offers made. These offers are presented immediately to the applicant on Sortter's website, as shown in Figure A1.

While a lender may extend a loan offer, it is not guaranteed that if the applicant selects that offer, the funds will be received. This is because the applicant will need to provide the bank with proof of income, and that verification process, conducted off the Sortter platform after the applicant selected the offer, does not always complete successfully. For example, the lender may be unsatisfied with the documentation provided by the applicant, or the applicant may not provide any documentation. In that case, the bank terminates that loan offer, and no funds are paid out to the applicant. If the document verification process is successful and the funds are paid out, we observe the date when the lender disburses the funds to the borrower.

In the data, 38,338 individuals representing 18.35% of the applicants using the platform and 34% of those who receive at least one loan offer, eventually obtain an actual loan from a lender. While some of the other applicants who had loan offers do not reach the payout stage because they fail the income verification process, other applicants do not select any of the offers received, or may select one and then decide to not continue the income verification process with that lender but instead go back to the menu of offers and select another one. An applicant can only actively be pursuing funds with only one lender at a time – in other words, an applicant can not select two or more loan offers simultaneously.

When comparing the summary statistics characterizing the individuals submitting applications on Sortter shown in Table 1 to statistics as of 2022 for the overall population in Finland obtained from Statistics Finland[7] we find that applicants on Sortter are younger and less educated but earn similar incomes as the broad Finnish population. Specifically, relative to the adult population in Finland (i.e., people 18 years or older), applicants on

[7] All Statistics Finland's data can be downloaded at https://pxdata.stat.fi/PxWeb/pxweb/en/StatFin/.

the platform are younger, as the median age is 40 years in our data, and 50 years for all Finnish adults. About 18% of applicants have completed an undergraduate or graduate degree, which is lower than the 34% figure for the overall population. Part of this difference may be explained by the fact that applicants are younger than the overall population. The median total net income in the sample is close to the median net income for the broader Finnish population: 2100 euros/month in our sample, versus 2017 euros/month across all Finnish adults.

In terms of indebtness, too, loan applicants on Sortter are similar to the broad Finnish population. Statistics Finland reports that in 2022 the mean total debt per person was 25,544 euros, and the mean annual interest paid per year was 350 euros, which implies an APR with monthly compounding of around 1.36%. This figure is in line with the very low interest rates observed prior to 2022 in Europe. As shown in Table 1, individuals submitting loan applications on Sortter have on average 24,033 euros outstanding debt, which is close to the figure of 25,544 euros reported by Statistics Finland for the broad population, and pay on average 372 euros per month to service their debt.[8] This figure includes both monthly interest paid and principal paid down per month, but is in line with what would be implied using the 1.36% APR across the broad population, assuming the existent debt of Sortter participants has a term of 60 months, which is the most common term observed in loan offers made by lenders in our sample. Under these assumptions, given the 24,033 euros mean outstanding debt per person we see among Sortter applicants, their monthly debt payment would be 415 euros. Assuming an 120 month term, which is the next most popular across the lenders we see, the monthly debt payment would be 214 euros. The amount we see in the data, 371 euros is between these two estimates.

Approximately 45% of applications are coming from women, which shows a relatively balanced gender distribution among the users of this online loan marketplace.[9]

[8] We use means in this comparison instead of medians because Statistics Finland does not report median outstanding debt or median interest expense per person – rather, they report these per household.

[9] This gender distribution in terms of applying for loans in this marketplace appears more balanced compared to other financial decisions. For example, in terms of investing in the stock market,

Also, 30% of loan applications are coming from individuals who are home owners. This figure is less than half the size of the home ownership rate in Finland, which was 69.5% in 2022. A likely explanation as to why renters, as opposed to home-owners, are over-represented on the platform is because this is a marketplace for non-collateralized loans. Individuals who need to borrow and own a home might be able to borrow at lower rates by offering their house as collateral, using other venues than Sortter. Another explanation for the low home ownership rate in the sample is that participants in this online marketplace are younger by about 10 years relative to the adult population in Finland.

From the credit registry data, which was merged by the Finnish credit registry Suomen Asiakastieto with the application data from Sortter, we find that at the time of applying for a loan, 68% of individuals in the sample have credit ratings that are either AA, A+, or A, which are relatively good categories. People in the very best categories, AAA or AA+, represent 7% of the sample, while those in categories B and C make up 4.17%, and 17.55% of the sample, respectively. (About 3.85% of loan applicants do not have a credit rating in the national registry.) For each person, we also know their specific numeric credit risk score at the time of each application they made on the platform. Credit risk scores correspond to credit ratings: 0-3 for AAA, 4-6 for AA+, 7-18 for AA, 19-30 for A+, 31-54 for A, 55-87 for B, and 88-100 for C. In the sample, the median credit score is 25, which implies the median applicant has an A+ rating.

As can be seen in the bottom panel of Table 1, across the 747,855 loan offers made on the platform, the average loan amount is 10,442 euros, with a standard deviation of 9,529 euros. The median amount offered is 7,300 euros. The average APR for offered loans is 13.50%, with a standard deviation of 3.77%, and median value of 12.97%. Including fees charged by the lender (e.g., monthly service fees), the APR is on average 17.32%, with a standard deviation of 5.44%, and a median value of 16.57%. The average maturity of loans offered is

Finnish women have a significantly lower participation rate (37%) relative to Finnish men (50%). See the 2023 report from the Bank of Finland at https://www.suomenpankki.fi/globalassets/en/media-and-publications/calendar/2023/finlit/finlit_kalmi_presentation.pdf

76 months, with a standard deviation of 43 months, and median value of 60 months.

3 Results

3.1 Demand and supply in the online loan marketplace, and learning

Demand for loans in the online marketplace increased substantially during the sample, in particular during 2022 - 2024. This can be seen in Figure 1, which shows the number of applications per month (top left panel) and the number of new individuals using the platform each month (top right).

The supply of loans also increased over time, even though the number of lenders active on the platform has been rather constant over time, around 18 each month. The second row of Figure 1 shows the number of loan offers made by lenders per month (note that an applicant can get multiple loan offers) and the probability that an application will receive at least one offer from a lender, which on average is 29%, but shows noticeable time variation. The probability of an application resulting in at least one offer is highest from mid-2021 to mid-2022, at around 37%, after which it declines. It is the lowest at the end of 2023, around 20%, after which it stabilizes at around 28% during 2024. All together, these facts suggest that the very fast increase in demand, especially during 2023-2024, did not happen concurrently with an equally fast expansion of supply. In other words, lenders on the platform may have reached constraints during 2023 - 2024, whether related to financing or to business strategy – which in turn could have led to changes in how they decided whom to lend to in this setting. The bottom row of Figure 1 shows the number of loans actually disbursed each month, and shows a cooling off in lending during 2023 after a fast paced increase from late 2021 to the end of 2022, followed by a recovery in 2024.

Why did demand (i.e., applications) increase so much over time? There are several reasons. First, the online marketplace has been advertising and has gained popularity. Second, as in many other countries, interest rates in Finland increased in 2022 and again in 2023. Most mortgages, credit card debt and other loans in Finland are adjustable rate mortgages and most borrowers do not have hedging strategies against increases in the reference rate for their debt.[10] The fact that on this platform borrowers can get fixed-rate loans might make this borrowing avenue appealing to those concerned about increases in Euribor interest rates, especially if they worry about having to roll over the debt they currently have outstanding. Demand for loans on the platform might have also increased in late 2019 because of new regulation that came into effect in September 2019 that lowered the cap on interest rates from 50% APR to 20% APR. Effectively, this regulation made it difficult for providers of potentially predatory loans to lend to consumers, and might have led some borrowers to use the newly available online marketplace.

Supply might also expand when interest rates increase, as lenders' profitability has been shown to be better in higher-rate environments (e.g., Stijn, Coleman, and Donnelly (2018)). In our sample, we observe an increase in supply, as measured by loan offers made, or the number of loans paid out, up until late 2022 (during a period where the reference interest rate, i.e., euribor indeed increased, mainly during 2022), but that is followed by a decrease in 2023, which is also a time of increases in reference interest rates. This patterns could be driven by the fact that in December 2022 a regulatory changed occur which made it easier for borrowers with problematic credit records to have those records wiped clean. Specifically, starting in December 2022 credit default flags were removed immediately after the individual in question paid down their bill or debt they were delinquent on, rather than after a multi-year waiting period. In other words, individuals who could not have obtained a loan prior to that month due to a default flag on their credit record were now able to appear as low-risk borrowers, without any delinquency flags. Hence the pool of applicants became riskier in December 2022, and the data in the middle and bottom row in Figure 1 are consistent with the idea that lenders became more cautious as a result of this increase in the unobserved credit risk of applicants. This suggests that the change in the rules regarding the presence

[10] See the June 9, 2023 article in the Bank of Finland Bulletin titled "Strong rise in interest rates puts strain on mortgage borrowers", available at https://www.bofbulletin.fi/en/2023/1/strong-rise-in-interest-rates-puts-strain-on-mortgage-borrowers/.

of default flags in Finnish individuals' credit records in December 2022 might have the effect of reducing the informational value of those records, and might also hurt lower-risk loan applicants. Evidence for such a reaction by lenders has been observed in U.S. data. Berger, Bouwman, Norden, Roman, Udell, and Wang (2024) document that impediments to reporting consumer delinquencies to credit bureaus, designed through the CARES Act to protect customers, reduced the informational value of credit scores, which ultimately penalized safer consumers.

Table 2 shows the decisions and screening occurring during the various stages of interactions between applicants and lenders. Out of 736,802 applications, 211,954 (29%) receive at least one loan offer. The applicant selects at least one of the offers received in 112,360 (or 53%) of these 211,954 applications. This implies applicants with offers decide to pursue none of them in 47% of cases. In 39.36% of the cases when an offer is selected by the applicant (44,222 out of 112,360), a loan is disbursed from the lender to the individual. Using time stamps received from lenders, we infer that in the case of offers pursued by an applicant which do not result in a loan disbursed, 57% of the time this occurs because the lender ultimately rejects the applicant, and 43% of the time because the applicant rejects the offer.

3.2 The benefits of search

3.2.1 Applications have a high probability of being rejected

As documented earlier, only 29% of applications result in offers, hence searching is not guaranteed to result in positive feedback. Unsurprisingly, lenders are significantly more likely to make offers to individuals with better credit worthiness, as measured by their credit rating, or by their credit risk score, at the time of application. This is shown in Figure 2. Applications from people with a AAA rating (or credit risk score no higher than 3) have a 53% probability of success, whereas those with a C rating (or credit risk score from 84 to the maximum level of 100) have virtually 0% chance of getting loan offers.

3.2.2 There is high dispersion within-applicant in offered loan terms

In Table 3 we examine the drivers of the APRs offered by lenders and find that there exists high dispersion in terms offered by lenders to the same applicant. While applicant characteristics (fixed or time varying) and time fixed effects account for 38.5% of variation in APRs, lender fixed effects are sizeable also – they account for 25% of variation across loan offers in terms of their APRs.

The evidence in Figure 4 indicates that dispersion within person in APRs received is more than double the dispersion in APRs across the income distribution.[11] The left panel in the figure shows that the average APR (including fees) that is offered to an individual decreases with the person's income, as would be suggested by the results in Table 3. In the analysis in the figure we control for the average of the loan amounts offered to the individual, and the average of the maturities offered, as well as for application time FEs. The right panel of the figure on the other hand, shows that with a similar set of controls, the standard deviation across the APRs offered to an individual increases with the income of the person. Dispersion within-person in APRs received is significant, relative to the average level of APRs seen in the sample.

Table 4 examines the drivers of the loan amount offered by a lender to an applicant, conditional on an offer being made. Comparing the first column in Table 4 to the first column in Table 3 we observe that applicant characteristics, from the credit risk score to a rich set of socio-demographic variables, explain much less of the variation in the loan amount offered, compared to the variation in the APR offered (13.7% R^2 vs. 25.4% R^2, respectively). The biggest contributor to understanding variation across offers in terms of the amount the lender is willing to lend out is by far the loan amount that is requested by the applicant. When this variable is added to the set of factors already present in the model in the first column in Table 4, the R^2 of the regression moves from 13.7% to 46.8%. Adding

[11] Using data on APRs in the U.S. credit card market, Dempsey and Ionescu (2025) document a puzzling fact that is similar to what we observe in the Finnish data. Namely, APRs increase with default risk less steeply than predicted by standard models, hence variation across borrowers in APRs is surprisingly small.

the requested loan maturity as a control has a minimal effect on the explanatory power, as shown in the third column in the table. The results in the fourth and fifth columns show that lender fixed effects increase the explanatory power by 10%, and applicant fixed effects by another 8%. Overall, the regressions Table 4 show that an applicant can face very different loan amounts approved by lenders on this platform depending on how much they ask for, and who the lender is.

We investigate further the positive correlation between the requested loan amount and that offered by a lender by plotting in Figure 3 the distribution of the shortfall in the offered loan amount as a percent of the amount requested by the applicant. Specifically, this shortfall is defined as (Loan amount requested - Loan amount offered)/ Loan amount requested. A shortfall equal to 0 means the lender offered exactly the amount the applicant asked for. A shortfall equal to 0.25 means that the lender approved 75% of the amount requested, while a shortfall of -1 means that the lender approved an amount that is twice as large as what the applicant requested. Figure 3 shows that the largest mass in the distribution is at 0, meaning for many offers – specifically, 60% of them – the lender matches exactly the amount the individual requested. Also, in the case of 33% of offers the shortfall is positive, meaning that the lender approves less than the requested amount. There are instances where lenders offer more than what the applicant asked for, but these account for only 7% of offers.

In Table 5 we examine the drivers of the maturity of loans offered by lenders to applicants. Here we also observe differences relative to what drives the APRs offered by lenders. In the first column of Table 5 we document that applicant characteristics only explain 7.4% of variation across offers in terms of the maturity of the loan. This is lower than the 25.4% R^2 in the first column in Table 3 where the dependent variable was the APR of the offer, not the maturity. However, when we add in the loan maturity requested by the applicant as an additional explanatory variable, the R^2 moves from 7.4% in the first column of Table 5 to 68.6% in the second column, indicating that by far the most important factor that drives of the offered loan maturity is the maturity the applicant is interested in. Adding the loan amount requested has a minimal impact on the offered loan maturity. However, as can be seen in the last two columns in the table, lender fixed effects add 7% to the R^2, and person fixed effects contribute an additional 5%.

Overall, the results in Tables 3, 4 and 5 suggest two clear patterns: first, applicants can find prices (i.e., APRs) for the specific types of loans they search for at a particular point in time (meaning, for a desired combination of amount and maturity). Changing these inputs in the search will yield different offers, with different prices, as it appears that lenders compete on the interest rate margin, and less so by adjusting the amount or the loan maturity margins. The second pattern that emerges from these tables is that lender fixed effects matter significantly for all the terms of the offer – APR, loan size, and loan maturity – but particulary highly for the APR dimension. Therefore, applicants have to much to gain by searching repeatedly, whether at different points in time, when different lenders might be online, or in different parts of the supply space (i.e., for different amount and maturity combinations).

Lastly, Figure 5 presents evidence that lenders do not sort strongly into specific types of applicants, as applications which receive the highest number of offers also get the lowest average APR. In other words, this result suggest that good applicants with low risk receive low interest rate offers and that most lenders will make offers to these individuals.

3.3 Fintech nudges and consumer search

Online marketplaces for financial products can be quite difficult to navigate by consumers who may not have a sufficiently high level of financial literacy. This might be one of the reasons why some of the people in our data do not pursue any of the loan offers they receive. It is possible, however, that fintech nudges may help some individuals better understand these complex settings and may impact the way search is conducted. We investigate two such nudges introduced by Sortter.

The first such innovation is that loan offers are presented in descending order, from best to worst, where offer quality is determined by the platform based on whether the amount is close to what the applicant requested, the APR is low, and the lender has had a high probability of disbursing loans in the past. This is supposed to help consumers with multiple offers make a decision as to which one to pursue.

The second innovation, which is a stronger nudge, is that the platform introduced the "autoselection" feature in November 2021. This feature allows applicants to opt in to have the platform automatically tag the best offer, and push this via a direct link to the lender's website, sent by email, instead of directing applicants to the complete list of offers received (though this list was available on Sortter's website, if the customer were to log in to check the results of the application). Applicants who do not chose to have the autoselection on would still see a remark on Sortter's website containing all offers received that the offer at the top of the list is the best one, but emails from the platform would not specify which is the best offer or provide a link to pursue the best offer specifically. Emails would instead state that offers have been received and the applicant has to go back to Sortter's website to see the list of offers and make their selection. This is the same as the process that was in place before the platform introduced this autoselection feature. In short, the goal of the autoselection nudge is to make it very simple for applicants who choose that option to focus on one offer. The choice of the applicant whether or not to opt into having the platform autoselect the best offer was not communicated to lenders.

We find that fintech innovation can help people learn in this complex setting, with lower income individuals being most impacted by the information provided by the platform. That being said, our results suggest that strong nudges may not work well.

In Figure 6 we show that the probability of a loan being disbursed is significantly higher if that lender's offer was ranked first by the platform, and this is true for applicants who opted into autoselection, and for those who did not. The latter group includes people who applied for loans before the introduction of this feature, as well as those who had the choice to opt into having autoselection turned on but decided not to. The chance that the offer that is ranked first results in a loan is more than twice as high as the chance that the offer that is ranked second results in a loan.

The second nudge introduced by the platform, the ability to opt in to have the best offer be autoselected, impacts consumer behavior, as in the case of 52% of applications made after the introduction of this feature, the applicant chose to have autoselection on.

A natural hypothesis is that individuals who are more comfortable with making financial decisions will be those choosing to not to have the platform narrow down the salient information for them. These people should be better borrowers, and the data support this conjecture. First, as seen in Figure 7, generally, lower income individuals have a higher likelihood of opting into having the platform autoselect the best loan offer on their behalf. That being said, at the lowest end of the income distribution (for people earning less than 1000 euros/month), the reverse pattern is occurring. Second, we find that the probability of at least one offer being made in response to a loan application is higher for applicants who did not choose the autoselect option relative to those who chose that option (29.56% vs. 27.18%, respectively). After controlling for applicant characteristics including the credit risk score, the difference between these two groups in terms of the probability of getting an offer is reduced, but is still positive and significant (0.51%, $p < 0.01$). This is shown in Table 6. The same table shows that conditional on receiving an offer, the amount the lender is extending is 380 euros lower, the APR on the loan offer is 0.11 percentage points higher, and the loan term is 0.68 months shorter compared to the loan terms offered to individuals who did not opt into autoselection. These differences are statistically significant ($p < 0.01$). Since an individual's choice to have autoselection on is not communicated by the platform to the lender, these results indicate that this choice proxies for other characteristics that the lender can observe about the applicant that are included in the algorithms that determine if an offer should be made, and if so, at which terms.

While the choice to have autoselection on is present on the platform every day from November 2021 on, there exists variation within day across applicants, and within-applicants across multiple dates in terms of whether or not they see an autoselected offer, if they opted into having this feature on, and at least one offer is made. This happens due to a technical reason unrelated to the applicant. Specifically, the platform can not autoselect an offer if it is made by a lender that requires applicants to provide a bank account number before logging in to the lender's own website to pursue the offer by providing income verification documents. Ten out of the 37 lenders participating in the online marketplace during 2019-2024 require a bank account number to be provided prior to following up on an offer. These 10 lenders make up 40% of offers observed in the data. This is not a costly request, since if a loan is made, the borrower will need to have a bank account where the lender can transfer the funds, and virtually all Finish residents have bank accounts. In other words, applicants on the platform must provide their bank account number to a lender who has made them a loan offer, but some are asked to type in the number as soon as they select an offer, while others can select the offer and then provide the account number as they approach the time when the loan is finalized. Whether or not the top offer to an individual is coming from a lender with this requirement is orthogonal to the characteristics of the applicant - we found no evidence to the contrary. Hence, this technical aspect of the platform induces random variation among people who chose to have Sortter autoselect the best offer for them in terms of whether or not they actually receive the strong push from the platform to select that offer. That being said, offers are always posted on the platform's website in the order of their rank, as determined by Sortter's algorithm.

We find that actually receiving the strong nudge has a significant effect on the probability of receiving a loan. In Table 7 we examine the sample of applications from people who chose to opt into autoselection, and received at least one loan offer. Some of these individuals receive the strong nudge email with the autoselected offer, whereas some do not, because of the technical issue related to whether or not the top ranked offer happened to come from a lender that needed the person's bank account number earlier in the underwriting process rather than later. We find that relative to people who wanted to see an autoselected offer but did not, those who actually received the strong nudge have a 2.04% lower probability of having a loan disbursed. This suggests that this strong nudge may have unintended consequences. Perhaps being directly sent to the website of a lender, without seeing simultaneously what other offers one received (even though all offers would be listed on Sortter's website if the person were to log into their account), leads potential borrowers to question just how good that offer is in the distribution of what is potentially available.

3.4 Search intensity and motives

We find that loan applicants search significantly, by applying multiple times, and asking for loans with different terms, while rejecting a majority of offers. Details regarding the distribution of the number of applications made by individuals on this platform are presented in Table 8. The mean number of applications per person is 3.56, with a standard deviation of 7.12, while the median number of applications per person is 2. About 44.58% of people on the platform apply only once, 17.30% apply twice, 11.16% apply three times, and 27% of people apply four or more times.

Search intensity and offer rejection probability vary with the applicant's credit score in ways that suggest that individuals understand their own type. In the top panel of Figure 8, we document that individuals with a C credit rating at the time of their first loan application on the platform have a 73.7% probability of defaulting in the 12 months post-application on any type of debt or bills. This probability is lower for better-ranked applicants but even among those, it is sizeable: 28.3% for B-ranked applicants, 30.3% for A-ranked ones, 19.9% for those ranked A+, 14.5% for AA-ranked applicants, 11.8% for AA+ applicants, and 7.05% for those AAA-ranked.

The bottom panel of Figure 8 presents the average number of applications per person, by their credit rating at the time of the first application. The highest number is for B-rated applicants, who on average apply about 4 times. People rated C or A apply about 3.6 times, and for the rest of the population the number of applications decreases as the credit rating gets better. AAA-rated individuals on average apply 2.8 times. Looking at medians also indicates the most credit worthy individuals apply fewer times. The median number of applications per person is 2 for individuals C, B, A, A+, or AA -rated and 1 for those rated AA+ or AAA. Overall, the data in Figure 8 is consistent with the idea that search intensity depends on applicants' credit worthiness. In general, better credit risk individuals search less, but there is the notable exception of the B-rated applicants who search more intensely than those C-rated. This might be driven by the fact that some of those B-rated need immediate liquidity to pay down existing debt or bills, to avoid delinquency and thus, a downgrade to being C-rated, which happens when a default flag is added to the credit profile of the individual. In other words, there are non-linear incentives at play that vary across the distribution of credit ratings which will impact the extent to which people sample from the supply side.

The idea that the need for immediate liquidity drives some of the search behavior on this platform is also supported by the evidence in Figure 9. The figure shows that search intensity depends on credit worthiness and on the outcome of first loan application in a way that suggests that credit ratings do not capture the full extent of financial distress or credit needs of the individual. Specifically, those who receive an offer at the time of the first application search significantly less afterwards compared to people who did not get an offer, and this difference is the largest (2.3 vs. 4.6 applications, respectively) for applicants with the best (i.e., AAA) rating. The exception are individuals with a C rating, who search similarly after the first application whether or not that resulted in a loan offer. These results suggests that higher rated individuals benefit more from securing credit to protect their good credit standing, and will continue searching if their first application does not yield a loan offer.

We also find evidence that better rated applicants are more selective in whether or not to take loan offers received in this marketplace. As reported earlier, among all applications resulting in at least one loan offer, in 53% of cases the individual applying will select at least one offer. As shown in the regression results in Table 9, we find that the probability of selecting at least an offer for people with a credit rating of A or better is 20 pp lower than for those with a C rating, and 5 pp lower probability relative to those with a B rating. These differences are significant at $p < 0.01$, and control for the averages of the terms of the offers received by the person (APR, loan maturity and loan amount), and for application date fixed effects. That being said, there are no significant differences in selectivity among applicants with a credit rating of A or better – those with better credit risk scores, or better credit ratings, do not differ in how likely they are to select at least one of the offers received. This suggests that the learning motive is relatively constant for applicants who are not in financial distress, or close to it. For applicants with B or C ratings, who are in distress, it is likely that securing funds is more important than learning more about the cost of credit offered by the supply side.

3.5 Evidence of dynamic adverse selection

Search is close to zero cost in this online marketplace, as loan seekers can apply multiple times, immediately or later on, either by changing the terms of the loans they apply for or by asking for the same loan, and do not pay any fees to have these applications shared with lenders. There is also no penalty for applying multiple times in terms of what is recorded in the Suomen Asiakastieto national credit registry. That being said, we find evidence of a reputation cost that repeat applicants are incurring. Lenders observe repeat applicants, and infer them to be worse types, as would be predicted by models of dynamic adverse selection (e.g., Zhu (2012) and Kaya and Kim (2018)).

In Figure 10 we show evidence consistent with this conjecture. There we plot the probability that a lender makes an offer to an applicant, as a function of the person's credit rating at the time, and of whether or not this is the first time the lender received an application from the individual. Repeat interactions (namely, situations which are not the first time when the person has applied for a loan on the platform and the lender received their application) result in substantially lower probabilities that an offer is made. For example, during a first-time interaction, a AA-rated applicant has a 18% chance of having the lender make an offer, but that number drops to 5% for a subsequent interaction. This three-fold drop from the first to subsequent interactions in the chance of having the lender respond positively to the application is observed across all credit rating categories, except for applicants rated C. Those individuals have a close to 0 probability of having the lender make an offer, whether or not this is the first or a repeated interaction between that individual and the lender.

In the analysis presented in Figure 11, we also find that the APR (including fees) quoted by lenders to applicants they see for the first time is 0.7 pp lower ($p < 0.01$) than the APR quoted to applicants seen by lenders in later interactions, controlling for lender and application time fixed effects, as well as for the applicant's credit risk score. This increase in APR due to repeat interactions stays almost constant across the distribution of credit risk scores.

We also find evidence that among individuals who receive at least a loan offer, the likelihood that a loan is actually received by an applicant is significantly smaller among applicants who are seen by a lender for the first time versus applicants seen by the lender previously, even when we examine just applicants who have previously searched for loans on the platform. This is shown in Figure 12. Here we restrict the sample to applications from people who used the Sortter platform previously, in order to keep constant the quality of the applicant pool (which is worse for repeat applicants versus first timers, as indicated by our prior results), while varying the extent of applicant-lender familiarity or prior interactions. We can use this approach because there are differences across lenders in when they are present on Sortter, and therefore in terms of which applications they observe. Thus an individual applying for a loan a second time on Sortter will look like a first-time applicant to a lender who was not on the platform when the person applied for the first time, and will look like a repeat applicant to another lender, who was on the platform at the time of the person's first application and is also present at the moment when this individual applies for the second time.

In the analysis in Figure 12, we control for the loan terms (APR, maturity and amount offered by the lender), as well as lender fixed effects, and loan application year-month fixed effects. We find that the probability that an offer results in a disbursed loan, which in this sample is 29.66%, is 4.5 pp larger ($p < 0.01$) if the offer is from a lender who sees the applicant for the first time, relative to situations when the offer is from a lender who previously observed the person applying on the platform. This difference is highest, at 10 pp ($p < 0.01$), for people with the lowest credit risk (i.e., a risk score of less than 10, which covers people with credit ratings of AAA or AA+ and the top quarter of those with an AA rating). These results suggest that lenders scrutinize people with more stringency at the income verification process stage, when these individuals are repeat applicants to this lender vs. applying for the first time to the lender, providing yet more evidence that repeated search comes with increased reputation costs for applicants in this loan marketplace.

4 Implications and conclusion

Fintech innovations can make it much easier for consumers to observe what financial products are available to them, and what their features and costs are. This can also cause consumers to face large and complex sets of potential choices. How do people search and make decisions in these types of settings, characterized by close to zero search costs for information acquisition, but potentially high cognitive costs of parsing a large set of choices, or reputation costs occurring from searching repeatedly?

Here we examine a large dataset of loan applications, offers, and loans disbursed from the most popular online loan marketplace in Finland, Sortter.fi. We complement this dataset covering about 200,000 individuals, 730,000 loan applications, and 750,000 loan offers from 37 financial institutions, all generated by machine-learning algorithms, with credit registry information that allows us to assess these individuals' credit worthiness at the time of applying for a loan as well as afterwards. In this setting, loan applicants are able to learn with minimal cost information about the supply of credit available to them. Although loan applications involve verifiable information, including via lenders' access to applicants' credit records, this is a setting with significant asymmetric information regarding an individual's type, i.e., their likelihood of repaying the loan. At the same time, this setting allows applicants to learn about the supply curve by seeing offers (or lack thereof) from many lenders at the same time, and by applying multiple times and asking for different terms, with close to zero search costs.

We find that there are significant benefits to individuals from learning about the credit supply curve, and hence high benefits to searching, as there exists high dispersion in terms offered by lenders to the same applicant. Also, we find that fintech nudges – when not too strong – can help people make decisions in this complex setting, with lower income individuals being those most impacted. We find that loan applicants search significantly, by applying multiple times, and asking for loans with different terms, while rejecting a majority of offers. Search intensity and offer rejection probability vary with the applicant's credit score in ways that imply that individuals understand their own type in terms of creditworthiness. Lastly, suggesting that this is a dynamic adverse selection setting, we find the lenders are less likely to make loans to repeat applicants, which are inferred to be worse types.

Overall, our evidence highlights the hidden costs that exist in what first appear to be zero-cost search marketplaces for consumer finance products: namely, consumers' reputational and cognitive costs of acquiring information about a large set of options. More work is needed to understand how to best design these marketplaces in the future, for which products they may be more successful, which features or nudges would be more welcomed by consumers and financial intermediaries, and what would be the optimal strategies of these financial firms when competing in these novel marketplaces.

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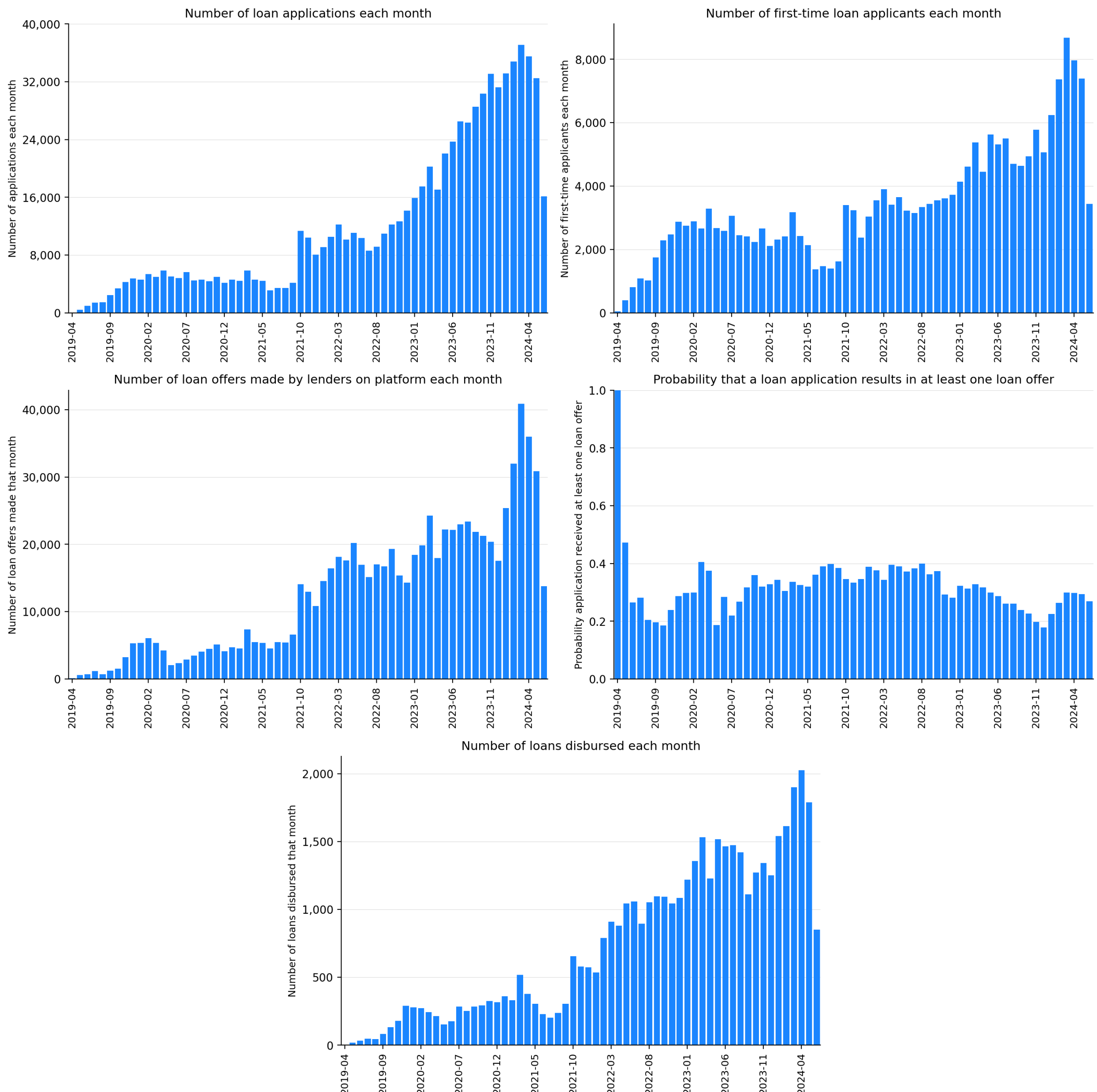


Figure 1: **Demand and supply over time.** The top row shows the number of applications newly created in the online marketplace (left panel), and the number of new individuals applying for loans in the online marketplace each month (right panel). The second row shows the number of loan offers made by lenders (left panel), and the probability of an applicant receiving at least one loan offer, by month when loan application is made (right panel). The number of loans disbursed each month is shown in the bottom row.

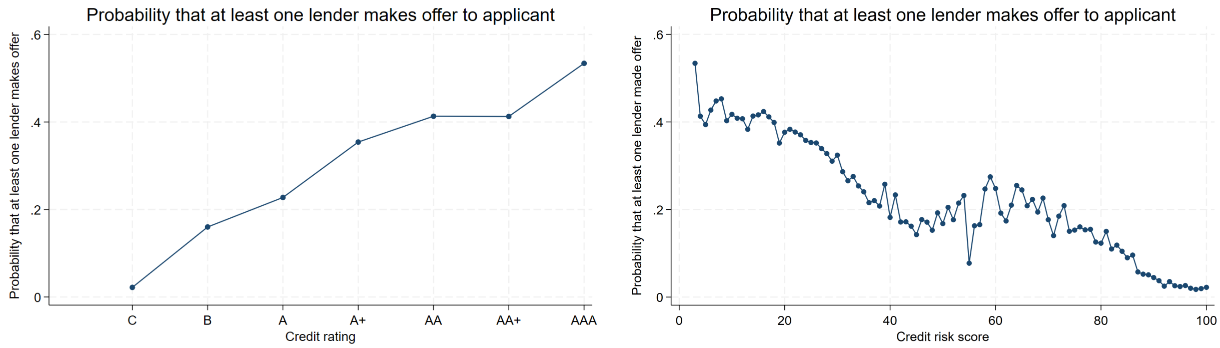


Figure 2: **Probability of getting a loan offer, by credit worthiness.** The figure shows lenders' willingness to make loan offers, as a function of the credit worthiness of the applicant (measured as credit rating in the left panel, and as credit risk score in the right panel).

Figure 3: **Lenders tendency to match the amount requested.** The figure plots the distribution of shortfalls in loan amounts offered by lenders as a percent of the amount the borrower requested.

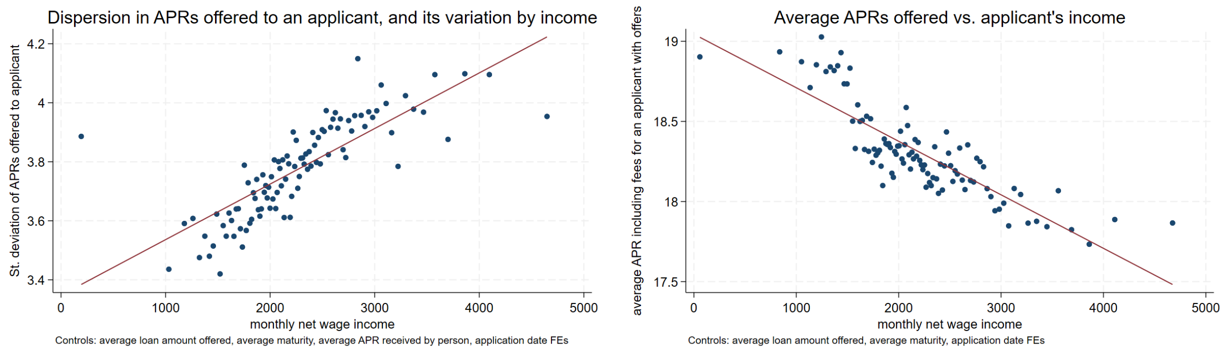


Figure 4: **Within and across applicants dispersion in APRs.** Left panel: Within-person dispersion in APRs, and its relation to applicant's income. Right panel: Average APR offered to an individual, and its relation to applicant's income

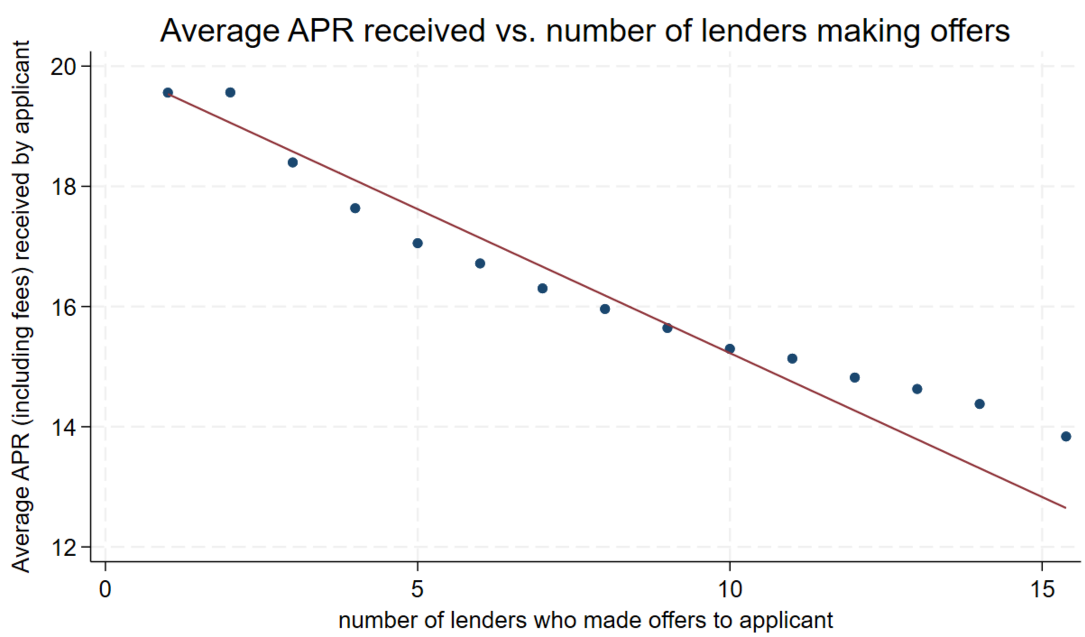


Figure 5: **Low APR offers go to people who get many offers.**The figure shows the average APR offered to an individual versus the number of offers the person received.

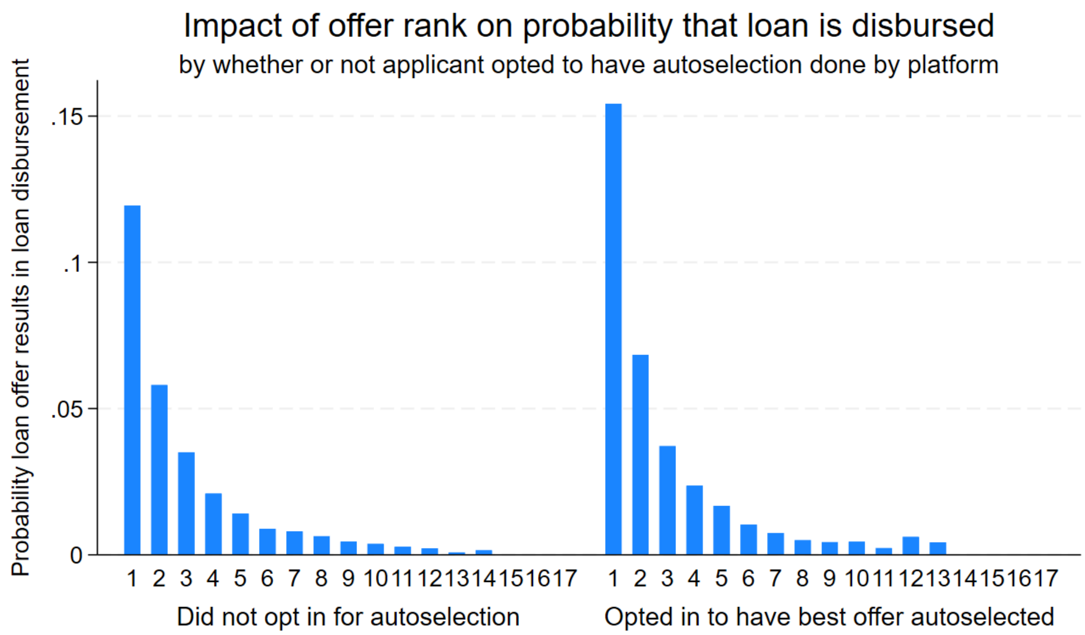


Figure 6: **Light nudge.** Impact of offer rank on loan disbursement, for people who did not opt to have the best offer autoselected (or did not have the option to do so), and for those who opted into autoselection.

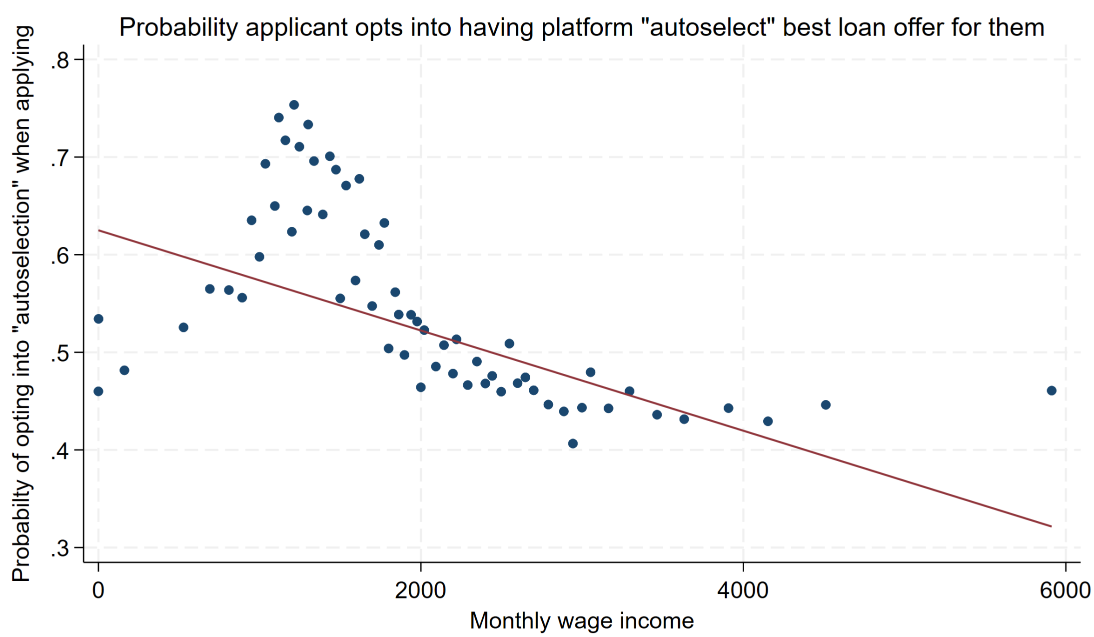


Figure 7: **Stronger nudge. Who chooses to opt into having best offer autoselected?** The graph shows the probability that applicants opted into having the platform autoselect the best loan offer, as a function of the applicants' monthly wage income.

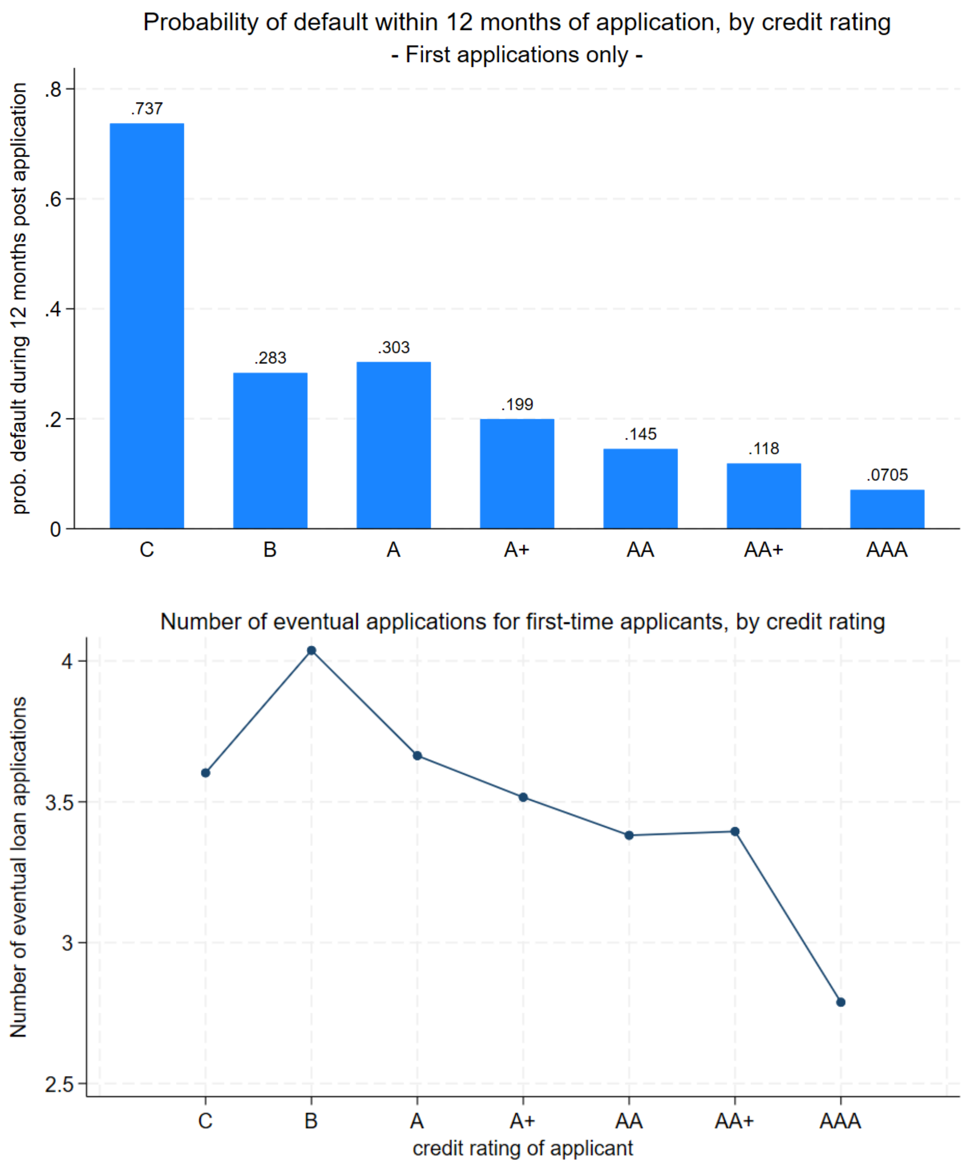


Figure 8: **Search intensity and financial distress.** Top panel: Post-application probability of distress (defaulting on any type of debt or bill), by credit rating. Bottom panel: Number of loan applications of an individual, by their credit rating at the time of the first application. The median number of applications per person is 2 for individuals C, B, A, A+, or AA -rated and 1 for those rated AA+ or AAA.

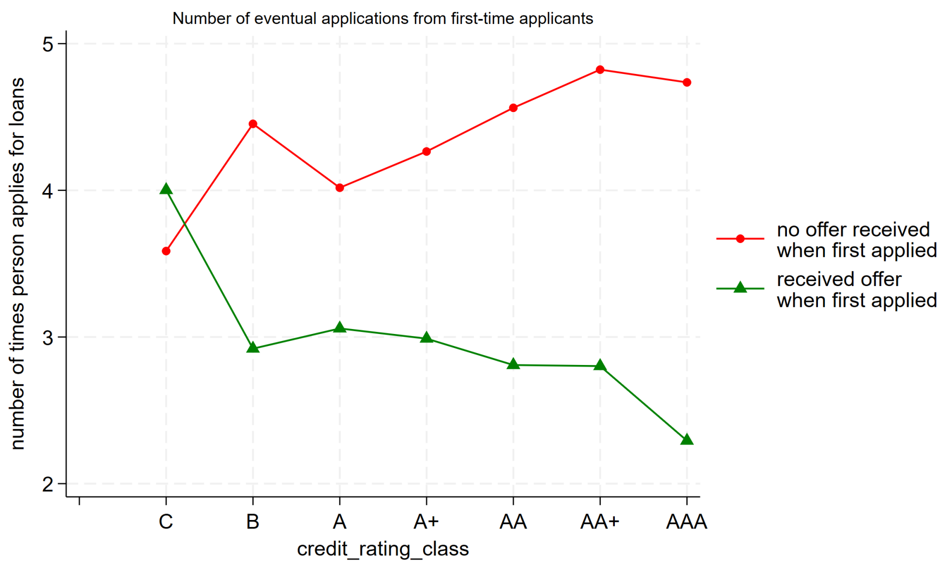


Figure 9: **Search intensity and outcome of first application** Number of loan applications of an individual, by their credit rating at the time of the first application, and whether or not a loan offer was received at the time of that application.

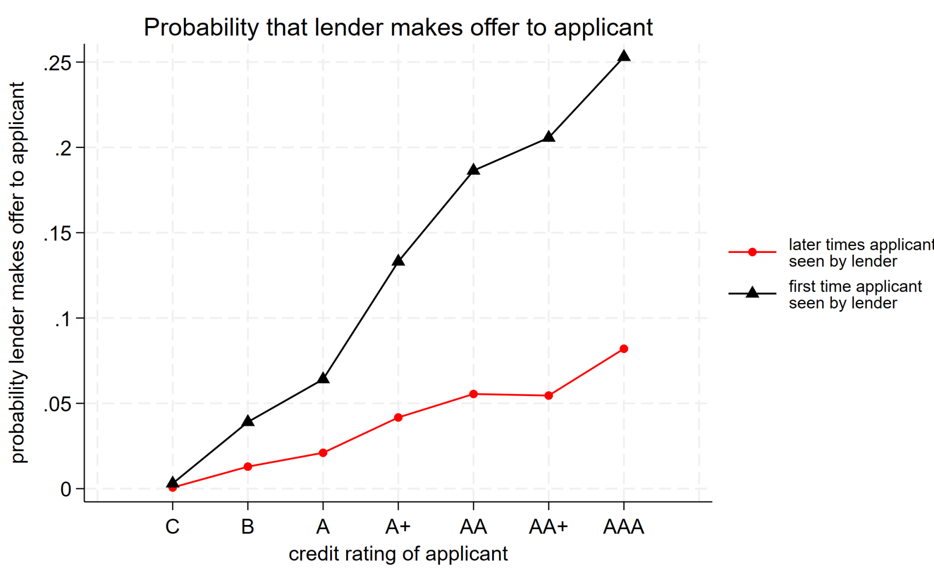


Figure 10: **Evidence of dynamic adverse selection: Who receives loan offers?** Probability that a lender makes an offer to an applicant, as a function of the person's credit rating at the time, and of whether or not this is the first time the lender received an application from the individual.

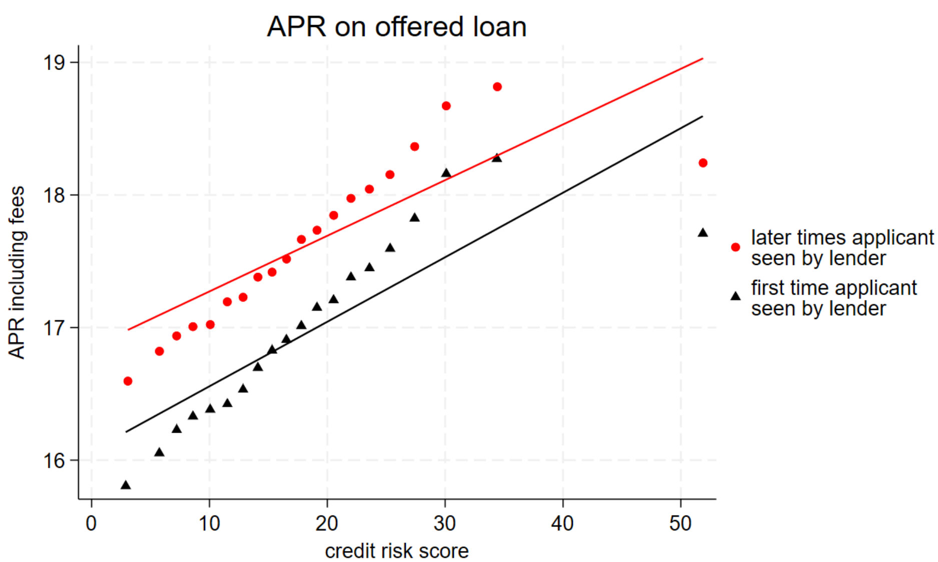


Figure 11: **Evidence of dynamic adverse selection: APR offered to applicant** APR if loan offer is made by a lender, by applicant's credit rating, for the first vs. later interactions between the applicant and the lender. The analysis controls for application date as well as lender fixed effects.

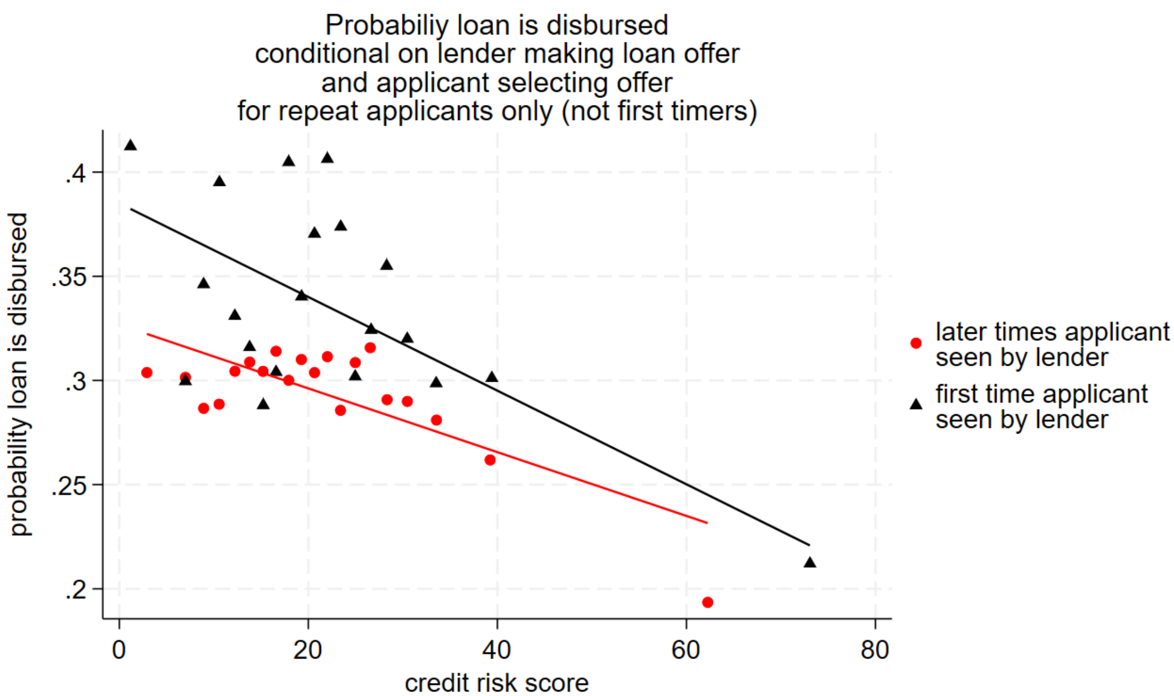


Figure 12: **Evidence of dynamic adverse selection: Loan disbursement** Probability that loan is disbursed to applicant, conditional on the lender making a loan offer and the applicant selecting that offer, as a function of the person's credit risk score and of whether or not this is the first time the lender received an application from the individual. The sample is restricted to applications from individuals who had applied on the platform previously (i.e., they are not first-timers in this online loan marketplace).

Table 1: Summary statistics.

The summary statistics below refer to the loan applications submitted through the online marketplace during April 2019 - June 2024.

Number of applications in the sample	736,802
Number of individuals applying for loans	208,932
Percent of loan applications from women	45%
Percent of loan applications from people with (under)graduate degree	18%
Percent of loan applications from home owners	30%
Fraction of applications that receive at least one offer	29%
Credit rating: AAA: 1.05%; AA+: 5.85%; AA: 25.55%; A+: 25.08%	
A: 17.30%; B: 4.17%; C: 17.15%; None: 3.85%	
Credit risk score: Median =25; Mean=37.57; St.dev=31.57	

Statistics referring to N=736,802 applications			
	Mean	St. Deviation	Median
Age (years)	42.57	15.51	40
Monthly net wage income (euros)	2,044.93	912.05	2,000
Monthly other income (euros)	234.44	596.07	0
Monthly total net income (euros)	2,279.37	1,090.38	2,100
Total debt outstanding (euros)	24,032.84	39,853.74	6,800
Monthly debt payments (euros)	371.82	442.12	220
Living expenses per month (euros)	361.45	264.88	350
Requested loan amount (euros)	11,995.22	13,911.76	6,000
Requested loan term in months (euros)	81.77	57.45	60

Statistics referring to N=747,855 loan offers			
	Mean	St. Deviation	Median
Loan amount offered (euros)	10,441.84	9,528.76	7,300
APR	13.50%	3.77%	12.97%
APR including fees	17.32%	5.44%	16.57%
Loan maturity (months)	75.65	43.32	60

Table 2: Stages, decisions, and screening.

The table shows the decisions and screening occurring during the various stages of interactions between applicants and lenders.

% applications that received at least one loan offer (211,954 out of 736,802 applications)	29%
% applications which get at least one offer where the applicant selects one of them (112,360 out of 211,954 applications) $\implies$ no offer is selected in 47% of cases	53%
% applications where an offer is selected by applicant that result in actual loan (44,222 out of 112,360 applications)	39.36%
why are the rest not resulting in loans? 57% due to bank rejections; 43% due to applicant rejections	

Table 3: Drivers of interest rates offered by lenders.

The dependent variable in the table is the interest rate (APR) charged by lenders (not including arrangement fees). The data are at the loan offer level (note that there can be multiple loan offers made per application, and only some of the applications receive offers). Euro amounts are expressed in thousands. Demographic controls included but not shown due to space constraints include gender, race, marital status, whether there is a co-applicant, the amount of non-wage income, total debt outstanding, and monthly living expenses. Standard errors are clustered by application date, and t-statistics are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	APR offered by lender to applicant			
Credit risk score	0.01	0.01	0.00	0.00
	(22.90)***	(26.33)***	(1.37)	(3.03)***
College or higher education	–0.32	–0.37	–0.08	–0.17
	(–24.14)***	(–33.61)***	(–1.40)	(–3.32)***
Monthly net income ('000 €)	0.01	–0.02	–0.05	–0.03
	(1.62)	(–2.43)**	(–2.19)**	(–1.69)*
Homeowner	–1.00	–0.94	–0.34	–0.33
	(–59.98)***	(–69.01)***	(–7.61)***	(–8.88)***
Monthly interest expense ('000 €)	0.73	0.46	0.97	0.43
	(33.93)***	(25.98)***	(22.30)***	(12.69)***
Low income indiv rel to postal code	0.18	0.06	0.09	0.04
	(10.91)***	(4.44)***	(2.59)***	(1.40)
Low income postal code	0.08	0.06	–0.01	–0.04
	(7.12)***	(5.80)***	(–0.10)	(–0.95)
Loan amount offered ('000 €)	–0.11	–0.08	–0.13	–0.08
	(–64.73)***	(–76.57)***	(–58.59)***	(–56.15)***
Loan maturity offered (years)	0.04	0.07	–0.17	–0.02
	(11.91)***	(25.84)***	(–23.20)***	(–5.57)***
Loan application date FEs	YES	YES	YES	YES
Demographic controls	YES	YES	YES	YES
Lender ID FEs	NO	YES	NO	YES
Person FEs	NO	NO	YES	YES
R^2	0.254	0.480	0.385	0.569
Observations	731,469	731,469	709,413	709,413

Table 4: Drivers of loan amounts offered by lenders.

The dependent variable in the table is loan amount (expressed in thousands of euros) offered by a lender to an applicant, if a loan offer is made. Demographic controls included but not shown due to space constraints include gender, race, marital status, whether there is a co-applicant, the amount of non-wage income, total debt outstanding, and monthly living expenses. Standard errors are clustered by application date, and t-statistics are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Loan amount offered by lender to applicant ('000 €)				
Credit risk score	0.00	–0.01	–0.01	–0.00	–0.00
	(1.52)	(–5.80)***	(–5.69)***	(–4.37)***	(–1.25)
College or higher education	0.26	0.35	0.39	0.43	0.03
	(4.18)***	(11.80)***	(12.94)***	(15.38)***	(0.21)
Monthly net income ('000 €)	1.05	0.31	0.35	0.37	0.04
	(6.51)***	(5.85)***	(5.94)***	(6.35)***	(0.76)
Homeowner	0.69	1.04	1.02	0.66	0.42
	(11.82)***	(33.10)***	(32.55)***	(23.79)***	(4.44)***
Monthly interest expense ('000 €)	5.50	0.87	1.01	0.63	0.85
	(49.06)***	(16.49)***	(18.89)***	(13.02)***	(8.84)***
Low income indiv rel to postal code	–1.26	–0.65	–0.66	–0.44	–0.25
	(–8.30)***	(–12.11)***	(–11.27)***	(–8.02)***	(–3.64)***
Low income postal code	–0.34	–0.22	–0.23	–0.17	–0.11
	(–5.11)***	(–7.47)***	(–7.35)***	(–5.98)***	(–0.96)
Loan amount ('000 €)		0.44	0.41	0.42	0.33
requested by applicant		(172.60)***	(151.88)***	(159.42)***	(102.74)***
Loan maturity			0.01	0.01	0.01
requested by applicant			(32.59)***	(31.82)***	(25.91)***
Loan application date FEs	YES	YES	YES	YES	YES
Demographic controls	YES	YES	YES	YES	YES
Lender ID FEs	NO	NO	NO	YES	YES
Person FEs	NO	NO	NO	NO	YES
R^2	0.137	0.468	0.470	0.597	0.680
Observations	731,603	731,603	731,603	731,603	709,518

Table 5: Drivers of loan maturity offered by lenders.

The dependent variable in the table is loan maturity, measured in number of months, that is offered by a lender to an applicant, if a loan offer is made. Euro amounts are expressed in thousands. Demographic controls included but not shown due to space constraints include gender, race, marital status, whether there is a co-applicant, the amount of non-wage income, total debt outstanding, and monthly living expenses. Standard errors are clustered by application date, and t-statistics are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Loan maturity (months) offered by lender to applicant				
Credit risk score	0.04	0.01	0.00	0.00	–0.03
	(3.28)***	(1.94)*	(1.03)	(0.83)	(–2.36)**
College or higher education	–3.51	–0.69	–0.78	–0.59	–0.40
	(–12.30)***	(–6.76)***	(–7.71)***	(–6.49)***	(–0.80)
Monthly net income ('000 €)	–0.06	0.06	–0.32	–0.30	–0.08
	(–0.35)	(0.88)	(–4.51)***	(–4.49)***	(–0.43)
Homeowner	1.89	1.87	2.05	1.12	0.26
	(5.74)***	(15.40)***	(16.91)***	(10.46)***	(0.69)
Monthly interest expense ('000 €)	11.91	3.43	1.50	0.50	1.26
	(26.75)***	(21.50)***	(9.91)***	(3.56)***	(3.74)***
Low income indiv rel to postal code	–3.32	–1.63	–1.40	–0.66	–0.07
	(–9.84)***	(–13.08)***	(–11.44)***	(–5.79)***	(–0.22)
Low income postal code	–0.55	–0.31	–0.26	–0.12	0.08
	(–2.13)**	(–3.34)***	(–2.88)***	(–1.47)	(0.17)
Loan maturity		0.67	0.63	0.63	0.52
requested by applicant		(308.75)***	(237.89)***	(238.14)***	(149.78)***
Loan amount ('000 €)			0.22	0.22	0.26
requested by applicant			(29.93)***	(33.30)***	(26.50)***
Loan application date FEs	YES	YES	YES	YES	YES
Demographic controls	YES	YES	YES	YES	YES
Lender ID FEs	NO	NO	NO	YES	YES
Person FEs	NO	NO	NO	NO	YES
R^2	0.074	0.686	0.688	0.757	0.810
Observations	731469	731469	731469	731469	709413

Table 6: Choosing autoselect feature relates to loan application outcomes.

The regression models in the table show the correlations between the choice to have the online platform tag the best loan offer and outcomes of applications: whether an application results in at least one offer, and, for each offer made, the amount the lender extended to the applicant, he APR of this loan offer, and the term in months. An individual's choice to have autoselection on is not communicated by the platform to lenders. Standard errors are clustered by application date, and t-statistics are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Did application receive at least one offer? (indicator = 100 or 0)	Loan amount offered (thousand euros)	APR offered (percent)	Term offered (months)
Chose autoselection	–0.50	–0.38	0.11	–0.68
when applying	(–2.97)***	(–15.63)***	(8.76)***	(–7.39)***
Application date FEs	YES	YES	YES	YES
Applicant controls	YES	YES	YES	YES
R^2	0.198	0.488	0.168	0.696
Observations	599,828	610,238	610,238	610,238

Table 7: Impact of the autoselect nudge on loan disbursement.

The table shows the impact of actually seeing an autoselected offer on the probability that a loan is disbursed to the applicant. The sample consists of applications from individuals who chose to opt in to the platform autoselect the best offer for them, and received at least one loan offer. Whether or not the best offer was autoselected and pushed to the customer was randomly determined due to technical constraints. Standard errors are clustered by application date, and t-statistics are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Probability that application results in having a loan disbursed
Saw autoselected offer	–2.04
	(–6.68)***
Credit risk score	–0.09
	(–8.43)***
Loan amount requested	–0.28
	(–24.14)***
Loan term requested	–0.02
	(–4.87)***
Monthly net income ('000 euros)	0.60
	(5.87)***
Number offers received	1.73
	(32.80)***
Loan application date FEs	YES
R^2	0.044
Observations	88,032

Table 8: How often do people apply for a loan?

The table shows the distribution of the number of applications per person in this online marketplace.

Number of applications	% People
1	44.58%
2	17.30%
3	11.16%
4	6.88%
5	4.60%
6 – 10	9.80%
11 – 25	4.65%
$\geq$ 26	1.02%
Mean: 3.56; St.dev: 7.12; Median: 2	

Table 9: Probability the applicant selects at least one of the available offers

The dependent variable in the table is an indicator equal to 1 if an applicant who has received loan offers will select at least one of the offers, and 0 otherwise. Controls include application date fixed effects, and average characteristics of the loan offers received by that application (amount, maturity, and total APR. Standard errors are clustered by application date, and t-statistics are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Applicant selects at least one offer
Credit rating A or better	–0.15
	(–8.25)***
Credit rating B	–0.20
	(–13.36)***
Controls (avg amt, term, APR)	Yes
Loan application time FEs	YES
R^2	0.039
Observations	207,433

Appendix

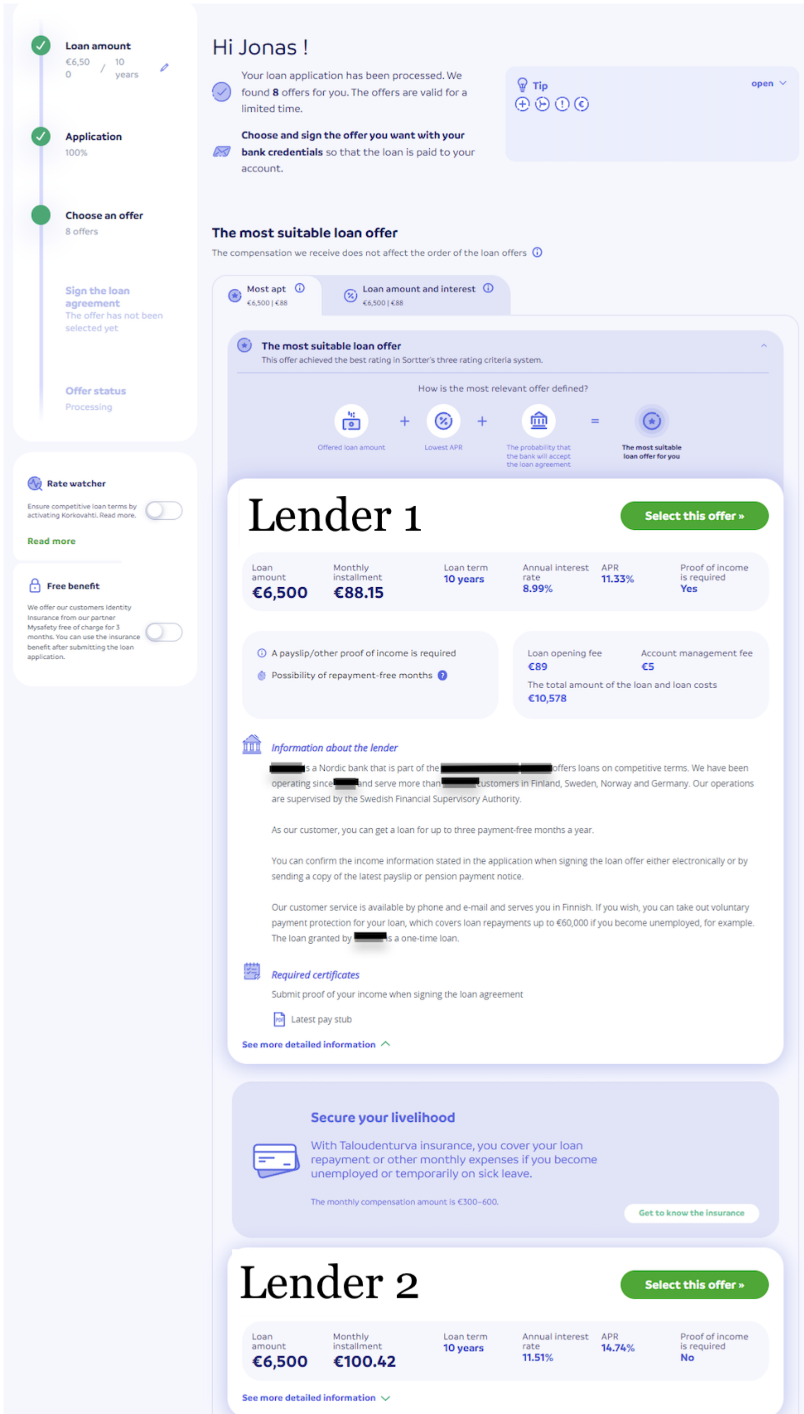
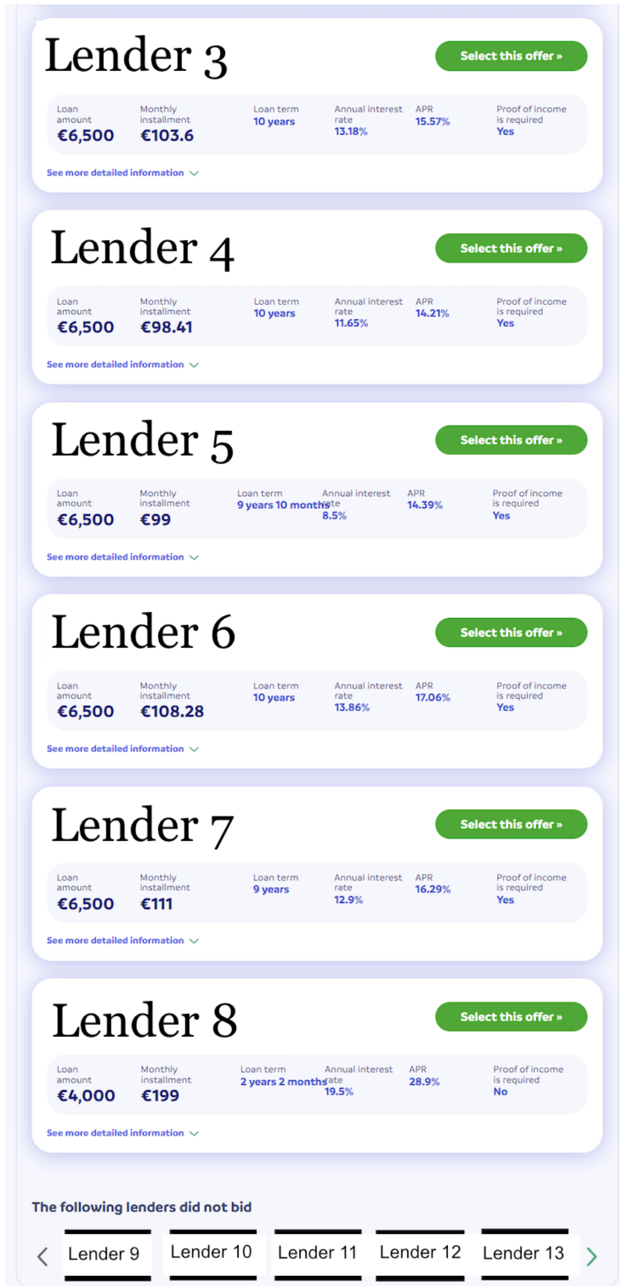


Figure A1: **Screenshot of an offer list a loan applicant could see on the platform**(continued on next page)



Lender 3
Select this offer »
Loan amount €6,500
Monthly installment €103.6
Loan term 10 years
Annual interest rate 13.18%
APR 15.57%
Proof of income is required Yes
See more detailed information
Lender 4
Select this offer »
Loan amount €6,500
Monthly installment €98.41
Loan term 10 years
Annual interest rate 11.65%
APR 14.21%
Proof of income is required Yes
See more detailed information
Lender 5
Select this offer »
Loan amount €6,500
Monthly installment €99
Loan term 9 years 10 months
Annual interest rate 8.5%
APR 14.39%
Proof of income is required Yes
See more detailed information
Lender 6
Select this offer »
Loan amount €6,500
Monthly installment €108.28
Loan term 10 years
Annual interest rate 13.86%
APR 17.06%
Proof of income is required Yes
See more detailed information
Lender 7
Select this offer »
Loan amount €6,500
Monthly installment €111
Loan term 9 years
Annual interest rate 12.9%
APR 16.29%
Proof of income is required Yes
See more detailed information
Lender 8
Select this offer »
Loan amount €4,000
Monthly installment €199
Loan term 2 years 2 months
Annual interest rate 19.5%
APR 28.9%
Proof of income is required No
See more detailed information
The following lenders did not bid
Lender 9
Lender 10
Lender 11
Lender 12
Lender 13