Attention Discrimination under Time Constraints: Evidence from Retail Lending

June 2, 2021

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Abstract

Using proprietary loan screening data, we document that loan officers engage in "attention discrimination": they exert less effort reviewing ex-ante disadvantage applicants, leading to higher rejection rates than otherwise justified by those applicants' credit quality. Attention discrimination increases with the officers' time constraints induced by quasi-random workload variations. When officer workload rises from the bottom to the top decile, they devote 70% less time to disadvantaged applicants, and the approval rate for those applicants declines by three-fifths. Our results indicate that attention constraints magnify discrimination, which provides policy implications about how to reduce discrimination in practice.

Keywords: Attention Constraint, Discrimination, Retail Lending

JEL classification: D83, D91, G21

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1 Introduction

Discrimination has been documented in a wide range of high-stakes settings including court sentences, labor recruitment, rental application screening, college admissions, and so on. Worse, decision makers often overly rely on group attributes such as ethnicity and gender, leading to discrimination against members of disadvantaged groups.[2] However, while discrimination may be widely documented, it is often unclear how to alleviate it. Simple-minded policy "remedies," such as making certain group attributes unavailable to decision makers, can backfire and result in other undesirable discriminatory practices.[3]

Drawing on recent work on *attention discrimination*, which refers to discrimination arising from differential attention allocation to applicants (Bartoš, Bauer, Chytilová, and Matějka, 2016), we propose and find evidence that discrimination is exacerbated by decision makers' attention constraints. The idea is intuitive: in selective screening processes, attention-constrained decision makers would choose to pay less attention to learning about candidates from disadvantaged groups, who may have lower average qualifications or are harder to learn about.[4] This inattention leads to discrimination: applicants from the ex-ante disadvantaged groups are more likely to be rejected because they do not receive sufficient attention in the first place. Further, the stronger the attention constraint of the decision maker, the stronger the discrimination. This mechanism, if true, has important policy implications: alleviating attention constraints of decision makers can help alleviate discrimination against

[2] Altonji and Blank (1999) summarize evidence of discrimination in the labor market. Yinger (1998) survey evidence on consumer markets. List (2004) find evidence of statistical discrimination using data from the market that trades sports cards. Ewens, Tomlin, and Wang (2014) finds evidence of race-based statistical discrimination in a large-scale field experiment of rental applications.

[3] For instance, the policy of "banning the box" forbids employers from asking about job applicants' criminal records until later in the recruiting process. While the goal here is to reduce discrimination against those with criminal records, research found that this policy led to stronger statistical discrimination against demographic groups that include more ex-offenders (Agan and Starr, 2018; Doleac and Hansen, 2020).

[4] While the set up and mechanism are different, Davies, Van Wesep, and Waters (2020) also shows that endogenous information acquisition can magnify biases in decision making.

disadvantaged groups.[5]

We illustrate the essence of the attention discrimination mechanism via an example of our annual recruiting exercise. Consider the case of reviewing junior job market applicants for a finance faculty position at a well-regarded school. In principle, reviewers should carefully read through all papers written by each candidate to make informed choices. But this is often unrealistic. Faced with time constraints, reviewers may use simple signals — such as the applicant's affiliation, or whether the research topic reads interesting at first glance — to guide how much effort to spend learning about a candidate. Because recruiting is a selective process, if an applicant does not get enough attention, she is more likely to be rejected. Therefore, applicants from ex-ante disadvantaged backgrounds — e.g., those who attended a lower-ranked school, or who had less well-known advisors — are more likely to be rejected without careful review of their research quality. Further, the more time-constrained the reviewer, the more likely he is to engage in such discrimination induced by attention rationing.

The idea that time constraints exacerbate discrimination is plausible, but it is challenging to test through real-world decision processes. First, it is hard to find plausibly exogenous variations in time constraints. Second, it is also difficult to measure attention allocation, which is required to validate the attention discrimination mechanism.[6] Using administrative data on retail loan screening processes, our paper overcomes these challenges. We document strong evidence that loan officers engage in attention discrimination and that they tend to reject ex-ante disadvantaged applicants without thorough review. More importantly, they discriminate more when they face stronger attention constraints, which are induced by quasi-random workload variation.

Our proprietary data contains detailed screening processes of retail loan applications from

[5] For instance, The Chronicle of Higher Education (2017) reports that admission officers at the University of Pennsylvania spend four minutes on the initial read of each college application. Time Magazine (2002) cites a study that shows recruiters spend an average of only six seconds on each resume. Court judges and patent examiners often have years of backlog to work through (Frakes and Wasserman, 2017).

[6] As noted by Gabaix (2019), "measuring attention is ... a hard task — we still have only a limited number of papers that measure attention in field settings."

one of the largest Chinese banks. The data includes approximately 146,000 applications, and the screening process is relatively selective; only around one-third of applications are approved.[7] Two features are worth noting. First, because we observe accurate timestamps of when each officer makes each decision, we can measure the number of minutes spent reviewing each application. Second, the data includes the full set of information that loan officers have access to. Hence, we can investigate a loan officer's decision while conditioning on all other relevant borrower and loan characteristics.

Our empirical exercise proceeds in three parts. In the first, we show evidence of attention discrimination by loan officers. A key premise of attention discrimination is that decision makers face attention constraints. This is indeed the case because officers must review a large amount of material in a short period of time. The median time spent reviewing each application is only 18 minutes. Unlike the U.S., China does not have the equivalent of FICO scores, and officers have to read through at least 20 to 30 pages of material per application and find useful information. In some cases, the loan officer also need to dig into hundreds of pages of supporting materials in order to make a decision.

Facing attention constraints, loan officers use simple observables to guide how much effort to spend on each application. In our sample, a subset of applicants can provide official certificates (letters of verification) for their income, employment, housing property, and residence.[8] We find that applicants without these certificates receive less review time and are much more likely rejected, even after controlling for a comprehensive list of applicant and loan characteristics.

Why do loan officers use these certificates? We find that applicants with certificates indeed have higher average credit quality as judged by conventional credit worthiness met-

[7] This rate differs significantly from U.S. mortgage applications, for which approval rates are over 60% for all ethnicity groups (Giacoletti, Heimer, and Yu, 2021). The fact that average approval rates are low is important; attention discrimination is only exacerbated by time constraints in processes that are sufficiently selective — a requirement called the "cherry-picking" condition in Bartoš et al. (2016). The illustrative model in Section 2 provides more details.

[8] As explained in Section 3.3, whether an applicant can obtain certificates is largely exogenous. For instance, those working for major companies are often able to obtain official certificates for their income and employment, while those self-employed cannot.

rics such as leverage ratio, loan to income ratio, etc.[9] Therefore, attention-constrained loan officers can use them as screeners to save time (Phelps, 1972; Arrow, Kenneth J, 1972). However, this leads to discrimination against disadvantaged applicants with fewer certificates. Although there are differences in the average credit quality between applicants with or without certificates, the gap is small.[10] Many no-certificate applicants still have high credit quality by conventional standards. Hence, when officers overly rely on the certificates, disadvantaged applicants suffer more from undue rejections, compared to a hypothetical world in which all applicants are given the same amount of attention.

In the second part of empirical results, we test the key prediction that stronger attention constraints exacerbate discrimination. For this exercise, we exploit variations in the degree of loan officer *busyness*, defined as the number of applications processed on a given day. The gist is that officers face stronger attention constraints on busier days, because they have to spend less time on each application in order to finish their work. Busyness varies significantly, with the 10% and 90% percentiles equal to 10 and 27 applications per day, respectively.

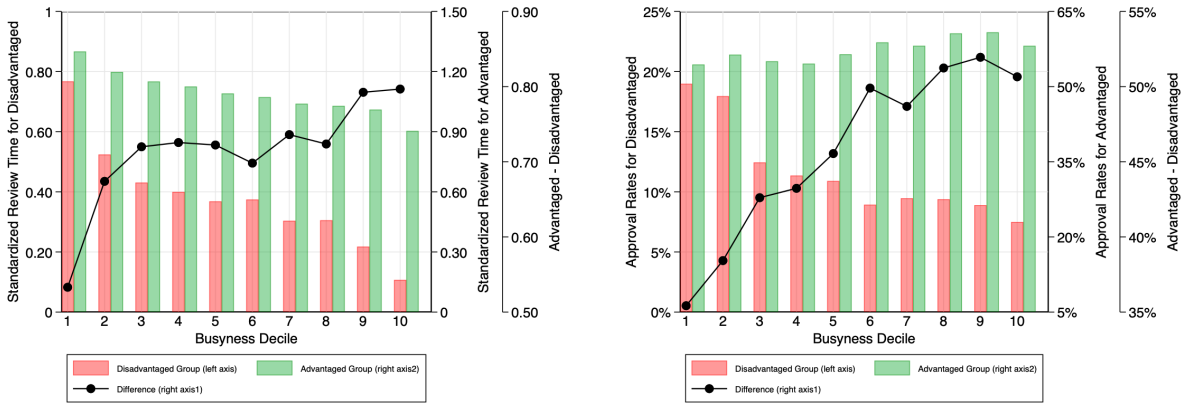
We find strong evidence that officers are more discriminatory against the disadvantaged applicants when they face stronger time constraints. This result is illustrated in Figure 1. In this plot, we classify applicants into advantaged and disadvantaged groups based on their possession of certificates. Specifically, we estimate the "certificates-implied approval rate" using a regression that combines all possible certificates and classifies applicants with below-median values as the disadvantaged group. Panel (a) plots officer attention — measured using average log number of minutes spent on each application — as a function of officer busyness. When officers are busier, they unavoidably spend less time on all applications. But the pattern is particular pronounced for the disadvantaged group. When busyness varies from the bottom to the top decile, review time of the disadvantaged applicants declines by

[9]Textual comments written by officers when screening applications also indicate that some certificates can help loan officers reduce information processing costs, as shown in Section 5.2.

[10]The most diagnostic certificate in our sample is the housing certificates. Applicants with housing certificates have 28.4% higher income, which is comparable to the income gap of White versus Black borrowers in U.S. mortgages (Bhutta and Hizmo (2021); Fuster, Goldsmith-Pinkham, Ramadorai, and Walther (2021)). The other certificates have weaker relationship with borrower quality .

Figure 1. Attention and Approval Rates by Officer Time Constraint.

We sort the sample into deciles by officer busyness, which is defined as the number of applications processed per day, and plot the average officer attention allocation in Panel (a) and loan application approval rate in Panel (b). The bars plot the average values for the advantaged and disadvantaged groups of applicants, and the black line plots the difference between the two groups. The advantaged group are the top half of applicants as judged by whether they possess various additional certificates, while the rest are the disadvantaged group. In Panel (a), officer attention is measured by a standardized version of how much time is spent by officers in reviewing the application. For visualization purposes, we also add back the full-sample mean to this variable. See Section 4.1 for more details.



(a) Officer attention allocation

(b) Application approval rate

almost 70%. Panel (b) plots the approval rates and shows that, when officers are more time constrained, the approval rate for the disadvantaged group declines monotonically from 19% to 7.5% — a three-fifths reduction. Meanwhile, the advantaged group is barely affected by officer business.

Using *realized* busyness of loan officers has a potential endogeneity issue, as officers can decide to work faster or slower. To alleviate this concern, we instrument the busyness measure by the number of applications *assigned* to the officer over the current and recent past days. Because the assignments are made by a central dispatcher algorithm over which officers have no control, this induces exogenous variation on loan officers' attention constraints. Although officers can keep a backlog, they almost always finish each assigned application in a few days, and assignments can explain 53% of realized loan officer busyness variation. We verified that assignments do not depend on backlogs, and that assignment-predicted busyness is not correlated with loan-level characteristics. Therefore, in subsequent work,

we use the assignment-predicted busyness as a measure of quasi-random variation in time constraints instead of the realized busyness measure.

After controlling for a comprehensive list of loan-level characteristics, we find the same results as that illustrated in Figure 1. When officers are busier, they shift more attention away from disadvantaged applicants and reject them more frequently. Our results are obtained after controlling for officer-month-year–fixed effects, so they are not driven by officer-specific preferences or aggregate variation over time. The findings are robust to alternative definitions of disadvantaged groups, and the effects on attention and approval are monotonic in assignment-predicted busyness variation.

In the last part of the empirical exercises, we provide further details about the nature of discrimination. First, we find that the reasons cited by officers to justify rejections also indicate attention discrimination. Among the rejected sample, advantaged applicants are more likely to receive a reason that indicates an officer has conducted further due diligence, such as calling reference contacts. However, disadvantaged applicants tend to be rejected based on information readily available on application materials. Second, internal notes and comments written by loan officers sheds further light on why officers use certain certificates to allocate attention: those certificates can reduce information processing costs. For instance, if an applicant has an income certificate, then officers do not need to check for regular salary payments on her bank statements. Finally, we discuss whether the certificates-based discrimination is statistical or taste-based. Unlike common taste-based discriminatory signals, such as physical beauty or religion affiliations, these certificates — by their very nature as information certificates — indicate that tasted-based discrimination is unlikely.[11] Results of the "outcomes test" of Becker (1957) is consistent with this view: the delinquency rate of approved loans in the advantaged and disadvantaged groups are not statistically different.

By showing that time constraints exacerbate discrimination, our paper contributes to the understanding of the mechanisms of discrimination. We show evidence consistent with

[11] We find no evidence of gender, race, or age-based discrimination in our data.

attention discrimination — i.e., discrimination due to differential attention allocation — and that this discrimination worsens when decision makers are busier.[12] While the behavior of "discrimination based on certificates" we document is perhaps more socially acceptable, the exact same mechanism can apply to more nefarious forms such as gender and racial discrimination. Because many real world decision makers are severely time constrained, we expect that our central insight about attention constraints will extend beyond our immediate context.[13] Our findings suggest that policies designed to relax attention constraints, such as by making use of automatic reporting programs to make information easier to process for decision makers, may reduce discrimination. Apart from the seminal paper on attention discrimination by Bartoš et al. (2016), our paper also connects to a long literature on discrimination, which we discuss in Section 1.1.

The documented behavior of loan officers may be efficient given their limited attention span. Some economists might wonder, if there is no clear inefficiency, why we should care about the differential treatment of groups? We believe the answer is that society cares. Widespread perception of unfairness in credit allocation can erode public trust and discourage participation (Zingales, 2015). Further, individual institutions also do not want to be perceived as unfair. Even though discrimination using certificates in lending is relatively socially acceptable, the bank we study would *cringe* to let the borrowers know that their applications, which take hours if not days to put together, may be quickly dismissed by a busy loan officer within a few minutes. It would be even more damaging to the bank's reputation if the public knows that the approval rate of an application can be reduced by more than half if it is assigned to a busy officer by chance.

[12] While we motivate the attention discrimination mechanism using a model with rational attention allocation (Section 2), our findings may also be driven by behavioral heuristics. Kahneman (2011) argues that people are more likely to engage in time-saving "System one" heuristics when acting under time pressure. From this perspective, it is also natural for loan officers to use simple signals such as certificates to *heuristically* guide their attention allocation. These two interpretations are hard to differentiate in our setting. However, regardless of the interpretation, both forms of discrimination lead to unfair treatment of disadvantaged borrowers.

[13] While the certificates-based discrimination is likely statistical in nature, preference-based discrimination can also be exacerbated by time constraints. See the illustrative model in Section 2 for details.

The rest of the paper is organized as follows. Section 2 uses a simple model to illustrate the attention discrimination mechanism and makes testable predictions. Section 3 describes the data and relevant institutional details on the loan-screening process. Section 4 shows that officers discriminate more when they face stronger attention constraints. Section 5 provides additional details on the mechanism and Section 6 concludes.

1.1 Related Literature

This paper is most related to the seminal work of Bartoš et al. (2016), who propose the idea of attention discrimination. Using experiments, they find that decision makers exert more effort collecting information on the advantaged (disadvantaged) group in selective (non-selective) markets, which is consistent with the notion of attention discrimination.[14] The key difference in this paper is our focus on the effects of attention constraint variation. More broadly, our paper is related to studies on decision making where attention is a scarce resource. For instance, Hirshleifer, Levi, Lourie, and Teoh (2019) show that financial analysts resort to more heuristic decisions on forecasts made later in the day. Liao, Wang, Xiang, Yan, and Yang (2020) document that peer-to-peer investors tend to use "system one thinking" and ignore credit-relevant information when acting under time pressure. Gabaix (2019) and Mackowiak, Matejka, and Wiederholt (2020) provide extensive reviews on modeling the effects of endogenous attention allocation. A number of papers have applied also the ideas of limited attention and endogenous attention allocation to finance settings.[15]

This paper also relates to the literature that investigates discrimination in financial markets. Copious studies have documented discriminatory practices in the mortgage credit (Bayer, Ferreira, and Ross, 2018; Bartlett, Morse, Stanton, and Wallace, 2019; Giacoletti et al., 2021; Ambrose, Conklin, and Lopez, 2021), consumer credit (Montoya, Parrado, Solís,

[14] Using a different set up, Davies et al. (2020) also shows theoretically that biases in decision-making can be magnified by endogenous information acquisition.

[15] For instance, see Peng (2005), Peng and Xiong (2006), Van Nieuwerburgh and Veldkamp (2010), Mondria (2010), Mondria and Quintana-Domeque (2012), Andrei and Hasler (2015), Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016), Hasler and Ornthanalai (2018), Huang, Huang, and Lin (2018), Liu, Peng, and Tang (2019), and Hirshleifer and Sheng (2019).

and Undurraga, 2020; Dobbie, Liberman, Paravisini, and Pathania, 2020), bank lending (Fisman, Paravisini, and Vig, 2017; Fisman, Sarkar, Skrastins, and Vig, 2020), auto loans (Charles, Hurst, and Stephens, 2008; Butler, Mayer, and Weston, 2020; Lanning, 2021), small business lending (Ongena and Popov, 2016; Brock and De Haas, 2021), microlending (Beck, Behr, and Madestam, 2018), and entrepreneurial financing arenas (Hebert, 2020; Ewens and Townsend, 2020; Hu and Ma, 2020; Zhang, 2020).

Different from these studies, in addition to documenting discrimination, we provide empirical evidence of attention discrimination which may be an underlining mechanism in some of the aforementioned studies. Interest in studying the impact of machine learning and artificial intelligence on discrimination has recently surged (Bartlett et al., 2019; Fuster et al., 2021; Jansen, Nguyen, Shams, et al., 2020; D'Acunto, Ghosh, Jain, and Rossi, 2020). Discrimination in lending is considered a serious threat to social fairness. In response, regulators in the U.S. and around the world have created anti-discrimination measures to combat discrimination in financial practices. For example, The Equal Credit Opportunity Act (ECOA) prohibits creditors from discriminating against credit applicants on the basis of race, color, religion, national origin, sex, marital status, and age.[16] Our paper adds to the literature by showing how discrimination in lending is amplified by attention constraints.

2 Conceptual Framework

Building on the model in Bartoš et al. (2016), we illustrate the attention discrimination mechanism and derive testable predictions in the retail loan application setting. Less interested readers can skip it with little cost as the intuition is already explained in the introduction. Proofs appear in Appendix A.

[16]See https://www.govinfo.gov/content/pkg/USCODE-2011-title15/html/USCODE-2011-title15-chap41-subchapIV.htm for more details.

Model set up. Consider a risk neutral loan officer deciding whether to approve an application to borrow one unit of capital for one period of time. Applicants come from different groups denoted by G, and the group identities are observable at no cost. The officer makes two decisions: 1) whether to incur an attention cost of c to learn more about the applicant, and 2) whether to approve or reject the application. Empirically, we think of the attention cost as the time and energy consumed in reading credit reports, scrutinizing the applicant's application forms, and so forth.

The interest rate r is fixed for simplicity. If the loan officer approves the application, the expected profit (not considering attention cost) is:

$$-\text{distaste}_G + \underbrace{(1-p)\cdot r}_{\text{interest payments if does not default}} - \underbrace{p}_{\text{loss from default}} \tag{1}$$

where distaste_G is a possible group-specific distaste and p is the expected default rate. For simplicity, Equation (1) assumes a zero recovery rate upon default. We also assume risk neutrality and zero time discounting.

The applicant's default probability p decomposes into three components:

$$p = \bar{p}_G + p_I + \epsilon \tag{2}$$

where $\bar{p}_G$ is a group-specific component known to the officer, $p_I \sim N(0, \sigma_G^2)$ is an applicant-specific component that can be learned by paying the attention cost c, and ϵ represents a mean-zero residual term that cannot be learned. p_I and ϵ are independent from each other.[17]

To match the fact that the loan screening process in our data is selective, we assume that $\bar{p}_G$ is high enough so that officers will not accept applications before paying attention.[18]

[17] Technically, using normal distributions for p_I can lead to default rates above 1 or below 0. But the results are qualitatively the same if we use other mean-zero distributions with bounded support.

[18] Formally, we need:

$$r \cdot (1 - \bar{p}_G) < \bar{p}_G + \text{distaste}_G. \tag{3}$$

Bartoš et al. (2016) calls this the "cherry-picking" condition. Importantly, this condition means that the *status quo* decision without paying attention is to *reject* the application.

This assumption should be uncontroversial in our setting, as it simply requires that no group of applicants is so uniformly good that its members' applications can be approved without any scrutiny. In our sample, the application process is fairly selective; only approximately one out of three applications is approved.[19]

Optimal loan officer behavior. As illustrated in Panel A of Figure 2, the optimal strategy for the loan officer is characterized by two threshold decisions. First, she will pay attention cost c if and only if the applicant is from a sufficiently advantaged group. Groups with lower $\bar{p}_G$, lower distaste_G, or higher σ_G are more advantaged. If c is sufficiently high, applicants from less advantaged groups will be rejected without attention.

Second, conditional on learning about p_I, the loan officer will accept applicants with default probability $\bar{p}_G + p_I$ lower than a threshold $\frac{r-\text{distaste}_G}{1+r}$ that guarantees non-negative profits (after adjusting for distaste) when lending to such an applicant.[20] The acceptance region is illustrated by the shaded areas in Panels (b) and (c) of Figure 2.

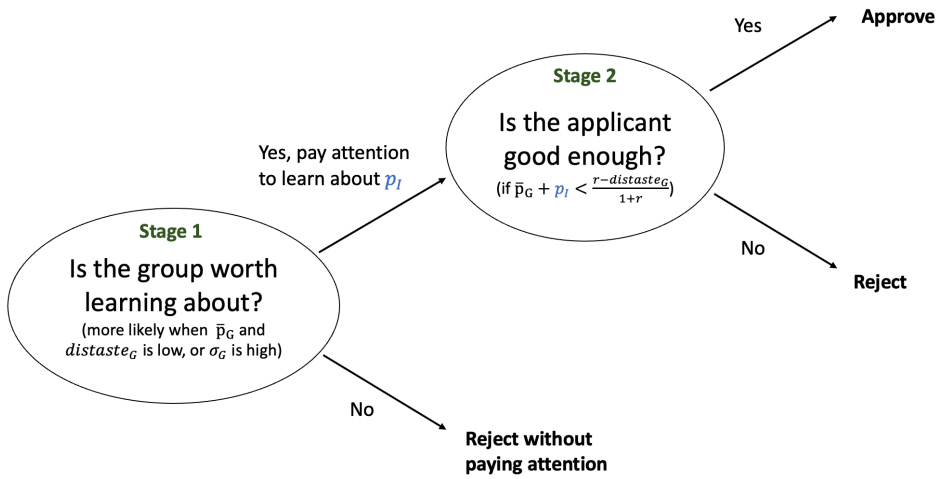
Which applicant groups are advantaged? The first-stage threshold of whether to acquire information arises from the trade-off between attention cost c and the expected benefit from learning about a group. In this paper, we call the applicant groups which loan officers are more willing to learn "advantaged." Groups can be advantaged for three reasons:

[19] This argument can be shown more formally using a simple back-of-the-envelope cost-benefit analysis. Consider a random loan application. The average interest rate in our data is approximately 8.6%. If the bank's cost of capital is equal to China's central bank rate of 3.25% in our sample period, this would mean the bank can only make a cost-adjusted annual return of 5.35% if the applicant does not default. In contrast, if the application defaults, if we assume a 40% recovery rate, the bank stands to loose 60%. Therefore, as long as the expected default rate of an average applications is higher than $\frac{5.35\%}{5.35\%+60\%} \approx 8\%$, the default action without sufficient information acquisition is rejection.

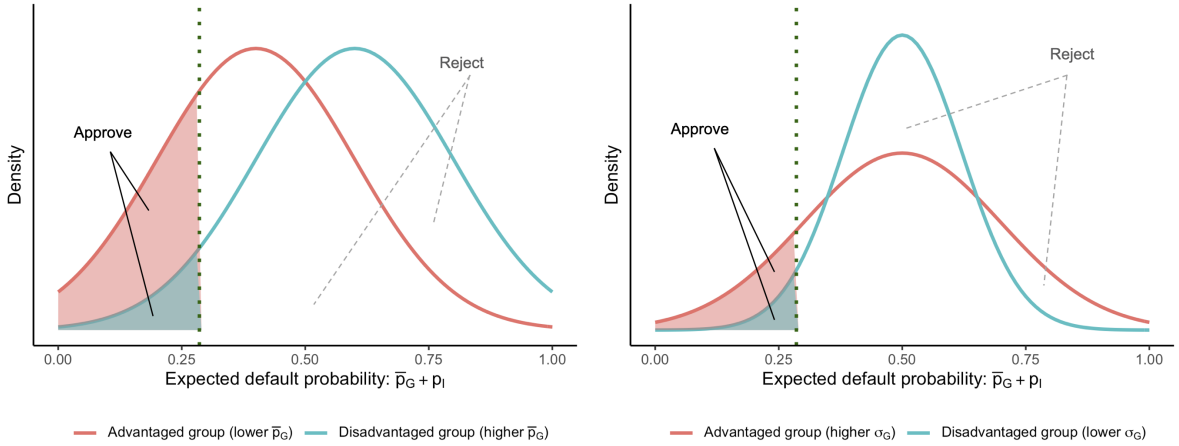
[20] The threshold is solved from:

$$\underbrace{(1-p^{\text{threshold}}) \cdot r - p^{\text{threshold}}}_{\text{expected profit from approving}} - \text{distaste}_G = 0 \quad \Rightarrow \quad p^{\text{threshold}} = \frac{r - \text{distaste}_G}{1+r}, \tag{4}$$

Figure 2. Illustration of The Model.
Panel (a): the optimal decision process of loan officers. At stage 1, the officer decides whether to incur attention cost c to learn the applicant-specific quality information p_I, given knowledge of which group the applicant comes from. Conditional on doing so, at stage 2, the officer decides whether to approve or reject the application. Panel (b): distribution of applicants from two hypothetical groups with different ex-ante average default probabilities $\bar{p}_G$. After acquiring applicant-specific information p_I, applicants with expected default rate $\bar{p}_G + p_I$ lower than a threshold, i.e., those in the shaded areas, will be approved. Panel (c): distribution of applicants from two groups with the same $\bar{p}_G$ but different σ_G^2, the variance of p_I which can be learned.



(a) Optimal decision of loan officers



(b) Groups with different means ($\bar{p}_G$) **(c)** Groups with different learn-able variances (σ_G^2)

1. Groups with lower distaste$_G$ are obviously advantaged. This reason maps squarely into standard preference-based discrimination a la Becker (1957).

2. Groups with lower $\bar{p}_G$ are advantaged. This is because, for such groups, the loan officer is more likely to end up being able to lend profitability after learning about p_I (Panel (b) of Figure 2).

3. Groups with higher σ_G are also advantaged. Under the cherry-picking condition, higher σ_G means that the officer is more likely to receive realizations of p_I that are large enough to make the applicant worth lending to (Panel (c) of Figure 2).

Testable predictions. Standard discussions of discrimination do not take into account attention costs. However, once non-negligible attention costs are considered, applicants from different groups will form an ordered ranking from the most to the least preferable (advantaged) ones. When attention cost increases, the loan officer will first reduce her attention to the most disadvantaged group, followed by the second disadvantaged group, etc.

The model is, by construction, very stark, as it predicts that, when the loan officer gets busy, she may discard all disadvantaged applicants without review. In practice, we can only imperfectly observe the groups into which loan officers classify applicants. Further, there are also variations in attention costs not observable to the econometrician. Therefore, the empirical result will not be as stark as our model predicts. Nevertheless, we anticipate the two model predictions will be *qualitatively* reflected in the data.

Prediction 1 (Attention discrimination) Applicants from ex-ante less advantaged groups (those with higher $\bar{p}_G$, higher distaste$_G$, or lower σ_G) will receive weakly less officer attention and be rejected more often.

Prediction 2 (Attention cost magnifies discrimination). Consider two groups, G_1 and G_2, where the former is more disadvantaged (those with higher $\bar{p}_G$, higher distaste$_G$, or lower σ_G)). If the existing attention cost c is sufficiently low that both groups receive

attention from loan officers, then the *gaps* of both attention and approval rate between the two groups will weakly increase with the attention cost.

What is the main innovation? Prediction 1 is also proposed and tested in Bartoš et al. (2016). The interpretation of discriminatory *attention allocation* can be consistent with the findings in the existing literature on discrimination. For instance, Bertrand and Mullainathan (2004) shows that résumés with Black-sounding names receive fewer interview callbacks. Callbacks are not the final hiring decision, but rather an attempt to gather more information. Hence, this evidence can also be interpreted as revealing attention discrimination.

Prediction 2 is the main innovation in this paper. In our empirical exercise, we use quasi-random variations in loan officer workload to perturb attention cost c, and we examine whether the attention and approval rate gaps between advantaged and disadvantaged groups widen. This mechanism, if true, is also policy relevant: policy makers can reduce discrimination by easing attention constraints of decision makers.

3 Data and Institutional Background

In this section, we describe our data and provide background information on the retail loan screening process.

We obtained the internal screening records of retail lending applications from one of the largest national banks in China. The data covers approximately 146,000 loan applications screened by 92 officers during April 2013 to April 2014. The borrowers include both wage/salary workers and small business owners. The loan terms and targeted borrowers are comparable to the retail financing products in the US. The loan maturity is 1–3 years; the median (mean) loan amount is 60,000 (66,461) Chinese RMB, equivalent to $9,787 ($10,841) US dollars, while the average personal installment loan size of around $16,000 in the U.S.[21] The average annual interest rate in our sample is 8.56%, which is similar to the the 2-year

[21]Source: `https://www.experian.com/blogs/ask-experian/research/personal-loan-study/`.

U.S. personal loan interest rate of about 10%, over the same sample period.[22] Summary statistics are presented in Table 1. Definitions of variables are in Appendix Table A1.

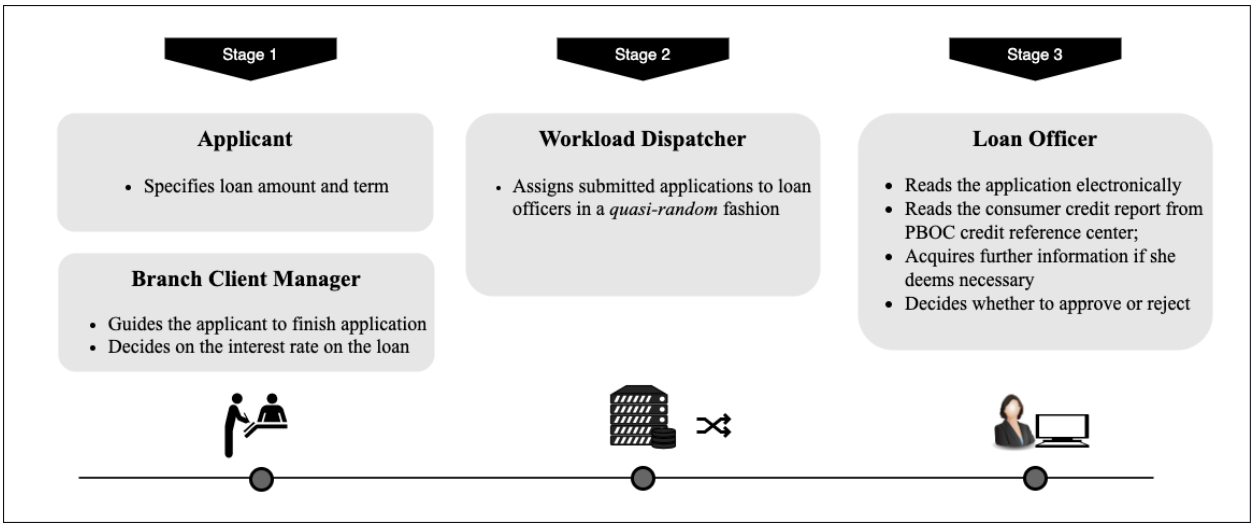
An unique feature of our data is that they include all the records from the application package, enabling us to investigate a loan officer's decision making behavior after controlling for the full set of applicant- and loan-level observables. The data provided by the bank include 111 variables extracted from application materials and 295 variables from central bank reports. These variables include almost all commonly used metrics for credit worthiness, such as leverage ratio, existing debt, credit history, income, education, and so forth. We construct a list of credit-relevant variables as controls for our analysis.

3.1 The Loan Screening Process

The screening process is illustrated in Figure 3. Our study focuses on the decisions of headquarter loan officers in stage three.

Figure 3. Flow Chart of Loan Origination and Screening.

In stage 1, loan applications are originated from regional bank branches across the country. Loan amount, maturity, and interest rate are already determined at this stage. In stage 2, a central algorithm randomly assigns applications to headquarter loan officers, who, in stage 3, read all relevant materials and decide whether to approve or reject the applications.



[22]Source: `https://www.federalreserve.gov/releases/g19/hist/cc_hist_tc_levels.html`.

Table 1. Summary Statistics.

This table presents summary statistics for the entire sample. The sample period is April 2013 through April 2014. *Delinquent* is only measurable on loan applications that are approved and issued. See Appendix Table A1 for variable definitions.

	N	Mean	SD	10%	25%	50%	75%	90%
Officer screening activities								
Approval	145,982	0.342	0.474	0	0	0	1	1
Delinquent	38,905	0.180	0.384	0	0	0	0	1
ReviewTime *(min)*	145,977	30.674	40.615	2.433	6.712	18.354	36.536	72.392
Busyness	145,982	19.150	6.979	10	15	19	24	27
Predicted Busyness	145,982	17.323	5.241	10.408	13.866	17.531	20.756	23.873
LOO Predicted Busyness	145,982	16.406	4.951	9.843	13.041	16.534	19.786	22.636
Assignment	145,982	17.621	9.410	5	11	18	24	30
Borrower certificates								
EmploymentCert	145,982	0.620	0.486	0	0	1	1	1
IncomeCert	145,982	0.342	0.474	0	0	0	1	1
HouseCert	145,982	0.223	0.417	0	0	0	0	1
ResidentCert	145,982	0.455	0.498	0	0	0	1	1
Borrower characteristics								
NoCreditHistory	145,982	0.173	0.379	0	0	0	0	1
LeverageRatio	145,982	0.268	0.850	0	0.017	0.103	0.276	0.543
OverdueMonth	145,982	1.073	1.829	0	0	0	1	3
CreditInqury	145,982	3.274	5.907	0	0	1	4	9
HasInvestmentAcc	145,982	0.007	0.081	0	0	0	0	0
NonStandardPay	145,982	0.634	0.482	0	0	1	1	1
SocialSecurity	145,982	0.406	0.491	0	0	0	1	1
Litigation	145,982	0.002	0.043	0	0	0	0	0
PrivateSector	145,982	0.890	0.313	0	1	1	1	1
Peasant	145,982	0.114	0.317	0	0	0	0	1
NonCollege	145,982	0.296	0.457	0	0	0	1	1
Female	145,982	0.240	0.427	0	0	0	0	1
Age	145,982	35.767	8.258	25.458	28.951	34.723	42.145	47.866
Income *(RMB)*	145,982	57,131	112,254	8,000	12,000	22,000	50,000	150,000
Loan characteristics								
LoanSize *(RMB)*	145,982	66,461	28,057	40,000	50,000	60,000	80,000	100,000
LoanToIncome	145,982	3.285	2.733	0.600	1.286	2.609	4.444	6.667
ShortTerm	145,982	0.279	0.449	0	0	0	1	1
InterestRate (%)	145,982	8.558	0.208	8.400	8.400	8.610	8.610	8.610

Stage one: loan origination. Loan applications are sourced from local bank branches all over China. Each applicant submits an application for a specific maturity and loan amount among one of the loan product types. The interest rate has already been determined at this stage by the local branches, but the application needs to be sent to headquarter loan officers — whose decisions we study — for approval.

Stage two: assignment of application to officers. After an application is complete, it is stored electronically in the bank's systems and then distributed by a central workload-dispatcher algorithm. The algorithm effectively randomly assigns the application to a headquarter officer, creating *quasi-random* variations in officer busyness that we later exploit (Section 4.2).

Stage three: headquarter loan officers' decisions. The assigned headquarter loan officer accesses applicant information electronically, conducts further due diligence if necessary, and subsequently decides whether to approve the application. Our sample includes a total of 92 officers. Out of a total of 145,982 applications, 34.2% are approved, and the rest are rejected. Our data contains the exact timestamps when applications are assigned to officers and when officers make a decision.[23]

3.2 Loan Officer Are Attention-Constrained

A key premise of the attention discrimination mechanism is that the decision maker faces attention constraints. This certainly holds for loan officers, who must scrutinize a wealth of material within a short period of time.

Officers receive numerous documents and forms in each application. Unlike the U.S., which has FICO scores, or Germany, which has Schufa scores, China did not have any widely

[23] Our conversations with loan officers reveal that their compensation scheme provides incentives to screen out high-risk applications, since their bonus can be affected by the default rate of loans they approve. Meanwhile, their compensation is also affected by the volume of loan origination, which suggests that these loan officers' screening criteria generally align with the bank's.

used numerical consumer credit-risk score during our sample period.[24] The bank we study also has no internal credit rating system that summarizes the credit quality of applicants. Therefore, the loan officers have no choice but to go through many pages of documentation and reports to extract information.

In our sample, the officers have access to the following three information sources:

1. Application forms and supplementary materials submitted by the applicant that contain information about the applicant's biography, purposes of borrowing, occupation, income and assets, etc. We estimate that the typical length of application forms is 10 to 20 pages, comparable to the length of mortgage application forms in the U.S.[25] Supplementary materials, such as bank statements or professional certificates, can easily contain hundreds of pages.

2. A report about the applicant from the central bank's credit reference center that includes detailed information about each borrower collected by the People's Bank of China (PBOC). This report contains, for instance, demographic information (e.g., the individual's personal identity, marital status, education background, and working status), credit payment information (e.g., detailed credit history on personal loans, credit cards, mortgage loans, guarantee and other credit accounts), and other public records from public administration authorities (e.g., past civil or criminal records). We estimate a typical report length here of around 10 pages.

3. Before approving an application, loan officers sometimes conduct further due diligence, such as researching the applicant online or making phone calls to relevant contacts like the applicant's employer.

Although officers do not always conduct further due diligence, they are required to review the first two sources of information.

[24] Only in 2015 did Alibaba's Zhima Credit launch the first credit agency in China; it uses a scoring system for individual users that leverages machine learning and big data within Alibaba's platform. However, Zhima Credit is not widely used in lending decisions at Chinese banks.

[25] https://themortgagereports.com/26785/mortgage-do-you-have-to-read-everything.

Because loan officers review applications in sequence, we can measure the amount of time spent reviewing each application as the amount of time elapsed between each consecutive decision made by the same loan officer.[26] Despite the large amount of materials to read, due to the heavy workload, officers only spend a median (mean) of 18 (31) minutes on each application. The time spent on each application in our sample is significantly shorter than equivalent loan review time in the U.S.[27]

3.3 Applicants without Certificates Are Disadvantaged

Given the time constraint, it is natural to expect loan officers to use simple signals to allocate their attention. That is, for applications that appear less advantaged based on some observable characteristics, the officers may decide to render a quick rejection.

In private conversations, multiple Chinese retail lending officers told us that they use supplementary certificates to help make quick decisions. In addition to regular loan application materials, some applicants provide official certificates for their employment, income, housing property, and residence location. Employment and income certificates are letters of verification issued by the applicant's employer, usually with the employer's letterhead, a company stamp, and the signature of the relevant company officials (e.g., from a manager or human resources). Appendix Figure A1 provides an example. Housing certificates are official ownership title documents issued by government agencies. Finally, residence certificates are usually, but not exclusively, utility bills. In our sample, the fractions of applicants with employment, income, house, and residence certificates are 62.0%, 34.2%, 22.3%, and 45.5%, respectively (Table 1).

[26] For instance, if a loan officer made one decision at 15:10:00 and another at 15:45:00, we measure the review time of the second application to be 35 minutes. The reviewing time is the total working minutes for reviewing each application. We also subtract lunch breaks (12pm–13pm) and all non-working period (including weekends, national holidays, and other off days) in computing review time. However, all our results are not sensitive to how we clean the review time measure.

[27] For a crude comparison, when examining a U.S. commercial bank, Agarwal and Ben-David (2018) find that 133 loan officers screened 30,268 loan applications over two years (their Table 1). In our data, 92 loan officers screened 145,982 applications over two years. This implies that their average review time is $\frac{133\times 2/30{,}268}{92\times 1/145{,}982} \approx 13.9$ times higher than that in our data.

Why would officers consider these certificates? First, applicants with these certificates have higher credit quality on average. For instance, those with house certificates obviously own real estate, while those without house certificates often do not and are thus less wealthy. Those who can provide residence certificates are more likely to stay at the same location for a longer period of time and thus are arguably more stable and dependable. Second, some of these certificates reduce the information processing cost of officers. For instance, income certificates state up front that the applicant receives a specific monthly salary. Without such a certificate, loan officers often need to look into applicants' historical bank statements to verify regular salary payments, which takes more effort. Section 5.2 provides more details on this cost-reduction aspect of certificates.

Which applicants can obtain these certificates? This is largely determined by types of employers or occupations. For instance, those working for large companies or the government can usually obtain employment and income certificates, while those who work for small private companies usually cannot. Self-employed and freelancing individuals cannot provide these certificates. As for house certificates, securing one largely depends on whether the applicant owns a house under his or her name. Finally, those who have been living in the current location for over a year are more likely to be able to provide residence certificates, while migrant workers often cannot.[28]

Applicants with certificates enjoy much higher approval rates. Our discussion so far suggests that applicants with no or fewer certificates are likely disadvantaged in the loan screening processing. Table 2 confirms that applications with certificates are much more likely approved. We regress the indicator variable of approval on dummies of whether the four

[28]There are also other institutional frictions that sometimes prevent applicants from providing certificates. Internal memos written by local bank branch officers, for example, reveal that some applicants cannot provide housing certificates because their houses are officially listed under the names of their spouse, children, or parents. This friction became more complex after 2010, when China placed restrictions on how many houses each individual can own. This policy is intended to cool down housing inflation by restricting demand, but it has also made "whose name to put on the official ownership title" a strategic choice, often not reflecting the actual ownership of property. There are also complications with the residence certificate. If the applicant lives with the family or friends, it is common for the utilities bill account to be under others' names and thus cannot be used by the applicant as residence certificates.

certificates are provided. After controlling for a comprehensive list of loan-level observables, we find that the existence of *each* of the four certificates leads to higher approval rates.[29] In the main specification in column 1, we control for loan type, bank branch, and officer-year-month–fixed effects. In terms of the marginal effects on approval rate, the most important certificate is the employment certificate, which increases the approval rate by 37.5%, followed by the house certificate (23.1%), residence certificate (14.0%), and the income certificate (3.2%). Columns 2 to 4 show that the result is not sensitive to which fixed effects are included.

Defining advantaged and disadvantaged applicants. Because all four certificates impact approval rate, it would be convenient to summarize their effects in a single variable. To do this, we compute the regression-predicted value of approval using the four certificates (without controls):

$$\begin{aligned}\text{AdvantageContinuous}_i &\equiv \widehat{\text{Approval}}_i|\{\text{EmploymentCert}_i, \text{IncomeCert}_i, \text{HouseCert}_i, \text{ResidentCert}_i\} \\ &= \hat{b}_{\text{EmploymentCert}} \cdot \text{EmploymentCert}_i + \hat{b}_{\text{IncomeCert}} \cdot \text{IncomeCert}_i \\ &\quad + \hat{b}_{\text{HouseCert}} \cdot \text{HouseCert}_i + \hat{b}_{\text{ResidentCert}} \cdot \text{ResidentCert}_i. \qquad (5)\end{aligned}$$

In other words, this is a continuous measure of how "advantaged" an application is as a result of having the certificates. For simplicity, in subsequent analysis, we also create an indicator variable of Advantage_i, which equals one for applications with values of $\text{AdvantageContinuous}_i$ above median. We call that group of applicants the "advantaged

[29] We control for log total income, log applied loan amount to income ratio, the applicant's pre-existing debt to total income ratio, log of one plus the longest number of months that the applicant has been overdue on payments in the recent two years, log of one plus the number of inquiries of applicant credit history in the recent two years, whether the applicant has no credit history, receives salary payment in a non-standard way (e.g., through cash payments), and has an investment account in the bank we study. We also control for the applicant's gender and age, and whether the applicant works for an private firm or is self-employed, has reported that she holds agricultural registered permanent residence in the application, has a non-college degree, has a social security allowance, and has been involved in legal cases. Finally, we control for the interest rate and maturity of the applied loan, both of which are already determined at local bank branches.

group" and the others the "disadvantaged group".[30]

Table 2. Applications with Certificates Enjoy Higher Approval Probability.

This table reports regressions of loan approval on dummy variables of whether the applicants have the four certificates, after controlling for other application-level characteristics. The outcome variable equals one if the application is approved and zero otherwise. EmploymentCert, IncomeCert, HouseCert, and ResidentCert are indicator variables of whether the applicant has official certificates on her employment, income, housing properties, and place of residence, respectively. The columns differ in whether certain fixed effects or controls are included. Controls include log(Income), Log(Loan/Income), log(1+LeverageRatio), log(1+OverdueMonth), log(1+CreditInqury), HasInvestmentAcc, NonStandardPay, Female, log(Age), PrivateSector, Peasant, NonCollege, SocialSecurity, Litigation, ShortTerm, and log(InterestRate). See Table A1 for variable definitions. Standard errors are double clustered at month-year and officer-loan type levels. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	Dependent variable: Approval			
	(1)	(2)	(3)	(4)
EmploymentCert	0.375***	0.377***	0.396***	0.372***
	(15.214)	(14.994)	(17.065)	(13.004)
IncomeCert	0.032*	0.033*	0.032*	0.025
	(2.051)	(2.026)	(2.153)	(1.516)
HouseCert	0.231***	0.237***	0.241***	0.238***
	(13.808)	(13.713)	(13.526)	(11.522)
ResidentCert	0.140***	0.144***	0.118***	0.121***
	(5.146)	(5.260)	(5.341)	(4.306)
Controls	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	N
Branch FE	Y	N	N	N
Loan type FE	Y	Y	N	N
Observation	145,982	145,982	145,982	145,982
Adjusted R-squared	0.368	0.359	0.359	0.339

Applicants with certificates have higher credit quality, but only on average. By comparing credit worthiness measures, we verify that the advantaged group of applicants indeed has higher credit quality, on average. However, there is still substantial overlap between the groups. That is, many applicants in the disadvantaged group are of better quality, based on commonly used credit worthiness metrics, than many in the advantaged group.

[30]Because $\text{AdvantageContinuous}_i$ is a weighted average of four dummy variables, it only takes $2^4 = 16$ discrete values. So the number of observations above the median is slightly different from 50%.

In Panel A of Table 3, we regress a number of credit worthiness metrics on an indicator variable of whether the applicant comes from the advantaged group. As with all other regressions at the application level in this paper, we control for officer-month-year–, bank branch–, and loan type–fixed effects. All these metrics indicate that the advantaged group has higher credit quality. Relative to the disadvantaged group, the advantaged group has 10.1% lower leverage ratio (existing debt to income), is 23.3% less likely to lack credit history, has 7.2% higher income, and has 5.6% lower loan to income ratio on its loan applications. All differences are statistically significant.

In Appendix Table A5, we examine each individual certificate separately and arrive at the same conclusion: those with certificates have higher credit quality. House certificate turns out to the most diagnostic signal, as those with the certificate have 28.4% higher income, which is comparable to the gap between black and white applicants in equivalent U.S. settings.[31] The other certificates produce smaller, but still statistically significant differences in the same direction.

If almost all disadvantaged applicants are worse than the advantaged ones, even without attention constraints, it would be efficient for loan officers to ignore members of the disadvantaged group. However, Panel B of Table 3 shows that there is substantial overlap between the two groups, according to all metrics. Panel B presents the distribution of the credit quality metrics after regressing out the fixed effects, as in Panel A, and adding back the full-sample averages. The final column reports the fraction of disadvantaged applicants with characteristics better than the median advantaged applicant. In fact, 46.1% (and 47.1%) of disadvantaged applicants have higher income (and lower loan to income ratio) than the median advantaged applicant; 33.5% have lower pre-existing leverage. Therefore, quick rejection of the disadvantaged group without careful review would be unfair to the applicants.

[31] For example, Bhutta and Hizmo (2021) show that African American borrowers' income is about 10% lower than white borrowers. In Fuster et al. (2021), the income gap between black and white borrowers is about 17%.

Table 3. Credit Quality of Advantaged and Disadvantaged Applicants.

This table compares the creditworthiness of applicants from different groups. The advantaged group is defined as applicants with sufficient certificates so that her AdvantageContinuous (Equation (5)) is above median. LeverageRatio is defined as existing debt to income ratio for the subset of applicants with credit history, and NoCreditHistory is an indicator that equals one for those without credit history. LoanToIncome is the loan amount to income ratio. Panel A reports regressions of creditworthiness measures on whether the applicant is in the advantaged group. The regressions control for officer-month-year–, bank branch–, and loan type–fixed effects. Standard errors are double clustered at month-year and officer-loan type levels; $*p < 0.1; **p < 0.05; ***p < 0.01$. Panel B reports, by applicant group, the distribution of the residual of credit measures after regressing out the fixed effects and adding back sample mean. The last column reports the fraction of disadvantaged applicants with better quality than the median advantaged applicant according to each measure.

Panel A. Credit quality measures by whether applicants are advantaged

	log(1+LeverageRatio) (1)	NoCreditHistory (2)	log(Income) (3)	log(LoanToIncome) (4)
Advantaged	-0.101^{***}	-0.233^{***}	0.072^{***}	-0.056^{***}
	(−9.520)	(−12.706)	(4.207)	(−3.915)
Officer-Month-Yr FE	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y
Observation	120,649	145,982	145,982	145,982
Adjusted R-squared	0.071	0.141	0.490	0.413

Panel B. Distribution of credit quality measures

Credit quality measure	Group	N	Mean	SD	10%	25%	50%	75%	90%	% better
log(1+LeverageRatio)	Disadvantaged	54,019	0.222	0.351	-0.013	0.039	0.120	0.272	0.535	33.5%
	Advantaged	66,634	0.147	0.194	-0.025	0.026	0.103	0.219	0.361	
NoCreditHistory	Disadvantaged	73,021	0.267	0.430	-0.049	-0.008	0.044	0.895	1.001	31.6%
	Advantaged	72,961	0.080	0.281	-0.070	-0.034	0.002	0.042	0.085	
log(Income)	Disadvantaged	73,021	10.165	0.801	9.209	9.622	10.104	10.643	11.192	46.1%
	Advantaged	72,961	10.240	0.775	9.315	9.711	10.181	10.696	11.231	
log(LoanToIncome)	Disadvantaged	73,021	0.854	0.730	-0.061	0.425	0.903	1.342	1.707	47.1%
	Advantaged	72,961	0.795	0.716	-0.113	0.382	0.854	1.274	1.634	

4 Does Attention Constraint Exacerbate Discrimination?

This section tests the main empirical prediction of our paper: when officers face stronger attention constraints, they will pay less attention to ex-ante disadvantaged applicants and reject them more frequently.

4.1 Do Loan Officers Discriminate More When Busier?

As mentioned in Section 3.1, because we have access to internal timestamps of actions in the bank, we can use the time elapsed between two consecutive officer decisions to measure how much time is spent reviewing each application. To remove review time variation that is likely not due to active officer choices, we define "standardized review time" as the log deviation of review time from the values implied by the fixed effects.[32] As reported in Table 1, the interquartile range of this attention measure (standardized review time) is -0.580 to 0.408.

To proxy for officer time constraint, we use variable $\text{Busyness}_{j,d}$, defined as the number of applications that officer j processes on day d. The reasoning is straightforward: the more applications the officer has to process, the less time she can afford to spend on each one. As shown in Table 1, the median officer processes 19 applications in a day, and the 10th and 90th percentiles are 10 and 27, respectively. Therefore, there is a substantial variation in officer busyness and the concomitant time constraint on each application.

We are now ready to test the main prediction. We start by simply plotting average at-

[32] Specifically, we compute:

$$\text{StandardizedReviewTime} = \log\left(\frac{\text{ReviewTime}}{\text{Median ReviewTime by Bin}}\right) + \text{Average } \log(\text{ReviewTime}) \tag{6}$$

where the bins in the denominator are Officer $\times$ Month-Year $\times$ Loan Type $\times$ Bank Branch buckets. In other words, we remove the review time variation explained by the interaction of all the fixed effects we have used in regressions, and then we add back the sample average. These fixed effects explain up 36% of log review time variation, as shown in Table A7 in the Appendix. We remove the fixed effects–spanned variation because it likely does not represent active officer choices. For instance, less experienced officers may take longer to process each application. Also, officers may become more proficient at processing applications over time, so we also include year-month–fixed effects.

tention and approval rates in Figure 1. We sort the sample into deciles by realized officer busyness and plot the average standardized review time for the advantaged and disadvantaged groups separately. In Panel (a), consistent with the notion of attention discrimination, the disadvantaged applicants receives significantly less attention, on average. More importantly, the attention *gap* between the two groups increases as officers get busier, as shown by the black line. That is, when officers become busier, they shift attention *away* from the disadvantaged applicants. The right panel plots the approval rate. When officers become busier, the approval rate of the disadvantaged group declines steadily, from 19% in the bottom busyness decile to around only 7.5% in the top busyness decile, while the advantaged group is barely affected.

To more formally estimate the effects of officer time constraint, we now use regressions and include loan-level controls and various fixed effects. In columns (1) and (2) of Table 4, we regress standardized review time on interactions of continuous or discrete measures of applicant advantage and officer busyness decile. The continuous advantage variable is the certificates-predicted approval rate in Equation (5), and the discrete measure is an indicator that equals one if the applicant is in the advantaged group. We cluster standard errors by month-year and officer $\times$ loan types. Similar to the visual trend in Figure 1, when officers are busier, the attention gap between the advantaged and disadvantaged groups widens. For instance, column (2) shows that, when officer busyness varies from the top to the bottom decile, the attention on disadvantaged applicants decline by $(10-1) \times -0.06 \approx 54\%$. This relationship has a t-statistic of -9.647. Columns (1) and (2) in Table 5 present results on approval rates. Column (2) shows that, for the disadvantaged group of applicants, top to bottom decile variation of officer busyness implies that the approval rate declines by $(10-1) \times -0.007 \approx 6.3\%$. In contrast, the approval rate for the advantaged group increased modestly. Overall, these results are consistent with the main prediction that, when facing tighter attention constraints, loan officers shift attention away from disadvantaged applicants, leading to a lower approval rate.

It is worth noting that our regressions control for officer × month-year–fixed effects. Therefore, our findings do not stem from differences in officer-specific preferences or time trends. We have also controlled for the variables related to borrower creditworthiness. In unreported robustness checks, we find that our results are not sensitive to the choice of control variables.

Table 4. The Effect of Officer Time Constraint on Application Review Time.

This table reports the interaction effect of application advantage and officer busyness on attention allocation to loan applicants. The dependent variable is the standardized application review time, defined as the logarithm of the excess time spent by officers in reviewing each application (Equation (6)). AdvantageContinuous is the fitted value of average approval rate using the four certificates (Equation (5)). Advantage is a dummy variable for whether AdvantageContinuous is above median. BusynessDecile is the officer's daily busyness, defined as the number of applications processed on a day, sorted into deciles. Columns (1) and (2) use realized busyness; Columns (3) and (4) use the assignment-predicted busyness; Columns (5) and (6) use the leave-one-out (LOO) assignment-predicted busyness. The regressions include officer × month-year–fixed effects, origination bank branch–fixed effects, and loan type–fixed effects. Controls includes log(Income), Log(Loan/Income), log(1+LeverageRatio), log(1+OverdueMonth), log(1+CreditInqury), HasInvestmentAcc, NonStandardPay, Female, log(Age), PrivateSector, Peasant, NonCollege, SocialSecurity, Litigation, ShortTerm, and log(InterestRate). See Table A1 for variable definitions. T-statistics are reported in parentheses. Standard errors are double clustered at month-year and officer-loan type levels. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	Dependent Variable: Standardized Review Time					
	Actual Busyness		Predicted Busyness		Predicted Busyness(LOO)	
	(1)	(2)	(3)	(4)	(5)	(6)
BusynessDecile	−0.060***	−0.060***	−0.028***	−0.028***	−0.022***	−0.022***
	(−9.647)	(−9.825)	(−5.409)	(−5.469)	(−4.152)	(−4.199)
Advantage	0.456***		0.477***		0.483***	
	(9.534)		(10.862)		(10.866)	
Advantage× BusynessDecile	0.018**		0.015**		0.014**	
	(2.470)		(2.497)		(2.316)	
AdvantageContinuous		0.764***		0.808***		0.819***
		(9.359)		(10.736)		(10.774)
AdvantageContinuous× BusynessDecile		0.032**		0.026**		0.024**
		(2.658)		(2.503)		(2.289)
Controls	Y	Y	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y
Observation	145,977	145,977	145,977	145,977	145,977	145,977
Adjusted R-squared	0.088	0.086	0.081	0.080	0.082	0.080

Table 5. The Effect of Officer Time Constraint on Application Approval Rate.

This table reports the interaction effect of application advantage and officer busyness on attention allocation to loan applicants. The dependent variable is a dummy variable of whether the officer approves the application. AdvantageContinuous is the fitted value of the average approval rate using the four certificates (Equation (5)). Advantage is a dummy variable for whether AdvantageContinuous is above median. BusynessDecile is the officer's daily busyness, defined as the number of applications processed on a day, sorted into deciles. Columns (1) and (2) use realized busyness; Columns (3) and (4) use the assignment-predicted busyness; Columns (5) and (6) use the leave-one-out (LOO) assignment-predicted busyness. The regressions include officer × month-year–fixed effects, origination bank branch–fixed effects, and loan type–fixed effects. Controls includes log(Income), Log(Loan/Income), log(1+LeverageRatio), log(1+OverdueMonth), log(1+CreditInqury), HasInvestmentAcc, NonStandardPay, Female, log(Age), PrivateSector, Peasant, NonCollege, SocialSecurity, Litigation, ShortTerm, and log(InterestRate). See Table A1 for variable definitions. T-statistics are reported in parentheses. Standard errors are double clustered at month-year and officer-loan type levels. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	Dependent Variable: Approval					
	Actual Busyness		Predicted Busyness		LOO Predicted Busyness	
	(1)	(2)	(3)	(4)	(5)	(6)
BusynessDecile	-0.007***	−0.007***	−0.004**	−0.004**	−0.005**	−0.005**
	(−7.222)	(−6.541)	(−2.973)	(−2.654)	(−3.020)	(−2.681)
Advantage	0.534***		0.511***		0.510***	
	(25.713)		(22.768)		(21.843)	
Advantage× BusynessDecile	0.007***		0.011***		0.011***	
	(3.631)		(6.137)		(5.750)	
AdvantageContinuous		0.951***		0.914***		0.913***
		(28.329)		(24.701)		(23.859)
AdvantageContinuous× BusynessDecile		0.013***		0.019***		0.020***
		(3.517)		(5.204)		(5.043)
Controls	Y	Y	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.357	0.367	0.358	0.367	0.358	0.367

4.2 Quasi-Random Variations of Officer Busyness

Using realized loan officer busyness suffers from a potential endogeneity problem: officers can choose to work more or less quickly. For instance, an officer who wants to slack off on a particular day may choose to quickly reject many applications carelessly, leading to a negative correlation between busyness and approval rate.

To overcome this endogeneity challenge, it is important to find an external source of busyness variation that is not controlled by officers. Fortunately, as described in Section 3.1, applications are assigned to officers by a central-dispatcher algorithm over which officers have no control over. Therefore, we can use of the algorithm assignment–induced workload variation to obtain a cleaner measure of officer busyness.

Though the bank does not disclose how its exactly algorithm assigns applications to officers, we are informed that officers have no influence on this assignment process, and also that the algorithm does not take loan characteristics into account when making assignments. Thus, the number of assignments is exogenous from the officer's point of view.

In Appendix Table A3, we verify whether the algorithm takes into account the existing backlog of officers when assigning applications. This verification is important, because if the algorithm slows down assignments to those with larger backlogs, officers can indirectly control their own busyness. For example, they can end up having fewer assignments by shirking. Consistent with the description that the bank provided, we find that assignments are not related by current or earlier backlogs.

We now use assignments as an instrument to predict officer busyness:

$$\text{Busyness}_{j,d} = a + \sum_{\tau=0}^{3} b_\tau \cdot \text{Assignment}_{j,d-\tau} + \epsilon_{j,d} \tag{7}$$

where $\text{Assignment}_{j,d}$ is the number of applications assigned to officer j on day d. We also include three lagged business days in addition to the contemporaneous one because some applications are reviewed a few days after assignment. This regression has an R^2 of 52.7%,

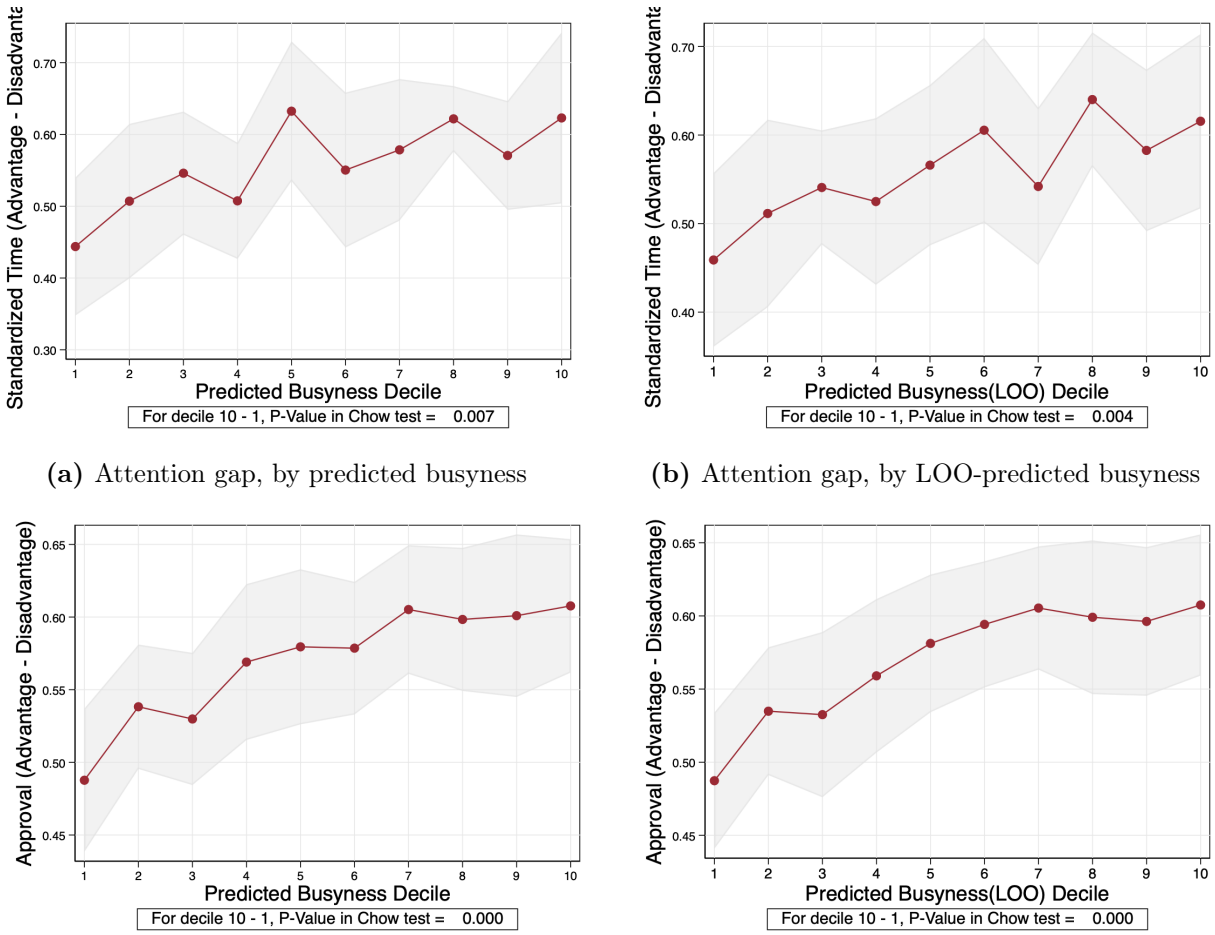
showing that assignments account for over half of the variation in realized busyness. Appendix Table A2 shows regression details. From now on, we call the predicted value of regression (7) "Predicted Busyness" and, to alleviate the endogeneity concern, use it instead of realized busyness. In Panel A of Appendix Table A4, we verify that this predicted busyness measure is uncorrelated with observable loan characteristics, consistent with our understanding that the dispatcher algorithm does not take into account loan characteristics when assigning workload.

Because we do not have the source code of the dispatcher algorithm, even though we find no correlation of the predicted busyness measure with loan observables, one might still worry about correlations with unobservables. To partially address this concern, we also construct a loan-level, leave-one-out instrument using the number of applications from other provinces assigned to the same loan officer. Recall that the loan officers we study are at the headquarter office, while applications are sourced from bank branches all over the country. The idea of this instrument is that, if a large number of assignments from province A makes the loan officer busy, this could affect her decisions on applications from province B. In this case, the quality of loans from province B is independent of the application volume from province A that drives the busyness of the loan officer (after controlling for the application volume in the province B). Panel B of Table A4 verifies that the busyness measure constructed using this method, which we call LOO-Predicted Busyness, is also not correlated with loan observables. In subsequent analysis, we report results using both Predicted and LOO-Predicted Busyness.

We re-examine our main results using these instrumented busyness measures. In Tables 4 and 5, columns (3) and (4) report results using predicted busyness, and columns (5) and (6) report results using LOO-predicted busyness. In all cases, the results are qualitatively unchanged. In all specifications, we find that the disadvantaged applicants receive less attention and have lower approval rates when officers become busier. In Appendix Figure A2, we reproduce Figure 1 using these predicted busyness measures and find qualitatively similar results.

Figure 4. The Effect of Officer Time Constraint is Monotone.

We estimate the effect of officer busyness on the attention and approval differences between advantaged and disadvantaged applicants. Specifically, we regress officer attention and the loan approval indicator variable on the interaction between an applicant advantage indicator and ten decile indicators of officer busyness. We then plot the interaction of busyness indicators with the advantage indicator. The top panels plot the results on officer attention, measured as the standardized log review time on each application. The bottom panels plot the results on approval. The left panels use assignment predicted busyness, while the right panels use leave-one-out (LOO) assignment-predicted busyness. The use of fixed effects, controls, and standard error clustering are the same as those in Tables 4 and 5. The shaded areas represent 95% confidence intervals. The Chow-test reported in the legend is a test of the coefficient differences between the first and last deciles.



(a) Attention gap, by predicted busyness

(b) Attention gap, by LOO-predicted busyness

(c) Approval gap, by predicted busyness

(d) Approval gap, by LOO-predicted busyness

We also verify that the effects of busyness on attention and approval rates are monotonic. Although this pattern is suggested in Figures 1, we formally test it using regressions and plot the results in Figure 4. Instead of using busyness decile as a numerical variable from 1 to 10, we now include it as decile indicators in the regressions. We then plot the estimated

interaction effects with the advantaged applicant indicator. Finally, Table A6 shows that our results are robust to measuring advantage using each of the four individual certificates.

5 Additional Findings about the Mechanism

This section provides additional details on the mechanism of attention discrimination by using textual comments and remarks on the applications of loan officers. Although the texts are less standardized and harder to use for formal quantitative analysis, Sections 5.1 and 5.2 shed further light on the thinking process of officers.

5.1 Evidence of Attention Discrimination Based on Rejection Codes

This section provides suggestive evidence of differential attention allocation using the rejection reasons cited by loan officers. At the bank we study, loan officers need to select from a list of reasons as they render a rejection. 127 rejections reasons are available to select from, but some are much more commonly chosen than the others. In the sample, top 10 (50) reasons covers 69% (96%) of all rejections.

Some rejection reasons indicate that the loan officer, before rejecting, attempted further due diligence to gain knowledge beyond that available in application materials, while other reasons do not. We manually classify all rejection reasons and list them in Table 6. Panel A lists the rejection reasons that reveal further due diligence. Most of them show that the loan officer has attempted to make phone calls to the applicant, her employer, or other contacts. In some cases, the officer also gathered third-party information, which may include online searches, about the applicant. Overall, 25.5% of rejected applications have rejection reasons that fall under this category. In contrast, the other applications' rejection reasons in Panel B only cite reasons immediately available using the application materials. These reasons are usually about leverage, credit history, employment history, or vague reasons such as "Other reasons."

This classification is admittedly crude, but, nonetheless, the review times associated with these rejection reasons indicate that the classification meaningfully correlates with officer attention. The last column in Table 6 shows the median review time when each of the rejection reasons is used, and the last row in each panel shows the observation-weighted average. Overall, when citing rejection reasons associated with due diligence, officers spend 20.4 minutes in review and only 10.4 minutes otherwise.

Table 6. Most Commonly Cited Rejection Reasons

Loan officers are asked to select from a list of rejection reasons when rejecting an application. We manually separate them into two categories by whether they indicate that the officer has engaged in additional due diligence, such as making phone calls or conducting online searches. Panel A lists the ten most frequently cited rejection reasons that indicate further due diligence, and Panel B lists those that do not. The last column shows the median review time by officers when citing a particular rejection reason.

Panel A: Cited rejection reasons indicating further due diligence				
Rank	Cited rejection reasons	Obs	Fraction	Review time (min)
1	Called and found discrepancies	13,402	54.8%	24.0
2	Employer phone number does not exist	3,254	13.3%	16.4
3	Cannot reach employer by phone	2,753	11.2%	10.1
4	Employer said that applicant does not work there	1,537	6.3%	14.4
5	Invalid references contact information	1,420	5.8%	26.0
6	References cannot be reached	573	2.3%	12.5
7	Cannot verify employment information	487	2.0%	19.0
8	Found issues when contacting third party	461	1.9%	18.2
9	Applicant/references did not cooperate with due diligence	169	0.7%	20.5
10	Discovered issues in further investigation	158	0.6%	27.1
Others		262	1.1%	18.7
Average				20.4
Panel B: Cited rejection reasons that do not indicate further due diligence				
Rank	Cited rejection reasons	Obs	Fraction	Review time (min)
1	Leverage is too high	19,430	27.1%	12.1
2	Unfavorable credit card history	7,920	11.1%	4.4
3	Insufficient credit history	7,334	10.2%	4.7
4	Other reasons	4,524	6.3%	14.9
5	Overall too risky	3,124	4.4%	15.2
6	Unfavorable loan repayment history	2,759	3.9%	4.6
7	Unfavorable credit card history per the PBOC	2,216	3.1%	6.3
8	Too many credit requests	1,672	2.3%	4.6
9	Unstable employment	1,183	1.7%	16.5
10	Insufficient employment or business history	1,123	1.6%	14.4
Others		20,283	28.3%	12.8
Average				10.4

If officers engage in attention discrimination, we would expect advantaged applicants with certificates to more likely receive rejection reasons that indicate further information acquisition. Table 7 confirms that this is the case. Column (1) shows that applicants in the advantaged group are 22.5% more likely to receive such rejection reasons; column (2) estimates the effect using the continuous advantage measure. Columns (3) to (6) show that similar effects are present when using each individual certificate.

Table 7. Frequency of Rejection Reasons Indicating Further Due Diligence

We estimate regressions on the sample of rejected applications. The outcome variable is an indicator that equals one if the cited rejection reason indicates that the loan officer has engaged in further due diligence (Panel A in Table 7), and zero otherwise. Column (1) estimates the effect of an applicant in the advantaged group, and column (2) estimates the effect of AdvantageContinous, a continuous measure that summarizes the benefits of having certificates. Columns (3) to (6) estimate the effects of individual certificates. As in Table 5, we control for applicant-level characteristics and officer-month-year, loan type, and bank branch–fixed effects. Standard errors are double clustered at month-year and officer-loan type levels. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	Dependent variable: HasInfoAcquisition					
	(1)	(2)	(3)	(4)	(5)	(6)
Advantage	0.225***					
	(13.585)					
AdvantageContinuous		0.407***				
		(14.388)				
EmploymentCert			0.221***			
			(13.313)			
IncomeCert				0.143***		
				(8.928)		
HouseCert					0.219***	
					(10.851)	
ResidentCert						0.144***
						(8.785)
Controls	Y	Y	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y
Observation	96,009	96,009	96,009	96,009	96,009	96,009
Adjusted R-squared	0.163	0.164	0.162	0.145	0.156	0.142

5.2 Some Certificates Reduce Information Processing Costs

Why do officers use the certificates to guide their attention allocation? In the case of house certificate, the reasoning is relatively straightforward. We find that applicants with house certificates have, on average, 28.4% higher income and 17.2% lower loan-to-income ratio than those who do not, a differences comparable to the black–white borrower applicant gap in the U.S. However, the use of the other certificates is less transparent. Although applicants with those certificates also have higher income and lower leverage, the difference is much smaller (Table A5).

So why do officers still rely on these other certificates? We find anecdotal evidence that the certificates are valuable because they reduce information-acquisition costs for loan officers.[33] As officers process loan applications, they often also write textual comments, which provide us a lens into their thinking process. Table 8 provides sample comments. When missing employment certificates, officers sometimes feel the need to call the employer (as shown by the first sample comment), or check the central bank (PBOC) report, to verify employment information. When missing income certificate, officers often need to check the applicant's banking statement for regular salary payments. The case of missing resident certificates sometimes also results in officers making additional phone calls to verify applicant's residence. In other words, officers can still obtain these information without certificates, but doing so can be time consuming.

Informal conversations with personal loan officers in China confirm this view. Besides the fact that applicants with certificates have higher credit quality, certificates are very valuable to officers for reducing information processing time. From the perspective of attention discrimination, the loan officers' reliance on certificates creates a disadvantage for applicants who cannot provide these certificates. The discussion in this section is anecdotal in nature, so the conclusion should be viewed as suggestive. Nevertheless, the evidence suggests that

[33] In the terminology of the model in Section 2, applications with these certificates have higher σ_G^2. That is, the loan officer can learn more about the applicant by paying the same amount of attention cost.

Table 8. Sample Comments Written by Officers on Applications.

Loan officers often write textual comments when they process applications that give a glimpse into their thinking process. This table provides sample comment excerpts. When certificates are lacking, officers often need to do further work to ascertain information about applicants.

Lacking	No.	Officer comment excerpts
Employment certificate	1	...no employment certificate. Verified with applicant's employer via phone ...
	2	...no employment certificate... Has been working at the same place, and can verify that against PBOC report ...
Income certificate	1	...No income certificate. Checked that receive monthly salary over online banking account of 5,859, so verified monthly income to be 5,859 ...
	2	...No income certificate. Used bank statement to verify salary payments. Applicants receives additional subsidies, so actual income is higher than stated salary income.
	3	...Has labor contract but not income certificate ...Verified that monthly income is 5207 ...
Resident certificate	1	...applicant currently lives in an apartment owned by the spouse's employer ...
	2	...called. Spouse says he lives in his own house ...

the information cost-reduction benefit of certificates likely plays a role in our main findings.

5.3 Statistical- versus Taste-Based Discrimination

The discussion so far indicates that discrimination based on certificates is likely statistical in nature. Applicants with these certificates have a higher credit quality and are arguably easier to learn about. Further, because these variables are not sensitive demographic characteristics such as race or gender, they are unlikely to induce taste-based discrimination ex-ante.

To be more certain about our interpretation, we use the "outcome test" of Becker (1957) to examine possible taste-based discrimination. If the discrimination against disadvantaged applicants is taste-based, then we should expect that only the very high quality disadvantaged applicants would be approved, resulting in much lower delinquency rates among the marginally disadvantaged applicants whose applications are approved. Of course, this test suffers from the classic "infra-marginality" problem: we do not observe the marginal cases, so we can only examine *average* outcome which is only a noisy proxy of the marginal outcome (Simoiu, Corbett-Davies, Goel, et al., 2017).

We apply the outcomes test and find no evidence for taste-based discrimination. In Table A8, we predict whether a loan becomes delinquent after being approved using OLS, logit, and Cox regressions. In all cases, we find no statistically significant delinquency rate differences between the advantaged and disadvantaged groups. We also find no evidence that delinquency rate varies with officer busyness.[34] Therefore, the results are consistent with the certificates-based discrimination being statistical in nature.[35]

6 Conclusion

Discriminatory treatment of disadvantaged groups has been documented in many settings, including labor markets, credit access, and college admissions, among many others. But while it is easy to document discrimination, it has been hard to find ways to combat discrimination. Our paper hardly offers a magic bullet to tackling an enormous social problem, but it does hint at some realistic reforms to make a dent at discrimination.

Motivated by Bartoš et al. (2016), we propose that discrimination is exacerbated by attention constraints. Our *attention discrimination* predicts that, acting under attention constraints in selective processes, decision makers can endogenously choose to pay less attention to ex-ante disadvantaged counterparts, leading to more unfavorable outcomes for the disadvantaged than a hypothetical world in which officers cannot allocate attention. Moreover, this attention-based discrimination exacerbates when attention constraints become stronger.

Using the proprietary retail loan screening records of a large Chinese bank, we show that loan officers indeed discriminate more when they are busier. The loan officers are quite time constrained, only spending a median of 18 minutes on each application. Under this backdrop, applicants who can submit a number of certificates — which indicate higher average credit quality and also help officers process information more quickly — are advantaged. In

[34]This outcome test result needs to be qualified by the fact that we only have incomplete observation of delinquency. Because our data records ended in April 2014, many loans have not yet matured. Due to this shortcoming, we also estimated Cox regressions, which have hazard rates as the dependent variable, in columns (5) and (6) of Table A8.

[35]We did not find evidence of taste-based discrimination based on gender, ethnicity, or age in our data.

contrast, those who cannot submit certificates are disadvantaged, even though many of them are of high credit quality. Consistent with our predictions, we find that loan officers spend much less time on disadvantaged applicants and reject them more frequently. Further, when officers become busier due to quasi-random variations in workload assignment, the attention discrimination against the disadvantaged applicants is more severe.

Our findings have important implications for designing policies to combat discrimination. Many high-stakes decision makers are usually busy and face serious time constraints, suggesting that the attention discrimination mechanism might be one of the key factors behind discrimination in many settings. Therefore, relaxing decision makers' attention constraints may help alleviate discrimination. Anecdotal evidence suggests that the connection between attention and discrimination is not fully appreciated. For instance, it is often recommended that recruiters solicit a larger applicant pool to reduce discrimination and promote diversity. However, if the number of recruiters cannot keep up with the increasing application volume, each application will be given even less time. Our findings suggest that more discrimination, rather than less, will result from such policies.

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APPENDIX

A Solving the Model

In the second stage, after acquiring information about p_I, the expected profit of lending to such an applicant is:

$$\Pi(\bar{p}_G + p_I) \equiv E_\epsilon[(1-p)\cdot r - p] \tag{8}$$

$$\overset{E(\epsilon)=0}{=} [1-(\bar{p}_G + p_I)]\cdot r - (\bar{p} + p_I) \tag{9}$$

$$= r - (1+r)\cdot(\bar{p}_G + p_I) \tag{10}$$

where, recall, $p = \bar{p}_G + p_I + \epsilon$, and the expectation in Equation (8) is taken over ϵ. As the attention cost c is sunk cost, the loan officer will make this loan if and only if $\Pi(\bar{p}_G + p_I) - \text{distaste}_G > 0$.

Thus, in the first stage, the benefit from paying attention to a group G is:

$$E_{p_I}\left[\max(0, \Pi(\bar{p}_G + p_I) - \text{distaste}_G)\right] \tag{11}$$

where the expectation is taken over the distribution of $p_I \sim N(0, \sigma_G)$. Such a group is worth paying attention to if and only if the expected benefit in Equation (11) exceeds the cost of attention c.

Prediction 1. Because $\Pi(\bar{p}_G + p_I)$ is decreasing in $\bar{p}_G$, clearly, lower $\bar{p}_G$ means a higher value in Equation (11). Similarly, lower distaste_G also means a higher value. Finally, because the max operator is convex, and because $\Pi(\bar{p}_G + p_I)$ is linear in p_I, a mean-preserving spread in p_I (larger σ_G) also increases the value. This proves the comparative statics on attention.

We now derive the result on approval probability. Groups that do not receive attention will be rejected 100% of the time. For groups to which officers will pay attention, approval

probability is given by:

$$P\left(p_I < \frac{r - \text{distaste}_G}{1+r} - \bar{p}_G\right) = P\left(\frac{p_I}{\sigma_G} < \frac{\frac{r-\text{distaste}_G}{1+r} - \bar{p}_G}{\sigma_G}\right) \tag{12}$$

$$= \Phi\left(\frac{\frac{r-\text{distaste}_G}{1+r} - \bar{p}_G}{\sigma_G}\right) \tag{13}$$

where $\Phi(\cdot)$ is the standard normal CDF that is decreasing in $\bar{p}_G$ and distaste_G. Further, the "cherry-picking" condition in Equation (3) implies that $\frac{r-\text{distaste}_G}{1+r} - \bar{p}_G < 0$, so the probability also increases in σ_G (and converges towards 1/2, as σ_G tends to infinity). Therefore, we conclude that the disadvantaged groups are more often rejected.

Prediction 2. Consider the case in which two groups, G_1 and G_2, both receive positive attention. Suppose G_1 is more disadvantaged. Consider increasing c slightly. It could be that both groups are unaffected, or that G_1 is affected — so attention and approval rate drops to zero — while G_2 is unaffected. Therefore, the attention and approval rate gaps between the two groups increase weakly.

B Additional Empirical Results

B.1 Variable Definition and Institutional Details

1. Table A1 provides the definitions of key variables in the paper.

2. Figure A1 shows a sample Chinese employment certificate translated into English.

Table A1. Variable Definitions.

Variable	Definition
Approval	equals one if the officer has approved the application, and zero otherwise.
ReviewTime	the number of minutes that the officer spent to review an application, measured as the time elapsed since the officer's previous decision to the current decision.
StandardizedTime	the log of reviewing time divided by its within officer-month-year-branch-loan type median. See Equation (6).
HasInfoAcquision	equals one if cited rejection reason indicates that the loan officer has made further due diligence (e.g. phone calls), and zero otherwise.
Delinquent	equals one if the loan has delinquency subsequently, and zero otherwise.
Busyness	the total number of applications reviewed by an officer during a day.
Predicted Busyness	the predicted number of applications reviewed by an officer during a day using the total number of applications in the current and three lagged business days that are assigned to an officer. See Equation (7)
LOO-Predicted Busyness	the predicted number of applications reviewed by an officer during a day using the number of applications from other provinces in the current and three lagged business days that are assigned to an officer.
Assignment	the total number of applications assgined to an officer during a day.
Backlog	the number of applications that has been assigned to an officer, but not yet reviewed, at the beginning of a day.
EmploymentCert	equals one if the applicant provides certificates related to current employment,and zero otherwise.
IncomeCert	equals one if the applicant provides certificates related to income, and zero otherwise.
HouseCert	equals one if the applicant provides certificates related to housing property owned, and zero otherwise.
ResidentCert	equals one if the applicant provides certificates related to where he lived in the recent history, and zero otherwise.
LeverageRatio	the applicant's preexisting debt to income ratio.
NonCreditHistory	equals one if the applicant has no credit history, and zero otherwise.
OverdueMonth	the longest number of months that the applicant has been overdue on payments in the recent two years.
CreditInquiry	the number of inquiry of applicant credit history in the recent two years.
HasInvestmentAcc	equals one if the applicant has an investment account, and zero otherwise.
NonStandardPay	equals one if the applicant receives salary payment in a non-standard way (e.g. through cash payments), and zero otherwise.
SocialSecurity	equals one if the applicant has social security allowance, and zero otherwise.
Litigation	equals one if the applicant has involved in any legal cases, and zero otherwise.
PrivateSector	equals one if the applicant employments for an private firm or is a owner of a private firm, and zero otherwise.
Peasant	equals one if the applicant has filled that she holds agricultural registered permanent residence in the application, and zero otherwise.
NonCollege	equals one if the applicant has a non-college degree, and zero otherwise.
Female	equals one if the applicant is female, and zero otherwise.
log(Age)	the log of applicant's age.
log(Income)	the log of the applicant's total income.
Loan/Income	the applicant's applied loan amount to total income ratio.
ShortTerm	equals one if the applied loan term is less than 3 years.
InterestRate	the applied loan interest rate at origination.

Figure A1. An Employment Certificate Template Sample
This shows an employment certificate template translated from Chinese. Loan applicants use these letters, issued by their employers, to provide verification of their employment status.

CERTIFICATE OF WORK

_____:

This is to verify that Mr./Mrs./Ms./Miss_____ (id number: _____) has been employed by our company since ___(YYYY)__(MM) till this date for a period of ____ year(s).

He/she current position is _____ at the department of _____. His/her employment type is _____ (tenure; contract; temperate; others), and job title is _____. This further certifies that he/she has __(Yes/No) violated any rules and regulations.

This certificate is being issued upon the employee's request for any legal purpose it may serve.

Form completed by (name and signature): _____

Company name and stamp: _____

Company's contact number: _____

Company's business license number: _____

Company's location: _____

Date: _____

B.2 Additional Details About the Instrumented Busyness Measures

In Section 4.2, we use the application assignments to instrument for officer busyness. This section provides more details:

1. Table A2 uses assignments to predict loan officer busyness.
2. Table A3 verifies that assignments do not depend on pre-existing officer backlog.
3. Table A4 verifies that the predicted busyness measures are not correlated with application-level observables.

Table A2. Predicting Loan Officer Busyness Using Assignments

This table reports the prediction of officer busyness using the number of applications assigned to them by the workload dispatcher algorithm. Observations are at the officer-day level. $\text{Busyness}_{j,d}$ is the total number of applications processed by loan officer j on day d, while $\text{Assignment}_{j,d}$ is the total number of assignments she received. Columns (1) to (4) do not include fixed effects, while columns (5) and (6) include officer and officer $\times$ month-year–fixed effects, respectively. Standard errors are double clustered at officer and month-year levels. We use specification (4) to compute "predicted busyness" in our paper. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$

	Dependent variable: $\text{Busyness}_{j,d}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Assignment}_{j,d}$	0.520***	0.419***	0.393***	0.367***	0.332***	0.239***
	(10.995)	(11.767)	(12.108)	(11.104)	(10.168)	(8.569)
$\text{Assignment}_{j,d-1}$		0.215***	0.173***	0.162***	0.142***	0.088***
		(5.887)	(5.246)	(5.411)	(4.608)	(3.488)
$\text{Assignment}_{j,d-2}$			0.125***	0.080***	0.064**	0.015
			(5.741)	(3.773)	(2.762)	(0.772)
$\text{Assignment}_{j,d-3}$				0.141***	0.120***	0.054***
				(10.259)	(8.331)	(5.199)
Officer FE	N	N	N	N	Y	N
Officer-Month-Yr FE	N	N	N	N	N	Y
Observation	9,498	9,498	9,498	9,498	9,498	9,498
Adjusted R-squared	0.421	0.482	0.502	0.527	0.555	0.638

Table A3. Whether New Assignments Depend on Existing Backlog.

This table reports the effect of the existing officer backlogs (number of assigned and undecided applications) on incoming applications assigned by the algorithm. We construct the test at the officer-day level. The dependent variable is the number of assignments given to one officer in a day. $\text{Backlog}_{j,d}$ is the number of applications assigned to but not yet reviewed by officer j at the beginning of day d *before* new assignments take place. The regressions control for officer × month-year– and day–fixed effects and also cluster standard errors at those levels. T-statistics are reported in parentheses. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

	Dependent Variable: $\text{Assignment}_{i,d}$			
	(1)	(2)	(3)	(4)
Backlog	−0.016	−0.016	−0.016	−0.016
	(−1.133)	(−1.138)	(−1.139)	(−1.136)
$\text{Backlog}_{j,d-1}$		0.005	0.005	0.005
		(1.613)	(1.627)	(1.634)
$\text{Backlog}_{j,d-2}$			0.000	0.000
			(0.123)	(0.113)
$\text{Backlog}_{j,d-3}$				0.001
				(0.407)
Officer-Month-Yr FE	Y	Y	Y	Y
Day FE	Y	Y	Y	Y
Observation	9,235	9,235	9,235	9,235
Adjusted R-squared	0.604	0.604	0.604	0.604

Table A4. Application Observables by Predicted Busyness Measures.

Officer busyness is defined as the number of applications processed by an officer in a day. As explained in Section 4.2, we use the number of applications assigned to officers to create instrumented versions of busyness, which we call predicted busyness and leave-one-out (LOO) predicted busyness. In Panels A and B, we regress loan-level observables on deciles of predicted and LOO-predicted busyness. As in the main regressions in Tables 4 and 5, we control for loan type, bank branch, and officer × month-year–fixed effects. T-statistics are reported in parentheses and standard errors are double clustered at month-year and officer-loan type levels. Variable definitions are in Table A1. $*p < 0.1; **p < 0.05; ***p < 0.01$.

Panel A. Predicted busyness as independent variable

	(1) EmploymentCert	(2) IncomeCert	(3) HouseCert	(4) ResidentCert	(5) log(1+LeverageRatio)	(6) NoCreditHistory	(7) log(1+OverdueMonth)
PredictBusynessDecile	−1.602	−1.084	−0.075	−1.800	0.656	−1.283	1.205
	(−0.610)	(−0.581)	(−0.078)	(−0.839)	(1.446)	(−1.324)	(1.451)
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.089	0.316	0.387	0.345	0.042	0.060	0.031

	(8) log(1+CreditInqury)	9) HasInvestmentAcc	(10) NonStandardPay	(11) SocialSecurity	(12) Litigation	(13) PrivateSector	(14) Peasant
PredictBusynessDecile	4.809***	0.122	1.348	0.806	−0.069	−0.251	−1.887
	(5.130)	(0.980)	(0.793)	(1.332)	(−0.689)	(−0.543)	(−0.956)
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.114	0.010	0.301	0.082	0.011	0.068	0.445

	(15) NonCollege	(16) Female	(17) log(Age)	(18) log(Income)	(19) log(DebtToIncome)	(20) ShortTerm	(21) log(InterestRate)
PredictBusynessDecile	0.269	0.101	−0.140	−0.092	0.318	0.104	−0.015
	(0.648)	(0.226)	(−0.423)	(−0.063)	(0.249)	(0.454)	(−1.215)
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.117	0.010	0.056	0.489	0.412	0.785	0.868

Panel B. Leave-one-out predicted busyness as independent variable

	(1) EmploymentCert	(2) IncomeCert	(3) HouseCert	(4) ResidentCert	(5) log(1+LeverageRatio)	(6) NoCreditHistory	(7) log(1+OverdueMonth)
LOOPredictBusynessDecile	0.019	−0.008	0.238	−0.338	0.329	−1.478	0.464
	(0.008)	(−0.006)	(0.249)	(−0.176)	(1.024)	(−1.568)	(0.563)
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.089	0.316	0.387	0.345	0.042	0.060	0.031

	(8) log(1+CreditInqury)	9) HasInvestmentAcc	(10) NonStandardPay	(11) SocialSecurity	(12) Litigation	(13) PrivateSector	(14) Peasant
LOOPredictBusynessDecile	4.571***	0.085	0.005	0.499	−0.108	−0.412	−1.565
	(4.699)	(0.702)	(0.003)	(1.060)	(−1.153)	(−0.854)	(−0.883)
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.114	0.010	0.301	0.082	0.011	0.068	0.445

	(15) NonCollege	(16) Female	(17) log(Age)	(18) log(Income)	(19) log(DebtToIncome)	(20) ShortTerm	(21) log(InterestRate)
LOOPredictBusynessDecile	0.656	−0.452	−0.215	−0.626	0.930	0.235	−0.021
	(1.066)	(−1.032)	(−0.565)	(−0.381)	(0.629)	(0.687)	(−1.264)
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.117	0.010	0.056	0.489	0.412	0.785	0.868

B.3 Additional Empirical Results

This section contains supplemental results.

1. Figure A2 provides a robustness check to Figure 1 by using predicted and leave-one-out (LOO) predicted busyness.

2. Table A5 reports a robustness check to Table 3 by using different certificates.

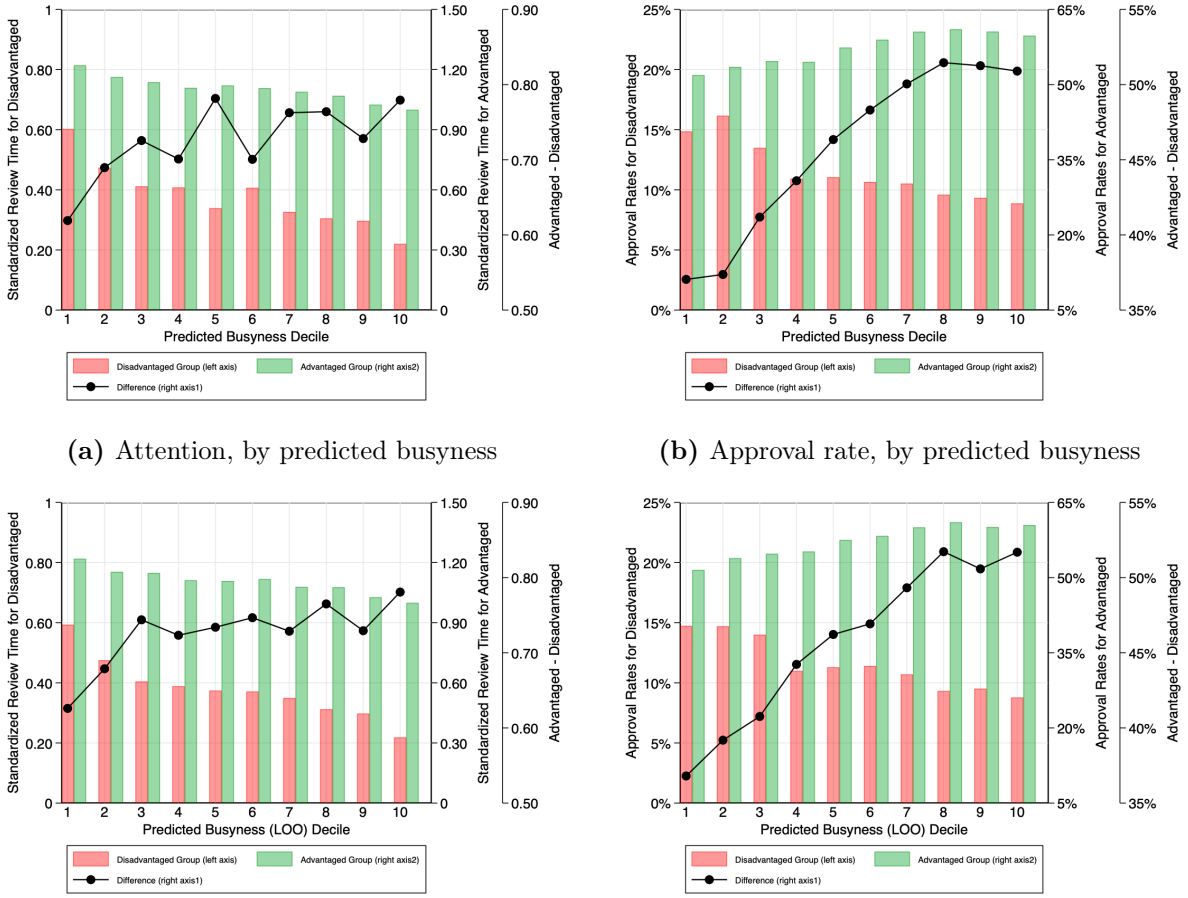
3. Table A6 estimates the interaction effect of officer busyness and each of the four certificates on attention and approval. We only present results using LOO-predicted busyness for brevity. The results using raw or predicted busyness are similar.

4. Table A7 runs regressions of log officer review time on different fixed effects and reports the resulting explanatory power.

5. Table A8 performs the "outcome test" of Becker (1957) to examine whether applicant advantage and busyness predict delinquency rates.

Figure A2. Robustness Test of Figure 1: Attention and Approval Rates by Officer Time Constraint

We sort the sample into deciles by two assignment-instrumented officer busyness measures. Officer busyness is defined as the number of applications processed per day. In Panels (a) and (b), we use busyness instrumented by the number of assignments that each officer receives, and, in Panels (c) and (d), we used a modified version in which the instrument takes a leave-one-out (LOO) format. Section 4.2 provides further details. In Panels (a) and (c), the outcome variable is officer attention, measured by a standardized version of how much time an officer spends reviewing each application. For visualization purposes, we also add back the sample mean to this variable. In Panels (b) and (d), the outcome variable is approval rate. In all panels, the bars plot the average values for the advantaged and disadvantaged groups of applicants, and the black line plots the difference between the two. The advantaged group are the top half of applicants, who are given more attention in the screening process due to having various additional certificates, while the rest are the disadvantaged group.



(a) Attention, by predicted busyness

(b) Approval rate, by predicted busyness

(c) Attention, by LOO-predicted busyness

(d) Approval rate, by LOO predicted busyness

Table A5. Credit Quality of Applicants With or Without Certificates.

This table reports regressions of borrower credit quality characteristics on whether they have employment, income, house, or resident certificates. Following Panel A of Table 3, we control for officer-month-year–, loan type–, and bank branch–fixed effects. Standard errors are double clustered at month-year and officer-loan type levels. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	log(1+LeverageRatio)	NoCreditHistory	log(Income)	log(DebtToIncome)
	(1)	(2)	(3)	(4)
EmploymentCert	-0.100^{***}	-0.236^{***}	0.072^{***}	-0.056^{***}
	(−9.401)	(−12.627)	(4.275)	(−4.036)
Officer-Month-Yr FE	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y
Observation	120,649	145,982	145,982	145,982
Adjusted R-squared	0.070	0.143	0.490	0.413

	log(1+LeverageRatio)	NoCreditHistory	log(Income)	log(DebtToIncome)
	(5)	(6)	(7)	(8)
IncomeCert	-0.072^{***}	-0.209^{***}	0.048^{***}	-0.033^{***}
	(−7.577)	(−9.946)	(3.833)	(−3.505)
Officer-Month-Yr FE	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y
Observation	120,649	145,982	145,982	145,982
Adjusted R-squared	0.056	0.106	0.489	0.412

	log(1+LeverageRatio)	NoCreditHistory	log(Income)	log(DebtToIncome)
	(9)	(10)	(11)	(12)
HouseCert	-0.045^{**}	-0.177^{***}	0.284^{***}	-0.172^{***}
	(−3.013)	(−13.474)	(13.886)	(−10.622)
Officer-Month-Yr FE	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y
Observation	120,649	145,982	145,982	145,982
Adjusted R-squared	0.049	0.083	0.496	0.416

	log(1+LeverageRatio)	NoCreditHistory	log(Income)	log(DebtToIncome)
	(13)	(14)	(15)	(16)
ResidentCert	-0.084^{***}	-0.237^{***}	0.060^{***}	-0.041^{***}
	(−7.909)	(−11.274)	(3.821)	(−3.416)
Officer-Month-Yr FE	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y
Observation	120,649	145,982	145,982	145,982
Adjusted R-squared	0.059	0.123	0.489	0.412

Table A6. The Effect of Time Constraint by Individual Certificates

This table reports the interaction effect of individual certificates with busyness on officer attention allocation in Panel A and approval rate in Panel B. The regressions are the same as in Tables 4 and 5, except that the indicator variable of Advantage is replaced by indicators of whether applicants have each of the four individual certificates. BusynessDecile is the LOO-predicted officer busyness sorted into deciles. Controls includes log(Income), Log(Loan/Income), log(1+LeverageRatio), log(1+OverdueMonth), log(1+CreditInqury), HasInvestmentAcc, NonStandardPay, Female, log(Age), PrivateSector, Peasant, NonCollege, SocialSecurity, Litigation, ShortTerm, and log(InterestRate). See Table A1 for variable definitions. Standard errors are double clustered at month-year and officer-loan type levels. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$

Panel A: Officer attention by LOO-predict busyness

	Dependent variable: StandardizedReviewTime			
	(1)	(2)	(3)	(4)
BusynessDecile	-0.022^{***}	-0.018^{***}	-0.016^{***}	-0.019^{***}
	(−4.054)	(−4.668)	(−4.726)	(−4.657)
EmploymentCert	0.496^{***}			
	(10.414)			
EmploymentCert × BusynessDecile	0.013^{*}			
	(2.037)			
IncomeCert		0.303^{***}		
		(6.731)		
IncomeCert × BusynessDecile		0.013^{***}		
		(3.266)		
HouseCert			0.270^{***}	
			(8.803)	
HouseCert × BusynessDecile			0.010^{**}	
			(2.942)	
ResidentCert				0.525^{***}
				(13.147)
ResidentCert × BusynessDecile				0.013^{**}
				(2.735)
Controls	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y
Observation	145,977	145,977	145,977	145,977
Adjusted R-squared	0.082	0.063	0.060	0.070

Panel B: Approval rate by LOO-predict busyness

	Dependent variable: Approval			
	(1)	(2)	(3)	(4)
BusynessDecile	−0.005***	−0.002	−0.002	−0.003
	(−3.129)	(−1.098)	(−0.776)	(−1.454)
EmploymentCert	0.515***			
	(22.211)			
EmploymentCert × BusynessDecile	0.011***			
	(5.381)			
IncomeCert		0.249***		
		(10.010)		
IncomeCert × BusynessDecile		0.010***		
		(5.103)		
HouseCert			0.377***	
			(11.111)	
HouseCert × BusynessDecile			0.012***	
			(3.205)	
ResidentCert				0.469***
				(20.178)
ResidentCert × BusynessDecile				0.009***
				(5.648)
Controls	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y
Observation	145,982	145,982	145,982	145,982
Adjusted R-squared	0.356	0.232	0.279	0.266

Table A7. Explaining Variation in Review Time.

This table reports regression R^2 of log application review time (in minutes) on different sets of fixed effects. Columns (1), (2), and (3) include loan type–fixed effects, loan originating bank branch–fixed effects, and officer-year-month–fixed effects, respectively. Column (4) uses the interaction of all the above three fixed effects.

	Dependent variable: log(ReviewTime)			
	(1)	(2)	(3)	(4)
Officer-Month-Yr FE	N	N	Y	N
Branch FE	N	Y	N	N
Loan type FE	Y	N	N	N
Loan type × Branch × Officer-Month-Yr FE	N	N	N	Y
Observation	145,977	145,977	145,977	145,977
R-squared	0.003	0.005	0.065	0.360

Table A8. "Outcome Test": Delinquency Rate Prediction.

This table reports the prediction of loan delinquency rate in the sample of loan applications that are approved and also issued. A subset of loans are approved but not issued, because applicants decide to not take the loan, possibly because of better offers elsewhere. The dependent variable is an indicator variable of whether the loan is delinquent. AdvantageContinuous is the fitted value of average approval rate using the four certificates. Advantage is a dummy variable for whether AdvantageContinuous is above median. BusynessDecile is the leave-one-out (LOO) predicted officer busyness (number of applications processed on a day) sorted into deciles (1 to 10). We only show results using LOO-predicted busyness for brevity; results using actual or predicted busyness are similar. Columns (1) and (2) are ordinary least square regressions; columns (3) and (4) report logit regressions; columns (5) and (6) report Cox regressions. All regressions include the same fixed effects and controls as in Table 4. Standard errors are double clustered at month-year and officer-loan type levels. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	Dependent variable: Delinquent					
	OLS		Logit		Cox	
	(1)	(2)	(3)	(4)	(5)	(6)
BusynessDecile	−0.004	−0.004	−0.029	−0.017	−0.030	−0.008
	(−0.709)	(−0.808)	(−0.600)	(−0.425)	(−0.719)	(−0.227)
Advantage	−0.009		−0.087		−0.094	
	(−0.205)		(−0.270)		(−0.323)	
Advantage× BusynessDecile	0.003		0.023		0.024	
	(0.475)		(0.438)		(0.528)	
AdvantageContinuous		−0.047		−0.234		−0.121
		(−1.019)		(−0.639)		(−0.350)
AdvantageContinuous× BusynessDecile		0.005		0.020		0.003
		(0.578)		(0.257)		(0.046)
Controls	Y	Y	Y	Y	Y	Y
Officer−*Month*-Yr FE	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y
Observation	38,892	38,892	38,892	38,892	38,892	38,892
Adjusted R-squared	0.048	0.048				
Pseudo R-squared			0.069	0.069	0.069	0.069