Attention Constraints and Financial Inclusion

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December 28, 2022

Abstract

We show that attention constraints on decision-makers create barriers to financial inclusion. Using administrative data on retail loan-screening processes, we find that attention-constrained loan officers exert less effort reviewing applicants from lower socioeconomic status (SES) backgrounds and reject them more frequently. More importantly, when externally imposed increases in loan officers' workloads tighten attention constraints, loan officers are even more prone to quickly rejecting low-SES applicants but quickly accepting very high-SES applicants without careful review. Such attention allocation further widens the approval rate gap between high- and low-SES applicants—a unique prediction of the attention-based mechanism.

JEL classification: D83, D91, G21

Keywords: Attention Constraint, Financial Inclusion, Diversity, Retail Lending

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1 Introduction

Having access to basic financial services is crucial to one's well-being in contemporary society.[1] Even in the U.S., however, nearly one-fifth of adults remain unbanked or underbanked, and there exist significant financial inclusion barriers for those in lower socioeconomic status (SES) groups.[2] In this study, we show that *attention constraints* on key decision-makers, such as loan officers, can further restrict financial inclusion for low-SES borrowers even when many are qualified for financial access, resulting in potentially inequitable and inefficient allocation of financial resources.

How do attention constraints impact inclusion? We use a simple model to illustrate the mechanism. If loan officers had infinite time, they would review every application carefully and make informed decisions based on borrower credit quality. If loan officers are attention-constrained, however, they may choose to ration their attention based on easily observed signals, such as labels that indicate borrowers' SES status. In the *base case*, our model predicts that, when loan officers face tighter attention constraints, they will allocate disproportionately less attention to low-SES borrowers, leading to "rash rejections", even when a significant portion of those borrowers are qualified and should otherwise be approved if adequate attention were paid to their applications. Further, in the *special case* where some borrowers have extremely high SES status, they may even face the opposite fate and be "rashly accepted" without careful screening. Regardless of the situation, tighter loan officer attention constraints will widen the inclusion gap between high- and low-SES applicants. Even though such loan officer behavior can be (constrained) optimal from the perspective of lender profitability, this behavior does create distributional consequences for financial inclusion.

We face two challenges in studying the impact of attention on inclusion empirically. First, it is difficult to measure attention allocation, 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."* Second, it is hard to find orthogonal variations in attention constraints. Using administrative data on the screening processes associated with approximately 146,000 retail loans in one of the largest national banks in China, our paper overcomes both difficulties. First, as we observe accurate timestamps in the decision-making process, we can track the

[1] It has been found that financial inclusion plays an important role in determining household human capital investment (e.g., Stein and Yannelis (2020)), wealth accumulation (e.g., Célerier and Matray (2019)), and long-term financial health (e.g., Brown, Cookson, and Heimer (2019)), etc.

[2] Source: Report on the Economic Well-Being of U.S. Households in 2020. According to the report, almost half of all families with incomes below $50,000 experienced credit denials or could not obtain sufficient credit. Across all income levels, on average, about one-third reported experiencing difficulty obtaining credit.

amount of time that loan officers spend reviewing each application—a direct measure of attention allocation. Second, the bank allocates applications across loan officers using an algorithm that induces externally imposed variations in loan officer workloads. Further, such variations are orthogonal to borrower creditworthiness and loan-officer behaviors, enabling us to identify the consequences of attention constraints. In addition, the data include detailed information that allows us to investigate loan officer decisions while conditioning on the full set of borrower and loan characteristics the loan officers observe.

Our empirical work begins with a preliminary examination of whether applicants from contrasting SES backgrounds are treated differently. In our sample, each application package includes a number of salient labels related to the applicant's social and economic status, such as whether the applicant is a local resident (rather than a migrant), a public employee (i.e., employed by a government agency or a state-owned firm), a worker with stable long-term employment and income, and/or a homeowner. Based on these labels, we sort applicants into "attractive" and "unattractive" groups and then find that the unattractive groups experience significantly lower approval rates. Specifically, groups with unattractive social (economic) status find their loans approved only 18.1% (25.4%) of the time, which is much lower than the 51.9% (65.5%) rates for attractive social (economic) status groups. These wide approval rate differences cannot be justified by gaps in creditworthiness: for a wide range of credit-quality indicators, the two groups exhibit only small differences on average and there is significant overlap.[3]

What are the drivers of this large approval-rate gap? We first provide suggestive evidence that loan officer attention constraints may play a role. We find that loan officers are very time-constrained and spend only a median of 18 minutes screening each applicant, even though every application contains 20–30 pages of dense forms plus hundreds of pages of supporting materials. Needless to say, loan officers do not have time to carefully read through each application and need to ration their attention. We then find that low-SES applicants receive significantly less attention, suggesting that many of their applications may not be read carefully but are simply *rashly rejected*. Specifically, the group with unattractive social (economic) status receives only 12.1 (16.1) minutes of median review time, while the socially (economically) attractive group receives 24.9 (25.2) minutes, which is approximately twice as much. In addition, loan officers have to provide reasons for rejections, which provides

[3] For instance, 48% (47%) of the socially (economically) unattractive applicants earn higher incomes than the median attractive applicant. These numbers are only slightly lower than 50%, which is what we would expect if the two groups were identical. Even the overlap between rejected applicants from the unattractive group and approved applicants from the attractive group is large. Of course, it is still possible that the two groups differ along *unobservable* dimensions of credit quality. Our main analysis tackles this concern using orthogonal variations in loan officer attention constraints.

us with a glimpse at how they approach high- and low-SES applicants differently. We find that low-SES applicants are more likely to be rejected based on boilerplate reasons such as "leverage is too high," indicating that loan officers often reject low-SES borrowers without having carefully read the applications; in contrast, high-SES applicants are more often rejected for reasons that are application-specific. Of course, these results are only suggestive of the attention-based mechanism, as they are merely *associations* between attention allocation and approval outcomes.

We next test the key theoretical prediction that tighter attention constraints *widen* the financial inclusion gap. To measure loan officer attention constraints, we first exploit variations in loan officer *busyness*, which is defined as the number of applications processed by an officer on a given day. The idea behind this measure is simple: loan officers face tighter attention constraints on busier days because they have less time to spend on each application. In our sample, there are sizeable variations in officer busyness, with the 10% and 90% percentiles equal to 10 and 27 applications per day, respectively. In other words, while loan officers are always busy (time spent on each application is always low), they sometimes become even busier.[4] We then examine how variations in loan officers' busyness impact their screening behavior of high- and low-SES applicants.

[**Figure** 1 about here.]

What happens when loan officers are busier? We first plot these patterns in Figure 1 as an exploratory illustration. Panels (a) and (b) plot officer attention allocation, measured by the average log number of minutes spent on each application as a function of busyness. When officers are busier, they unavoidably spend less time on all applications, but the reduction in attention is more pronounced for the socially or economically unattractive groups, resulting in an increase in the attention gap between the attractive and unattractive groups. Panels (c) and (d) further show that, when loan officers get busier, the approval rate for socioeconomically unattractive applicants declines sharply, suggesting that some of the low-SES borrowers are rashly rejected without being paid equal attention by the busy loan officers. As a consequence, the approval rate gap between the attractive and unattractive groups widens, which is consistent with the *base case* predictions of the attention-driven mechanism. Also, the average approval rate for attractive applicants seems even to increase slightly when loan officers are busier, which could be consistent with the *special case* where some extremely high-SES applications are "rashly approved" without careful review.

[4]Even though mortgage applications are more complex and involve larger loan sizes, which may require more careful screening, it is worth noting that the average number of applications processed by our sample loan officers is significantly larger than that the number processed by U.S. mortgage loan officers (e.g., `https://www.bancorp.com/employment-opportunities/loan-processor/`.)

We then formally estimate these effects using regressions in which we control for officer-month-year, week, bank branch, and loan-type fixed effects as well as a comprehensive list of applicant-level characteristics. The results are similar to those plotted in Figure 1. When loan officer busyness varies from the bottom to the top deciles, their allocated review time on socially (economically) unattractive applicants declines by 53% (52%), which is larger than the 38% (37%) decline observed for socially (economically) attractive applicants; the difference is statistically significant. More importantly, the approval rate for the socially (economically) unattractive group drops by 45% (39%) relative to the average levels, while approval rates for the attractive groups were not significantly affected and in some cases even increased slightly.

Two empirical concerns might arise in using *realized* loan officer busyness to measure attention constraints. First, loan officers may have leeway to work faster or more slowly, so realized busyness may reflect an endogenous choice rather than an external constraint. To address this concern, we instrument the busyness measure by the number of applications *assigned* to officers. Because the assignments are made by a central dispatcher algorithm over which officers have no influence, this assignment process induces externally imposed variations in loan officers' attention constraints. The number of assignments explains approximately 40% of the variation in realized busyness. Further, conditioning on loan officer-month-year fixed effects in all our specifications, we are effectively utilizing the residual assignment variation that is unrelated to loan officer preferences or systematic shifts in risk-management criteria over time.

The second empirical concern is that loan officer busyness may be correlated with the average quality of the application pool received by the bank. To alleviate this concern, we first verify that the assignment-instrumented busyness measure is orthogonal to a comprehensive list of application- and applicant-level measures of creditworthiness. That said, one may still worry about the potential for correlations with unobservable characteristics. We further address this concern by constructing another leave-one-out (LOO) Bartik-type instrument. The idea is as follows: suppose Province A experiences an idiosyncratic spike in the number of applications that increases the busyness of an loan officer; this would tighten the loan officer's attention constraints, which would also affect her decision-making regarding loan applications from Province B, even if there is no change in either the number or quality of applications from Province B. In this sense, by utilizing variations in officer busyness driven by assignments from *other* provinces (and directly controlling for busyness driven by assignments from the local province), we capture variations in a loan officer's attention constraints that are independent of a particular application she is screening.

We then re-estimate our key findings using loan officer busyness instrumented by the above-mentioned instrumental variables. We find that our main results are qualitatively unchanged: when officers are busier because of assignment-induced idiosyncratic variations in busyness, the attention- and approval-rate gaps between attractive and unattractive applicants both widen, consistent with the *base case* predictions. In some specifications, we also note that the instrumented busyness of loan officers appears to *increase* approval probability for attractive applicants, which may be consistent with the *special case* predictions. Overall, all our results are consistent with the idea that tighter attention constraints wideb the gap in the allocation of financial resources through an attention-based mechanism.

This paper's main contribution lies in showing that decision-makers' attention constraints can worsen financial inclusion. This attention-driven mechanism can amplify both taste-based and statistical discrimination by decision-makers: as long as they have differential priors across different groups, whether driven by prejudice or statistics, their attention constraints can widen the inclusion gap between applicants with ex-ante attractive and unattractive signals.

Regarding policy implications, the attention-based mechanism suggests that policies and technologies that relax decision-maker attention constraints may promote more balanced financial resource allocation. For instance, recent developments in financial technologies ("fintech"), which use automated underwriting algorithms (and thus are subject to low or no attention constraints) to assist in screening borrowers, may improve financial access for low-SES applicants in the current financial system where most decisions are currently made by attention-constrained humans.[5][6] In addition, to the extent that loan officer specialization in screening applicants from specific backgrounds can make information-processing more efficient, this may also improve outcomes for low-SES applicants. Finally, taking attention constraints more seriously also generates additional insights into optimal workload allocation. For instance, in our setting, while each loan officer may be acting optimally given their attention constraints, the bank is likely behaving suboptimally in distributing workloads unevenly across officers (See Appendix A.2).

[5]This rationale is aligned with the argument in Philippon (2019), which presents a conceptual framework in which big data and machine-learning algorithms are likely to reduce the impact of negative prejudice in the credit market. Dobbie, Liberman, Paravisini, and Pathania (2021) show that using a machine learning-based algorithm to make lending decisions could reduce bias against immigrant and older borrowers. Bartlett, Morse, Stanton, and Wallace (2022) find that the discrepancy in FHA mortgage rates between majorities and minorities is smaller with fintech lenders. Empirically, Fuster, Plosser, Schnabl, and Vickery (2019) show that fintech lenders can process mortgage applications 20% faster than other lenders.

[6]Of course, recent studies also emphasize the importance of ensuring that fintech algorithms themselves are not biased by design. There are concerns that the application of big-data fintech may generate new distributional issues because they enable lenders to triangulate otherwise excluded borrower features (e.g., Fuster, Goldsmith-Pinkham, Ramadorai, and Walther (2022)). Therefore, the net distributional effect of fintech might not be clear-cut (Morse and Pence, 2021).

While we obtain our results in a specific setting, we argue that the attention-based mechanism is likely applicable to many other situations in which important decisions are made by individuals facing attention constraints. Many high-stakes decision-makers—college admissions officers, recruiters, court judges, and reviewers of scientific research grant applications—are usually busy. The Chronicle of Higher Education (2017) reports that admissions officers at the University of Pennsylvania spend four minutes on an initial read of each college application. Time Magazine (2002) cites a study indicating that recruiters spend on average only six seconds on each résumé. Court judges often have years-long backlogs of cases to work through. Frakes and Wasserman (2017) argue that the U.S. patent office is chronically short-staffed relative to the number of patent applications it receives. As a consequence, it is natural for the same mechanism to be at play: when they are busy, decisions-makers pay less attention to ex-ante unattractive candidates, and those candidates are rejected more frequently than justified by their intrinsic merits.

There are two empirical limitations that we cannot fully address, but we believe that they do not invalidate our conclusions. First, we do not observe the ex-post default outcomes for our sample borrowers and thus cannot conclude how loan officers' attention-driven behavior affects bank loan losses. As previously noted, though, it is entirely possible that loan officers' behavior is constrained optimally; our focus instead is on the *distributional* consequences of their behavior, for which we show a robust inclusion gap conditional on the same ex-ante default probability predicted by all information observable by loan officers. Second, the bank does not disclose how exactly the algorithm assigns applications. Despite assurances from loan officers regarding its idiosyncrasy (see Section 5.2 for details), one may still worry about correlations between the number of assignments and borrower credit quality. We are able, however, to verify that the assignment-instrumented busyness measures are orthogonal to a comprehensive list of creditworthiness measures. More importantly, when loan officers are busier, their approval rates for high- and low-SES applicants often move in *opposite* directions, which is a unique prediction of the attention-based mechanism. While we can conjure up alternative explanations in which assignments co-move with average credit quality, it is harder to find mechanisms that generate *opposite* correlations with high- and low-SES applicants. Our LOO instrument also addresses this concern.

The remainder of the paper is organized as follows. Section 2 presents a simple model to illustrate the attention-based mechanism and derive testable predictions. In Section 3 we describe the data and relevant institutional details regarding the loan-screening process. In Section 4 we show that unattractive applicants receive less attention and are rejected more often when officers face tighter attention constraints. In Section 5 we present estimates of the causal effects of attention constraints using assignment-instrumented officer-workload variation and in Section 6 we conclude the study.

1.1 Related Literature

This paper is related most closely to the seminal work on selective attention allocation by Bartoš, Bauer, Chytilová, and Matějka (2016). Using experiments, they find that decision-makers exert greater effort in collecting information on attractive (unattractive) groups of candidates in selective (non-selective) markets. The key innovation in our paper is testing the impact of variations in decision-maker attention constraints and providing more direct field evidence pertaining to the distributional consequences of attention constraints. More broadly, this paper is related to a burgeoning literature based on endogenous attention allocation, a theme of which Gabaix (2019) and Mackowiak, Matejka, and Wiederholt (2022) provide extensive reviews. A number of papers have applied the framework of endogenous attention allocation to other financial settings.[7]

This paper also contributes to the literature that investigates distributional issues in financial resource allocation. Many studies have documented discriminatory practices in mortgage credit (Bayer, Ferreira, and Ross, 2018; Bartlett et al., 2022; Giacoletti, Heimer, and Yu, 2021; Ambrose, Conklin, and Lopez, 2021), consumer credit (Montoya, Parrado, Solís, and Undurraga, 2020; Dobbie et al., 2021), bank lending (Fisman, Paravisini, and Vig, 2017; Fisman, Sarkar, Skrastins, and Vig, 2020), auto loans (Charles, Hurst, and Stephens, 2008; Butler, Mayer, and Weston, 2022; Lanning, 2021), small business lending (Ongena and Popov, 2016; Brock and De Haas, 2021), microlending (Beck, Behr, and Madestam, 2018), and entrepreneurial finance (Hebert, 2020; Ewens and Townsend, 2020; Hu and Ma, 2021; Zhang, 2020). In addition to documenting the lack of inclusion for borrowers from unattractive groups, we also provide empirical evidence of attention-based credit allocation that could conceivably function as the mechanism underlying some of the findings in the aforementioned studies.[8]

Our paper finds that constraints on loan officers' attention restrict financial inclusion. Focusing largely on economic efficiency, previous researchers have shown evidence that attention constraints lead to suboptimal decisions. Müller (2022) shows that bankruptcy-court congestion leads to lower recovery values in defaults and also impacts pre-default credit

[7]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 (2019), Liu, Peng, and Tang (2022), and Hirshleifer and Sheng (2022).

[8]Interest in studying the distributional impact of machine learning and artificial intelligence has recently surged (Bartlett et al., 2022; Fuster et al., 2022; Jansen, Nguyen, and Shams, 2021; D'Acunto, Ghosh, Jain, and Rossi, 2021).

spreads. Shu, Tian, and Zhan (2022) find that busy patent examiners grant lower-quality patents. Hirshleifer, Levi, Lourie, and Teoh (2019) show that financial analysts who suffer from fatigue resort to heuristic decisions when making forecasts. Huang et al. (2019) show that attention-constrained investors pay less attention to firm-specific news. Of greater relevance to lending decisions, Liao, Wang, Xiang, Yan, and Yang (2021) document that peer-to-peer investors tend to use "system one thinking" a la Kahneman (2011) and ignore credit-relevant information when acting under time pressure.

Existing studies have documented a variety of constraints and frictions that can affect credit allocation and financial inclusion, and some of these factors correlate with borrowers' economic and financial fundamentals. For example, economically unattractive consumers and businesses are likely to be informationally opaque and possess less collateral, and such frictions can further worsen the credit rationing they face (e.g., Adelino, Schoar, and Severino, 2015; Schmalz, Sraer, and Thesmar, 2017; Agarwal, Chomsisengphet, Mahoney, and Stroebel, 2018; Han, Keys, and Li, 2018; DeFusco and Mondragon, 2020). Moreover, capital and liquidity constraints on lenders during economic downturns can further widen the gaps in credit access faced by a range of borrowers (e.g., Iyer, Peydró, da Rocha-Lopes, and Schoar, 2014; Deyoung, Gron, Torna, and Winton, 2015; Rodano, Serrano-Velarde, and Tarantino, 2018). More broadly, recent papers show that institutional design and politics impact other aspects of economic disparities (Aneja and Avenancio-Leon, 2019; Avenancio-Leon and Howard, 2022). Our paper extends these studies by proposing and testing a new attention-based constraint; attention constraints on decision-makers can *amplify* the effects of some existing mechanisms.

2 Conceptual Framework

Building on Bartoš et al. (2016), we use a simple model to illustrate how decision-maker attention constraints can exacerbate financial-inclusion concerns. Less interested readers can skip the model at little cost as we have explained the intuition in the introduction.

Model set-up. Consider a risk-neutral loan officer faced with the task of deciding whether to approve an application to borrow one unit of capital for one period of time. Applicants come from a continuum of groups denoted by G, and the associated group identities are observable at zero 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 $r > 0$ is fixed exogenously.[9] If the loan officer approves the application, the expected profit (before considering attention cost) is

$$- \text{distaste}_G + \underbrace{(1-p) \cdot r}_{\text{interest payments if paid back}} - \underbrace{p}_{\text{loss from default}} \tag{1}$$

where $\text{distaste}_G \geq 0$ captures group-specific *preference-based* attributes and p is the default rate. For the sake of simplicity, Equation (1) assumes a zero recovery rate upon default. We also assume risk neutrality and zero time discounting. To ensure that lending can happen in equilibrium, we assume that $r > \text{distaste}_G$, so an applicant for whom the default probability is zero is worth lending to.

Apart from possible differences in distaste_G, groups can also differ in average credit quality. For every applicant, his default probability p decomposes into two components,

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

where $\bar{p}_G$ is a group-specific average observable at no cost and $p_I \sim N(0, \sigma^2)$ is an applicant-specific component that can be learned by paying the attention cost c.[10] As such, differences in distaste_G capture taste-based discrimination and differences in $\bar{p}_G$ capture statistical discrimination.

Optimal loan officer behavior. We explain the solution intuitively and refer the reader to Appendix A.1 for formal proofs. As illustrated in Panel A of Figure 2, loan officers can adopt any of three strategies. The optimal strategy falls into three regions and depends on how ex-ante attractive the group is:

1. Applicants from *extremely attractive groups* (low $\bar{p}_G$ or distaste_G) are *immediately approved* without information acquisition. While paying attention to them can enable the loan officer to screen out the occasional bad borrower, the probability that this occurs is sufficiently low that the cost of attention outweighs the benefit.

    - In our empirical setting, this should apply to only a very small subset of borrowers. The average approval rate over the full sample is only 34%, indicating that most applicants are not considered worthy borrowers. A simple back-of-the-envelope

[9] This is true in our empirical setting. The loan officer needs to decide only whether to approve or reject the application.

[10] Technically, using normal distributions for p_I can lead to default rates above 1 or below 0. The results are qualitatively unchanged if we use modified zero-mean distributions with bounded support such as truncated normal distributions.

analysis suggests that the occurrence of such extremely attractive groups should be rare.[11]

2. For an applicant from an *intermediate group*, the loan officer will first conduct information acquisition and then approve the application if and only if the revealed information indicates sufficiently high credit-worthiness.

3. An applicant from an *unattractive group* (high $\bar{p}_G$ or distaste$_G$) is *immediately rejected* without information acquisition. Even though paying attention can identify some good borrowers, the benefit is not large enough to justify the attention cost.

The two cutoffs between these three regions are graphically illustrated in Panel (b) of Figure 2. We plot the loan officer's expected utility when employing each of the three strategies as a function of the group-specific average default rate $\bar{p}_G$.[12] Findng the optimal strategy in each region amounts to simply choosing the strategy with the highest expected utility.

[**Figure** 2 about here.]

The distributional consequences of higher attention costs. When attention cost c rises, the "immediately approve" and "immediately reject" regions both expand. This is easy to see in Panel (b) of Figure 2. A higher cost c causes a downward parallel shift in the blue curve. As a consequence, the blue curve's crossing point with the red and green curves will shift rightward and leftward, respectively. This result should be intuitive: when attention becomes more costly, loan officers are less likely to acquire information and are more likely to make a decision based on ex-ante group attributes.

Therefore, increases in attention costs lead to *asymmetric* consequences for applicants from different groups. When loan officers are busier, applicants from unattractive groups will

[11] How good does an applicant group have to be for it to be worth approving without information acquisition? 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 earn a cost-adjusted annual return of only 5.35% if the applicant does not default. In contrast, if the application defaults and we assume a 40% recovery rate as the loan is uncollateralized, the bank stands to lose 60%. Therefore, as long as the average application default rate is higher than $\frac{5.35\%}{5.35\%+60\%} \approx 8\%$, the default loan officer's action without information acquisition is rejection.

[12] The attractiveness of a group is also impacted by distaste$_G$, but we show in Appendix A.1 that variation in distaste$_G$ is equivalent to variation in $\bar{p}_G$ with a different scaling parameter applied. Therefore, Panel (b) of Figure 2 illustrates the behavior of the various model regions without loss of generality.

be rejected more often; applicants from extremely attractive groups may even be accepted more often.[13] This discussion is formalized into the testable predictions presented below.

Testable predictions. Consider two groups, G_1 and G_2, where the former is less attractive (has higher $\bar{p}_G$ or higher distaste$_G$). Then:

1. (Average effect) G_1 will receive weakly less attention and be approved less often.
2. (Comparative statics) If loan officer attention cost c increases, then:
   (a) In the *base case* where the more favorable group (G_2) is in the intermediate region, both groups will receive weakly less attention, and the *gaps* between their attention and approval rates will weakly widen.
   (b) In the *special case* where the favorable group (G_2) is in the extremely attractive region, then its approval rate will in fact increase.

It is worth emphasizing that we think the base case should dominate our empirical setting. As explained earlier with respect to the three possible loan officer strategies, there should be only a small subset of applicants who are so attractive that they can be approved without loan officer attention.

What is the main innovation? As discussed at the start of this section, our model builds on Bartoš et al. (2016), who were the first to propose this "attention discrimination" mechanism. They also present experimental evidence for prediction 1 above: the differential attention received by more and less attractive groups. Our main contribution is testing prediction 2: the comparative statics on attention cost c. In our empirical tests, we use orthogonal variations in loan officer workloads to perturb attention cost c.

3 Data and Institutional Background

In this section, we describe the data and provide background information on the retail loan-screening process. We then show preliminary evidence that applicants without certain

[13] Approval/rejection decision quality also declines. To see this, consider applicants positioned exactly to the right of the boundary between the "immediately approve" and "learn" regions. Before an increase in attention cost, the loan officer acquires information and makes an informed decision, so the bad applicants—those whose default rates $\bar{p}_G + p_I$ are high—are screened out. After an increase in attention cost, those applicants are also approved without scrutiny. By the same reasoning, the decision quality for those at the boundary between "learn" and "immediately reject" regions also declines: before an increase in attention cost, the good marginal applicants are approved, but after the increase they are automatically rejected without review.

socioeconomic status labels receive less review time and are rejected more frequently than would be justified by creditworthiness metrics, suggesting that attention rationing by loan officers negatively impacts their application outcomes. The main empirical results, where we investigate the impact of variations in officer attention constraints on financial inclusion, are reported in Sections 4 and 5.

3.1 Data Source

We obtain internal retail-lending screening records from one of the largest national banks in China. The sample data cover approximately 146,000 loan applications screened by 92 loan officers working at the bank's headquarters office from April 2013 through April 2014. Borrowers include both wage/salary workers and self-employed individuals running small/micro-scale businesses. The loan terms and targeted borrowers are comparable to those associated with retail financing products in the United States. Loan maturity is one to three years; the median (mean) loan amount is 60,000 (66,461) Chinese RMB, which is equivalent to \$9,787 (\$10,841) U.S. dollars and comparable to the average personal installment loan of around \$16,000 in the U.S.[14] The average annual interest rate in our sample is 8.56%, which is also similar to the two-year U.S. personal loan interest rate of about 10% over the same sample period.[15] Summary statistics are presented in Table 1 and variable definitions are listed in Appendix Table B.1.

[**Table** 1 about here.]

Our data include all information that loan officers can see in each application during the screening process, which allows us to control for a rich set of applicant- and loan-level characteristics that are potentially related to the borrower's credit quality. The data include 111 variables extracted from application materials and 295 variables extracted from borrower personal credit reports issued by the Chinese Central Bank. These variables include almost all commonly used metrics for credit-worthiness, such as leverage ratio, existing debt, credit history, income, and so forth.

More importantly, the data contain detailed timestamps for each step in the loan officer's screening and decision-making process, which allows us to infer the amount of attention paid by loan officers to each applicant.

[14] Source: `https://www.experian.com/blogs/ask-experian/research/personal-loan-study/`.
[15] Source: `https://www.federalreserve.gov/releases/g19/hist/cc_hist_tc_levels.html`.

3.2 The Loan-Screening Process

The three-stage loan origination and screening process is illustrated in Figure 3. Stage one, which occurs at the local bank-branch level, is not captured by our data. Our study focuses on stage two, which generates workload variations via an external algorithm that is not affected by loan officer discretion, as well as stage three, during which headquarters loan officers screen the applications and make lending decisions.

[**Figure** 3 about here.]

Stage one: Application submission. Loan applications are sourced from local bank branches all over the country. Each applicant submits an application for a specific maturity and loan amount. The local bank branch manager ensures that the application materials are complete and determines the appropriate interest rate for each application, but approval decisions need to be made by loan officers at bank headquarters in stage three.

Stage two: Assignment of applications to headquarters loan officers. After an application is completed in stage one, it is stored electronically in the bank's systems and then distributed to the headquarters loan officers by a central workload-dispatcher algorithm over which loan officers have no control. As for how exactly the algorithm assigns applications, see Section 5 for an in-depth discussion.

Stage three: headquarters loan officers make approval/rejection decisions. The assigned loan officer accesses applicant information electronically, evaluates the information, and decides whether to approve the application. Our sample comprises 92 officers. Of a total of 145,982 applications, only 34.2% are approved, so the process is relatively selective. Our data include precise timestamps when applications are assigned to officers and when officers make decisions, enabling us to measure officers' attention allocation to each application by calculating the length of time they spend reviewing the application.

While we do not observe loan officer pay, we learned from private conversations that their incentives generally align with the bank's interests. Specifically, they are paid fixed salaries plus bonuses, and their bonuses are determined by a mix of the default rate of the loans they approve and the originated loan volume, such that their objective is generally consistent with the bank's goal of maximizing interest income after adjusting for the expected loan losses.

3.3 Loan Officers Are Attention-Constrained

A key premise of the attention-based mechanism is that decision-makers face attention constraints. In this section, we show that officers are indeed constrained because they have to read lengthy documents within short periods of time.[16] At the bank we study, loan officers receive two sets of documents with each application:

1. *An application form (10–20 pages) and supplementary materials.* The application form contains information about the applicant's demographic information (e.g. age, gender, education, birthplace, and current residential address), personal wealth and income information, purpose of borrowing, etc. The application package also includes lengthy supplementary materials that are used to support the applicant's self-reported information. These materials could include third-party-issued official documentation such as photocopies of personal ID cards, employment certificates, property deeds, and bank statements. These additional documents usually run into hundreds of pages.

2. *A credit report issued by the central credit bureau (around 10 pages).* This report includes detailed information about the borrowers' credit history and is issued by a central credit bureau operated by the central bank (People's Bank of China, PBOC). Like credit reports issued by credit bureaus in the U.S. market, this report from the PBOC contains information about the individual's credit payment history and public records (e.g., past civil or criminal records).[17]

In addition to reviewing these documents, loan officers sometimes conduct additional due diligence, which for example includes searching an applicant's employer or even making phone calls. While due diligence is not mandatory, officers must always review the two sets of documents listed above before making decisions.

We argue that loan officers face attention constraints because we find that they can spend only a limited amount of time on each application. As loan officers review applications *in sequence*, we can measure the time spent reviewing each application as the amount of time

[16] In many other credit markets, applicants also submit lengthy documents. For example, mortgage applications in the U.S. can be hundreds of pages long (https://money.cnn.com/2013/12/12/real_estate/mortgage-applications).

[17] During our sample period, there is no widely used consumer credit score (like the FICO in the U.S.) in China. 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. Zhima Credit is not, however, widely used in bank lending decisions.

that elapses *between two consecutive decisions* rendered by the same loan officer.[18] Despite the large volume of materials that a loan officer must read, the need to make many application decisions within short time frames results in a meager median (mean) review time of 18 (31) minutes per application.[19]

3.4 Applicants without Certain Socioeconomic Labels are Considered Unattractive

Given the above-mentioned loan officer attention constraints, it is natural to hypothesize that they may use simple signals to decide how much time to spend reviewing each application. As a consequence, applications with unattractive signals may be quickly rejected without careful review. This section presents preliminary evidence for such behavior and Section 4 provides formal analyses.

Loan officers use socioeconomic labels to guide attention allocation. In private conversations, loan officers explain that they find a few easily observable socioeconomic labels useful for guiding time allocation. Some of these labels are related to applicant social status while others are related to applicant economic status, and we call them "socioeconomic labels" collectively in subsequent discussions. These are zero-or-one indicator labels that can be easily observed on application forms.

Two labels are usually considered signals of an applicant's *social status*:

1. *PublicEmployee*: whether the applicant works for the public sector. Chinese society treats public employees, including those working in the government, public schools or hospitals, state-owned firms, or any other government-sponsored institutions, as

[18] For instance, if a loan officer made one decision at 15:10:00 and another at 15:45:00, we measure the review time for the second application as 35 minutes. To improve the review time measure as a proxy for the number of *working* minutes spent, we also subtract lunch breaks (12:00 to 13:00) and all non-working periods (including weekends, national holidays, and other days off). Our results are not sensitive to this specific method for measuring review time.

[19] The per-application review time in our sample is shorter than in similar loan review processes in the U.S. To mention 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 (see their Table 1). In our data, 92 loan officers screened 145,982 applications over two years. This implies that the average review time in the U.S. is $\frac{133\times 2/30{,}268}{92\times 1/145{,}982} \approx 13.9$ times longer than that in our data. In addition, Wei and Zhao (2022) show that the median processing time is 8–29 days in the U.S. mortgage market. However, this number includes processing time across all steps, from the submission of an application to the final origination of a loan, not just the review time spent by loan officers, and thus is not directly comparable to our review time measure.

meriting higher social status.[20] Insofar as an applicant needs to fill in her position on the first page of the application form, this is a salient and easily observable signal for loan officers.

2. *LocalResident*: whether the applicant is a local city resident rather than a migrant worker. Local residents are typically thought to be of higher status than migrant workers (i.e., people who grow up in rural areas and migrate to work in a city) as the former generally have access to better public services such as education and healthcare because of local policy restrictions.[21] The Chinese "Hukou" (household registration) system makes it easy to distinguish local residents from migrant workers, making this another salient signal that loan officers use.

There are also several labels that reflect an applicant's *economic status*.

1. *EmploymentCert*: whether the applicant has an official certificate that verifies her position of employment. Such a certificate is considered acceptable to the bank only when 1) the employer's official stamp and a top manager's signature are on the certificate; and 2) the employer's identity can be recognized and verified by the bank. In practice, only employees with long-term positions with large employers can provide acceptable employment certificates, while most short-term contractors, employees of microscale businesses, and self-employed entrepreneurs have difficulty providing one. Thus, loan officers generally consider the availability of an employment certificate as a signal of superior economic status.

2. *IncomeCert* and *RegularPay*: whether the applicant can provide proof of stable—in terms of both timing and amount—income. This is confirmed either through an employer-issued income certificate (*IncomeCert*) or a label that summarizes cash-flow information from the applicant's bank statements (*RegularPay*), or both.[22]

3. *HomeOwner*: whether the applicant owns real estate, which can be assessed via photocopies of property deeds.

[20] Public employees are colloquially described as "the insiders of the system" in China, and public positions are very attractive in Chinese society. For example, in 2022, over 2 million young people are competing for 16,745 government positions, suggesting that on average about one out of 60 candidates can land a job "inside the system".

[21] In fact, discrimination against migrant workers concerns many in China.

[22] In stage one of the loan screening process, the bank's local branch employees analyze the information from applicants' bank statements and create easily observable labels indicating income stability (or not) and add it to the application form.

It is important to note that, at the time of application, these social- and economic-status labels are exogenous to the applicant's discretion, as they are determined by the applicant's ex-ante occupation type, migration status, etc. As the economic labels are correlated with applicants' fundamental credit risk, using them as screening signals might lead to some degree of statistical discrimination. Meanwhile, using social labels might reflect loan officers' taste-based biases. When these signals are used to determine attention allocation, our attention-driven mechanism suggests that the associated inclusion gap could be further widened, no matter which kind of motivation drives the differential priors.

Applicants without socioeconomic labels are rejected more frequently. In Table 2 we report the results of an exploratory examination of the relationship between applicants' socioeconomic labels and application approval rates. The results show that applications with the aforementioned socioeconomic labels are significantly more likely to be approved. We regress the dummy variable indicating approval on an applicant's loan application on indicators of each of the aforementioned social or economic status labels possessed by the corresponding applicant. In the estimations we control for a comprehensive list of application-level observables that may be related to credit quality.[23] To rule out confounding effects such as loan officer-specific leniency and changes in risk-management criteria over time, we also control for loan type, bank branch, week, and officer-year-month–fixed effects. As shown in the table, each of the six social or economic status indicators contributes significantly to higher approval rates, and their effects on approval rates remain statistically and economically significant when examined together (see columns (7) through (9)).

[**Table** 2 about here.]

Defining applicants from unattractive SES backgrounds. The attention-based mechanism, which is formally analyzed in Section 2, suggests that applicants with fewer socioeconomic status labels may be considered "unattractive" and receive less attention from officers. That is, even if the credit quality of such an applicant is high enough to warrant approval, her

[23] We control for log total income, the log applied loan-amount-to-income ratio, the applicant's pre-existing debt-to-total-income ratio, the log of one plus the longest number of months that the applicant has been overdue on payments in the two most recent years, the log of one plus the number of inquiries into the applicant's credit history in the two most recent years, and whether the applicant has no credit history or has an investment account in the bank we study. We also control for the applicant's gender and age, as well as whether the applicant has reported on the application that she holds agricultural registered permanent residence, has earned a non-college degree, receives a social security allowance, or has been involved in legal cases. Finally, we control for the interest rate and maturity of the applied-for loan, both of which have already been determined at local bank branches.

application may still be hastily “passed up” by loan officers who are busy and intend to reserve their attention for applicants from more attractive backgrounds. We test this prediction in Section 4.

Given that loan officers are considering multiple social- and economic-status labels, we use a data-driven approach to summarize the combined effects of the aforementioned status indicators into two variables, “Social Status“ and “Economic Status,“ to classify which applicants are “attractive.” Specifically, we compute the regression-predicted value of application approval for the two social-status labels and four economic-status labels, separately:[24]

$$\begin{aligned}\text{SocialStatus}_i &\equiv \widehat{\text{Approval}}_i|\{\text{PublicEmployee}_i, \text{LocalResident}_i\}\\ &= \hat{b}_{\text{PublicEmployee}} \cdot \text{PublicEmployee}_i + \hat{b}_{\text{LocalResident}} \cdot \text{LocalResident}_i \end{aligned} \tag{3}$$

$$\begin{aligned}\text{EconomicStatus}_i \equiv\ & \widehat{\text{Approval}}_i|\{\text{EmploymentCert}_i, \text{RegularPay}_i, \text{IncomeCert}_i, \text{HomeOwner}_i\}\\ &= \hat{b}_{\text{EmploymentCert}} \cdot \text{EmploymentCert}_i + \hat{b}_{\text{RegularPay}} \cdot \text{RegularPay}_i +\\ &\quad \hat{b}_{\text{IncomeCert}} \cdot \text{IncomeCert}_i + \hat{b}_{\text{HomeOwner}} \cdot \text{HomeOwner}_i \end{aligned} \tag{4}$$

In other words, these two variables are single-dimension summaries of the multiple social and economic labels carried in a given application. For simplicity, in subsequent analyses we create two indicator variables, Attractive $(\text{Social})_i$ and Attractive $(\text{Economic})_i$, which equal one for applicants whose SocialStatus_i and EconomicStatus_i values, respectively, are above the sample median. That is, we consider the group of applicants with above-median Attractive $(\text{social})_i$ or Attractive $(\text{economic})_i$ to be socially or economically attractive, while applicants with the corresponding status measures falling below the median to be unattractive. The correlation between the two attractiveness indicators is -0.133.

3.5 Credit Qualities of Attractive and Unattractive Applicants Largely Overlap, but Approval Rates Differ Significantly

When we compare the approval rates reported in Panel B of Table 1, we find that the gaps between attractive and unattractive groups are large. Specifically, the socially (economically) unattractive groups experience average approval rates of only 18.1% (25.4%), while the

[24]Here we use a version of the regression without additional controls. Our results are not sensitive to the exact methodology through which the socioeconomic status indicators are combined.

socially (economically) attractive groups experience much higher approval rates of 51.9% (65.5%).

[**Figure** 4 about here.]

What might explain such large gaps? When examining a number of major credit-worthiness measures, we indeed find some evidence that applicants from more attractive socioeconomic groups exhibit higher average credit quality (Panels A and B of appendix Table B2). The difference is small, however, and there is a substantial overlap between the attractive and unattractive groups. This can be seen easily in Figure 4, where we plot the kernel densities of creditworthiness measures for the attractive groups in green and the unattractive groups in red, with the vertical dashed lines representing group averages. As is clear from these plots, while the attractive groups are slightly more creditworthy on average, the difference is very small, and there is a substantial overlap in credit quality between the two groups. Panels C and D of appendix Table B2 present further numerical details about the extent of the overlap: 48% (47%) of the socially (economically) unattractive applicants earn incomes higher than the median attractive applicant, and 38% (39%) exhibit lower leverage ratios. The fact that these numbers are only slightly below 50% implies that the unattractive group demonstrates almost the same credit quality as the attractive group based on the observable metrics. Moreover, as shown in Panels E and F of appendix Table B2, even among those applicants from the unattractive groups who are rejected, a significant portion demonstrate credit quality that is higher than that of the median applicant in the attractive groups whose applications are *accepted*.

These puzzlingly large approval gaps led us to suspect that some unattractive applicants might be rashly rejected by busy officers without careful review. Following this train of thought, we examined the amount of officer review time and found significant differences: the socially (economically) unattractive group receives only 12.2 (16.1) minutes of median review time, while the socially (economically) attractive group receives 24.9 (25.2) minutes—approximately twice as much time. In Section 4.1 we provide further details regarding this analysis.

Studying loan officers' reasons for rejection paints a similar picture. At the bank we study, loan officers have to provide reasons for rejections, but some reasons are boilerplate while others indicate that loan officers have acquired application-specific information before rendering a rejection—we regard the loan officer as having conducted due diligence in the latter case. We find that socially (economically) unattractive groups receive due diligence only 22.2% (22.7%) of the time, while socially (economically) attractive groups receive due diligence 32.8% (49.5%) of the time on average.

Overall, these patterns suggest that the wide gap in approval rates might be related to loan officers' paying less attention to low-SES applicants. This finding is merely a correlation, however, so we further exploit variations in loan officer attention constraints in subsequent sections to better understand the mechanism.

4 The Impact of Loan Officer Attention Constraints

In this and the following sections we present tests of our main empirical prediction: when loan officers face tighter attention constraints, they disproportionately reduce attention on low-SES applicants and reject them much more frequently. We start in this section by using a simple measure of loan officer busyness to proxy for their attention constraints and then in the next section we construct instruments for the constraints that enable us to infer causal effects.

4.1 Measuring Loan Officer Attention Allocation and Attention Constraints

Measuring attention allocation to each application. Our access to internal timestamps for officer actions enable us to use elapsed time between two consecutive decisions by the same officer to measure how much time is spent reviewing each application. To remove variations in application review times that are unlikely to reflect active loan officer choices,[25] we define "standardized review time" as the log deviation of review time from the median level within each Officer × Month-Year × Loan-Type × Bank-Branch group. Specifically, we compute

$$\text{StandardizedReviewTime} = \log\left(\frac{\text{ReviewTime}}{\text{Median ReviewTime by group}}\right) + \underbrace{\text{Median}\ \log(\text{ReviewTime})}_{\text{full sample}} \tag{5}$$

where the groups in the denominator of the first term are Officer × Month-Year × Loan-Type × Bank-Branch buckets. In other words, we remove review-time variations that are explained by interaction between all of the fixed effects we use in our regressions; these fixed effects, combined, explain 36% of log review time variations, as shown in column (4) of Appendix Table C1. The second term in equation (5) simply adds back the overall sample median of log review time. As reported in Table 1, the inter-quartile range of this attention measure (standardized review time) runs from 0.488 to 1.476.

[25] 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.

Measuring loan officer attention constraints. To proxy for loan officer attention constraints, we compute a day-officer level variable $\text{Busyness}_{j,d}$, which is defined as the number of applications officer j processes on day d. The reasoning is straightforward: the higher the number of 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 on a given day, and the 10^{th} and 90^{th} percentiles are 10 and 27 applications, respectively. Therefore, there are substantial variations in officer busyness and the concomitant time constraint on each application.

[**Figure** 5 about here.]

We argue that loan officer busyness is relevant to attention constraints. First, when officers are busier, they work longer hours and are more likely to work overtime. To examine this claim, we sort the sample into deciles differentiated by busyness and, in Panel (a) of Figure 5, plot the average starting and ending times for each decile for a typical work day.[26] On a lowest-busyness-decile day, a typical officer begins working just before 9:00 a.m. and finishes before 6:00 p.m. Assuming that the officer takes a one-hour lunch break, this amounts to a standard eight-hour work day. In contrast, on a day that features top-decile busyness, officers begin working before 8:30 a.m. on average and finish after 7:30 p.m. Panel (b) of Figure 5 shows that the probability that officers work overtime rises from approximately 20% in a lowest-busyness-decile day to over 60% in the highest-busyness-decile day.[27] Second, when officers are busier, they spend less time reviewing each application. This is reflected in both Panels (a) and (b) of Figure 1, as well as in the subsequent analyses presented in this and the next section.[28] Overall, these findings are consistent with our view that officers are more severely attention constrained when they are busy.

Unattractive applicants are accorded significantly less attention. Having developed our measure of officer attention to each application, we note that unattractive applicants receive less attention on average. The median (average) time that officers spend reviewing an application with unattractive social status is only 12.17 (24.53) minutes, which is approximately 50% (33%) lower than that for attractive applicants who receive 24.86 (37.42) minutes. Similarly, the median (average) time that officers spend reviewing an application that is unattractive because of economic status is 16.12 (28.76) minutes as opposed to 25.16 (37.41) minutes for applicants accorded attractive economic status.

[26]The starting and ending times are measured using the timestamps for the first and last actions submitted by each officer on each day.

[27]Working overtime is defined as working before 8:30 a.m. or after 7:30 p.m.

[28]Appendix Figure C1 and Table C2 also indicate that the longer an officer works on a given day, the less time she spends reviewing each individual application.

Auxiliary attention allocation measures. In Appendix B.3, we use another loan officer action—conducting further due diligence when screening applicants—to measure officer attention allocation. This measure yields the same conclusion, as officers are less likely to conduct due diligence for applicants from unattractive groups. In particular, by comparing the reasons loan officers cite when rejecting applications, we find that, when a loan officer rejects an attractive applicant, she is much more likely to have engaged in further due diligence (e.g., searching up the applicant online) beyond simply browsing the documents already provided. In contrast, a loan officer is more likely to reject an unattractive applicant based on boilerplate reasons such as "leverage is too high." In sum, these preliminary comparisons suggest that unattractive applicants receive less attention from loan officers.

4.2 The Impact of Loan Officer Attention Constraints

Having defined measures of loan officer attention constraints and attention allocation, we now examine the the impact of tighter attention constraints on attention allocation and approval rates. In this section we use the realized officer busyness measure to proxy for attention constraints. In the next section we develop instruments for loan officer busyness.

In an exploratory analysis, we first simply plot (without controls) average attention and approval rates as a function of busyness. For Figure 1 Panels (a) and (b), we sort the sample into deciles differentiated by officer busyness and plot the average standardized review time for the attractive and unattractive groups as measured by their social or economic status, respectively. Attention declines for both groups, but the decline is more noticeable for the unattractive group: when officers become busier, they appear to shift attention *away* from unattractive applicants. Panels (c) and (d) plot the approval rates. When officers become busier, the approval rate for the unattractive group declines steadily relative to the rate for the attractive group. These patterns are consistent with the base case model predictions. Further, the approval rate for attractive applicants actually appears to increase slightly with loan officer busyness, which may be consistent with the special case predictions where some extremely high-SES applicants are quickly approved without careful screening.

[**Table** 3 about here.]

To formally investigate the effects of officer attention constraints, we now conduct regression analyses at the application level. For columns (1) and (2) of Table 3, we regress standardized review time—our measure of loan officer attention allocation—on loan officer busyness decile, the *Attractive(Social)* dummy that indicates whether the applicant's *SocialStatus* is above the sample median, as well as interaction between busyness decile and

Attractive(Social). We then run similar tests for columns (3) and (4), measuring attractiveness based on the applicant's economic status. Consistent with the visual patterns displayed in Figure 1, when officers are busier, the attention they pay to applicants decreases, but the decrease is disproportionately large for unattractive applicants. For instance, the results reported in column (2) indicate that, when officer busyness varies from the lowest to the highest decile, the attention paid to unattractive applicants declines by $(10-1)\times -0.059 \approx 53\%$. While it is unavoidable that officers will spend less time on each application when they are busier, the attention gap between attractive and unattractive applicants increases by $(10-1)\times 0.017 \approx 15.3\%$, and these effects are statistically significant at the 1% level. In columns (5) and (6), we show that the effects remain statistically and economically similar when both social and economic status are considered simultaneously. Appendix Table B6 verifies that the same conclusion holds when using officer due diligence as an additional measure of officer attention allocation.

[**Table** 4 about here.]

In Table 4, we use similar specifications to estimate the impact of officer busyness on approval decisions. The results reported in column (2) indicate that, for the socially unattractive group of applicants, increasing from the lowest to the highest busyness decile reduces approval probability by $(10-1)\times -0.009 \approx 8.1$ percentage points. This reduction is about 45% of the average approval rate for this group of applicants. Similarly, the results reported in column (4) show a decline in the approval rate by $(10-1)\times -0.011 \approx 9.9$ percentage points, which is about 39% of the group average. In contrast, the approval probability is roughly unchanged or even slightly increased for the attractive groups. The results remain broadly similar when both attractiveness measures are considered jointly for columns (5) and (6). Overall, these results are consistent with out main prediction that, when loan officers face tighter attention constraints, low-SES applicants receive disproportionately less attention and are rejected more frequently. In some specifications (see columns (3) through (5)), we even find evidence that attractive groups experience higher approval rates, suggesting that the special-case model predictions may have some bite.

It is worth noting that, in our regressions, we control for officer × month-year, week, bank branch, and loan-type fixed effects. Therefore, our findings do not stem from any differences regarding officer-specific preferences, branch-specific risk-management styles, or aggregate time trends. We also control for a comprehensive list of features that could be related to borrower credit-worthiness; in unreported robustness checks, we also find that our results are not sensitive to the choice of the controls. Appendix Figure C2 further shows that, conditional on all loan characteristics and fixed effects, the gaps between the attractive and unattractive applicant groups in terms of both attention allocation and approval rate widen almost monotonically when loan officers get busier.

5 Instrumented Variations in Officer Attention Constraints

One may be concerned that our measure of loan officer attention constraints using *realized* busyness could be endogenous. In this section, we construct two instruments for officer busyness to address these concerns. We show that our results are robust using these instruments.

5.1 Instruments for Officer Busyness

Instrument approach 1: assignment-predicted busyness. Using *realized* loan officer busyness raises an endogeneity concern: loan officers can set their own pace at work, which may lead to omitted variable problems. For instance, a loan officer who wants to relax on a particular day, possibly to attend to entertainment outside of work, may choose to quickly reject most applications perfunctorily, leading to a spurious negative correlation between busyness and the officer's loan-approval rate. To be clear, such situations *per se* cannot lead to our difference-in-differences result, which shows the *differential* impact of attention constraints on loan officer decisions for applicants from attractive and unattractive groups.[29] That said, we take this endogeneity concern seriously.

To resolve this endogeneity concern, we need to find a source of busyness variation that is external: i.e. *not controlled* by loan officers. As described in Section 3.2, loan applications are assigned to officers by a central dispatcher algorithm over which officers have no control. Apart from assurances from the bank we study, we also confirm that the assignment algorithm is external to loan officers by verifying that the number of assignments has no relationship with current or previous loan officer backlogs (Appendix Table B7).[30]

Adding controls for officer-month-year fixed effects, we can use the number of assignments as an instrument to capture the idiosyncratic variation in officer busyness through a regression

[29]To obtain these differential results, one needs to explain why a careless officer would rashly reject borrowers with unattractive labels but not those with attractive labels.

[30]Specifically, we are worried that loan officers may be able to *indirectly* influence the number of assignments they receive by working faster or slower. If an officer can face fewer assignments by having a larger backlog (through working more slowly), this would be a concern to our identification strategy.

at the officer–day level,

$$\text{Busyness}_{j,d} = a + \sum_{\tau=0}^{3} b_\tau \cdot \text{Assignment}_{j,d-\tau} + \epsilon_{j,d}, \tag{6}$$

where $\text{Assignment}_{j,d}$ is the number of applications assigned to loan officer j on working day d. We include three lagged working days because some applications are processed a few days after assignments are alloted. In Appendix Table B9, we present details associated with this regression. The instrument is strong and can explain around 40% of the variation in realized officer busyness.[31] Hereafter, we call the value predicted in regression (6) "predicted busyness."

Instrument approach 2: leave-one-out (LOO) assignment-predicted busyness. This second instrument can be thought of as a further refinement of the previous one. Even though we find no correlation between assignments and loan characteristics (explained in Section 5.2), one might still worry about correlations between assignments and unobservable loan quality. We argue that this concern is unlikely to explain our findings, for two reasons. First, we obtain the entire set of administrative records for these loan applications and control for a comprehensive list of group fixed effects and loan characteristics. Second, to explain our difference-in-differences results, the confounding driver of assignments has to be negatively correlated with the credit quality of low-SES borrowers but uncorrelated, or even positively correlated, with the credit quality of high-SES borrowers.

Although this concern is not very realistic, we address it by constructing a loan-level, leave-one-out (LOO) instrument using the number of applications from provinces other than the one from which the examined application comes. Recall that the loan officers we study work at the headquarters office, while applications are sourced from bank branches all over the country. Given this, the idea behind this instrument is that, if many assignments from province A make a given loan officer busy, this could affect her decision-making regarding applications from province B even when neither the quantity nor the quality of applications from province B changes. Specifically, when examining the decision-making associated with each application, we consider this LOO "Bartik"-type design by directly controlling for the number of assignments from the source province where the application originates and exploiting variations from the LOO assignments driven by the application volume from other provinces. In this way, we tease out the effect of loan officer attention constraints that is driven by *external* workload variations. Hereafter, we call the instrumented loan officer

[31] Appendix Figure **??** shows that, like the realized busyness measure, the instrumented busyness measures are related to longer work hours and more overtime.

busyness computed using this method "LOO-predicted busyness."

5.2 What drives the assignment algorithm?

The bank we study does not disclose exactly how the algorithm works, but we can catch a glimpse from discussions with bank employees. According to the employees, the algorithm groups loan applications based on a variety of factors such as the branch where the application is submitted, the loan type, size categories, etc. Every day, a loan officer is randomly assigned to one or several groups of applications.[32] The application volume is not evenly distributed across different groups at different times, however, so a loan officer does not always focus on one or several particular groups but instead is assigned a random set of group(s) every day. In this way, the law of large numbers ensures that different loan officers' workloads are on average similar over a longer horizon, although they experience idiosyncratic variations in their workloads on a day-by-day basis as a result of the randomness of the assignments. While the bank does not disclose the basis of the grouping algorithm, it affirms that loan officers have no influence over the assignment criteria and that the quantity of assignments is uncorrelated with the quality of applications. Therefore, this dispatcher algorithm generates idiosyncratic variations in officer attention constraints that are orthogonal to loan officer preferences and loan quality.

To test whether assignments are truly uncorrelated with credit quality, we examined the relationship between assignments and a comprehensive list of observable loan characteristics and report the results in Appendix Table B8. Consistent with our discussion with bank employees, the results provide no indication of a relationship between assignments and loan characteristics.

5.3 Results Based on Instrumented Busyness Measures

Using the two above-mentioned instrumented busyness measures, we re-examine our main results.

[**Table** 5 about here.]

In Table 5, we use *Predicted Busyness* (columns 1 through 3) and *LOO-Predicted Busyness* (columns 4 through 6) to estimate how idiosyncratic variations in loan officer attention constraints affect their allocation of review time. The instrumented busyness measures are

[32] Banks use this "assignment by group" algorithm so that each loan officer can process a set of relatively homogeneous applications on a given day. This makes loan processing more efficient and lending standards more consistent each day.

estimated in an earlier stage, so we estimate standard errors using the bootstrap method. As can be seen in column (1), while attention declines for all applicants as loan officers become busier, the attention gap between applicants with attractive and unattractive social status widens by $(10-1) \times 0.013 = 11.7\%$ when *Predicted Busyness* increases from the bottom to the top decile. As can be seen in column (2), an effect of similar magnitude is found between applicants with attractive and those with unattractive economic status, and the results are robust to simultaneously including both social and economic status group indicators (column (3)). When measuring loan officer attention constraints using *LOO-Predicted Busyness*, the effects are qualitatively and quantitatively similar, as shown in columns (4) through (6).

We then use the same instrumented busyness measures to estimate the effects of loan officer attention constraints on approval decisions. The results reported in columns (1) and (2) of Table 6 indicate that the approval gap between socially (economically) attractive and unattractive applicants is increased by $(10-1) \times 0.009 = 8.1\%$ ($(10-1) \times 0.013 = 11.7\%$) when Predicted Busyness increases from the bottom to the top decile. Similar results are also reported in columns (3) through (6) after measuring attention constraints by LOO-Predicted Busyness. The last rows of the table indicate that high-SES applicants actually experience increases in approval rates. Overall, these results are generally consistent with the attention-based mechanism. In Appendix Table C3, we further show that our main results hold up when we examine each of the six social or economic status labels separately.[33]

Overall, the results presented in this section suggest that our earlier findings based on realized busyness likely reflect the impact of officer attention constraints and are not attributable to omitted variables or reverse causality.

[**Table** 6 about here.]

6 Conclusion

Insufficient financial inclusion of individuals from unattractive SES backgrounds is a concern on both equity and efficiency grounds. Motivated by Bartoš et al. (2016), we propose that financial inclusion can be hindered by attention constraints on financial decision-makers. In the selection process, attention-constrained decision-makers may ration their attention allocation using ex-ante socioeconomic labels. As a result, low-SES applicants may be given insufficient attention and be rejected more often. For applicants from very high-SES backgrounds, the reverse often applies: they may be quickly approved without careful review.

[33] Using these two instrumented measures of busyness, we reproduce Figure 1 in Figures C3 and C4, and reproduce Figure C2 in Figures C5 and C6. We find qualitatively similar results in all cases.

As a result, this attention-based mechanism can lead to an inclusion gap between high- and low-SES borrowers.

We provide evidence for this mechanism using proprietary retail loan-screening records from a large national bank in China. Loan officers at the bank are time-constrained and spend a median of only 18 minutes on each loan application they review. Against this backdrop, applicants without certain socioeconomic labels are considered unattractive by loan officers who screen applicants and make lending decisions. The unattractive applicants receive less review time and their loan applications are more often rejected compared with those of otherwise similar applicants with attractive socioeconomic labels. Furthermore, when loan officers experience tighter attention constraints caused by orthogonal variation in their workloads, both review times and approval gaps between attractive and unattractive applicants widen.

Our findings imply that, in human-based decision processes, organizational arrangements or technologies that relax attention constraints may help improve inclusion and promote diversity. Our findings also suggest that the rise of fintech may—if properly used—promote financial inclusion through pre-processing of applicant information and relieving decision-makers of attention bottlenecks. Moving beyond our immediate setting, many high-stake decisions are made by humans, and key decision-makers—such as court judges, college admissions officers, and so on—are often very busy. Therefore, while our study focuses on the impact of attention constraints on the allocation of financial resources, we suspect that similar mechanisms are at play in other settings that are potentially more consequential.

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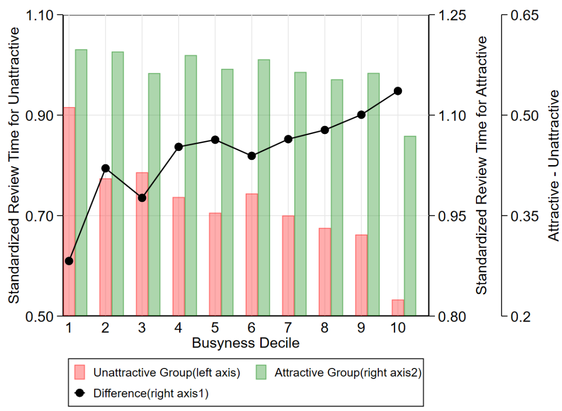
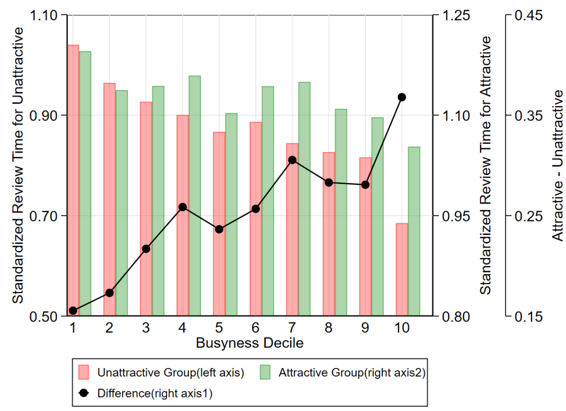
Figure 1. Attention Allocation and Approval Decisions by Loan Officer Attention Constraints

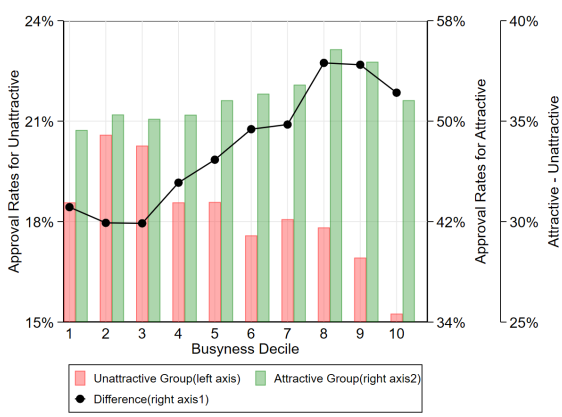
This figure exhibits how loan officer attention allocation and approval decisions for attractive and unattractive applicants vary by officer attention constraints. As explained in Section 3.4, we use the possession (or not) of various labels to classify applicants into attractive and unattractive groups based on social status (Panels (a) and (c)) or economic status (Panels (b) and (d)). In all panels, we sort the sample into deciles by officer attention constraints measured by *busyness*, which is defined as the number of applications processed per day. Panels (a) and (b) plot the average officer attention allocation, measured as the standardized review time on each loan in the screening process, by busyness decile. Panels (c) and (d) plot the average loan approval rate by busyness decile. The measurement of standardized review time is explained in Section 4.1. Each red (green) bar graphs the average for the unattractive (attractive) group of applicants. The black line plots the differences between the two groups.



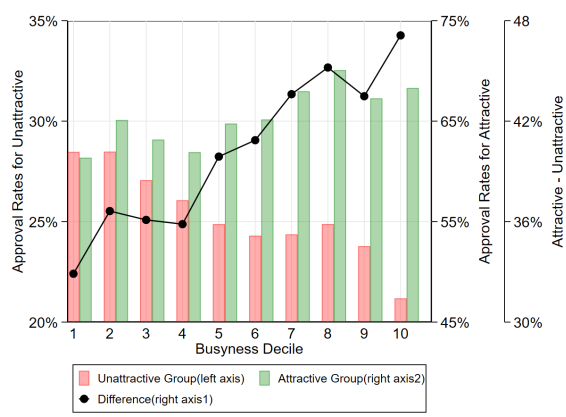
(a) Officer attention allocation by applicant social status



(b) Officer attention allocation by applicant economic status



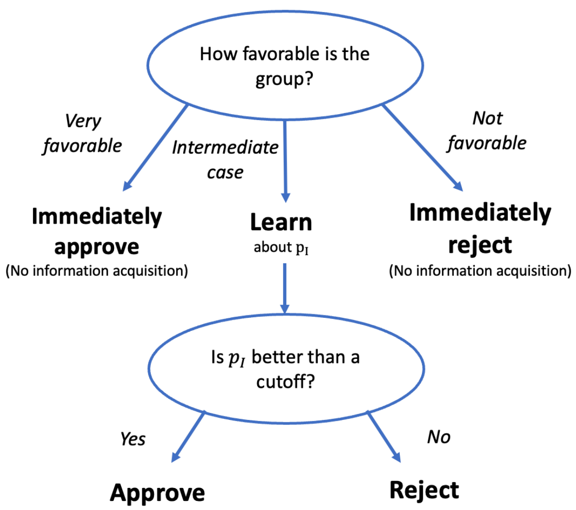
(c) Officer approval decisions by applicant social status



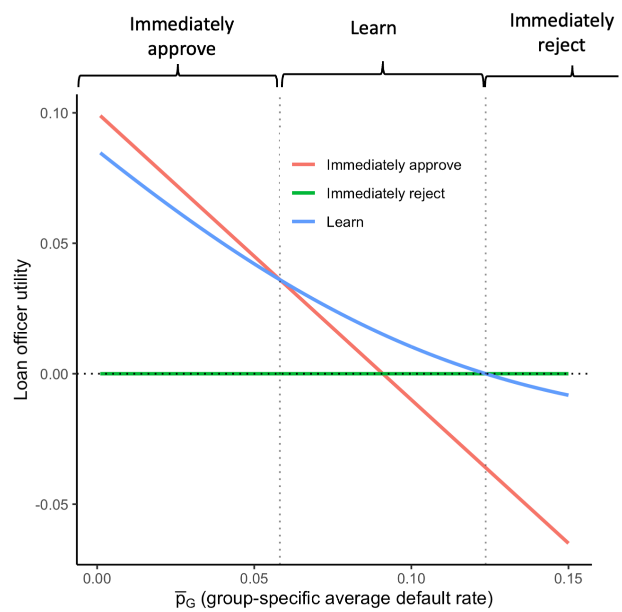
(d) Officer approval decision by applicant economic status

Figure 2. Illustration of The Model

Panel (a): The optimal loan officer decision process. At stage 1, the officer decides whether to incur attention cost c to learn applicant-specific quality information p_I, given knowledge of the applicant's group. Conditional on doing so, at stage 2 the officer decides whether to approve or reject the application. Panel (b): we plot the expected loan officer utility associated with the three strategies—immediately approve (red line), immediately reject (green line), and learn before making a decision (blue line)—as a function of the ex-ante group-specific average default rate $\bar{p}_G$. The optimal decisions are divided into three regions annotated at the top. Model parameters: $\sigma = 0.08, r = 0.1, \text{distaste}_G = 0$, and $c = 0.02$.



(a) Optimal loan officer decisions



(b) Solving for the optimal strategy across groups

Figure 3. Flow Chart of Loan Origination and Screening

In stage one, loan applications are submitted at regional bank branches across the country. Loan amounts, maturities, and interest rates are already determined at this stage. In stage two, a central dispatcher algorithm assigns applications to headquarters loan officers. In stage three, loan officers read each application and decide whether to approve or reject it.

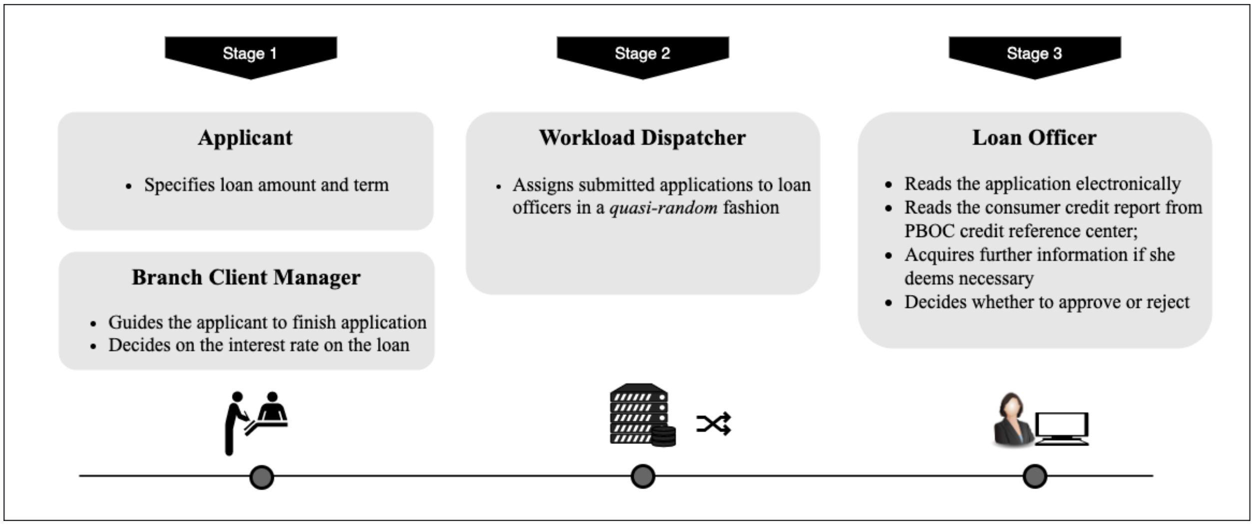
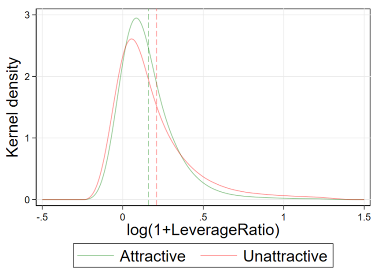


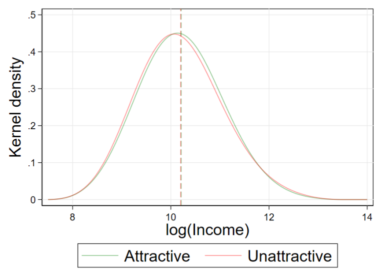
Figure 4. Distribution of Credit Quality: Attractive and Unattractive Applicants

We plot the kernel density distribution of credit quality measures for the attractive and unattractive applicant groups. The vertical dashed lines represent the averages for each group. Panel A compares applicants with attractive and unattractive social statuses. Panel B compares applicants with attractive and unattractive economic statuses. The definitions of these groups are provided in Section 3.4. From left to right, the plots examine the logarithm of the leverage ratio, income, and the ratio of applied-for loan amounts to applicant income for the applicants, respectively.

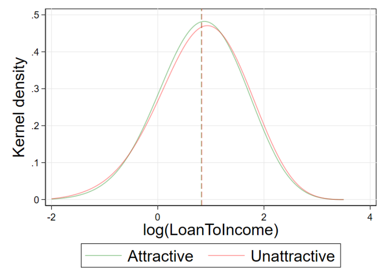
Panel A. Distribution of credit quality by applicant *social status*



(a) log(1+LeverageRatio)

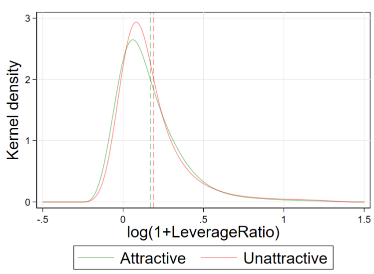


(b) log(Income)

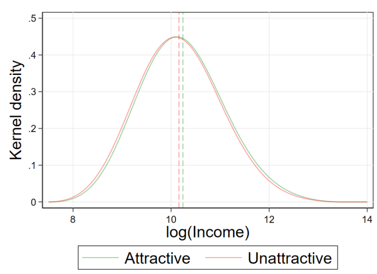


(c) log(LoanToIncome)

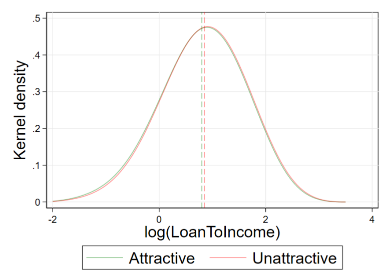
Panel B. Distribution of credit quality by applicant *economic status*



(d) log(1+LeverageRatio)



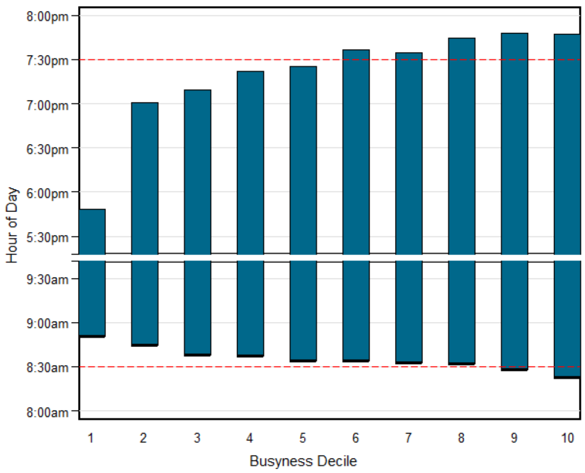
(e) log(Income)



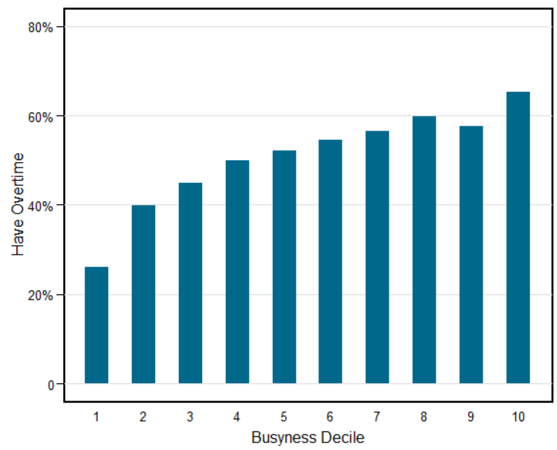
(f) log(LoanToIncome)

Figure 5. Officer Busyness and Work Schedules

We sort the sample into deciles differentiated by officer busyness, which is defined as the number of applications an officer processes on a given day. Panel (a) plots the average time of a work day at which officers start and end their work. The start and end times are measured by the timestamps indicating when officers submit the first and last loan decisions on each day. Panel (b) plots the fraction of days on which officers work overtime, defined as working before 8:30 a.m. or after 7:30 p.m. (the red dashed lines in Panel (a)).



(a) Officer work schedule



(b) Officer overtime

Table 1. Summary Statistics

This table presents summary statistics. In Panel A we report the summary statistics for the full sample. In Panel B we compare the means of applicants in groups with attractive and unattractive social/economics status. See Appendix Table B.1 for variable definitions.

Panel A. Summary statistics for the full sample

	N	Mean	SD	10%	25%	50%	75%	90%
Officer screening activities								
Approval	145,982	0.342	0.474	0	0	0	1	1
ReviewTime *(min)*	145,977	30.674	40.615	2.433	6.712	18.354	36.536	72.392
StandardizedReviewTime	145,977	0.933	1.082	−0.552	0.488	1.068	1.476	2.113
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 characteristics								
PublicEmployee	145,982	0.081	0.273	0	0	0	0	0
LocalResident	145,982	0.455	0.498	0	0	0	1	1
EmploymentCert	145,982	0.620	0.486	0	0	1	1	1
IncomeCert	145,982	0.342	0.474	0	0	0	1	1
RegularPay	145,982	0.117	0.321	0	0	0	1	1
HomeOwner	145,982	0.223	0.417	0	0	0	0	1
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
SocialSecurity	145,982	0.406	0.491	0	0	0	1	1
Litigation	145,982	0.002	0.043	0	0	0	0	0
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

Panel B. Comparison between the attractive and unattractive groups

Attractive measure:	SocialStatus		EconomicsStatus	
	Attractive	Unattractive	Attractive	Unattractive
Approval	0.519	0.181	0.655	0.254
StandardizedReviewTime	1.169	0.719	1.131	0.877

Table 2. Higher Approval Probability for Applicants with Attractive Social/Economic Labels

In this table, we estimate the relationship between loan approval probability and applicants' social and economic labels. The outcome variable equals one if the loan application is approved and zero otherwise. As discussed in Section 3.4, *PublicEmployee* and *LocalResident* are indicators of applicant social status, while the other four indicators are applicant economic-status labels. Application-level controls include log(*Income*), log(*Loan/Income*), log(1+*LeverageRatio*), log(1+*OverdueMonth)*, log(1+*CreditInqury)*, *HasInvestmentAcc*, *Female*, log(*Age*), *Peasant*, *NonCollege*, *SocialSecurity*, *Litigation*, *ShortTerm*, and log(*InterestRate*). See Table B.1 for variable definitions. Standard errors are double-clustered at the week and officer levels. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Dependent variable:	Approval									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
PublicEmployee	0.246***						0.098***		0.020***	0.023***
	(17.062)						(12.828)		(2.956)	(3.312)
LocalResident		0.467***					0.452***		0.161***	0.145***
		(28.719)					(28.729)		(7.524)	(5.961)
EmploymentCert			0.527***					0.399***	0.286***	0.278***
			(30.703)					(22.789)	(12.942)	(10.824)
IncomeCert				0.395***				0.088***	0.042**	0.034**
				(23.722)				(5.712)	(2.516)	(2.123)
RegularPay					0.419***			0.113***	0.159***	0.163***
					(22.675)			(9.521)	(12.228)	(10.936)
HomeOwner						0.460***		0.179***	0.217***	0.222***
						(27.833)		(17.394)	(17.502)	(14.873)
Application Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	N
Week FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	N
Branch FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	N
Loan type FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	N
Observation	145,982	145,982	145,982	145,982	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.140	0.265	0.354	0.222	0.170	0.217	0.268	0.369	0.372	0.342

Table 3. Effects of Officer Attention Constraints on Review Time

For this table, we estimate how loan office attention constraints affect the time they spend on reviewing each loan application by applicants from attractive and unattractive socioeconomic backgrounds. The dependent variable is the standardized review time for a loan application, defined as the logarithm of the excess time spent by officers in reviewing each application (Equation (5)). *Attractive(Social)* and *Attractive(Economic)* are dummy variables indicating whether the applicant has above-median *SocialStatus* and *EconomicStatus*, respectively, and the definition is explained in Section 3.4. *BusynessDecile* is the officer's daily busyness, defined as the number of applications processed on a given day, sorted into deciles. For the overall effect of loan office attention constraints on socially or economically attractive groups, we calculate the sum of two groups of coefficients ($\beta_1 + \beta_3$) and ($\beta_1 + \beta_5$), and report the P-values of their T-tests. The regressions include officer × month-year fixed effects, week fixed effects, origination-bank-branch fixed effects, and loan-type fixed effects. Application controls include log(*Income*), log(*Loan/Income*), log(1+*LeverageRatio*), log(1+*OverdueMonth)*, log(1+*CreditInqury)*, *HasInvestmentAcc*, *Female*, log(*Age*), *Peasant*, *NonCollege*, *SocialSecurity*, *Litigation*, *ShortTerm*, and log(*InterestRate*). See Table B.1 for variable definitions. T-statistics are reported in parentheses. Standard errors are double-clustered at the week and officer levels. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Dependent variable:	StandardizedReviewTime					
	(1)	(2)	(3)	(4)	(5)	(6)
$\beta_1 BusynessDecile$	-0.029^{***}	-0.059^{***}	-0.028^{***}	-0.058^{***}	-0.031^{***}	-0.061^{***}
	(−7.942)	(−17.248)	(−10.485)	(−19.538)	(−7.293)	(−16.167)
$\beta_2 Attractive(Social)$	0.276^{***}	0.439^{***}			0.321^{***}	0.413^{***}
	(9.640)	(13.854)			(10.162)	(12.801)
$\beta_3 Attractive(Social) \times$ BusynessDecile	0.019^{***}	0.017^{***}			0.019^{***}	0.017^{***}
	(4.457)	(3.949)			(4.306)	(3.922)
$\beta_4 Attractive(Economic)$			0.124^{***}	0.249^{***}	0.213^{***}	0.188^{***}
			(8.616)	(13.496)	(9.963)	(9.599)
$\beta_5 Attractive(Economic) \times$ BusynessDecile			0.016^{***}	0.017^{***}	0.016^{***}	0.014^{***}
			(6.290)	(6.639)	(5.563)	(5.117)
Application Controls	Y	Y	Y	Y	Y	Y
Officer-Month-Yr FE	N	Y	N	Y	N	Y
Week FE	N	Y	N	Y	N	Y
Branch FE	N	Y	N	Y	N	Y
Loan type FE	N	Y	N	Y	N	Y
Observation	145,977	145,977	145,977	145,977	145,977	145,977
Adjusted R-squared	0.057	0.076	0.035	0.046	0.070	0.082
$\beta_1 + \beta_3$	-0.010^{***}	-0.042^{***}			-0.011^{***}	-0.044^{***}
P-value of ($\beta_1 + \beta_3$)	(0.003)	(0.000)			(0.001)	(0.000)
$\beta_1 + \beta_5$			-0.011^{***}	-0.041^{***}	-0.015^{***}	-0.04^{***}
P-value of ($\beta_1 + \beta_5$)			(0.000)	(0.000)	(0.000)	(0.000)

Table 4. Effects of Attention Constraints on Approval Decisions

For this table, we estimate how loan office attention constraints affect their approval decisions on loan applications by attractive and unattractive applicants. The dependent variable is a dummy variable indicating whether the officer approves the application. *Attractive(Social)* and *Attractive(Economic)* are dummy variables indicating whether the applicant's *SocialStatus* and *EconomicStatus* are above the median, respectively, and the definition is explained in Section 3.4. *BusynessDecile* is the officer's daily busyness measure, defined as the number of applications processed on a given day, sorted into deciles. For the overall effect of loan office attention constraints on socially or economically attractive groups, we calculate the sum of two groups of coefficients $(\beta_1 + \beta_3)$ and $(\beta_1 + \beta_5)$, and report the P-values of their T-tests. The regressions include officer × month-year fixed effects, week fixed effects, origination-bank-branch fixed effects, and loan-type fixed effects. Application controls include log(*Income*), log(*Loan/Income*), log(1+*LeverageRatio*), log(1+*OverdueMonth)*, log(1+*CreditInqury)*, *HasInvestmentAcc*, *Female*, log(*Age*), *Peasant*, *NonCollege*, *SocialSecurity*, *Litigation*, *ShortTerm*, and log(*InterestRate*). See Table B.1 for the variable definitions. T-statistics are reported in parentheses. Standard errors are double-clustered at the week and officer levels. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Dependent variable:	Approval					
	(1)	(2)	(3)	(4)	(5)	(6)
β_1*BusynessDecile*	-0.005^{***}	-0.009^{***}	-0.007^{***}	-0.011^{***}	-0.004^{***}	-0.010^{***}
	(-3.977)	(-6.415)	(-5.950)	(-9.395)	(-6.850)	(-6.964)
β_2*Attractive*(*Social*)	0.253^{***}	0.408^{***}			0.326^{***}	0.375^{***}
	(16.803)	(26.896)			(21.170)	(23.928)
β_3*Attractive*(*Social*)× BusynessDecile	0.008^{***}	0.007^{***}			0.006^{***}	0.006^{***}
	(3.171)	(3.326)			(3.093)	(3.289)
β_4*Attractive*(*Economic*)			0.300^{***}	0.373^{***}	0.384^{***}	0.331^{***}
			(21.993)	(22.897)	(21.590)	(17.782)
β_5*Attractive*(*Economic*)× BusynessDecile			0.013^{***}	0.015^{***}	0.011^{***}	0.011^{***}
			(6.766)	(7.014)	(4.959)	(5.286)
Application Controls	Y	Y	Y	Y	Y	Y
Officer-Month-Yr FE	N	Y	N	Y	N	Y
Week FE	N	Y	N	Y	N	Y
Branch FE	N	Y	N	Y	N	Y
Loan type FE	N	Y	N	Y	N	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.166	0.269	0.180	0.217	0.306	0.338
$\beta_1 + \beta_3$	0.003	-0.002			0.002^{***}	-0.004^{***}
P-value of $(\beta_1 + \beta_3)$	(0.208)	(0.251)			(0.227)	(0.012)
$\beta_1 + \beta_5$			0.006^{***}	0.004^{*}	0.007^{***}	0.002
P-value of $(\beta_1 + \beta_5)$			(0.002)	(0.067)	(0.001)	(0.300)

Table 5. Effects of *Instrumented* Attention Constraints on Review Time

For this table, we estimate how instrumented loan officer attention constraints affect the time they spend reviewing loan applications submitted by attractive and unattractive applicants. These results are the *instrumented versions* of results reported in columns (2), (4), and (6) of Table 3. The dependent variable is the standardized application review time, defined as the logarithm of the excess time an officer spends reviewing each application (Equation (5)). *Attractive(Social)* and *Attractive(Economic)* are dummy variables indicating, separately, whether *SocialStatus* and *EconomicStatus* are above the median. *BusynessDecile* is the officer's instrumented daily busyness, defined as the number of applications processed on a given day sorted into deciles and instrumented by the total or leave-one-out (LOO) number of applications assigned to the loan officer over the preceding three working days. For columns (1) to (3), we use assignment-predicted busyness; for columns (4) to (6), we use LOO assignment-predicted busyness. For the effect of loan office attention constraints on socially or economically attractive groups, we calculate the sum of two groups of coefficients ($\beta_1 + \beta_3$) and ($\beta_1 + \beta_5$), and report the P-values of their T-tests. The regressions include officer × month-year fixed effects, week fixed effects, origination bank branch fixed effects, and loan-type fixed effects. Application controls include log(*Income*), log(*Loan/Income*), log(1+*LeverageRatio*), log(1+*OverdueMonth)*, log(1+*CreditInqury)*, *HasInvestmentAcc*, *Female*, log(*Age*), *Peasant*, *NonCollege*, *SocialSecurity*, *Litigation*, *ShortTerm*, and log(*InterestRate*). Local busyness controls include loan officer assignments from the same province. See Table B.1 for the variable definitions. T-statistics are reported in parentheses. Bootstrapped standard errors are double-clustered at the week and officer levels. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Dependent variable:	StandardizedReviewTime					
Busyness measure:	Predicted Busyness			LOO-Predicted Busyness		
	(1)	(2)	(3)	(4)	(5)	(6)
β_1BusynessDecile	-0.025^{***}	-0.024^{***}	-0.029^{***}	-0.019^{***}	-0.016^{***}	-0.022^{***}
	(-8.297)	(-9.248)	(-8.999)	(-6.393)	(-6.134)	(-6.397)
β_2Attractive(Social)	0.461^{***}		0.434^{***}	0.470^{***}		0.445^{***}
	(23.833)		(21.608)	(23.819)		(21.431)
β_3Attractive(Social) × BusynessDecile	0.013^{***}		0.015^{***}	0.013^{***}		0.013^{***}
	(4.722)		(5.152)	(4.668)		(4.334)
β_4Attractive(Economic)		0.285^{***}	0.215^{***}		0.289^{***}	0.220^{***}
		(13.311)	(10.031)		(13.975)	(11.090)
β_5Attractive(Economic)× BusynessDecile		0.013^{***}	0.012^{***}		0.012^{***}	0.011^{***}
		(4.139)	(3.645)		(3.980)	(4.022)
Application Controls	Y	Y	Y	Y	Y	Y
Local Busyness Controls	N	N	N	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y
Week 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	0.074	0.044	0.082	0.075	0.045	0.082
$\beta_1 + \beta_3$	-0.011^{***}		-0.014^{***}	-0.006^{***}		-0.009^{***}
P-value of ($\beta_1 + \beta_3$)	(0.000)		(0.000)	(0.001)		(0.000)
$\beta_1 + \beta_5$		-0.011^{***}	-0.017^{***}		-0.004^{*}	-0.011^{***}
P-value of ($\beta_1 + \beta_5$)		(0.000)	(0.000)		(0.070)	(0.000)

Table 6. Effects of *Instrumented* Attention Constraints on Approval Decisions

For this table, we estimate how instrumented loan officer attention constraints affect their approval decisions for loan applications submitted by attractive and unattractive applicants. These results are the *instrumented versions* of results reported in columns (2), (4), and (6) of Table 4. The dependent variable is a dummy indicating whether the officer approves the application. *Attractive(Social)* and *Attractive(Economic)* are dummy variables indicating, separately, whether *SocialStatus* and *EconomicStatus* are above the median. *BusynessDecile* is the officer's instrumented daily busyness, defined as the number of applications processed on a given day sorted into deciles and instrumented by the total or leave-one-out (LOO) number of applications assigned to the loan officer over the preceding three working days. For columns (1) through (3), we use assignment-predicted busyness; for columns (4) through (6), we use LOO assignment-predicted busyness. For the effect of loan officer attention constraints on socially or economically attractive groups, we calculate the sum of two groups of coefficients ($\beta_1 + \beta_3$) and ($\beta_1 + \beta_5$), and report the P-values of their T-tests. The regressions include officer × month-year fixed effects, week fixed effects, origination bank branch fixed effects, and loan-type fixed effects. Application controls include log(*Income*), log(*Loan/Income*), log(1+*LeverageRatio*), log(1+*OverdueMonth)*, log(1+*CreditInqury)*, *HasInvestmentAcc*, *Female*, log(*Age*), *Peasant*, *NonCollege*, *SocialSecurity*, *Litigation*, *ShortTerm*, and log(*InterestRate*). Local busyness controls include loan officer assignments from the same province. See Table B.1 for the variable definitions. T-statistics are reported in parentheses. Bootstrapped standard errors are double-clustered at the week and officer levels. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Dependent variable:	Approval					
Busyness measure:	Predicted Busyness			LOO-Predicted Busyness		
	(1)	(2)	(3)	(4)	(5)	(6)
β_1BusynessDecile	−0.004***	−0.003***	−0.006***	−0.004***	−0.003***	−0.006***
	(−4.380)	(−4.046)	(−8.048)	(−5.087)	(−4.382)	(−9.354)
β_2Attractive(Social)	0.399***		0.367***	0.403***		0.370***
	(56.706)		(50.568)	(58.399)		(53.776)
β_3Attractive(Social) × BusynessDecile	0.009***		0.008***	0.008***		0.008***
	(7.241)		(7.018)	(6.683)		(7.171)
β_4Attractive(Economic)		0.383***	0.331***		0.384***	0.331***
		(36.447)	(31.948)		(36.992)	(35.311)
β_5Attractive(Economic)× BusynessDecile		0.013***	0.012***		0.013***	0.012***
		(8.564)	(7.725)		(8.553)	(8.111)
Application Controls	Y	Y	Y	Y	Y	Y
Local Busyness Controls	N	N	N	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y
Week 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	0.272	0.219	0.342	0.272	0.219	0.342
$\beta_1 + \beta_3$	0.005***		0.002***	0.004***		0.001**
P-value of ($\beta_1 + \beta_3$)	(0.000)		(0.000)	(0.000)		(0.039)
$\beta_1 + \beta_5$		0.010***	0.006***		0.009***	0.005***
P-value of ($\beta_1 + \beta_5$)		(0.000)	(0.000)		(0.000)	(0.000)

APPENDIX

A Analytical Results

A.1 Solving the model

We first prove results with fixed distaste_G and vary $\bar{p}_G$, and then show that the results based on varying distaste_G are mathematically similar.

Optimal loan officer behavior. We first prove that the optimal loan officer decision is characterized by three regions with two cutoffs. For notational simplicity, we define the profit function (which includes the distaste term) in equation (1) as $\Pi(p)$:

$$\Pi(p) \equiv (r - \text{distaste}_G) - (1 + r) \cdot p \tag{7}$$

where $p = \bar{p}_G + p_I$ is the applicant's default probability, r is the interest rate, and distaste_G reflects loan officer prejudice. Note that, if the loan officer does not acquire information about p_I, the expected profit is given by $\Pi(\bar{p}_G)$

$$E_{p_I}\left[\Pi(\bar{p}_G + p_I)\right] = E_{p_I}\left[(r - \text{distaste}_G) - (1 + r) \cdot (\bar{p}_G + p_I)\right] \tag{8}$$

$$\stackrel{E(p_I)=0}{=} (r - \text{distaste}_G) - (1 + r) \cdot \bar{p}_G \tag{9}$$

The loan officer can choose one of three strategies: immediately accept (A), learn and then decide (L), or immediately reject (R). The expected utilities associated with these choices are:

$$U_A(\bar{p}_G) = \Pi(\bar{p}_G) \tag{10}$$

$$U_L(\bar{p}_G) = E_{p_I}[\max(\Pi(\bar{p}_G + p_I), 0)] - c \tag{11}$$

$$U_R(\bar{p}_G) = 0. \tag{12}$$

These utilities are plotted in Panel (b) of Figure 2 as a function of $\bar{p}_G$. For each $\bar{p}_G$, the loan officer chooses the strategy $\in \{A, L, R\}$ that maximizes expected utility. Let's now discuss the three possible regions.

- Immediately accept region. For small enough $\bar{p}_G$, $U_A > U_R$ because $\lim_{\bar{p}_G \downarrow 0} \Pi(\bar{p}_G) = r - \text{distaste}_G > 0 = U_R$. Further, as long as $c > 0$, as $\bar{p}_G$ decreases, there exists $\bar{p}_G$ small enough such that $U_A > U_L$. Intuitively, because the probability of rejection after information acquisition is sufficiently low, it is not worth paying the cost to acquire information.[34]

- Learning region. It is easy to show that U_L must cross with U_A once from below. We have just argued that, when $\bar{p}_G$ is sufficiently low, $U_L < U_A$. Also, as $\bar{p}_G$ increases, U_L converges to $-c$ in the limit while U_A diverges to negative infinity, so for sufficiently large $\bar{p}_G$, we must have $U_L > U_A$.

  To see that U_L crosses U_A only once, we just need to see that $\frac{dU_L(\bar{p}_G)}{d\bar{p}_G} > \frac{dU_A(\bar{p}_G)}{d\bar{p}_G}$:

$$\frac{dU_L(\bar{p}_G)}{d\bar{p}_G} = \frac{d}{d\bar{p}_G}\int_{-\infty}^{\frac{r-\text{distaste}_G}{1+r}-\bar{p}_G} \left[(r-\text{distaste}_G)-(1+r)(\bar{p}_G+p_I)\right] f(p_I)dp_I \tag{13}$$

$$= (-1)\times 0 + \int_{-\infty}^{\frac{r-\text{distaste}_G}{1+r}-\bar{p}_G} \frac{d}{d\bar{p}_G}\left[(r-\text{distaste}_G)-(1+r)(\bar{p}_G+p_I)\right] f(p_I)dp_I \tag{14}$$

$$= \int_{-\infty}^{\frac{r-\text{distaste}_G}{1+r}-\bar{p}_G} -(1+r)f(p_I)dp_I \tag{15}$$

$$= -(1+r)\cdot P\left(p_I < \frac{r-\text{distaste}_G}{1+r}-\bar{p}_G\right) \tag{16}$$

$$> -(1+r) = \frac{dU_A(\bar{p}_G)}{d\bar{p}_G} \tag{17}$$

- Immediately reject region. If $\bar{p}_G$ is high enough, U_A clearly becomes unboundedly negative while U_L converges to $-c$, both of which are lower than $U_R = 0$.

Note that it is possible for the first two regions to have zero length under certain parameters.[35]

Comparative statics on c. We simply need to show that the two crossing points between the three regions move in desired directions when c varies.

- The first crossing $\bar{p}_G^{(1)}$ is defined by $U_A(\bar{p}_G^{(1)}) = U_L(\bar{p}_G^{(1)})$. If c increases, this lowers $U_L(\bar{p}_G^{(1)})$ but does not change $U_A(\bar{p}_G^{(1)})$. Because U_A is a decreasing function, this means that $\bar{p}_G^{(1)}$ must increases.

[34] The crossing point between the U_L and U_A may be negative, which is an infeasible value for $\bar{p}_G \in [0,1]$. When this happens, the "immediately approve" region has zero length.

[35] When c is very high, the learning region can disappear. If r is low, c is low, and if σ (standard deviation of p_I) is high, the immediately accept region can disappear.

- <u>The second crossing</u> $\bar{p}_G^{(2)}$ is defined by $U_L(\bar{p}_G^{(2)}) = U_R = 0$. Recall that $U_L(\bar{p}_G) = E_{p_I}[\max(\Pi(\bar{p}_G + p_I), 0)] - c$ and that the first component is a decreasing function in $\bar{p}_G$. Thus, increases in c must be offset by decreases in $\bar{p}_G^{(2)}$.

Parallel results when groups differ by distaste$_G$. We have derived the results when varying $\bar{p}_G$. What if groups differ by distaste$_G$? Well, if we rearrange the profit function (7), we get

$$\Pi(p) = r - [\text{distaste}_G - (1+r)\bar{p}_G] - (1+r) \cdot p_I. \tag{18}$$

Note that distaste$_G$ and $(1+r)\bar{p}_G$ enter into the formula in identical ways. Therefore, all results based on varying $\bar{p}_G$ also apply to varying distaste$_G$ after adjusting for the $1+r$ scaling.

A.2 Uneven distribution of workload is suboptimal for lender profits

When attention constraints might be binding, it would be optimal for the bank to distribute workloads evenly to equalize the marginal benefit of attention across loan officers. This indicates that the empirically observed workload distribution method of the bank, which leads to uneven distribution, is likely suboptimal from a profit-maximization perspective.

Let's slightly modify the model to analyze the impact of workload distribution. Suppose there are a total of X applications to be assigned to N ex-ante identical loan officers, and let the number of assignments be denoted $\{X_1, X_2, ..., X_N\}$ such that $\sum_{i=1}^{N} X_i = X$. Suppose each loan officer can only read an expected number of K applications per day and $KN << X$: in other words, the attention constraint is binding in aggregate. Assume that each application has group identity G (which determines $\bar{p}_G$ and distaste$_G$) drawn i.i.d from some distribution and that workload assignments cannot depend on actual group identities.

We now argue that the profit-maximizing approach is to allocate workload evenly: $X_1 = X_2 = ... = X_N = \frac{X}{N}$. The proof is a simple application of a "water-filling" argument. Note that, for each loan officer, the marginal benefit of paying attention to an application is a function of the application's group identity G. In the notation of section A.1, the marginal benefit is given by

$$h(G) = (U_L(G) + c) - \max(U_A(G), U_R(A)),$$

where U_L is the expected profit if the loan officer pays attention to learn about the applicant before making a decision, and U_A and U_R are expected profits if the loan officer immediately accepts or rejects the application without attention. All groups can be re-ordered such that $h(G)$ becomes a decreasing function in the re-ordered group identities.

Clearly, for each loan officer $i = 1..., N$, the expected marginal benefit of being able to pay attention to one more applicant is decreasing in its amount of assignment X_i, as each loan officer always first pays attention to the group with the highest $h(G)$, followed by the second, etc. Therefore, the optimal decision for the bank is to assign workload evenly.

B Additional Empirical Results

B.1 Variable Definitions and Institutional Details

Table B.1 provides the definitions of the key variables used in our analyses.

[**Table** B1 about here.]

B.2 Credit Quality of Applicants by Social/Economic Statuses

As discussed in Section 3.5 and presented in Figure 4, the average difference in credit quality between the attractive and unattractive groups is small and masks substantial overlap. In this section, we provide additional information to compare the credit quality of the two groups of applicants.

For Panels A and B of Table B2, we regress each creditworthiness metric on an indicator variable that signifies whether the applicant belongs to the attractive group. In terms of social status (Panel A), the attractive group on average exhibits a 7% lower leverage ratio and are 22% less likely to have blank credit histories, and their income is marginally (1.7%) higher. Their loan-to-income ratio is not significantly different from that of the socially unattractive group. In terms of economic status (Panel B), the difference in leverage ratio and credit history is similar but the difference in income and loan-to-income ratio is larger. In unreported robustness checks, we further verify that each one of the six *individual* status labels is to some extent useful in explaining applicant credit quality. Specifically, we find that credit quality is higher for applicants who are public employees, are local residents, provide valid employment or income certificates, have stable income flow, or own real estate properties.

[**Table** B2 about here.]

However, as shown in Figure 4, there is a significant overlap in credit quality between the attractive and unattractive groups. To quantify the extent of overlap, for Panels C and D of Table B2, we measure the credit-quality metrics after controlling for the set of fixed effects in Panels A and B and then adding them back to the full-sample averages. The final column shows a significant fraction of unattractive applicants whose creditworthiness metric is better than that of the median attractive applicant.

B.3 Additional Evidence of Differential Attention Allocation: Extra Due Diligence Inferred from Cited Rejection Reasons

This section provides additional evidence of differential officer attention allocation to attractive and unattractive applicants. At the bank we study, a loan officer must select from a list of reasons when she renders a rejection. Out of the total of 127 rejection reasons from which she can choose, some indicate that the loan officer, before rejecting, attempted *further due diligence* to gain information beyond that readily available in the application package, while other reasons indicate that the officer makes rejection decisions based on information already in hand. We use this as another indicator for loan officer attention allocation in addition to their review time.

Measuring attention allocation via rejection reasons We manually classify all rejection reasons and list the most commonly used ones in Table B3. Panel A lists the top ten rejection reasons that reflect further due diligence. Most show that the loan officer has attempted to call the applicant, her employer, or other contacts. In some cases, the officer also gathers third-party information through online searches. Overall, 25.9% of rejected applications have rejection codes that fall into this category. In contrast, the other rejections listed in Panel B cite only reasons that involve information that is immediately available from the application package. These typically involve concerns about an applicant's leverage, credit history, employment history, or simply offer a vague indication such as "Other reasons."

We argue that the reasons cited to justify a rejection offer information about how much attention a loan officer has allocated to a given application. Consistent with this view, loan officer review time appears to be meaningfully correlated with our classifications. In the last column of Table B3, we report the median review time for each of the rejection reasons, and in the last row in each panel, we report the observation-weighted averages. Overall, a loan officers spends an average of 21.2 minutes reviewing an application before citing rejection reasons associated with further due diligence, but only 10.0 minutes otherwise.[36]

[**Table** B3 about here.]

Estimating the effects of socioeconomic labels on loan officer attention If loan officers use applicant socioeconomic labels to allocate their attention, we expect that the rejection reasons cited for attractive applicants will more likely involve further due diligence. The results reported in Table B4 confirm this prediction. Using the rejected sample, we regress a dummy variable for whether the rejection reason indicates further due diligence on the availability of a certain social (columns 2 and 3) or economic (columns 5–8) status label, or the overall attractiveness of the applicant based on her social (column 1) or economic (column 4) background. The results reported in column (1), for example, indicate that loan officers are 16.9% more likely to conduct further due diligence before rejecting an applicant in the group with attractive social status. The baseline average is 24.0%, implying that applications from the socially attractive group are almost two-thirds more likely to get further due diligence from loan officers. Column (4) shows that the effect of being in the economically attractive group is even larger, as the probability of getting due diligence doubles.

[**Table** B4 about here.]

In Table B5 we find that the effect of social and economic statuses on officer due diligence is more pronounced when loan officers are busier. As discussed in Section 4.1, we measure loan officer business by the number of applications she processes in a day. As in Table 3, we sort officer busyness into deciles and estimate a regression of an officer due diligence indicator on social and economic status indicators and busyness deciles as well as their interactions. When loan officers are busier, applicants from groups with lower social or economic status receive significantly less due diligence, but the effect is minor or non-existent for the high-socioeconomic-status applicants. Table B6 further verifies that the results are robust to using the two loan officer busyness instruments in Section 5.1. Overall, these results are consistent with the parallel findings where we measure attention allocation using loan officer review time (Table 3).

[**Table** B5 about here.]

[**Table** B6 about here.]

[36]This difference pertains only to the sub-sample of rejected applications as rejection reasons are not otherwise available. The review time for approved applications is on average longer.

B.4 Additional Details Regarding the Instrumented Busyness Measures

We present additional details and robustness checks regarding the two officer busyness instruments introduced in Section 5.1.

1. Figure **??** replicates the patterns shown in Figure 5 by using each of the two instrumented busyness measures instead of raw busyness. We show that loan officers work longer hours and are more likely to work overtime when they are more attention-constrained, as measured by the two instrumented busyness measures.

2. With Table B7, we verify that assignments do not depend on officer backlogs. This alleviates the concern that loan officers could influence their own assignments indirectly by working more quickly or slowly.

3. With Table B8, we verify that the instrumented busyness measures are not correlated with applicant and loan characteristics.

4. In Table B9 we present the relationship between assignments (or LOO-assignments) with loan officers' realized busyness. Column (4) reflects the exact specification we use in our first-stage regressions. The instruments are strong, as assignments and LOO-assignments explain over 40% of busyness variation.

[**Figure** B1 about here.]

[**Table** B7 about here.]

[**Table** B8 about here.]

[**Table** B9 about here.]

[**Table** B10 about here.]

Table B1. Variable Definitions.

Variable	Definition
Officer screening activities	
Approval	Equals one if the officer has approved the application and zero otherwise.
ReviewTime	The number of minutes that the officer spends reviewing an application, measured as the time that has elapsed between the officer's previous decision and the current decision.
StandardizedReviewTime	The log of reviewing time divided by the median values for each officer×month-year×branch×loan type. See Equation (5).
HasInfoAcquision	Equals one if the cited rejection rationale indicates that the loan officer has engaged in further due diligence (e.g. phone calls) and zero otherwise.
Busyness	The total number of applications reviewed by an officer on a given day.
Predicted Busyness	The predicted number of applications an officer reviews on a given day using the total number of applications on the current day and on three lagged business days that are assigned to an officer. See Equation (6)
LOO-Predicted Busyness	The predicted number of applications an officer reviews on a given day using the number of applications from other provinces on the current day and on three lagged business days that are assigned to an officer.
Assignment	The total number of applications assigned to an officer on a given day.
Backlog	The number of applications that have been assigned to an officer but have not yet been reviewed, at the beginning of a given day.
Borrower socioeconomic statuses	
PublicEmployee	Equals one if the applicant works in the public sector and zero otherwise.
LocalResident	Equals one if the applicant provides certificates indicating recent places of residency and zero otherwise.
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.
RegularPay	Equals one if the applicant receives fixed salary payments and zero otherwise.
HomeOwner	Equals one if the applicant provides certificates related to housing property owned and zero otherwise.
Borrower characteristics	
LeverageRatio	The applicant's preexisting debt-to-income ratio.
NonCreditHistory	Equals one if the applicant has no credit history and zero otherwise.
OverdueMonth	The highest number of months over which the applicant has been overdue making payments in the most recent two years.
CreditInquiry	The number of inquiries into the applicant's credit history in the most recent two years.
HasInvestmentAcc	Equals one if the applicant has an investment account and zero otherwise.
SocialSecurity	Equals one if the applicant receives a social security allowance and zero otherwise.
Litigation	Equals one if the applicant has been involved in any legal proceedings and zero otherwise.

Peasant	Equals one if the applicant reports holding a permanent agricultural residence registration in an 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.
Age	The applicant's age.
Income	The applicant's total income.
Loan characteristics	
Loan/Income	The ratio of the amount of the loan for which the applicant has applied to the applicant's total income.
ShortTerm	Equals one if the term of the loan for which the application has applied is less than 3 years.
InterestRate	The interest rate of the loan for which the application has applied at origination.

Table B2. Credit Quality of Attractive versus Unattractive Applicants

For this table, we compare the credit quality of applicants with attractive versus unattractive social or economic status. As explained in Section 3.4, the attractive group is defined as applicants whose level of *SocialStatus* (Equation (3)), or *EconomicStatus* (Equation (4)) is above the sample median. *LeverageRatio* is defined as the debt-to-income ratio in the applicant's credit report, and *NoCreditHistory* is a dummy indicator that equals one for those without credit histories. *LoanToIncome* is the loan-amount-to-income ratio. For Panels A and B we regress each credit quality measure on the *attractive* indicator. The regressions control for officer × month-year, week, bank branch, and loan-type fixed effects. Standard errors are double clustered at the week and officer levels, and t-statistics are reported in parentheses. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$. In Panels C and D we report, by applicant social and economic status group, summary statistics of the residual credit quality measures after regressing out the fixed effects and adding back the sample mean. In the last column, we report the fraction of unattractive applicants with higher credit quality than the median attractive applicant. In Panels E and F we report, by applicant social and economic status group and by whether the officer approves the application, summary statistics of the residual credit quality measures after regressing out the fixed effects and adding back the sample mean. In the last column, we report the fraction of unattractive applicants that are rejected with higher credit quality than the median attractive applicant that is approved.

Panel A. Credit quality by applicant social status

Dependent variable:	log(1+LeverageRatio)	NoCreditHistory	log(Income)	log(LoanToIncome)
	(1)	(2)	(3)	(4)
Attractive(Social)	-0.071^{***}	-0.221^{***}	0.017^{*}	0.001
	(−9.572)	(−11.949)	(1.992)	(0.091)
Officer-Month-Yr FE	Y	Y	Y	Y
Week 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	0.057	0.122	0.489	0.412

Panel B. Credit quality by applicant economics status

Dependent variable:	log(1+LeverageRatio)	NoCreditHistory	log(Income)	log(LoanToIncome)
	(1)	(2)	(3)	(4)
Attractive(Economic)	-0.043^{***}	-0.174^{***}	0.270^{***}	-0.159^{***}
	(−4.812)	(−12.496)	(22.778)	(−14.622)
Officer-Month-Yr FE	Y	Y	Y	Y
Week 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	0.495	0.415

Panel C. Credit quality Statistics by applicant social status

Credit quality measure	Group	N	Mean	SD	10%	25%	50%	75%	90%	% better
log(1+LeverageRatio)	Unattractive	54,613	0.207	0.346	−0.035	0.022	0.112	0.269	0.514	38.0%
	Attractive	66,036	0.159	0.200	−0.011	0.042	0.115	0.225	0.367	
NoCreditHistory	Unattractive	72,992	0.253	0.409	−0.067	0.002	0.065	0.589	0.989	34.4%
	Attractive	72,990	0.094	0.296	−0.118	−0.032	0.028	0.083	0.167	
log(Income)	Unattractive	72,992	10.196	0.800	9.262	9.650	10.118	10.658	11.235	47.5%
	Attractive	72,990	10.210	0.772	9.274	9.691	10.168	10.680	11.184	
log(LoanToIncome)	Unattractive	72,992	0.826	0.746	−0.126	0.402	0.896	1.329	1.686	48.0%
	Attractive	72,990	0.823	0.696	−0.048	0.403	0.862	1.281	1.652	

Panel D. Credit quality statistics by applicant economics status

Credit quality measure	Group	N	Mean	SD	10%	25%	50%	75%	90%	% better
log(1+LeverageRatio)	Unattractive	58,231	0.192	0.300	−0.009	0.044	0.116	0.237	0.434	38.6%
	Attractive	62,418	0.170	0.252	−0.033	0.023	0.111	0.245	0.413	
NoCreditHistory	Unattractive	72,992	0.209	0.388	−0.080	−0.005	0.055	z 0.128	0.980	40.9%
	Attractive	72,990	0.138	0.339	−0.108	−0.026	0.036	0.096	0.888	
log(Income)	Unattractive	72,992	10.163	0.784	9.220	9.637	10.115	10.638	11.156	46.9%
	Attractive	72,990	10.243	0.787	9.312	9.703	10.174	10.700	11.263	
log(LoanToIncome)	Unattractive	72,992	0.847	0.717	−0.053	0.421	0.890	1.319	1.692	48.5%
	Attractive	72,990	0.802	0.725	−0.117	0.384	0.866	1.291	1.647	

Panel E. Credit quality Statistics by applicant social status and approval

Credit quality measure	Group	N	Mean	SD	10%	25%	50%	75%	90%	% better
log(1+LeverageRatio)	Unattractive&Rejected	34,173	0.221	0.361	-0.037	0.025	0.117	0.288	0.570	31.5%
	Attractive&Approved	43,386	0.139	0.247	-0.045	0.020	0.097	0.197	0.329	
NoCreditHistory	Unattractive&Rejected	49,319	0.300	0.429	-0.066	0.011	0.083	0.779	1.007	40.2%
	Attractive&Approved	49,318	0.128	0.327	-0.140	-0.023	0.055	0.123	0.797	
log(Income)	Unattractive&Rejected	49,319	10.156	0.774	9.238	9.640	10.104	10.609	11.130	46.4%
	Attractive&Approved	49,318	10.231	0.777	9.309	9.706	10.170	10.691	11.219	
log(LoanToIncome)	Unattractive&Rejected	49,319	0.866	0.703	-0.008	0.459	0.912	1.333	1.683	47.7%
	Attractive&Approved	49,318	0.822	0.713	-0.076	0.401	0.876	1.303	1.657	

Panel F. Credit quality statistics by applicant economics status and approval

Credit quality measure	Group	N	Mean	SD	10%	25%	50%	75%	90%	% better
log(1+LeverageRatio)	Unattractive&Rejected	40,209	0.217	0.345	-0.020	0.038	0.125	0.272	0.513	35.1%
	Attractive&Approved	43,842	0.167	0.257	-0.045	0.016	0.110	0.247	0.416	
NoCreditHistory	Unattractive&Rejected	52,991	0.252	0.407	-0.086	0.011	0.085	0.191	1.001	36.4%
	Attractive&Approved	52,990	0.162	0.360	-0.132	-0.024	0.048	0.133	0.906	
log(Income)	Unattractive&Rejected	52,991	10.116	0.797	9.168	9.577	10.058	10.594	11.132	43.6%
	Attractive&Approved	52,990	10.246	0.786	9.313	9.705	10.179	10.700	11.261	
log(LoanToIncome)	Unattractive&Rejected	52,991	0.881	0.733	-0.041	0.450	0.930	1.368	1.745	45.4%
	Attractive&Approved	52,990	0.791	0.721	-0.126	0.377	0.852	1.279	1.631	

Table B3. Inferring Due Diligence from Rejection Reasons

When rejecting an application, the loan officer is asked to select from a list of reasons. We classify these rejection reasons into two categories. The first category includes reasons indicating that the officer has engaged in additional due diligence, such as making phone calls or conducting online searches, before rejecting the application. The remaining reasons are placed into the second category. 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 lists the median officer review time for each rejection reason. In the last row in each panel, we report the observation-weighted averages.

Panel A: Cited rejection reason indicating further due diligence				
Rank	Cited rejection reasons	Obs	Fraction	Review time (min)
1	Called applicant references and found discrepancies	13658	55.0%	24.5
2	Employer phone number does not exist	2598	10.5%	17.9
3	Cannot reach employer by phone	2387	9.6%	11.5
4	Found issues when contacting the third party	1828	7.4%	14.8
5	Employer said that the applicant does not work there	1537	6.2%	14.3
6	Invalid references contact information	1161	4.7%	24.2
7	References cannot be reached	573	2.3%	14.6
8	Cannot verify employment information	487	2.0%	19.6
9	Applicant/references did not cooperate with due diligence	169	0.7%	20.5
10	Discovered issues in further investigation	157	0.6%	28.5
Others		262	1.1%	19.4
Average				21.2
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	19370	27.2%	11.9
2	Unfavorable credit card history	7916	11.1%	4.4
3	Insufficient credit history	7331	10.3%	4.7
4	Other reasons	4523	6.4%	15.0
5	Overall too risky	3121	4.4%	15.2
6	Unfavorable loan repayment history	2757	3.9%	4.6
7	Unfavorable credit card history per the PBOC	2215	3.1%	6.4
8	Too many credit requests	1671	2.3%	4.6
9	Unstable employment	1182	1.7%	16.7
10	Insufficient employment or business history	1123	1.6%	14.6
Others		19932	28.1%	12.8
Average				10.0

Table B4. Applicant Socioeconomic Statuses and Due Diligence

For this table, we estimate the relationship between loan officers' extra due diligence and applicants' socioeconomic status. The outcome variable is an indicator that equals one if the loan officer's rejection reason suggests that she has engaged in further due diligence (among reasons listed in Panel A in Table B3) and zero otherwise. To obtain the results reported in columns (1) and (4), we estimate the effects of an applicant whose *SocialStatus* or *EconomicStatus* is above the median (same definition of "attractive" as in the earlier tables). For columns (2)–(3) and (5)–(7), we estimate the effects based on each single social or economic status label. As in Table 4, we control for applicant-level characteristics and officer × month-year, week, bank-branch, and loan-type fixed effects. Standard errors are double-clustered at the week and officer levels. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Dependent variable:	Loan officer due diligence							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Attractive(Social)	0.170***							
	(10.578)							
PublicEmployee		0.047***						
		(4.127)						
LocalResident			0.174***					
			(10.188)					
Attractive(Economic)				0.241***				
				(16.989)				
EmploymentCert					0.218***			
					(12.093)			
IncomeCert						0.195***		
						(11.184)		
StandardPay							0.265***	
							(19.721)	
HomeOwner								0.240***
								(16.780)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y	Y
Observation	96, 009	96, 009	96, 009	96, 009	96, 009	96, 009	96, 009	96, 009
Adjusted R-squared	0.126	0.101	0.125	0.123	0.148	0.128	0.116	0.123

Table B5. Effects of Attention Constraints on Due Diligence

For this table, we estimate how loan officer attention constraints affect their extra due diligence efforts on loan applications by attractive versus unattractive applicants. The outcome variable is an indicator that equals one if the loan officer's rejection reason suggests that she has engaged in further due diligence (among reasons listed in Panel A in Table B3), and zero otherwise. *Attractive(Social)* and *Attractive(Economic)* are dummy variables indicating whether *SocialStatus* and *EconomicStatus* are above the median, respectively. *BusynessDecile* is the officer's daily actual busyness measure, defined as the number of applications processed on a given day, sorted into deciles. As in Table 4, we control for applicant-level characteristics and officer × month-year, week, bank-branch, and loan-type fixed effects. Standard errors are double-clustered at week and officer levels. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Dependent variable:	Loan officer due diligence					
	(1)	(2)	(3)	(4)	(5)	(6)
BusynessDecile	-0.008^{***}	-0.011^{***}	-0.007^{***}	-0.011^{***}	-0.007^{***}	-0.011^{***}
	(-5.592)	(-8.627)	(-5.297)	(-9.421)	(-4.447)	(-7.958)
SocialStatus	0.048^{**}	0.143^{***}			0.061^{**}	0.133^{***}
	(2.548)	(6.973)			(2.627)	(6.192)
SocialStatus × BusynessDecile	0.005^{**}	0.005^{**}			0.004^{*}	0.004^{*}
	(2.266)	(2.125)			(1.677)	(1.783)
Attractive(Economic)			0.200^{***}	0.184^{***}	0.208^{***}	0.171^{***}
			(10.734)	(9.337)	(9.459)	(7.839)
Attractive(Economic) × BusynessDecile			0.011^{***}	0.011^{***}	0.011^{***}	0.010^{***}
			(3.930)	(3.979)	(3.411)	(3.174)
Application Controls	Y	Y	Y	Y	Y	Y
Officer-Month-Yr FE	N	Y	N	Y	N	Y
Week FE	N	Y	N	Y	N	Y
Branch FE	N	Y	N	Y	N	Y
Loan type FE	N	Y	N	Y	N	Y
Observation	96, 009	96, 009	96, 009	96, 009	96, 009	96, 009
Adjusted R-squared	0.052	0.127	0.080	0.125	0.088	0.146

Table B6. Effects of Instrumented Officer Attention Constraints on Due Diligence

For this table, we estimate how loan office attention constraints affect their extra due diligence efforts on loan applications by attractive versus unattractive applicants. The outcome variable is an indicator that equals one if the loan officer's rejection reason suggests that she has engaged in further due diligence (among reasons listed in Panel A in Table B3), and zero otherwise. *Attractive(Social)* and *Attractive(Economic)* are dummy variables indicating whether *SocialStatus* and *EconomicStatus* are above the median, respectively. *BusynessDecile* is the officer's instrumented daily busyness, defined as the number of applications processed on a given day sorted into deciles and instrumented by the total or leave-one-out number of applications assigned to the loan officer over the past three working days. For columns (1) through (3), we use assignment-predicted busyness; for columns (4) through (6), we use leave-one-out (LOO) assignment-predicted busyness. As in Table 4, we control for applicant-level characteristics and officer × month-year, week, bank-branch, and loan-type fixed effects. Local busyness controls include loan officer assignments from the same province. Standard errors are double-clustered at week and officer levels. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Dependent variable:	Loan officer due diligence					
Busyness measure:	Predicted Busyness			LOO-Predicted Busyness		
	(1)	(2)	(3)	(4)	(5)	(6)
BusynessDecile	-0.007^{***}	-0.007^{***}	-0.008^{***}	-0.005^{***}	-0.005^{***}	-0.006^{***}
	(-5.108)	(-5.740)	(-5.890)	(-3.373)	(-3.731)	(-4.566)
SocialStatus	0.148^{***}		0.139^{***}	0.148^{***}		0.139^{***}
	(13.746)		(13.211)	(14.072)		(13.200)
SocialStatus × BusynessDecile	0.004^{***}		0.004^{***}	0.004^{***}		0.004^{**}
	(2.949)		(2.582)	(2.920)		(2.413)
SocialStatus		0.181^{***}	0.166^{***}		0.178^{***}	0.164^{***}
		(12.305)	(11.024)		(12.827)	(10.510)
EconomicsStatus × BusynessDecile		0.012^{***}	0.011^{***}		0.013^{***}	0.012^{***}
		(5.744)	(5.221)		(6.691)	(5.676)
Application Controls	Y	Y	Y	Y	Y	Y
Local Busyness Controls	N	N	N	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y
Week 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	0.133	0.131	0.153	0.133	0.131	0.153

Table B7. Relationship between Assignments and Existing Backlogs

We estimate the relationship between the number of new applications assigned to a loan officer and her existing backlogs. Observations are reported at the officer-day level. The dependent variable, $Assignment_{j,d}$, is the number of applications assigned to officer j on day d by the workload dispatcher algorithm. $Backlog_{j,d}$ is the number of applications assigned to but not yet reviewed by officer j at the beginning of day d *before* new applications are assigned. The regressions control for officer-month-year and day fixed effects and standard errors are clustered at those levels. T-statistics are reported in parentheses. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Dependent Variable:	$\text{Assignment}_{j,d}$			
	(1)	(2)	(3)	(4)
$\text{Backlog}_{j,d}$	−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 B8. Relationship Between Applicant Characteristics and Predicted Busyness

Officer busyness is defined as the number of applications processed by an officer on a given day. As explained in Section 5.1, we use the total or leave-one-out 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 each of the two panels, we regress each applicant or loan characteristic on deciles (1 through 10) of predicted and LOO-predicted busyness. As with the regression results reported in Tables 3 and 4, we control for officer × month-year fixed effects, week fixed effects, origination-bank-branch fixed effects, and loan-type fixed effects. Local busyness controls include loan officer assignments from the same province. T-statistics are reported in parentheses and standard errors are double-clustered at the week and officer levels. Variable definitions are presented in Table B.1. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Panel A. Applicant characteristics by predicted busyness

Dependent variable:	StateOfficial	LocalResident	Employment Cert	IncomeCert	RegularPay	HomeOwner	log(1+LeverageRatio)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PredictBusynessDecile	−0.402	−1.976	−2.049	−1.155	0.205	−0.431	0.666
	(−1.179)	(−1.324)	(−1.122)	(−0.901)	(0.582)	(−0.562)	(1.576)
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y
Week 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	0.045	0.345	0.090	0.317	0.392	0.387	0.042

Dependent variable:	NoCredit History	log(1+OverdueMonth)	log(1+CreditInqury)	HasInvestmentAcc	SocialSecurity	Litigation	Peasant
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PredictBusynessDecile	−0.819	0.954	3.684***	0.042	0.396	−0.055	−0.207
	(−1.111)	(1.207)	(3.626)	(0.308)	(0.840)	(−0.640)	(−0.471)
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y
Week 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	0.061	0.031	0.114	0.010	0.082	0.011	0.459

Dependent variable:	NonCollege	Female	log(Age)	log(Income)	log(LoanTo Income)	ShortTerm	log(Interest Rate)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PredictBusynessDecile	0.479	0.522	−0.159	−0.717	0.481	0.141	−0.008
	(0.879)	(0.965)	(−0.506)	(−0.526)	(0.424)	(0.492)	(−0.728)
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y
Week 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. Applicant characteristics by leave-one-out (LOO) predicted busyness

Dependent variable:	StateOfficial	LocalResident	Employment Cert	IncomeCert	RegularPay	HomeOwner	log(1+Lever ageRatio)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LOOPredictBusynessDecile	−0.179	−0.705	−0.650	−0.094	0.767*	−0.184	0.247
	(−0.487)	(−0.489)	(−0.364)	(−0.080)	(1.785)	(−0.240)	(0.575)
Local Busyness Controls	Y	Y	Y	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y
Week 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	0.045	0.346	0.091	0.317	0.392	0.387	0.042

Dependent variable:	NoCredit History	log(1+Over dueMonth)	log(1+Cred itInqury)	HasInvest mentAcc	SocialSecurity	Litigation	Peasant
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LOOPredictBusynessDecile	−1.176	−0.300	4.075***	0.022	−0.019	−0.083	−0.180
	(−1.619)	(−0.351)	(3.649)	(0.170)	(−0.036)	(−0.863)	(−0.372)
Local Busyness Controls	Y	Y	Y	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y
Week 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	0.061	0.031	0.114	0.010	0.082	0.011	0.459

Dependent variable:	NonCollege	Female	log(Age)	log(Income)	log(LoanTo Income)	ShortTerm	log(Interest Rate)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LOOPredictBusynessDecile	0.293	0.244	−0.270	−0.350	0.268	0.256	−0.012
	(0.513)	(0.396)	(−0.755)	(−0.286)	(0.263)	(0.758)	(−0.952)
Local Busyness Controls	Y	Y	Y	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y
Week 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

Table B9. Predicting Loan Officer Busyness Using Assignments

We estimate the relationship between realized officer busyness on the number of applications assigned by the bank's workload dispatcher algorithm. The dependent variable $Busyness_{j,d}$ is the total number of applications processed by loan officer j on day d, $Assignment_{j,d}$ is the total number of assignments the loan officer receives, and $LOO\text{-}Assignment_{j,d}$ is the total number of assignments from other provinces she received. In Panel A we report the results obtained using total assignments, and in panel B we report the results obtained using LOO-assignments. For columns (1) through (4) we do not include fixed effects, while for columns (5) and (6), we include officer- and officer-month-year fixed effects, respectively. Standard errors are double-clustered at the officer and month-year levels. We use specification (4) to compute the "predicted busyness" instrument presented in Section 5. T-statistics are reported in parentheses. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$

Panel A. Using total assignments to predict busyness

Dependent Variable:	Busyness$_{j,d}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Assignment$_{j,d}$	0.420***	0.358***	0.338***	0.319***	0.286***	0.183***
	(8.194)	(8.570)	(9.566)	(9.209)	(8.380)	(9.265)
Assignment$_{j,d-1}$		0.161***	0.131***	0.129***	0.112***	0.063**
		(4.641)	(4.213)	(4.451)	(3.910)	(3.006)
Assignment$_{j,d-2}$			0.110***	0.080***	0.065**	0.020
			(4.081)	(3.111)	(2.480)	(0.855)
Assignment$_{j,d-3}$				0.115***	0.097***	0.037***
				(8.382)	(7.230)	(3.541)
Officer FE	N	N	N	N	Y	N
Officer-Month-Yr FE	N	N	N	N	N	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982
R-squared	0.321	0.369	0.391	0.415	0.457	0.599
Adjusted R-squared	0.321	0.369	0.391	0.415	0.457	0.597

Panel B. Using LOO-assignments to predict busyness

Dependent Variable:	Busyness$_{j,d}$					
	(1)	(2)	(3)	(4)	(5)	(6)
LOO-Assignment$_{j,d}$	0.452***	0.395***	0.379***	0.363***	0.323***	0.201***
	(8.275)	(8.551)	(9.391)	(9.124)	(8.281)	(9.347)
LOO-Assignment$_{j,d-1}$		0.157***	0.128***	0.126***	0.109***	0.060***
		(4.716)	(4.302)	(4.536)	(3.985)	(3.065)
LOO-Assignment$_{j,d-2}$			0.106***	0.077***	0.063**	0.018
			(4.114)	(3.126)	(2.484)	(0.805)
LOO-Assignment$_{j,d-3}$				0.111***	0.093***	0.034***
				(8.700)	(7.544)	(3.542)
Officer FE	N	N	N	N	Y	N
Officer-Month-Yr FE	N	N	N	N	N	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982
R-squared	0.317	0.363	0.384	0.406	0.450	0.596
Adjusted R-squared	0.317	0.363	0.384	0.406	0.450	0.595

C Supplemental Empirical Results

In this section, we report supplemental empirical results.

1. Figure C1 shows that, when officers work longer hours in a day, the average review time for each application is shorter.

2. Figure C2 plots the estimated conditional difference between the attractive versus unattractive applicants under each realized busyness decile.[37] For both review time and approval rate, the gap between the attractive and unattractive applicant groups keeps widening almost monotonically when loan officer gets busier and busier.

3. Figures C3 and C4 replicate Figure 1 using predicted and leave-one-out (LOO) predicted busyness instead of the actual busyness.

4. Figures C5 and C6 are similar to Figure C2 but based on predicted and LOO-predicted busyness measures rather than realized busyness.

5. In Table C1 we report results pertaining to the explanatory power of various fixed effects with respect to log officer review time. The final specification provides the basis for constructing the standardized review time measure presented in Section 4.1.

6. In Table C2 we report results pertaining to the relationship between officer attention constraints and work patterns. When officers are busier, they begin working earlier and/or work late. That is, when officers are busier, they face longer working hours and work more overtime hours.

7. Table C3 results resemble those of our main analyses reported in Tables 3 and 4, except that we estimate the effect of each individual social or economic status label instead of the overall social or economic status measure. For the sake of brevity, we present results using only LOO-predicted busyness. The results obtained using raw or predicted busyness are similar.

[**Figure** C1 about here.]

[37] That is, we modify regressions in Section 4.2 using ten dummy variables to indicate each busyness decile and regress standardized review time or approval on the ten decile dummies, the attractiveness indicator, and interaction with each decile dummy. The conditional difference between the attractive and unattractive groups for each busyness decile is then plotted in the figure.

[**Figure** C2 about here.]

[**Figure** C3 about here.]

[**Figure** C4 about here.]

[**Figure** C5 about here.]

[**Figure** C6 about here.]

[**Table** C1 about here.]

[**Table** C2 about here.]

[**Table** C3 about here.]

Figure C1. Review Time by Loan Officer Workday Length

We plot the average standardized review time by the number of hours that an officer works on a given day. The first bar from the left includes days with less than 5 hours of work and the last bar includes days with more than 11 hours of work. Standardized review time is a measure of officer attention to each application and is defined in Section 4.1.

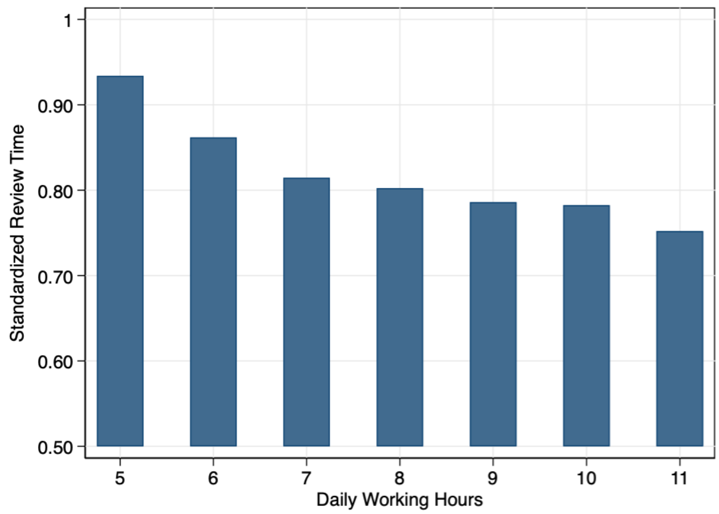
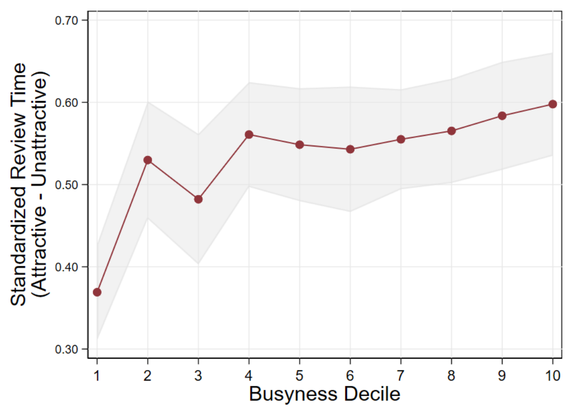
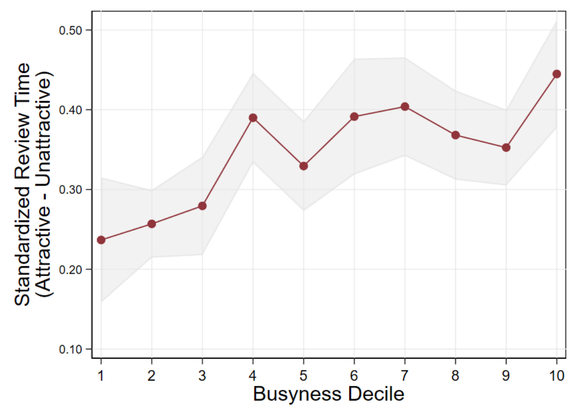


Figure C2. Difference-in-Differences Effects of Loan Officer Attention Constraints

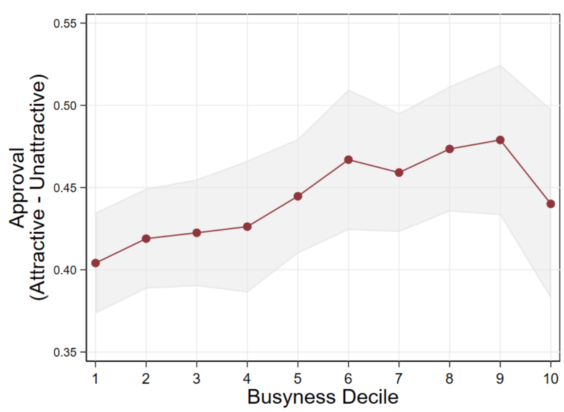
We estimate the differential effects of officer attention constraints, as measured by their busyness, on their attention allocation and approval decision over attractive and unattractive applicants. Specifically, we regress officer attention and approval decisions on interaction between an applicant-attractiveness indicator and each busyness decile dummy. We then plot estimated coefficients for these interaction terms. The top panels plot the results for officer attention, measured as the standardized review time the loan officer spent on each application. The bottom panels plot the estimations for loan approval. For Panels (a) and (c), applicant attractiveness is measured by their social status. For Panels (b) and (d), applicant attractiveness is measured by their economic status. Fixed effects, controls, and standard error clustering are the same as those in Tables 3 and 4. The shaded areas represent the 95% confidence intervals for the corresponding regression coefficients.



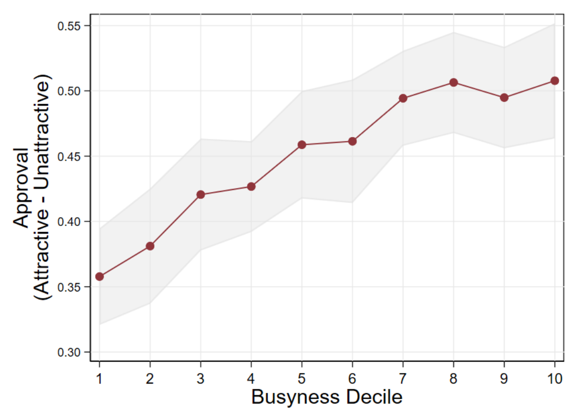
(a) Attention gap across social status



(b) Attention gap across economic status



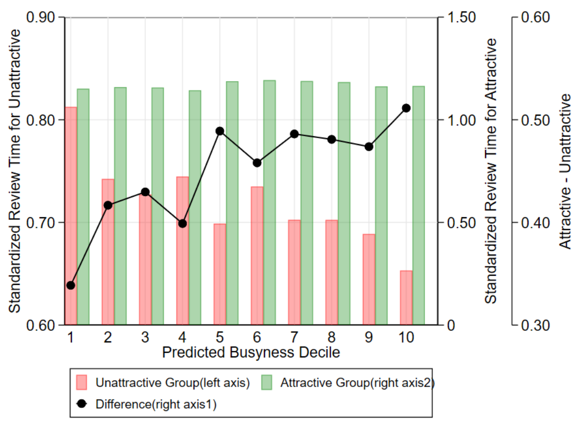
(c) Approval gap across social status



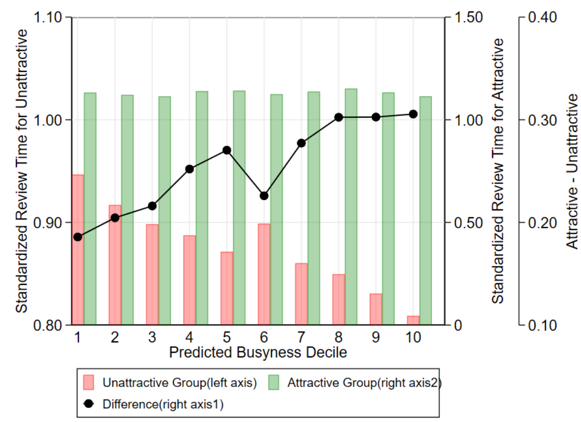
(d) Approval gap across economic status

Figure C3. Robustness Test of Figure 1: Attention and Approval Rates by Officer Attention Constraints, Instrumented Estimation

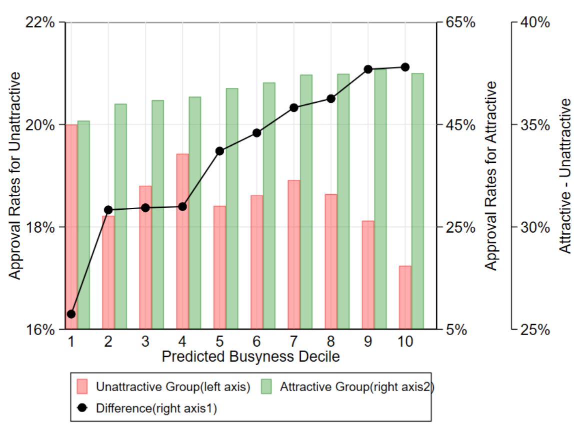
This figure is similar to Figure 1, except that we use loan officers' predicted busyness instrumented by the number of assignments as discussed in Section 5.1. As explained in Section 3.4, we use the possession (or not) of various labels to classify applicants into attractive versus unattractive groups based on social status (Panels (a) and (c)) or economic status (Panels (b) and (d)). In all panels, we sort the sample into deciles by officer attention constraints measured by their *busyness*, which is defined as the number of applications processed per day. Panels (a) and (b) plot the average officer attention allocation, measured as the standardized review time on each loan in the screening process, by busyness decile. Panels (c) and (d) plot the average loan approval rate by busyness decile. The measurement of standardized review time is explained in Section 4.1. Each red (green) bar graphs the average for the unattractive (attractive) group of applicants. The black line plots the differences between the two groups.



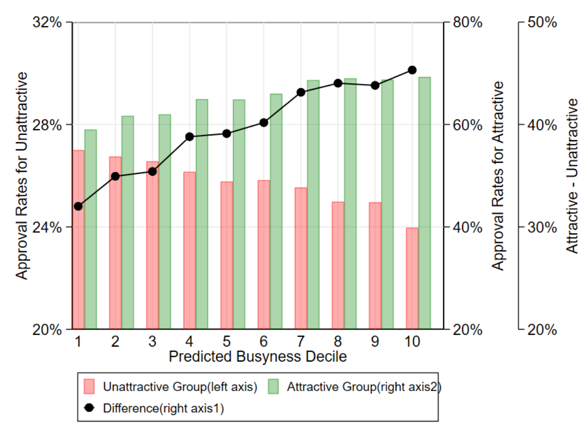
(a) Officer attention allocation by applicant social status



(b) Officer attention allocation by applicant economics status



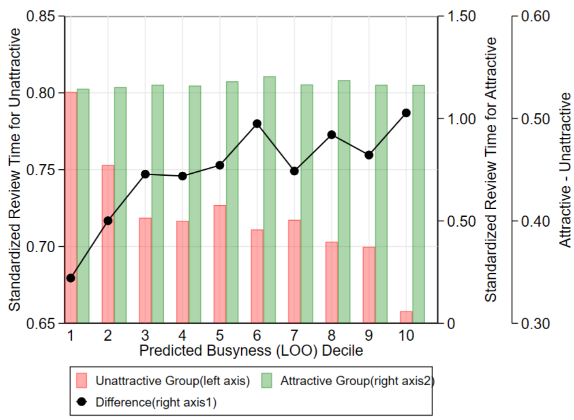
(c) Officer approval decision by applicant social status



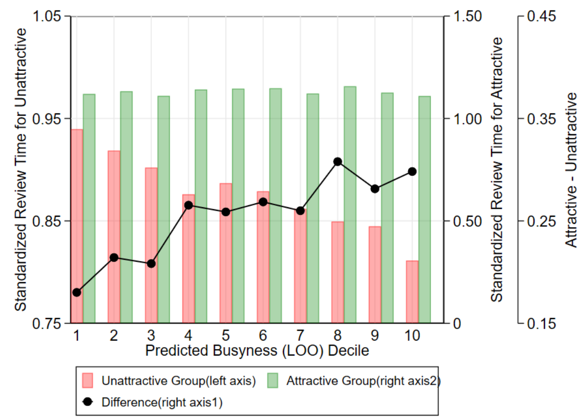
(d) Officer approval decision by applicant economics status

Figure C4. Robustness Test of Figure 1: Attention and Approval Rates by Officer Attention Constraints, LOO Instrumented Estimation

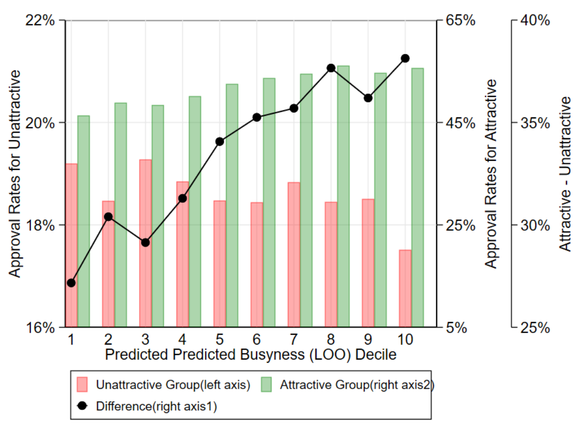
This figure is similar to Figure 1, except that we use loan officers' LOO predicted busyness instrumented by the number of assignments as discussed in Section 5.1. As explained in Section 3.4, we use the possession (or not) of various labels to classify applicants into attractive versus unattractive groups based on social status (Panels (a) and (c)) or economic status (Panels (b) and (d)). In all panels, we sort the sample into deciles by officer attention constraints measured by their *busyness*, which is defined as the number of applications processed per day. Panels (a) and (b) plot the average officer attention allocation, measured as the standardized review time on each loan in the screening process, by busyness decile. Panels (c) and (d) plot the average loan approval rate by busyness decile. The measurement of standardized review time is explained in Section 4.1. Each red (green) bar graphs the average for the unattractive (attractive) group of applicants. The black line plots the differences between the two groups.



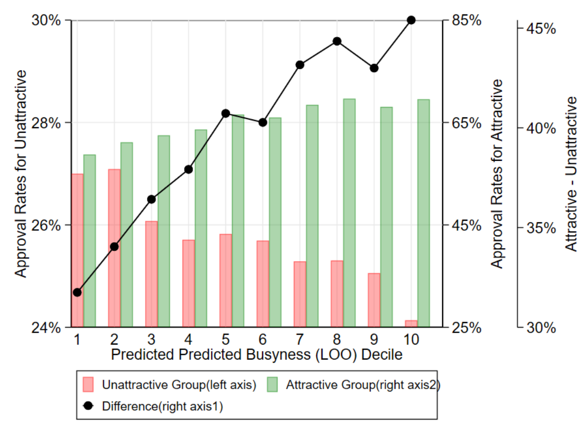
(a) Officer attention allocation by applicant social status



(b) Officer attention allocation by applicant economic status



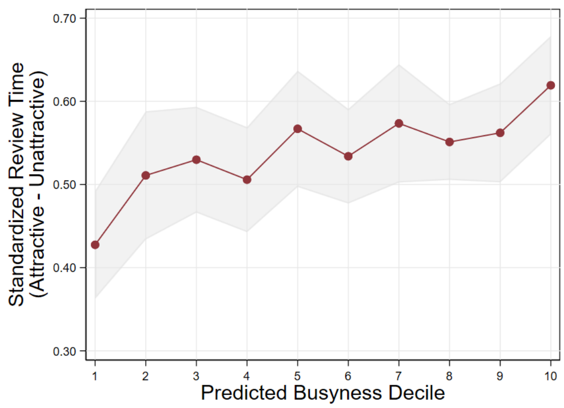
(c) Officer approval decision by applicant social status



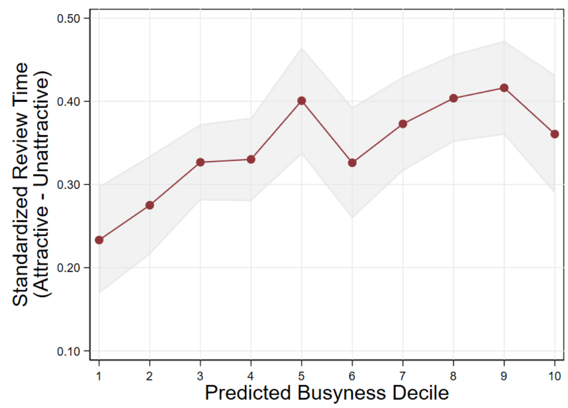
(d) Officer approval decision by applicant economic status

Figure C5. Difference-in-Differences Effects of Loan Officer Attention Constraints, Instrumented Estimations

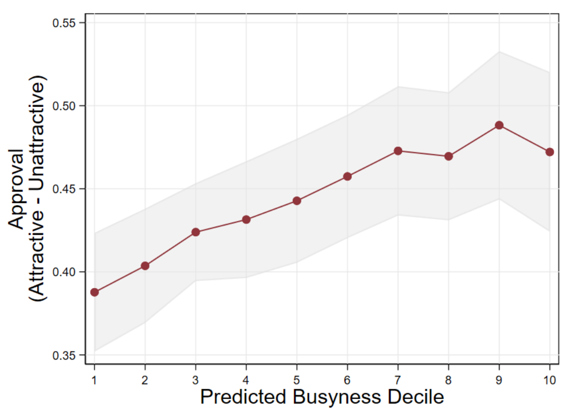
This Figure replicates Figure C2 except that we use the assignment-predicted busyness to measure loan officer attention constraints. The top panels plot the results for officer attention, measured as the standardized review time the loan officer spent on each application. The bottom panels plot the estimations for loan approval. For Panels (a) and (c), applicant attractiveness is measured by their social status. For Panels (b) and (d), applicant attractiveness is measured by their economic status. Fixed effects, controls, and standard error clustering are the same as those in Tables 3 and 4. The shaded areas represent the 95% confidence intervals for the corresponding regression coefficients.



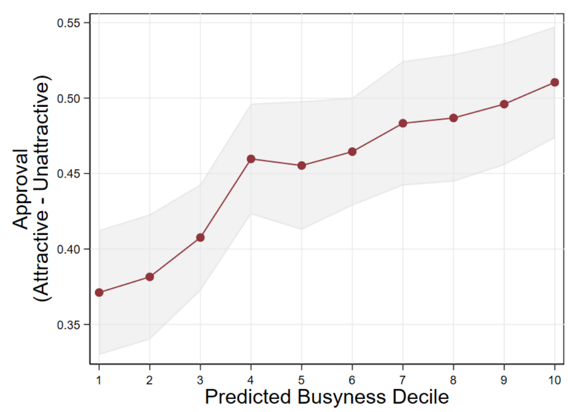
(a) Attention gap across social status



(b) Attention gap across economic status



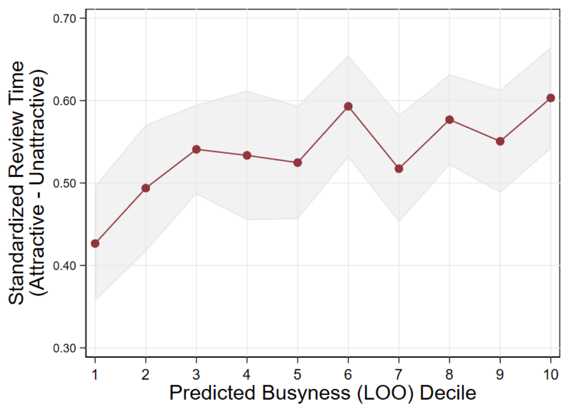
(c) Approval gap across social status



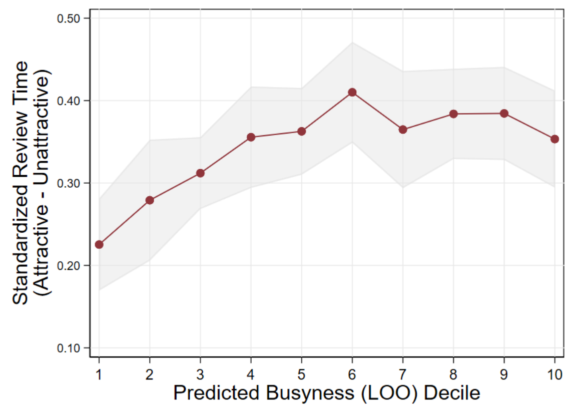
(d) Approval gap across economic status

Figure C6. Difference-in-Differences Effects of Loan Officer Attention Constraints, LOO Instrumented Estimations

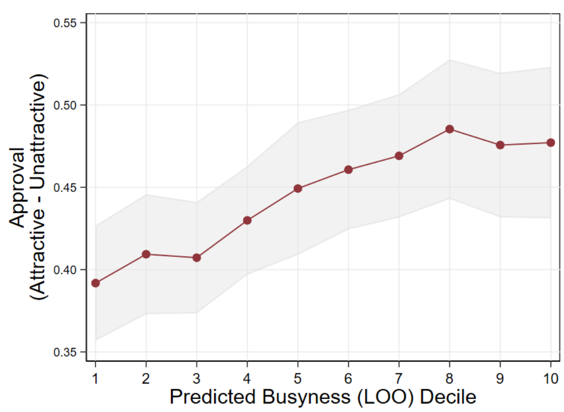
This Figure replicates Figure C2 except that we use the leave-one-out (LOO) assignment-predicted busyness to measure loan officer attention constraints. The top panels plot the results for officer attention, measured as the standardized review time the loan officer spent on each application. The bottom panels plot the estimations for loan approval. For Panels (a) and (c), applicant attractiveness is measured by their social status. For Panels (b) and (d), applicant attractiveness is measured by their economic status. Fixed effects, controls, and standard error clustering are the same as those in Tables 3 and 4. The shaded areas represent the 95% confidence intervals for the corresponding regression coefficients.



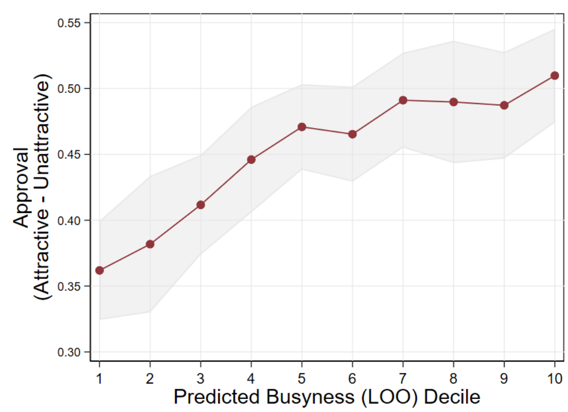
(a) Attention gap across social status



(b) Attention gap across economic status



(c) Approval gap across social status



(d) Approval gap across economic status

Table C1. Explaining Variations in Loan Officer Review Time

In this table, we report the R^2s from estimations that regress log application review time (in minutes) on various sets of fixed effects. For columns (1), (2), and (3), we include loan-type fixed effects, bank-branch fixed effects, and officer-year-month fixed effects, respectively. For column (4) we use interactions between all of the above-mentioned 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 $\times$ Branch $\times$ Officer-Month-Yr FE	N	N	N	Y
Observation	145,982	145,982	145,982	145,982
R-squared	0.003	0.005	0.065	0.360

Table C2. The Relationship between Officer Busyness and Work Hour Patterns

In this table, we report results pertaining to the relationship between officer attention constraints and work hour patterns. The results for the first three dependent variables are reported in hour units: *PunchInHour* marks the hour or time when an officer begins work; *PunchOutHour* is the time when an officer submits the last review of a given day; *DailyWorkingHours* is the total number of working hours in a given day. *HaveOverTime* is a dummy variable that equals one if the officer started work before 8:30 a.m. or finished work after 7:30 p.m. Application controls are similar to before. Local busyness controls include loan officer assignments from the same province. Standard errors are double-clustered at the week and officer levels. T-statistics are reported in parentheses. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Dependent variable:	PunchInHour	PunchOutHour	DailyWorkingHours	HaveOvertime
	(1)	(2)	(3)	(4)
BusynessDecile	-0.046***	0.355***	0.404***	0.041***
	(-11.767)	(12.261)	(14.339)	(13.759)
Application Controls	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y
Week FE	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y
Observation	9,235	9,235	9233.000	9,235
Adjusted R-squared	0.252	0.256	0.276	0.218

Dependent variable:	PunchInHour	PunchOutHour	DailyWorkingHours	HaveOvertime
	(1)	(2)	(3)	(4)
PredictedBusynessDecile	-0.028***	0.238***	0.274***	0.030***
	(-8.214)	(7.084)	(7.992)	(7.426)
Application Controls	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y
Week FE	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y
Observation	9,235	9,235	9,235	9,235
Adjusted R-squared	0.279	0.273	0.287	0.249

Dependent variable:	PunchInHour	PunchOutHour	DailyWorkingHours	HaveOvertime
	(1)	(2)	(3)	(4)
LOOPredictedBusynessDecile	-0.029***	0.154***	0.189***	0.025***
	(-6.336)	(4.992)	(6.202)	(6.255)
Application Controls	Y	Y	Y	Y
Local Busyness Controls	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y
Week FE	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y
Observation	9,235	9,235	9,235	9,235
Adjusted R-squared	0.286	0.273	0.291	0.253

Table C3. The Effects of Officer Attention Constraints by Individual Socioeconomic Labels

In this table, we report results pertaining to the effects of interaction between each individual socioeconomic status label and loan officer busyness. The outcome variable is review time (measuring attention allocation) for Panel A and approval for Panel B. The regression specification is the same as in Tables 3 and 4, except that the indicator variables for *Attractive(Social)* and *Attractive(Economic)* are replaced by indicators of the individual socioeconomic status labels, *PublicEmployee*, *LocalResident*, *EmploymentCert*, *RegularPay*, *IncomeCert* and *HomeOwner*. *BusynessDecile* is LOO-predicted officer busyness sorted into deciles. Application controls are similar to before. Bootstrapped standard errors are double-clustered at the week and officer levels. T-statistics are reported in parentheses. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$

Panel A: Officer attention by LOO-predicted busyness

Dependent variable:	StandardizedReviewTime					
	(1)	(2)	(3)	(4)	(5)	(6)
BusynessDecile	-0.011^{***}	-0.020^{***}	-0.022^{***}	-0.018^{***}	-0.016^{***}	-0.013^{***}
	(−4.478)	(−6.666)	(−6.563)	(−6.683)	(−5.936)	(−4.974)
PublicEmployee	0.178^{***}					
	(5.893)					
PublicEmployee× BusynessDecile	0.009^{*}					
	(1.705)					
LocalResident		0.504^{***}				
		(25.734)				
LocalResident× BusynessDecile		0.014^{***}				
		(5.152)				
EmploymentCert			0.508^{***}			
			(24.856)			
EmploymentCert× BusynessDecile			0.014^{***}			
			(4.457)			
IncomeCert				0.436^{***}		
				(23.277)		
IncomeCert× BusynessDecile				0.013^{***}		
				(4.483)		
RegularPay					0.201^{***}	
					(7.582)	
RegularPay× BusynessDecile					0.014^{***}	
					(3.732)	
HomeOwner						0.264^{***}
						(12.557)
HomeOwner× BusynessDecile						0.014^{***}
						(4.384)
Application Controls	Y	Y	Y	Y	Y	Y
Local Busyness Controls	Y	Y	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y
Week 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	0.037	0.076	0.088	0.066	0.038	0.044

Panel B: Approval rate by LOO-predicted busyness

Dependent variable:	Approval					
	(1)	(2)	(3)	(4)	(5)	(6)
BusynessDecile	-0.001	-0.004^{***}	-0.006^{***}	-0.004^{***}	-0.002^{**}	-0.013^{***}
	(-1.408)	(-5.109)	(-8.187)	(-4.808)	(-2.043)	(-4.314)
PublicEmployee	0.207^{***}					
	(12.313)					
PublicEmployee× BusynessDecile	0.006^{**}					
	(2.325)					
LocalResident		0.423^{***}				
		(57.907)				
LocalResident× BusynessDecile		0.008^{***}				
		(7.014)				
EmploymentCert			0.471^{***}			
			(64.769)			
EmploymentCert× BusynessDecile			0.010^{***}			
			(8.375)			
IncomeCert				0.345^{***}		
				(40.404)		
IncomeCert× BusynessDecile				0.010^{***}		
				(6.998)		
RegularPay					0.374^{***}	
					(26.591)	
RegularPay× BusynessDecile					0.008^{***}	
					(4.260)	
HomeOwner						0.389^{***}
						(36.741)
HomeOwner× BusynessDecile						0.013^{***}
						(8.517)
Application Controls	Y	Y	Y	Y	Y	Y
Local Busyness Controls	Y	Y	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y
Week 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	0.143	0.270	0.359	0.229	0.174	0.221