Attention Constraints and Financial Inclusion

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Abstract

We show that attention constraints of decision makers function as barriers to financial inclusion. Using administrative data on retail loan screening processes, we find that loan officers exert less effort reviewing applicants from unattractive social or economic backgrounds and reject them more frequently than justified by credit quality. More importantly, when quasi-random workload variations tighten officer attention constraints, unattractive applicants receive even worse treatment—review-time halves and approval rates drop by approximately 40%—while attractive applicants are not affected. Our findings suggest that financial technologies that reduce information-processing costs may promote more balanced financial access.

JEL classification: D83, D91, G21

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1 Introduction

Having access to finance is crucial to well-being in contemporary society.[1] However, even in the U.S., nearly one-fifth of adults remained unbanked or underbanked, and there exist significant financial inclusion gaps between socioeconomic groups.[2] While it is not surprising that individuals from "unattractive" socioeconomic backgrounds (e.g., migrants, renters, workers with unstable employment) face lower financial inclusion given their weaker economic and financial fundamentals, this study finds that attention constraints of key decision makers, such as loan officers, can become a further barrier to financial inclusion for those from unattractive backgrounds even when many of them are fully qualified for financial access. Such decision maker inattention results in *additional* hindrance in financial access and can lead to socially inequitable and inefficient allocation of financial resources.

To illustrate how inattention hinders inclusion, we use a stylized model to show that financial inclusion for applicants from unattractive backgrounds relies on sufficient attention from decision makers who allocate financial resources. Specifically, in the lending process, when loan officers face attention constraints, they may (rationally) pay less attention to borrowers who are labeled as socioeconomically unattractive. Such "attention rationing" can lead to quick rejections due to loan officers failing to thoroughly evaluate those borrowers' credit worthiness. As a consequence, unattractive borrowers will end up facing a higher probability of rejection than their actual creditworthiness warrants. In other words, when decision makers are attention constrained, borrowers with unattractive socioeconomic backgrounds may not be given a fair chance in evaluation. To be clear, such loan officer behaviors can be entirely rational and constrained optimal from the lender's perspective. Our paper, however, focuses on the distributional consequences of financial inclusion which lenders likely do not internalize.

To provide intuition, we illustrate the essence of this mechanism via an example of an annual recruiting exercise. Consider the case of reviewing junior job market applicants for a finance faculty position at a well-regarded school. If given infinite time and energy, reviewers could carefully read through all papers written by each candidate to make informed choices. Such a thorough review is, however, practically unrealistic. Faced with attention constraints, reviewers may use simple signals, such as an applicant's institutional affiliation, to guide

[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 the families with income below \$50,000 experience credit denial or cannot obtain sufficient credit they request. Across all income levels, on average, about one-third experience difficulty obtaining credit.

how much effort to spend learning about that candidate. Because recruiting is a selective process, an applicant who does not get a sufficient amount of review is much more likely rejected than an *otherwise similar applicant* who can obtain a fair amount of attention. Such hasty rejections can lead to inclusion issues in academic recruiting: qualified applicants from unattractive backgrounds—e.g., those who attend lower-ranked schools or work with less-known advisors—are systematically less likely to be considered for high-ranking academic jobs even when they have strong research capabilities.

Empirically studying the impact of attention on inclusion faces two challenges. 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 plausibly exogenous variations in attention constraints. Using administrative data on approximately 146,000 retail loans' screening processes from one of the largest national banks in China, our paper overcomes both difficulties. First, because we observe accurate timestamps in the decision-making process, we can track the exact number of minutes that loan officers spend reviewing each application—a direct measure of attention allocation. Second, the bank allocates applications across loan officers in a quasi-random manner which induces exogenous variations in loan officer workload, allowing us to infer the consequences of attention constraints. Further, the data includes detailed information which allows us to investigate loan officer decisions while conditioning on the full set of borrower and loan characteristics observed by the loan officers.[3]

Our model with endogenous attention allocation generates two testable predictions which we bring to the data. First, applicants from unattractive socioeconomic backgrounds will be accorded less attention and rejected more often than warranted by their credit quality. Second, and more importantly, this inclusion problem will be magnified when officers are busier and thus more attention-constrained. Empirically, the first prediction leads to a "single-difference" result between attractive and unattractive applicants, while the second leads to a "difference-in-differences" result which further varies with loan officer attention constraints. The existing literature has shown evidence for the first prediction in other settings (Bartoš, Bauer, Chytilová, and Matějka, 2016), but the second prediction is novel to the literature. Furthermore, the second prediction is a more direct test of the role of attention constraints in financial inclusion, and thus the focus of our paper.

Our empirical work begins with a preliminary examination of the first prediction. As expected, attention-constrained loan officers indeed use simple observable labels to guide

[3]Also, our data is suited for studying inattention because loan officers are time constrained: the median time period spent reviewing each application is only 18 minutes, yet loan officers must sift through at least 20 to 30 pages of dense documents, and sometimes also hundreds of pages of supporting materials, per application.

how much attention to give to each application. In our sample, each application package includes a number of salient labels related to the applicant's social and economic statuses, 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 classify applicants into the "attractive" and "unattractive" groups. We then find that, relative to others with attractive socioeconomic labels, many of the "unattractive" but actually creditworthy applicants are accorded significantly less attention and are much more likely to be rejected. When we compare groups of applicants, we find that the group with unattractive social (economic) status receives only 12.1 (16.1) minutes of median review time by loan officers, while the socially (economically) attractive group receives 24.9 (25.2) minutes, which is approximately twice as much attention. In terms of approval rate, the socially (economically) unattractive group finds their loans approved only 18.1% (25.4%) of the time, while those in the high social (economic) status group find their applications approved 51.9% (65.5%) of the time.

Such differential treatment could be justified if the difference in creditworthiness between the two groups is large. However, examining a wide range of observable credit quality indicators, we find that the two groups have only small average differences and have significant overlap. For instance, 48% (47%) of the socially (economically) unattractive applicants have income higher than the median attractive applicant, which is only slightly lower than 50%—if the two groups are identical. Given this, the significantly lower attention and approval rate for unattractive applicants may raise inclusion concerns, which could be driven by decision makers' attention constraints.[4]

Having documented preliminary evidence of differential attention allocation, we now test the key theoretical prediction that stronger attention constraints exacerbate "attention rationing" and widen the gap of financial resource allocation between applicants from attractive versus unattractive socioeconomic statuses. To compare the consequences under different extent of attention constraints, we exploit variations in loan officer *busyness*, defined as the number of applications processed by an officer on a given day. In our sample, there is sizeable variation in officer busyness, with the 10% and 90% percentiles equal to 10 and 27 applications per day, respectively. The key idea of this research design is that officers face tighter attention constraints on busier days because they have less time to spend on each application. We then examine whether officers exhibit stronger tendencies to ration

[4] Of course, it is still possible that the two groups differ in unobservable dimensions of credit quality. Our main analysis, which we discuss next, tackles this concern using orthogonal variations in loan officer attention constraints.

attention and financial resources when they are busier.

[**Figure** 1 about here.]

Consistent with the model prediction, when loan officers face stronger attention constraints, unattractive applicants are allotted even less attention and are rejected even more often, while the attractive applicants are barely affected. As an exploratory illustration, we plot these patterns in Figure 1. 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 much more pronounced for the socially or economically unattractive groups. Panels (c) and (d) further show that, when loan officers get busier, the approval rate for socioeconomically unattractive applicants declines sharply but that for attractive applicants does not.

We then formally estimate these effects using regression analyses which control for officer-month-year, week, bank branch, and loan type fixed effects as well as an exhaustive list of applicant-level characteristics based on the same set of information observed by the loan officers. The results are similar to those plotted in Figure 1. When loan officer busyness varies from the bottom to the top deciles, their review time on socially (economically) unattractive applicants declines by 53% (52%). Meanwhile, the approval rate for the socially (economically) unattractive group goes down by 45% (39%) relative to the group average, while the approval rate of the attractive group shows no decline. Overall, our results are consistent with the prediction that tighter attention constraints lead to disproportionally lower allocation of loan officer attention to unattractive applicants, which results in a disproportional reduction in the allocation of financial resources to applicants from unattractive socioeconomic backgrounds.

Two empirical concerns might arise when we use *realized* loan officer busyness to measure their attention constraints. First, loan officers may have leeway to work faster or more slowly, and thus their realized busyness may reflect an endogenous choice rather than external constraints on their attention capacity. To address this concern, we instrument the busyness measure by the number of applications *assigned* to officers. Because the assignments are made by a quasi-random central dispatcher algorithm over which officers have no influence, this assignment process induces exogenous variations in loan officers' attention constraints. We also control for loan officer-month-year fixed effects in all our specifications, so we are effectively utilizing the *idiosyncratic* 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 officers' busyness may be correlated with the average quality of the application pool received by the bank. While we show that officer busyness is not correlated to observable borrower characteristics, one may still worry about potential correlations with unobservable characteristics.[5] We address this concern further by constructing another instrumental variable based on a leave-one-out (LOO) assignment measure. The idea is that if, for example, Province A experiences an idiosyncratic spike in applications that increases the busyness of a given loan officer. Then, this tightens a loan officer's attention constraints which will 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 (controlling for busyness that is driven by assignments from the same province), we capture variations in a loan officer's attention constraints that are independent of a particular application she is screening.

The two measures introduced above are strong instruments as either the number of assignments or LOO assignments can explain approximately 40% of the variation in realized loan officer busyness. To further examine the validity of our instruments, we verify that assignments do not depend on backlogs; this ensures that officers not only lack direct control over the assignment process, but they also cannot *indirectly* influence the process by changing the speed at which they work. We also verify that loan officer busyness predicted by either of our instruments is not correlated with a variety of credit quality measures.

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 similar: when officers are busier due to exogenous and idiosyncratic variations in applications assignments, they shift more attention away from unattractive applicants and reject them more frequently.

Our paper's main contribution is to show that decision makers' attention constraints can hinder financial inclusion for the socioeconomically unattractive population. This effect has important distributional consequences: it suggests that the financial access obtained by the population with unattractive socioeconomic labels is even worse than what their economic and financial fundamentals would suggest. In other words, when decision makers are attention constrained, people who are already on the left tail of the socioeconomic distribution can be allocated even fewer resources than what they deserve.

[5]It should be noted that such a correlation *alone* cannot systematically bias our result: our difference-in-differences estimation can be biased only when loan officer busyness is somehow correlated with lower quality of unattractive borrowers but not with lower quality of attractive borrowers. Furthermore, we control for a rich set of applicant-level characteristics, so any omitted variables must also be orthogonal to all our credit-quality measures.

While we obtain our results in a specific setting, we believe that the attention-based mechanism we document can be applicable to other situations in which decision makers face attention constraints. Many high-stakes decision makers—college admission officers, recruiters, judges, or reviewers of 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 each initial read of each college application. Time Magazine (2002) cites a study that shows 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 not unimaginable for a similar mechanism to be at play: when they are busy, key decisions-makers choose to pay less attention to ex-ante unattractive candidates, and those candidates are rejected more frequently than intrinsically justified by their merits.

Regarding policy implications, our findings suggest that policies and technologies that relax decision maker attention constraints may promote equal financial resource allocation. For instance, the recent developments in financial technologies ("fintech"), which use automated underwriting algorithms (and thus have low or no processing constraint) to assist in screening borrowers, may improve financial access for individuals or businesses with unattractive labels in the financial system where most decisions are currently made by attention-constrained humans.[6] Of course, recent studies also raise the importance of ensuring that the fintech algorithms themselves are not biased by design.[7] 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 unattractive applicants.

The remainder of the paper is organized as follows. Section 2 uses 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

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

[7]Recent studies raise concerns that the application of big-data financial technologies may generate new distributional issues as they allow lenders to triangulate otherwise excluded borrower features (e.g., Fuster, Goldsmith-Pinkham, Ramadorai, and Walther (2022)). Therefore, the net distributional effect of financial technologies might still be ambiguous (Morse and Pence, 2021).

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 most related to the seminal work on selective attention allocation by Bartoš et al. (2016). Using experiments, they find that decision makers exert more effort collecting information on the 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 about the distributional consequence 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.[8]

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 loan (Charles, Hurst, and Stephens, 2008; Butler, Mayer, and Weston, 2020; Lanning, 2021), small business lending (Ongena and Popov, 2016; Brock and De Haas, 2021), microlending (Beck, Behr, and Madestam, 2018), and entrepreneurial finance (Hebert, 2020; Ewens and Townsend, 2020; Hu and Ma, 2020; Zhang, 2020). In addition to documenting the lack of inclusion for borrowers from unattractive groups, in this study, 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.[9]

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

[8]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).

[9]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, 2020; D'Acunto, Ghosh, Jain, and Rossi, 2020).

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 different 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, Forthcoming). Our paper extends these studies by proposing and testing a new attention-based constraint; attention constraints of 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 limited attention can hinder financial inclusion for unattractive loan applicants and derive testable predictions. Less interested readers can skip the model with little cost as the intuition is already explained 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 different groups denoted by G, and the associated group identities are observable with 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.

For the sake of simplicity, the interest rate r is fixed exogenously.[10] If the loan officer approves the application, the expected profit (before considering attention cost) is:

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

where distaste_G is a possible group-specific preference-based negative attribute and p is the expected 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.

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

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

where $\bar{p}_G$ is a group-specific component known to the officer, $p_I \sim N(0, \sigma_G^2)$ is an applicant-specific component that can be learned by paying the attention cost c, and ϵ represents a mean-zero residual term that cannot be learned. p_I and ϵ are independent of each other.[11]

To match the selectivity of the loan-screening process in our data, we assume that $\bar{p}_G$ is high enough so that officers will not accept applications without devoting attention to learning about the applicant.[12] Bartoš et al. (2016) refer to this as the "cherry-picking" condition. In other words, this condition is equivalent to assuming that the *status quo* decision in the absence of attention is to *reject* the application.

The assumption that the absence of attention results in rejection should be uncontroversial in our setting, as it simply requires that no group of applicants is so inherently creditworthy

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

[11] 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 other mean-zero distributions with bounded support.

[12] Formally, we need:

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

that its members' applications can be approved without being read.[13] In our sample, the application process is fairly selective; only approximately one out of three applications is eventually approved.

Optimal loan officer behavior. As illustrated in Panel A of Figure 2, the optimal strategy for the loan officer is characterized by two threshold decisions. First, she will pay attention cost c if and only if the applicant comes from a sufficiently attractive group. Groups with lower $\bar{p}_G$, lower distaste_G, or higher σ_G are relatively attractive. If c is sufficiently high, applicants from less attractive groups will be rejected in the absence of attention.

Second, conditional on learning about p_I, the loan officer will accept applicants at a default probability that is $\bar{p}_G + p_I$ lower than a threshold $\frac{r-\text{distaste}_G}{1+r}$ that guarantees non-negative profits (after adjusting for distaste) when lending to such an applicant.[14] The acceptance region is illustrated by the shaded areas in Panels (b) and (c) of Figure 2.

[**Figure** 2 about here.]

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

1. Groups with lower distaste_G are obviously attractive. This reason maps squarely into standard preference-based discrimination a la Becker (1957).

2. Groups with lower $\bar{p}_G$ are attractive. This is because, for such groups, the loan officer is more likely to end up concluding that she can profitable lend to the applicant after learning about p_I (Panel (b) of Figure 2).

[13]The validity of the "cherry-picking" condition in our empirical setting can be shown using a simple back-of-the-envelope cost-benefit analysis. Consider a random loan application. The average interest rate in our data is approximately 8.6%. If the bank's cost of capital is equal to China's central bank rate of 3.25% in our sample period, this would mean that the bank could make a cost-adjusted annual return of only 5.35% when the applicant does not default. In contrast, if the application defaults and has a 40% recovery rate upon default, the bank stands to lose 60%. Therefore, as long as the expected default rate for an average application is higher than $\frac{5.35\%}{5.35\%+60\%} \approx 8\%$, the default action in the absence of sufficient information acquisition is rejection.

[14]The threshold is solved based on:

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

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

In other words, groups can be attractive due to both prejudice (reason 1) and efficiency (2 and 3) reasons. In our empirical setting, we do not take a stance on the exact reason why applicants without certain socioeconomic labels are considered unattractive, but the context suggests that both types of forces are likely at play. Specifically, the use of social status labels may be more related to prejudice, while the use of economic status labels appears more related to efficiency.

Testable predictions. Most discussions of decision-making do not account for attention costs. Once non-negligible attention costs are considered, however, applicants from the various groups will form an ordered ranking in the mind of the loan officer, from the most to the least preferable (attractive). When the attention cost increases, the loan officer will first reduce the attention she pays to the most unattractive group, followed by reducing that to the second unattractive group, etc.

The model is highly stylized by construction. It predicts that when the loan officer becomes busier, she effectively discards all unattractive applicants without reviewing them. In practice, we can observe the groups into which loan officers classify applicants only imperfectly. Moreover, there are also variations in attention costs that are not observable to us. Therefore, the empirical results will not be as stark as our model predicts. Nevertheless, we anticipate that the two model predictions will be *qualitatively* reflected in the data.

Prediction 1 (selective attention and differential treatment) Applicants from ex-ante less attractive groups (those with higher $\bar{p}_G$, higher distaste$_G$, or lower σ_G) will receive less officer attention and be rejected more often.[15]

Prediction 2 (attention costs magnify treatment differences). Consider two groups, G_1 and G_2, where the former is more unattractive (those with higher $\bar{p}_G$, higher distaste$_G$, or lower σ_G)). If the existing attention cost c is sufficiently low that both groups receive attention from loan officers, then the *gaps* in both attention and approval rates between the two groups will weakly increase with the attention cost.

What is the main innovation? Prediction 1 has been proposed and tested experimentally in Bartoš et al. (2016) in a different context. Prediction 2 is the main innovation in this paper.

[15] This prediction is also called "attention discrimination" in Bartoš et al. (2016).

In our empirical tests, we use quasi-random variations in loan officer workloads to perturb attention cost c, and we examine whether the attention and approval-rate gaps between attractive and unattractive groups widen as attention costs rise. This mechanism, if it is truly operative, is policy-relevant: it implies that policymakers can address inclusion concerns by employing rules or technologies that ease attention constraints on decision makers.

3 Data and Institutional Background

In this section, we describe the data and provide background information on the sample retail loan-screening process. We then show preliminary evidence that applicants without certain socioeconomic status labels are considered unattractive by loan officers: they receive less review time and are rejected more frequently than would seemingly be justified by their credit quality. The main empirical results, where we investigate the impact of variations in office attention constraints on financial inclusion, are reported in Section 4.

3.1 Data Source

We obtain the internal retail lending screening records from one of the largest national banks in China. The sample data covers approximately 146,000 loan applications screened by 92 loan officers who work 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 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 size of around \$16,000 in the U.S.[16] 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.[17] 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 about each application, 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

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

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

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.

3.2 The Loan-Screening Process

The three-stage loan origination and screening process are illustrated in Figure 3. Stage one, which happens at the local bank branch level, is not captured by our data. Our study focuses on stage two which generates quasi-random workload variation and stage three when 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 makes sure 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 the 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. The algorithm effectively assigns the applications randomly, creating exogenous variations in officer busyness that are orthogonal to the quality of the applications. We exploit this quasi-random variation for our empirical analyses in Section 5.1.

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.[18] Our

[18]That average approval rates are low matters; inclusion concerns are exacerbated by inattention only in processes that are selective—an assumption called the "cherry-picking" condition in Bartoš et al. (2016). The illustrative model in Section 2 provides additional details.

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.[19]

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.[20] 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 resident address), personal wealth and income information, purposes 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). Similar to credit reports issued by the credit bureaus in the U.S. market, this report by PBOC contains information about the individual's credit payment history and public records (e.g., past civil or criminal records).[21]

In addition to these documents, loan officers sometimes conduct additional due diligence, which for example includes searching online about 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 a decision.

[19] Conversations with loan officers reveal that their compensation scheme provides incentives to screen out high-risk applications, as their bonuses can be affected by the default rate of the loans they approve. Their compensation is also affected by the volume of loan origination. Overall, this glimpse into loan officer compensation suggests that their incentives generally align with the bank's best interests.

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

[21] During our sample period, there is no widely used consumer credit score (like FICO in the US) 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 lending decisions by banks.

We argue that loan officers face attention constraints because we find that they can only spend 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 that elapses *between two consecutive decisions* rendered by the same loan officer.[22] 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.[23]

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 unfavorable signals may be quickly rejected without a 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 consider a few easily-observable socioeconomic labels useful for guiding time allocation. Some of these labels are related to social statuses while others are related to the economic statuses of the applicant, and we call them "socioeconomic labels" collectively in subsequent discussions. These are zero-or-one indicator labels that can be easily observed from the application form.

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

1. *PublicEmployee*: whether the applicant works for the public sector. The Chinese society considers public employees, including those working in the government, public

[22] 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.

[23] The per-application review time in our sample is shorter than 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 US mortgage market. However, this number includes processing time in all steps from the submission of application to the final origination of a loan, and not just the review time spent by loan officers, and thus is not directly comparable to our review time measure.

schools or hospitals, state-owned firms, or any other government-sponsored institutions to have a higher social status.[24] Since an applicant needs to fill in her position type 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 considered to be of higher status than migrant workers (i.e., people who grow up in rural areas and migrate to work in the city).[25] The Chinese "Hukou" (household registration) system makes it easy to distinguish the identity of 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 only considered acceptable to the bank 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 at a large employer can provide an acceptable employment certificate, while most short-term contractors, employees of micro 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 done either through an employer-issued income certificate (*IncomeCert*), or through a label that summarizes cash flow information from the applicant's bank statements (*RegularPay*),[26] or both.

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

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

[25] In fact, one of the most salient discrimination concerns in the Chinese society is the discrimination against migrant workers.

[26] In stage one of the loan screening process, the bank's local branch employees analyze the information from applicants' bank statements and create an easily-observable label of stable income (or not) and fill it in 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.

Applicants without socioeconomic labels are rejected more frequently. Table 2 reports 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 indicator variable for loan application approval on dummies indicating whether an applicant has each of the aforementioned social or economic status labels. The estimations control for a comprehensive list of application-level observables that may be related to credit quality.[27] To rule out potential 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 rate remain statistically and economically significant when examined together (columns (7) to (9)).

[**Table** 2 about here.]

Defining applicants from "unattractive" 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 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 will 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

[27] 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, and 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 in 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.

indicators into two variables, “Social Status“ and “Economic Status“, to help 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:[28]

$$\begin{aligned} \text{SocialStatus}_i &\equiv \widehat{\text{Approval}}_i | \{\text{PublicEmployee}_i, \text{LocalResident}_i\} \\ &= \hat{b}_{\text{PublicEmployee}} \cdot \text{PublicEmployee}_i + \hat{b}_{\text{LocalResident}} \cdot \text{LocalResident}_i \end{aligned} \tag{5}$$

$$\begin{aligned} \text{EconomicStatus}_i \equiv\ & \widehat{\text{Approval}}_i | \{\text{EmploymentCert}_i, \text{RegularPay}_i, \text{IncomeCert}_i, \text{HomeOwner}_i\} \\ &= \hat{b}_{\text{EmploymentCert}} \cdot \text{EmploymentCert}_i + \hat{b}_{\text{RegularPay}} \cdot \text{RegularPay}_i + \\ &\quad \hat{b}_{\text{IncomeCert}} \cdot \text{IncomeCert}_i + \hat{b}_{\text{HomeOwner}} \cdot \text{HomeOwner}_i \end{aligned} \tag{6}$$

In other words, these two variables are single-dimension summaries of the multiple social and economic labels carried by in a given application. For the sake of simplicity, in subsequent analyses, we create two indicator variables, Attractive $(\text{Social})_i$ and Attractive $(\text{Economic})_i$, which equal one for applicants whose values of SocialStatus_i and EconomicStatus_i are above the sample median, respectively. 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 measure below the median to be unattractive.[29] We compare the review time and approval rate of the attractive versus unattractive groups in Panel B of Table 1.

3.5 Credit Qualities of Attractive versus Unattractive Applicants Largely Overlap

Loan officers may make use of applicant socioeconomic labels in decisions either because these labels are strong signals of credit quality or because they lead to inherent prejudice. To begin with, officers may believe that applicants from less attractive socioeconomic backgrounds have substantially lower credit quality—statistical discrimination a la Becker (1957).[30] Of course, it is also possible that loan officers are simply subjectively biased against applicants from unattractive backgrounds, especially when it comes to the use of social status labels.

[28]We use a version of the regression without additional controls. Our results are not sensitive to the exact methodology of combining the socioeconomic status indicators.

[29]The cramér’s v correlation between the two attractiveness indicators is -0.133.

[30]For instance, public employees and people who can provide employment or income certificates on average may have better job security; local residents may have stronger social connections in the local area; homeownership could have a direct relationship with wealth.

[**Figure** 4 about here.]

When examining a number of major creditworthiness measures, we indeed find some evidence that applicants from more attractive socioeconomic groups have higher average credit quality (Appendix B.2). However, the difference is small and masks substantial overlap between the attractive and unattractive groups. This can be readily seen in Figure 4 where we plot the kernel densities of creditworthiness measures for the attractive groups in green and the unattractive groups in red, and the vertical dashed lines represent 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 substantial overlap in credit quality between the two groups.

Appendix Table B2 presents further numerical details about the extent of the overlap: 48% (47%) of the socially (economically) unattractive applicants have income higher than the median attractive applicant, and 38% (39%) have lower leverage ratios. The fact that these numbers are below 50% implies that the unattractive group indeed has slightly lower credit quality. However, the overlap is significant, and rashly rejecting applications from the unattractive group without careful review would, in our view, is detrimental to financial inclusion. To be clear, the higher rejection rate for the unattractive group is inevitably related to their lower average credit quality. However, the difference in credit quality may not fully explain the gap in rejection rates between the attractive and unattractive applicants. In fact, our results in the subsequent section suggest that the unattractive group is rejected disproportionately *more* frequently than justified by credit quality, and this differential treatment is exacerbated when loan officers face stronger attention constraints.

4 The Impact of Loan Officer Attention Constraints

This section presents tests of the main empirical prediction of our paper: when loan officers face tighter attention constraints, they pay less attention to applicants with unattractive socioeconomic backgrounds and reject their applications more often than justified by their credit quality. We start by using a simple measure of loan officer busyness to proxy for attention constraints in this section, and then construct instruments for the constraints to infer causal effects in the next section.

4.1 Measuring Loan Officer Attention Allocation and Attention Constraints

Measuring attention allocation to each application. Because we have access to internal timestamps for officer actions, we can use elapsed time between two consecutive decisions by the same officer to measure how much time is spent on reviewing each application. To remove variations in application review time that are unlikely to reflect active loan officer choices,[31] 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:

$$\text{StandardizedReviewTime} = \log\left(\frac{\text{ReviewTime}}{\text{Median ReviewTime by group}}\right) + \underbrace{\text{Median}\ \log(\text{ReviewTime})}_{\text{full sample}} \tag{7}$$

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 explained by the 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 (7) 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) is 0.488 to 1.476.

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$^{\text{th}}$ and 90$^{\text{th}}$ percentiles are 10 and 27, 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 for attention constraints. First, when officers are busier, they work longer hours and are more likely to work overtime. To examine

[31] 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.

this, we sort the sample into deciles differentiated by busyness and, for each decile, plot the average starting and ending time for a typical work day in Panel (a) of Figure 5.[32] 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 of officers working over time rises from approximately 20% in a lowest-busyness-decile day to over 60% in the highest-busyness-decile day.[33] 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 the subsequent analyses presented in this and the next section.[34] Overall, these findings are consistent with our view that officers are more attention constrained when busy.

Unattractive applicants are accorded significantly less attention. Having developed 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 unattractive economic status application is 16.12 (28.76) minutes as opposed to 25.16 (37.41) minutes for applicants with attractive economic status.

In Appendix B.3, we also use another loan officer action—whether they conduct 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 the 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.

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

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

[34]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.

4.2 The Impact of Loan Officer Attention Constraints on Unattractive Applicants

Having defined measures for loan officer attention constraints and attention allocation, we now start to test our main prediction that tighter attention constraints lead to less attention and a lower acceptance rate for unattractive applicants. We use the realized officer busyness measure to proxy for attention constraints in this section. The next section further develops instruments for loan officer busyness.

As an exploratory analysis, we first simply plot (without controls) average attention and approval rates as a function of busyness. In Figure 1's Panels (a) and (b), we sort the sample into deciles differentiated by officer busyness and plot the average standardized review time for the attractive versus unattractive groups as measured by their social or economic status, respectively. As expected, we find that unattractive applicants receive less attention. More importantly, the *attention gap* between the two groups increases as officers become busier, as shown by the black line which tracks the difference between the two groups. When officers become busier, they appear to shift attention disproportionally *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, while that for the attractive group does not.

[**Table** 3 about here.]

To formally investigate the effects of officer attention constraints, we now conduct regression analyses at the application level. In columns (1) and (2) of Table 3, we regress standardized review time—our measure for loan officer attention allocation—on loan officer busyness decile, the *Attractive(Social)* dummy which indicates whether the applicant's *SocialStatus* is above sample median, as well as their interaction. We then do the similar tests in columns (3) and (4), measuring attractiveness based on the applicant's economic status. Consistent with the visual patterns in Figure 1, when officers are busier, the attention they pay to applicants decreases, especially 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 for officers to spend less time on each application when 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)–(6), we show that the effects remain statistically and economically similar when both social and economic statuses are considered simultaneously. Appendix Table B6 verifies that the same conclusion is true 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. Column (2) shows 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 deduction is about 45% of the average approval rate for this group of applicants. Similarly, column (4) shows a decline in 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 for the attractive group does not reduce. The results remain similar when both attractiveness measures are jointly considered in columns (5) and (6).

Overall, these results are consistent with the main prediction that, when loan officers face tighter attention constraints, applicants with unattractive socioeconomic backgrounds receive disproportionately less attention and are rejected more frequently. The very fact that attention matters for approval rates suggests that less attractive applicants are, on average, allocated disproportionately fewer financial resources beyond that can be justified by their inherent credit quality, given that loan officers appear rather time constrained overall.

It is worth noting that our regressions control for officer $\times$ 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 potentially related to borrower creditworthiness; 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 become wider almost monotonically when loan officers get busier.

5 Exploiting Quasi-Random Variations in Officer Busyness

One may be concerned that our measure of *realized* officer busyness may be endogenous. In this section, we construct two instruments for officer busyness to address these potential 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 one potential endogeneity concern: officers can set their own pace at work.

This may lead to a problem with omitted variables in explaining loan approval rates. For instance, an officer who wants to relax on a particular day, possibly because of distractions outside of work, may choose to quickly reject many applications perfunctorily, leading to a negative correlation between busyness and the officer's loan-approval rate.[35]

To address this endogeneity challenge, we need to find a source of busyness variation that is *not controlled* by loan officers. Fortunately, as described in Section 3.2, loan applications are assigned to officers by a central dispatcher algorithm over which officers have no control. Although the bank does not disclose precisely how its algorithm assigns applications, we have been informed that officers have no influence on this assignment process. We further confirm this by showing that the assignment algorithm has no relationship with the current or earlier backlogs of loan officers (Appendix Table B7). Moreover, we also confirm that the assignment algorithm is independent of observable loan characteristics, as shown in Panel A of Appendix Table B8.

Thus, the variation in the number of assigned applications is orthogonal to both the officer's discretion and loan characteristics. This allows us to use the number of assignments as an instrument to capture the exogenous variation in officer busyness, through a regression at the officer–day level:

$$\text{Busyness}_{j,d} = a + \sum_{\tau=0}^{3} b_\tau \cdot \text{Assignment}_{j,d-\tau} + \epsilon_{j,d}, \tag{8}$$

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 assignment. 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. Hereafter, we call the value predicted in regression (8) "predicted busyness."

Instrument approach 2: leave-one-out (LOO) assignment-predicted busyness. This instrument can be thought of as a further refinement of the previous one. Even though we find no correlation between assignments and loan characteristics (Appendix Table B8), one might still worry about correlations between assignments and *unobservable* loan quality. It should be noted that such correlations alone cannot generate bias in our empirical framework. Our difference-in-difference estimation can be biased only when loan officer busyness is *only* correlated with lower unobservable credit quality among unattractive

[35]To be clear, this concern *per se* does not lead to our result which focuses on the *differential* impact on applicants from attractive and unattractive groups. One still needs to explain why a careless officer would primarily target unattractive candidates for rash rejections.

borrowers but not among attractive borrowers. Moreover, because we have controlled for an exhaustive set of applicant-level characteristics based on the full set of information loan officers can observe regarding an application, the omitted variables need to be orthogonal to all our existing credit-quality measures.

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 where the examined application comes from. Recall that the loan officers we study work at the headquarters office, while applications are sourced from bank branches all over the country. The idea behind this instrument is that, if many assignments from province A make the loan officer busy, this could affect her decision-making regarding applications from province B. In this case, the quality of loan applications in province B is independent of the application volume from province A that drives the busyness of the loan officer (after directly controlling for the application volume in province B, as we do in the analysis). The results reported in Panel B of Table B8 verify that the instrumented busyness measure constructed using this method, which we call "LOO-predicted busyness," is also not correlated with any of the observable loan quality measures. Also, Appendix Figure B1 shows that similar to the realized busyness measure, these two instrumented busyness measures are related to longer work hours and more overtime.

5.2 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 the *Predicted Busyness* (columns 1 to 3) and the *LOO-Predicted Busyness* (columns 4 to 6) to estimate how exogenous variations in loan officer attention constraints affect their allocation of review time on attractive versus unattractive applicants. Since the instrumented busyness measured is estimated in an earlier stage, we estimate standard errors using the bootstrap method. As can be seen in column (1), the attention gap between applicants with attractive versus unattractive social status widens by $(10-1) \times 0.013 = 11.7\%$ when exogenous attention constraints, as measured by *Predicted Busyness*, increase from the bottom to the top decile. In column (2), an effect of similar magnitude is found between applicants with attractive versus unattractive economic status. The results are robust to including both social and economic statuses (column (3)). When measuring loan officer attention constraints using *LOO-Predicted Busyness*, the effects are qualitatively and quantitatively similar, as shown in columns (4) to (6).

We then use the same instrumented busyness measures to estimate the effect of loan officer attention constraints on their approval decisions. According to columns (1) and (2) of Table 6, the approval gap between socially (economically) attractive versus 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 found in columns (3) to (6) when exogenous attention constraints are measured by *LOO-Predicted Busyness*. 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.[36]

Overall, results 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 people with unattractive socioeconomic 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 of financial decision makers. In the selection process, attention constrained decision makers will, endogenously, pay less attention to applicants with ex-ante unattractive socioeconomic labels. As a result of this lack of attention, unattractive applicants end up facing even less allocation of financial resources than their credit quality justifies. Moreover, the tighter the attention constraints, the greater the negative impact on unattractive applicants.

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 to otherwise similar applicants with attractive socioeconomic labels. Furthermore, when loan officers experience tighter attention constraints caused by *quasi-random* variation in their workloads, the review time and approval gaps between attractive and unattractive applicants both widen.

[36] 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 all find qualitatively similar results.

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 from attention bottlenecks. Moving beyond our immediate setting, many high-stake decisions are made by humans, and key decision makers—such as court judges, college admission 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 can be at play in other settings that are potentially more consequential.

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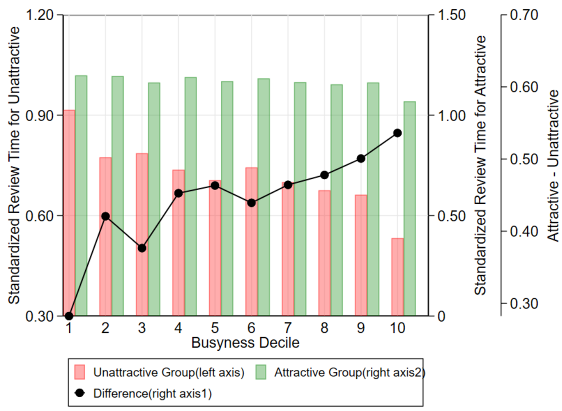
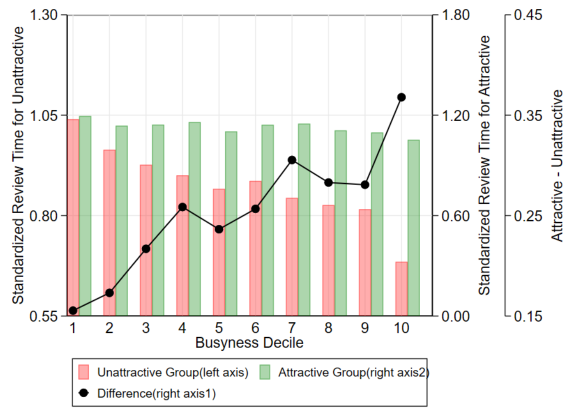
Figure 1. Attention Allocation and Approval Decisions by Loan Officer Attention Constraints

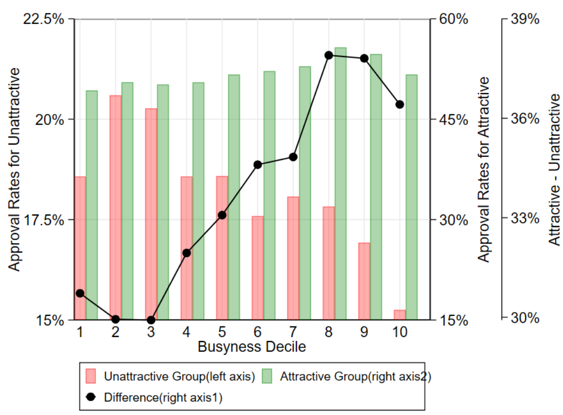
This figure exhibits how loan officer attention allocation and approval decisions on attractive versus unattractive applicants vary by officer attention constraints. As explained in Section 3.4, we use the possession (or not) of various labels to classify applicants into attractive versus unattractive 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 Sections 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.



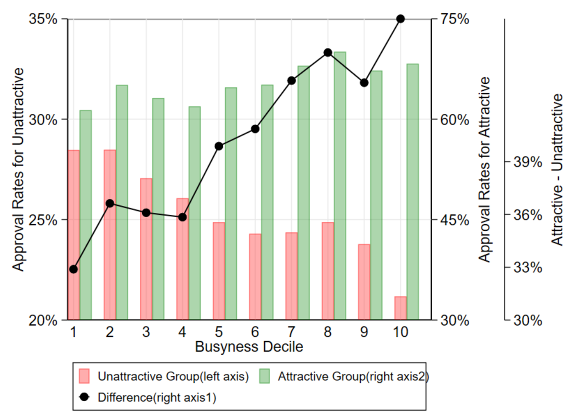
(a) Officer attention allocation by applicant social status



(b) Officer attention allocation by applicant economics status



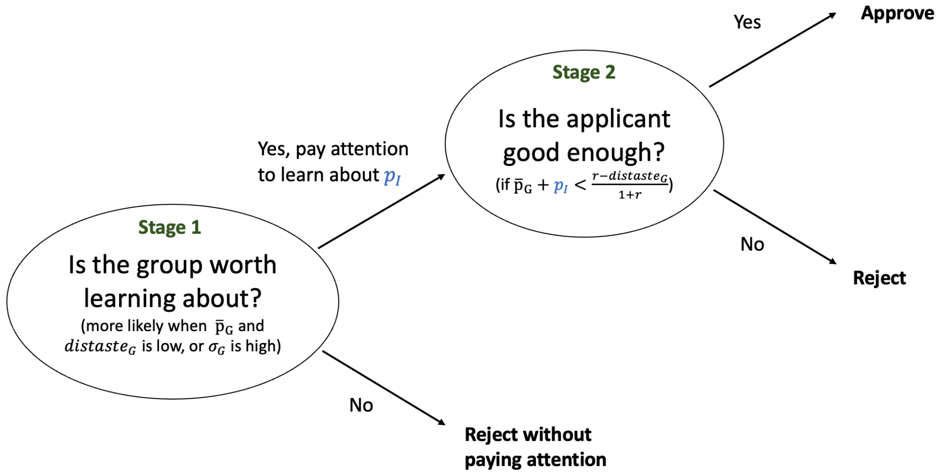
(c) Officer approval decision by applicant social status



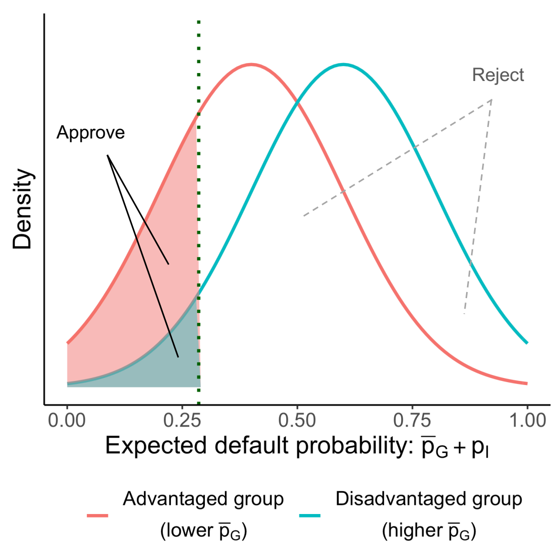
(d) Officer approval decision by applicant economics status

Figure 2. Illustration of The Model

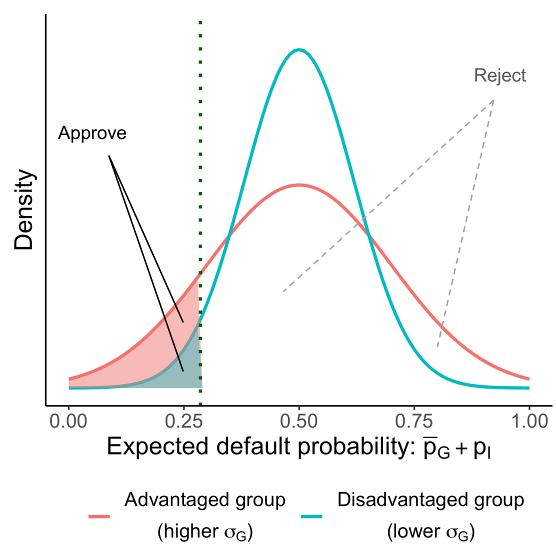
Panel (a): The optimal loan officer decision process. At stage 1, the officer decides whether to incur attention cost c to learn applicant-specific quality information p_I, given knowledge of the applicant's group. Conditional on doing so, at stage 2 the officer decides whether to approve or reject the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



(a) Optimal loan officer decisions



(b) Groups with differing means ($\bar{p}_G$)



(c) Groups with differing learnable variances (σ_G^2)

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 a quasi-random fashion. In stage three, loan officers read each application and decide whether to approve or reject.

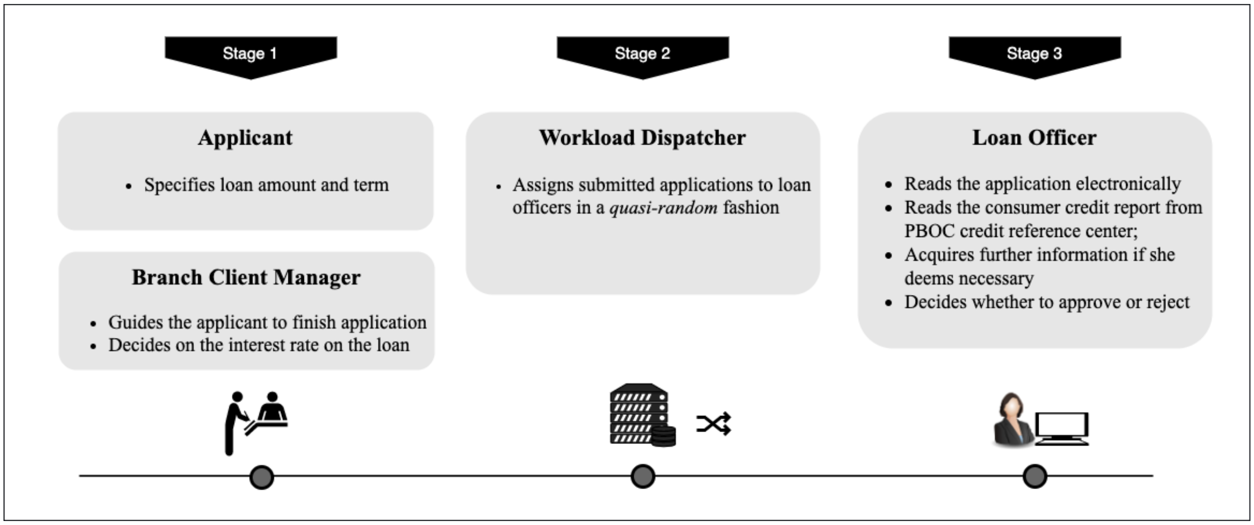
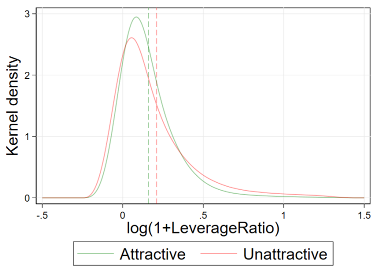


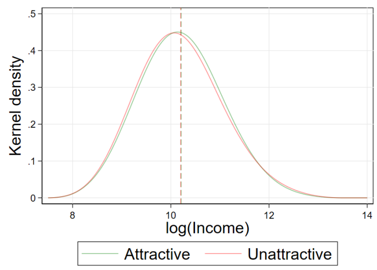
Figure 4. Distribution of Credit Quality: Attractive versus Unattractive Applicants

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

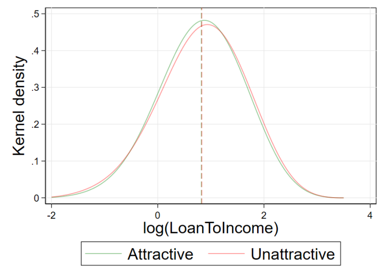
Panel A. Distribution of credit quality by applicant *social status*



(a) log(1+LeverageRatio)

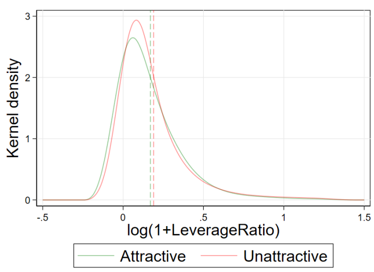


(b) log(Income)

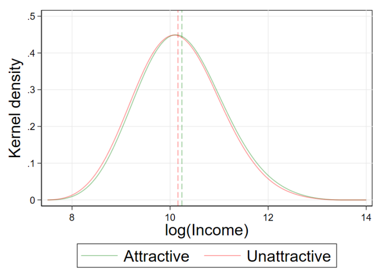


(c) log(LoanToIncome)

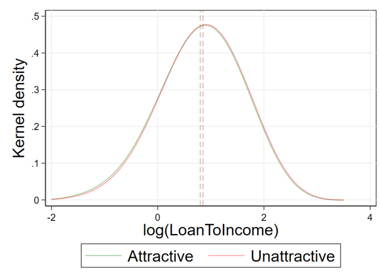
Panel B. Distribution of credit quality by applicant *economic status*



(d) log(1+LeverageRatio)



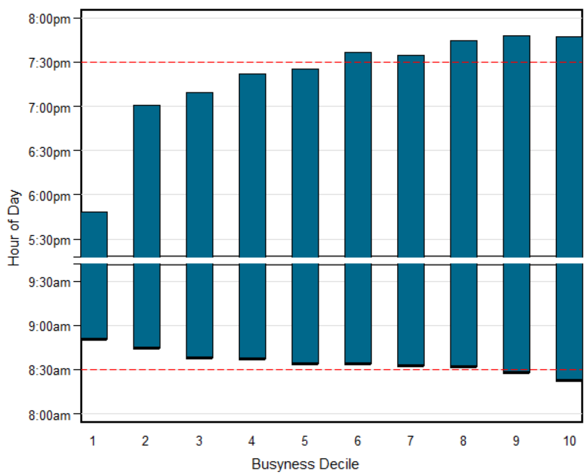
(e) log(Income)



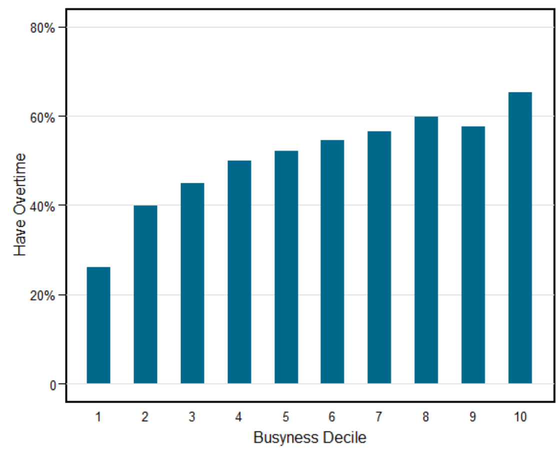
(f) log(LoanToIncome)

Figure 5. Officer Busyness and Work Schedule

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. Panel A reports the summary statistics of the full sample. Panel B compares the means of applicants in groups with attractive versus unattractive social/economics statuses . See Appendix Table B.1 for variable definitions.

Panel A. Summary statistics of 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 versus unattractive group

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 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

In this table, we estimate how loan office attention constraints affect the time they spend on reviewing each loan application by applicants from attractive versus 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 (7)). *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. 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)
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)
Attractive(Social)	0.276***	0.439***			0.321***	0.413***
	(9.640)	(13.854)			(10.162)	(12.801)
Attractive(Social) × BusynessDecile	0.019***	0.017***			0.019***	0.017***
	(4.457)	(3.949)			(4.306)	(3.922)
Attractive(Economic)			0.124***	0.249***	0.213***	0.188***
			(8.616)	(13.496)	(9.963)	(9.599)
Attractive(Economic)× 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

Table 4. Effects of Attention Constraints on Approval Decisions

In this table, we estimate how loan office attention constraints affect their approval decision on loan applications by attractive versus 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. The regressions include officer $\times$ 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)
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)
Attractive(Social)	0.253^{***}	0.408^{***}			0.326^{***}	0.375^{***}
	(16.803)	(26.896)			(21.170)	(23.928)
Attractive(Social) $\times$ BusynessDecile	0.008^{***}	0.007^{***}			0.006^{***}	0.006^{***}
	(3.171)	(3.326)			(3.093)	(3.289)
Attractive(Economic)			0.300^{***}	0.373^{***}	0.384^{***}	0.331^{***}
			(21.993)	(22.897)	(21.590)	(17.782)
Attractive(Economic)$\times$ 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

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

In this table, we estimate how instrumented loan office attention constraints affect the time they spend to review loan applications by attractive versus unattractive applicants. These results are the *instrumented versions* of 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 officer spend reviewing each application (Equation (7)). *Attractive(Social)* and *Attractive(Economic)* are dummy variables indicating whether *SocialStatus* and *EconomicStatus* are above the median, separately. *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) to (3), we use assignment-predicted busyness; for columns (4) to (6), we use leave-one-out (LOO) assignment-predicted busyness. 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)
BusynessDecile	-0.025^{***}	-0.024^{***}	-0.029^{***}	-0.019^{***}	-0.016^{***}	-0.022^{***}
	(−8.297)	(−9.248)	(−8.999)	(−6.393)	(−6.134)	(−6.397)
Attractive(Social)	0.461^{***}		0.434^{***}	0.470^{***}		0.445^{***}
	(23.833)		(21.608)	(23.819)		(21.431)
Attractive(Social) × BusynessDecile	0.013^{***}		0.015^{***}	0.013^{***}		0.013^{***}
	(4.722)		(5.152)	(4.668)		(4.334)
Attractive(Economic)		0.285^{***}	0.215^{***}		0.289^{***}	0.220^{***}
		(13.311)	(10.031)		(13.975)	(11.090)
Attractive(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

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

In this table, we estimate how instrumented loan office attention constraints affect their approval decisions on loan applications by attractive versus unattractive applicants. These results are the *instrumented versions* of 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 whether *SocialStatus* and *EconomicStatus* are above the median, separately. *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) to (3), we use assignment-predicted busyness; for columns (4) to (6), we use leave-one-out (LOO) assignment-predicted busyness. 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)
BusynessDecile	−0.004***	−0.003***	−0.006***	−0.004***	−0.003***	−0.006***
	(−4.380)	(−4.046)	(−8.048)	(−5.087)	(−4.382)	(−9.354)
Attractive(Social)	0.399***		0.367***	0.403***		0.370***
	(56.706)		(50.568)	(58.399)		(53.776)
Attractive(Social) × BusynessDecile	0.009***		0.008***	0.008***		0.008***
	(7.241)		(7.018)	(6.683)		(7.171)
Attractive(Economic)		0.383***	0.331***		0.384***	0.331***
		(36.447)	(31.948)		(36.992)	(35.311)
Attractive(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

APPENDIX

A Solving the Model

This section solves the model in Section 2 and proves the two predictions therein. Recall that the loan officer makes two sequence decisions: 1) whether to incur an attention cost of c to learn p_I, and 2) whether to approve or reject the application. We solve for the optimal decision backwards.

In the second step, when making the approval decision after acquiring information about p_I, the expected profit earned by lending to an applicant is:

$$\Pi(\bar{p}_G + p_I) \equiv E_\epsilon[(1-p)\cdot r - p] \tag{9}$$

$$\overset{E(\epsilon)=0}{=} [1-(\bar{p}_G + p_I)]\cdot r - (\bar{p} + p_I) \tag{10}$$

$$= r - (1+r)\cdot(\bar{p}_G + p_I) \tag{11}$$

where, as before, $p = \bar{p}_G + p_I + \epsilon$, and the expectation in Equation (9) is taken over ϵ. As the attention cost c is a sunk cost, the loan officer will approve this loan if and only if $\Pi(\bar{p}_G + p_I) - \text{distaste}_G > 0$.

Thus, in the first step of deciding whether to learn about p_I, the benefit of paying attention to any group G is:

$$E_{p_I}\left[\max(0, \Pi(\bar{p}_G + p_I) - \text{distaste}_G)\right] \tag{12}$$

where the expectation is taken over the distribution of $p_I \sim N(0, \sigma_G)$. Such a group is worth paying attention to if and only if the expected benefit indicated in Equation (12) exceeds the cost of attention c.

Prediction 1. Because $\Pi(\bar{p}_G + p_I)$ is decreasing with $\bar{p}_G$, clearly, lower $\bar{p}_G$ means a higher value in Equation (12). Similarly, lower distaste_G also means a higher value. Finally, because the max operator is convex, and because $\Pi(\bar{p}_G + p_I)$ is linear in p_I, a mean-preserving spread in p_I (larger σ_G) also increases the value. This proves the validity of the comparative statics on attention.

We now derive the results pertaining to approval probability. Groups that do not receive attention will be rejected 100% of the time. The probability of approval for groups to which officers will pay attention is given by:

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

$$= \Phi\left(\frac{\frac{r-\text{distaste}_G}{1+r} - \bar{p}_G}{\sigma_G}\right) \tag{14}$$

where $\Phi(\cdot)$ is the standard normal CDF, and the final expression is decreasing with $\bar{p}_G$ and distaste_G. Furthermore, the "cherry-picking" condition in Equation (3) implies that $\frac{r-\text{distaste}_G}{1+r} - \bar{p}_G < 0$, so the probability also increases with σ_G (and converges towards 1/2, as σ_G approaches infinity). Therefore, we conclude that loan applications submitted by unattractive groups are rejected more often than those submitted by attractive groups.

Prediction 2. Consider the case in which two groups, G_1 and G_2, both receive positive attention. Suppose that G_1 is more unattractive. Consider increasing c slightly. This could leave both groups unaffected, or perhaps G_1 is affected so its attention and the approval rate drops to zero while G_2 remains unaffected. Therefore, the attention and approval rate gaps between the two groups weakly widen.

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.

In 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 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 significant different from 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 all 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 certificate, 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, in 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 offers 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.[37]

[**Table** B3 about here.]

Estimating the effect 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 of 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 by 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.]

Table B5 further finds 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

[37]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.

in Table 3, we sort officer busyness into deciles and estimate a regression of officer due diligence indicator on social and economic status indicators, busyness deciles, as well as their interactions. When loan officers are busier, applicants from groups with lower social or economic statuses receive significantly less due diligence, but the effect is minor or non-existent on 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.]

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 B1 replicates the patterns shown in Figure 5 by using each of the two instrumented busyness measures instead of the 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) is 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.]

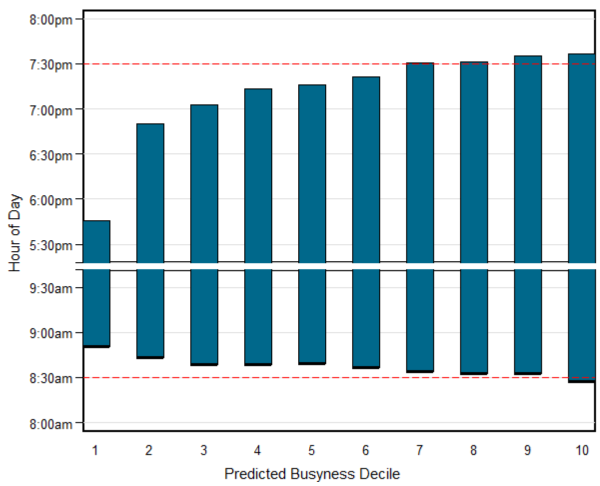
[**Table** B8 about here.]

[**Table** B9 about here.]

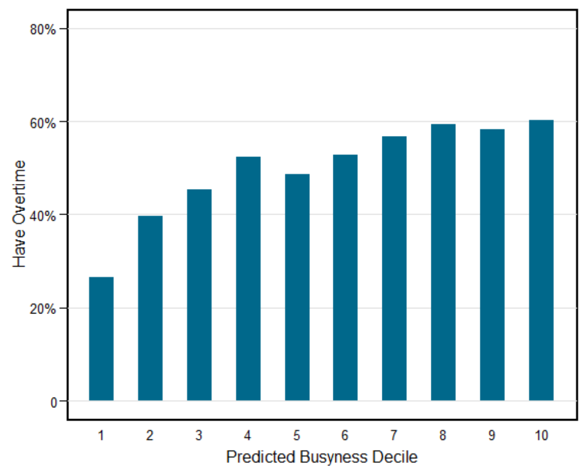
[**Table** B10 about here.]

Figure B1. Robustness: Loan Officer Busyness and Work Schedule

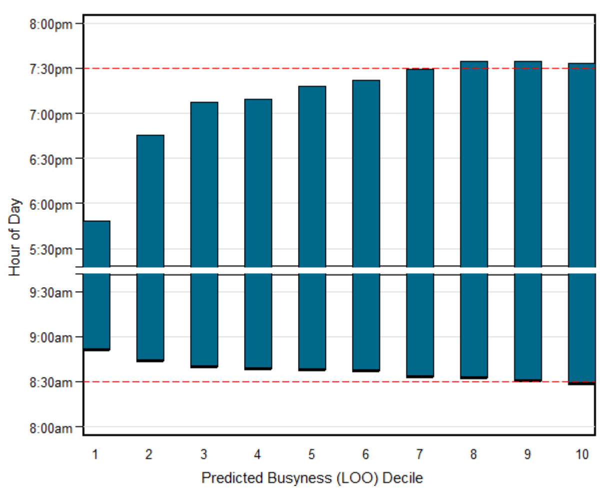
This figure replicates Figure 5, except that we sort loan officer busyness by each of the two instrumented measures. In Panels (a) and (b), we sort the sample into deciles using *predicted busyness*. For Panels (c) and (d), we sort by *LOO-predicted busyness*. The two instruments for officer busyness are described in Section 5.1. The left panels plot the average time at which officers start and end a work day. The right panels plot how frequently officers work overtime, defined as working before 8:30 a.m. or after 7:30 p.m. (the red dashed lines in the left panels).



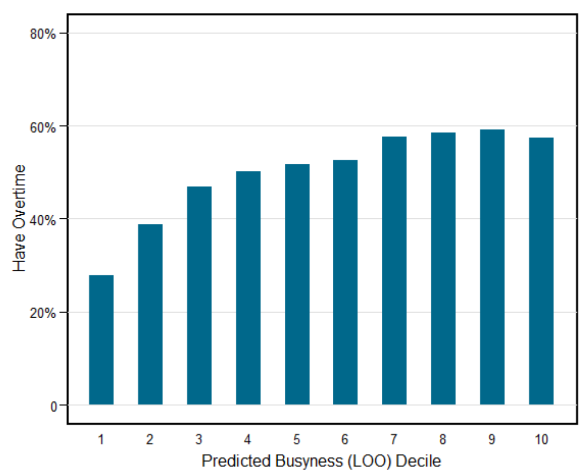
(a) Work Schedule by Predicted Busyness



(b) Overtime by Predicted Busyness



(c) Work Schedule by LOO-Predicted Busyness



(d) Overtime by LOO-Predicted Busyness

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 (7).
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 (8)
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 who 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 employmentand 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 applicants' total income.
ShortTerm	Equals one if the term of the loan for which the applicaiton 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

In 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 (5)), or *EconomicStatus* (Equation (6)) 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. In Panels A and B we regress each credit quality measure on the *attractive* indicator. The regressions control for officer $\times$ 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 Panel 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.

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	

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 third party	1828	7.4%	14.8
5	Employer said that 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

In this table, we estimate the relationship between loan officers' extra due diligence and applicants' socioeconomic statuses. 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 $\times$ 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)	(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

In 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 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)
Attractive(Social)	0.048^{**}	0.143^{***}			0.061^{**}	0.133^{***}
	(2.548)	(6.973)			(2.627)	(6.192)
Attractive(Social) × 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

In 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) to (3), we use assignment-predicted busyness; for columns (4) to (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)
Attractive(Social)	0.148^{***}		0.139^{***}	0.148^{***}		0.139^{***}
	(13.746)		(13.211)	(14.072)		(13.200)
Attractive(Social) × BusynessDecile	0.004^{***}		0.004^{***}	0.004^{***}		0.004^{**}
	(2.949)		(2.582)	(2.920)		(2.413)
Attractive(Social)		0.181^{***}	0.166^{***}		0.178^{***}	0.164^{***}
		(12.305)	(11.024)		(12.827)	(10.510)
Attractive(Economic) × 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 in 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+Lever ageRatio)
	(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+Over dueMonth)	log(1+Cred itInqury)	HasInvest mentAcc	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	EmploymentCert	IncomeCert	RegularPay	HomeOwner	log(1+LeverageRatio)
	(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:	NoCreditHistory	log(1+OverdueMonth)	log(1+CreditInqury)	HasInvestmentAcc	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(LoanToIncome)	ShortTerm	log(InterestRate)
	(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.[38] 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 replicates 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 they work late. That is, when officers are busier, they face longer working hours and work more overtime hours.

7. Table C3 is similar to our main analyses in Tables 3 and 4, except that we estimate the effect of each individual social or economic status label instead of the overall social

[38] That is, we modify regressions in Section 4.2 by 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 the interaction with each decile dummy. The conditional difference between the attractive and unattractive groups for each busyness decile is then plotted in the figure.

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.]

[**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.

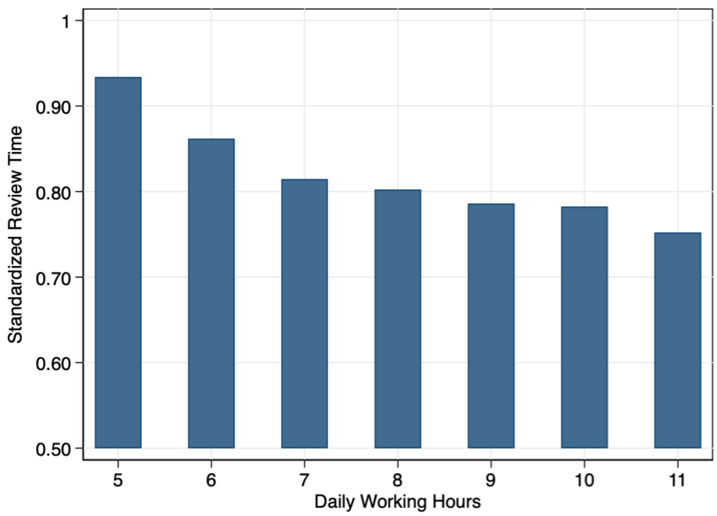
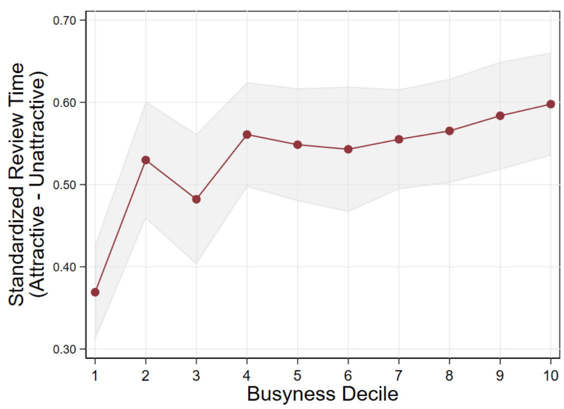
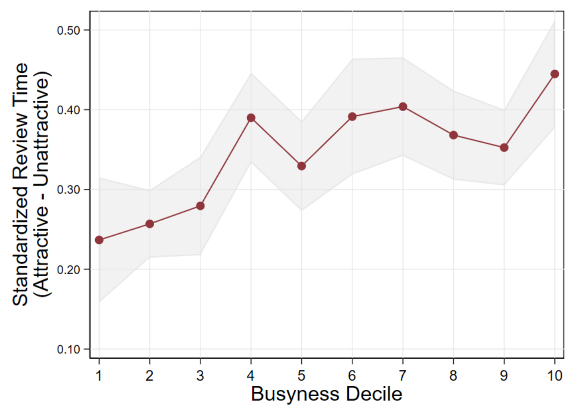


Figure C2. Difference-in-Difference Effect of Loan Officer Attention Constraints

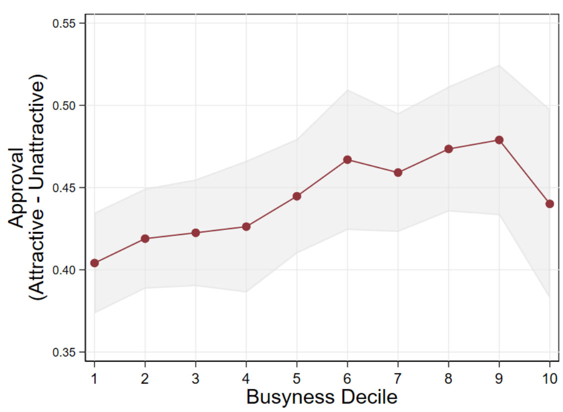
We estimate the differential effect of officer attention constraints, as measured by their busyness, on their attention allocation and approval decision over attractive and unattractive applicants. Specifically, we regress officer attention and approval decision on the interaction between an applicant-attractiveness 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. In Panels (a) and (c), applicant attractiveness is measured by their social status. In 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.



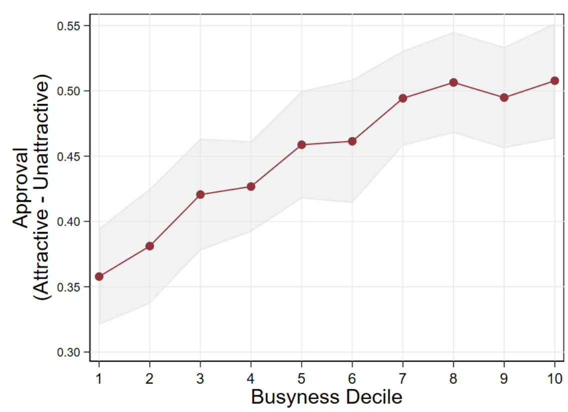
(a) Attention gap across social status



(b) Attention gap across economic status



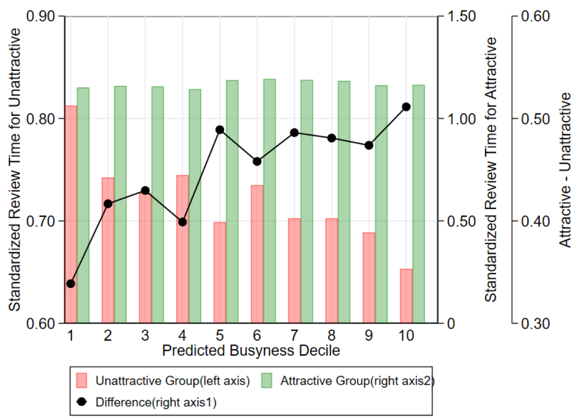
(c) Approval gap across social status



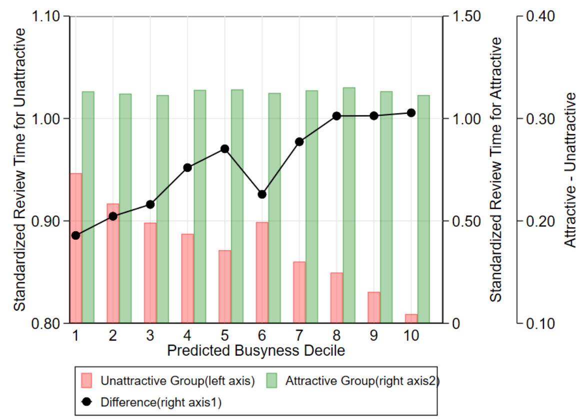
(d) Approval gap across economic status

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

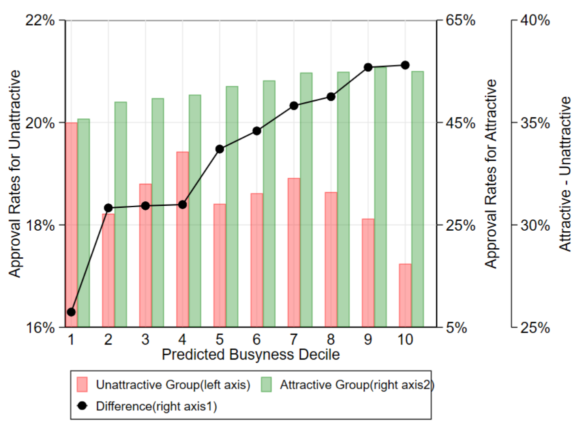
This figure is similar to Figure 1, except that we use loan officers' predicted busyness instrumented by the number of assignments as discussed in Section 5.1. As explained in Section 3.4, we use the possession (or not) of various labels to classify applicants into attractive versus unattractive groups 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 Sections 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.



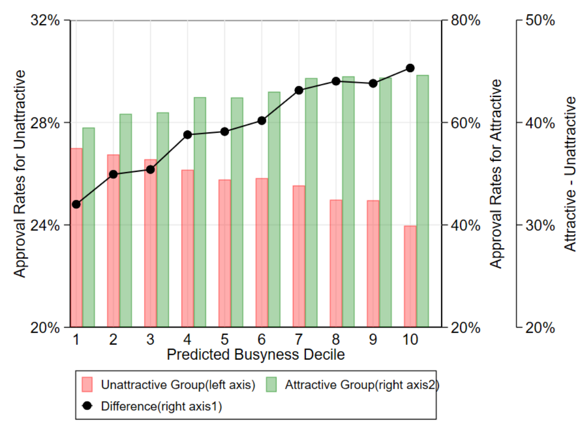
(a) Officer attention allocation by applicant social status



(b) Officer attention allocation by applicant economics status



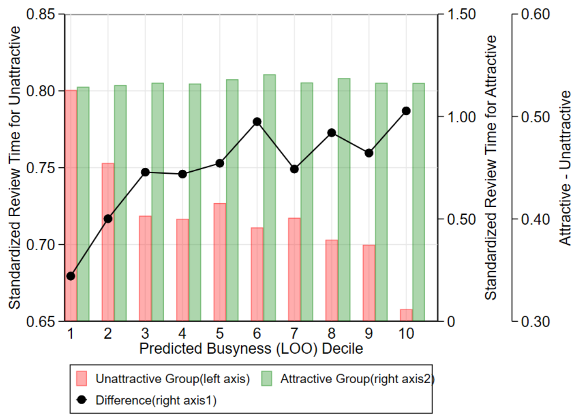
(c) Officer approval decision by applicant social status



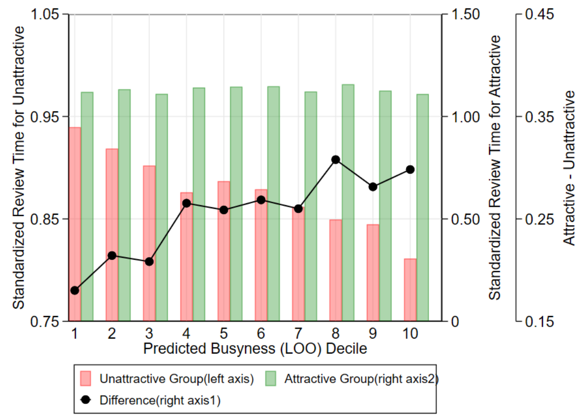
(d) Officer approval decision by applicant economics status

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

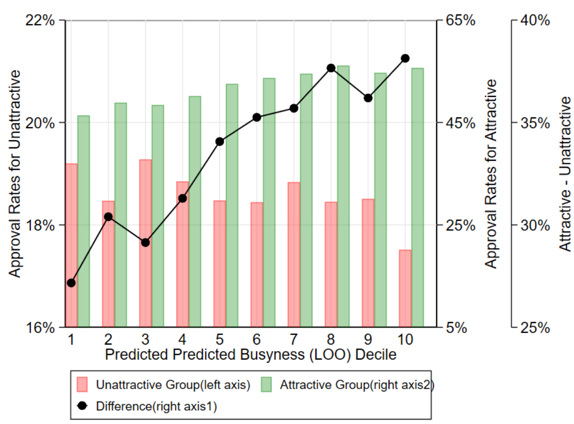
This figure is similar to Figure 1, except that we use loan officers' LOO predicted busyness instrumented by the number of assignments as discussed in Section 5.1. As explained in Section 3.4, we use the possession (or not) of various labels to classify applicants into attractive versus unattractive 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 Sections 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.



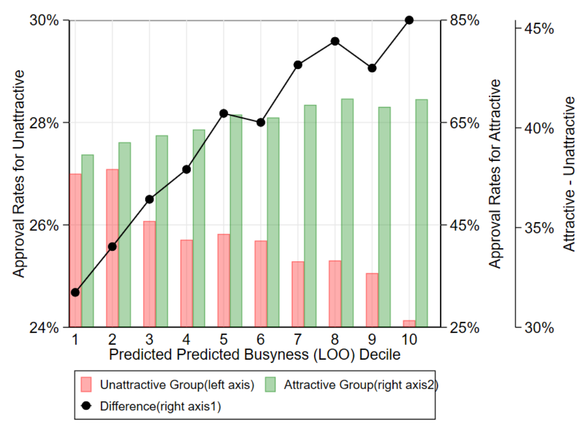
(a) Officer attention allocation by applicant social status



(b) Officer attention allocation by applicant economic status



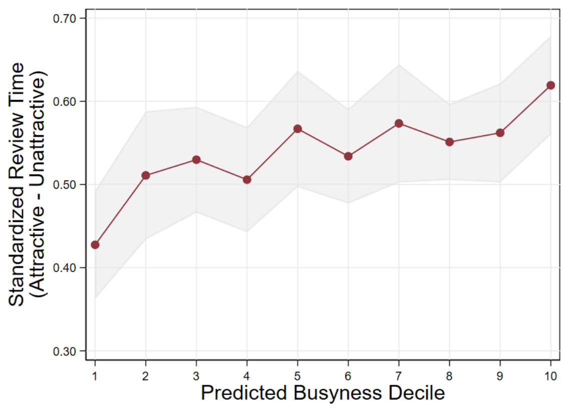
(c) Officer approval decision by applicant social status



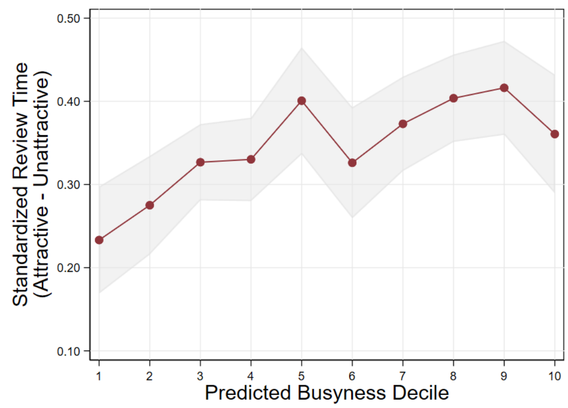
(d) Officer approval decision by applicant economic status

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

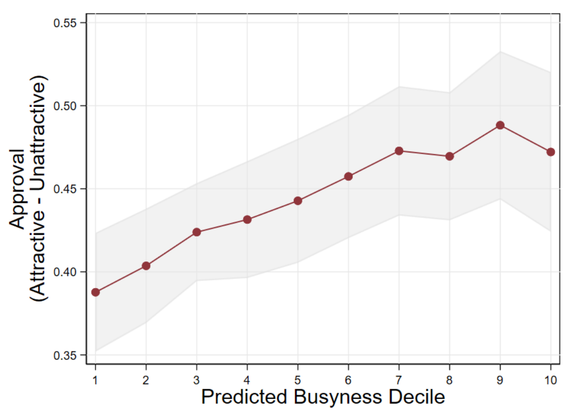
This Figure replicates Figure C2 except that we use the assignment-predicted busyness to measure loan officer attention constraints. The top panels plot the results for officer attention, measured as the standardized review time the loan officer spent on each application. The bottom panels plot the estimations for loan approval. In Panels (a) and (c), applicant attractiveness is measured by their social status. In 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.



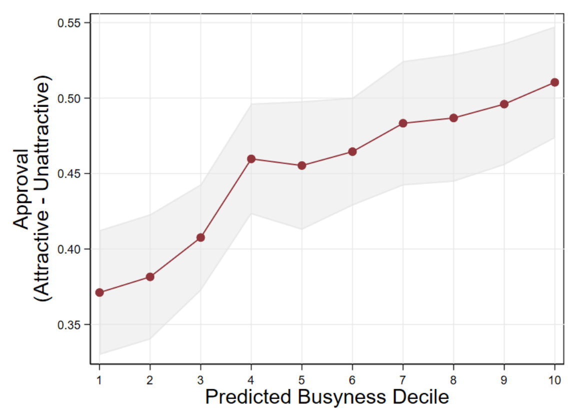
(a) Attention gap across social status



(b) Attention gap across economic status



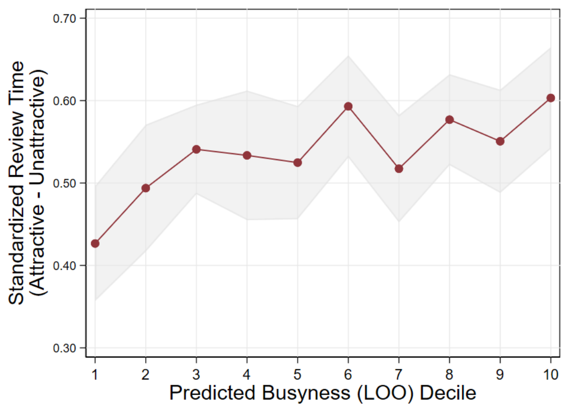
(c) Approval gap across social status



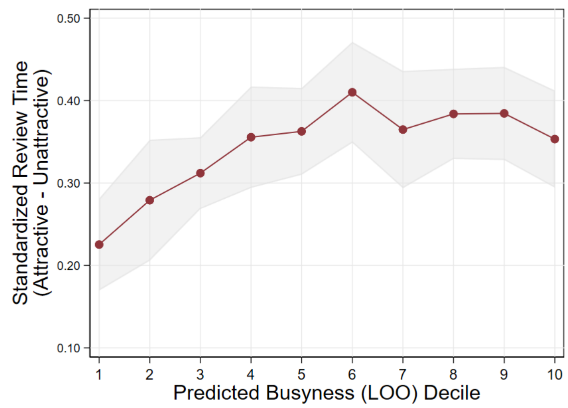
(d) Approval gap across economic status

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

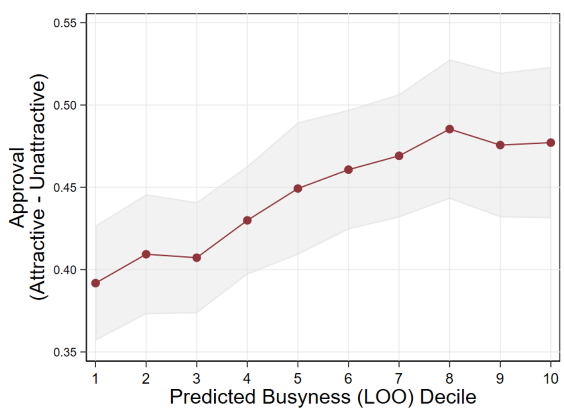
This Figure replicates Figure C2 except that we use the leave-one-out (LOO) assignment-predicted busyness to measure loan officer attention constraints. The top panels plot the results for officer attention, measured as the standardized review time the loan officer spent on each application. The bottom panels plot the estimations for loan approval. In Panels (a) and (c), applicant attractiveness is measured by their social status. In 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.



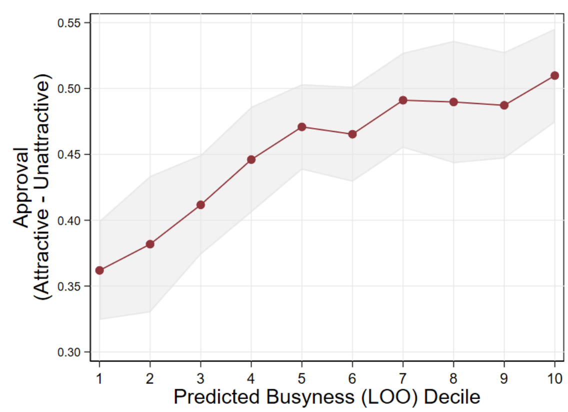
(a) Attention gap across social status



(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 × Branch × 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 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 labels and loan officer busyness. The outcome variable is review time (measuring attention allocation) in Panel A and approval in 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 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	
Local Busyness Controls	Y	Y	Y	Y	Y	
Officer-Month-Yr FE	Y	Y	Y	Y	Y	
Week FE	Y	Y	Y	Y	Y	
Branch FE	Y	Y	Y	Y	Y	
Loan type FE	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