Attention Constraints and Financial Inclusion

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Abstract

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

JEL classification: D83, D91, G21

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I. Introduction

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

How do attention constraints impact inclusion? We use a simple model to illustrate a mechanism that might explain this relationship. If loan officers had infinite time, they would review every application carefully and make informed decisions based on borrower credit quality. If loan officers are attention-constrained, however, they may choose to ration their attention based on easily observed signals, such as labels that indicate borrowers' SES status. Our model predicts that, in the *base case*, when loan officers face tighter attention constraints, they will allocate disproportionately less attention to low-SES borrowers, leading to "rash rejections," even when a significant portion of those borrowers are qualified and should otherwise be approved if adequate attention were paid to their applications. Moreover, in the *special case* where some borrowers enjoy extremely high SES

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

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

status, they may even experience the opposite fate and be "rashly accepted" without careful screening. As a result, tighter loan officer attention constraints will widen the inclusion gap between high- and low-SES applicants. We want to emphasize that such loan officer behavior can be fully rational and constrained optimal from the perspective of the lender. This behavior does, however, create distributional consequences for financial inclusion on low-SES borrowers, which is what we focus on in this paper.

We face two challenges in studying the impact of attention on inclusion empirically. First, it is difficult to measure attention allocation, as noted by Gabaix (2019): *"measuring attention is . . . a hard task—we still have only a limited number of papers that measure attention in field settings."* Second, we need variations in attention constraints that are orthogonal to candidate fundamentals. Using administrative data on the screening processes associated with approximately 146,000 retail loans in one of the largest national banks in China, our paper overcomes both difficulties. First, as we observe accurate timestamps in the decision-making process, we can track the amount of time that loan officers spend reviewing each application—a direct measure of attention allocation.

To overcome the second challenge, we utilize a unique institutional feature of our sample: the bank allocates applications across loan officers using an algorithm that induces variations in loan officer workloads. Such variations are orthogonal to borrower creditworthiness and loan-officer behaviors, enabling us to identify the consequences of attention constraints. To measure loan officer attention constraints, we begin by exploiting variations in loan officer *busyness*, which is defined as the number of applications processed by an officer on a given day. We then introduce two instrumental variables to capture variations in loan officer busyness that are orthogonal to loan officer behaviors and borrower credit quality.

When loan officers are busy, they consider certain salient socioeconomic labels as simple

signals to guide their attention allocation to each borrower. In each application form, the front page reports a number of indicators related to an applicant's SES, 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, applicants are sorted into high- and low-SES groups.

Our attention-driven mechanism suggests that, when loan officers are time-constrained, they allocate disproportionately less time to reviewing loan applications from low-SES applicants, which results in disproportionately lower financial inclusion for those borrowers. Our empirical findings support this main hypothesis. We first plot these patterns in Figure 1 as an exploratory illustration. Panels (a) and (b) show that, when officers are busier, their disproportionate reduction in attention results in an wider attention gap between the high- and low-SES groups. Panels (c) and (d) further show a sharper decline in approval rates for low-SES applicants, suggesting that some are rejected rashly by busy loan officers. This is consistent with the *base case* predictions associated with this attention-driven mechanism. Also, the approval rate for high-SES applicants seems even to increase slightly when loan officers are busier, which would be consistent with the *special case* where some extremely high-SES applications are "rashly approved."

[**Figure** 1 about here.]

We then formally test this attention-driven mechanism using difference-in-differences regression analyses, in which we control for officer-month-year, week, bank branch, and loan-type fixed effects as well as a comprehensive list of applicant characteristics. The results are similar to those plotted in Figure 1. When loan officer busyness varies from the bottom to the top decile, the review time they spend on low SES applicants declines by 53% (52%), which is larger than the 38%

(37%) decline observed for high SES applicants. More importantly, the approval rate for the low SES group drops by 45% (39%) relative to the average levels, while approval rates for the high-SES groups were not significantly affected and in some cases even increased slightly.

Two empirical concerns might arise in using *realized* loan officer busyness to measure attention constraints. First, loan officers may have leeway to work faster or more slowly, so realized busyness may reflect an endogenous choice rather than an external constraint. To address this concern, we instrument the busyness measure by the number of applications *assigned* to officers. Because applications are assigned by a central dispatcher algorithm over which officers have no influence, the process generates externally imposed variations in loan officers' attention constraints. Furthermore, conditioning on week, branch, loan type, and loan officer-month-year fixed effects in all our specifications, 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 officer busyness may be correlated with unobserved borrower quality. We should note that our results can be biased only if loan officer busyness and work assignments are *negatively correlated* with the credit quality of low-SES borrowers but *uncorrelated or even positively correlated* with the credit quality of high-SES borrowers, which is very unlikely in practice. Nevertheless, to alleviate this concern, we first verify that the assignment-instrumented busyness measure is orthogonal to a comprehensive list of creditworthiness metrics. We then further address this concern by constructing another leave-one-out (LOO) Bartik-type instrument. The idea is as follows: if a loan officer's attention constraint is tightened following an idiosyncratic spike in application volume from Province A, her decision-making on applications from Province B can also be affected, even if there is no change in either the quantity or quality of applications from Province B. In this sense, by utilizing variations

4

in officer busyness that are driven by assignments from *other* provinces and directly controlling for busyness driven by assignments from the *local* province, we capture variations in a loan officer's attention constraints that are orthogonal to a particular application she is screening. We find that, when using the abovementioned instrumental variables, our main results are qualitatively and quantitatively robust.

This paper's main contribution to the literature lies in showing that decision-maker attention constraints can have consequences for financial inclusion. This attention-driven mechanism suggests that, as long as attention-constrained decision-makers have small differential priors across SES groups, whether driven by prejudice or statistics, their prior-based disproportionate attention allocation can widen the inclusion gap between applicants with differing SES labels.

Regarding policy implications, our attention-based mechanism suggests that policies and technologies that relax decision-maker attention constraints may promote financial inclusion for borrowers from low-SES backgrounds. For instance, recent developments in financial technologies ("Fintech"), which use automated underwriting algorithms (and thus are subject to low or no attention constraints) to assist in screening borrowers, may improve financial access. Meanwhile, this use of technology could also change the way that soft and hard information are used in the screening process.[3] [4] By the same logic, the introduction of credit scores such as FICO scores,

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[3] See Liberti and Petersen (2019) for a review of the literature.

[4] This rationale is aligned with the arguments of Philippon (2019), Dobbie, Liberman, Paravisini, and Pathania (2021), Bartlett, Morse, Stanton, and Wallace (2022), Fuster, Plosser, Schnabl, and Vickery (2019), etc. Of course, there are also concerns that the application of big-data fintech may generate new distributional issues (e.g., Fuster, Goldsmith-Pinkham, Ramadorai, and Walther (2022)). Therefore, the net distributional effect of fintech might not be clear-cut (Morse and Pence, 2021).

which were not available in China during our sample period, may also help improve credit access for low-SES applicants. In addition, to the extent that loan officer specialization in screening applicants from specific backgrounds can make information processing more efficient, this may also improve outcomes for low-SES applicants. Finally, taking attention constraints more seriously also generates additional insights into optimal workload allocation. For instance, in our setting, while each loan officer may be acting optimally given their attention constraints, the bank is likely behaving suboptimally in distributing workloads unevenly across officers (See Appendix B).

There are two empirical limitations that we cannot fully address, but we believe that they do not invalidate our conclusions. First, we do not observe ex-post default outcomes for our sample borrowers and thus cannot determine how loan officers' attention-driven behavior affects bankloan losses. As previously noted, though, it is entirely possible that loan officers' behavior is constrained optimal; we focus instead on the *distributional* consequences of their behavior. Second, while we are assured by loan officers that the application-assignment algorithm is idiosyncratic (see Section D for details), the bank does not disclose the exact algorithm. Nevertheless, we verify that the assignment-instrumented busyness measures are orthogonal to a comprehensive list of creditworthiness measures. More importantly, when loan officers are busier, their approval rates for high- and low-SES applicants often move in non-parallel or even *opposite* directions, which is a unique prediction of this attention-based mechanism.

A. Related Literature

Previous researchers have investigated how attention constraints impact financial decisions. For example, Hirshleifer, Levi, Lourie, and Teoh (2019) show that financial analysts who suffer

6

from fatigue resort to heuristic decisions when making forecasts. Huang, Huang, and Lin (2019) show that attention-constrained investors pay less attention to firm-specific news. Müller (2022) shows that bankruptcy-court congestion leads to lower recovery values in defaults and also impacts pre-default credit spreads.[5] 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 (2017) under time pressure. In the broader literature on endogenous attention allocation,[6] our paper is related most closely to the seminal work on selective attention allocation by Bartoš, Bauer, Chytilová, and Matějka (2016). Our key innovation lies in testing the impact of decision-maker attention constraints and providing more direct field-based evidence pertaining to the distributional consequences of attention constraints.

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; Huo, Sun, Tai, and Xuan, 2023), consumer credit (Montoya, Parrado, Solís, and Undurraga, 2020; Dobbie et al., 2021), bank lending (Fisman, Paravisini, and Vig, 2017; Fisman, Sarkar, Skrastins, and Vig, 2020), auto loans (Charles, Hurst, and Stephens, 2008; Butler, Mayer, and Weston, 2023; Lanning, 2021), small business lending (Ongena and

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[5]Other papers that have applied the framework of endogenous attention allocation to financial settings include 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 et al. (2019), Liu, Peng, and Tang (2022), Shu, Tian, and Zhan (2022), and Hirshleifer and Sheng (2022).

[6]Gabaix (2019) and Mackowiak, Matejka, and Wiederholt (2022) provide extensive reviews.

Popov, 2016; Brock and De Haas, 2021), microlending (Beck, Behr, and Madestam, 2018), entrepreneurial finance (Hebert, 2020; Ewens and Townsend, 2020; Hu and Ma, Forthcoming; Zhang, 2020), and even housing returns (Goldsmith-Pinkham and Shue, 2023; Kermani and Wong, 2021). Our findings provide empirical evidence of attention-based credit allocation that could conceivably function as one of the mechanisms underlying some of the findings reported in the aforementioned studies.[7]

The remainder of the paper is organized as follows. In Section II we present a simple model to illustrate our attention-based mechanism and derive testable predictions. In Section III we describe the data and relevant institutional details. In Section IV we present our main empirical results. In Section V we conclude the study.

II. Conceptual Framework

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

Model set-up.   Consider a risk-neutral loan officer faced with the task of deciding whether to approve an application to borrow one unit of capital for one period of time. Applicants come from a continuum of groups denoted by G, and the associated group identities are observable at zero cost. The officer makes two decisions: 1) whether to incur an attention cost of c to learn more about the

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[7]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, Forthcoming; D'Acunto, Ghosh, Jain, and Rossi, 2021).

applicant and 2) whether to approve or reject the application. Empirically, we think of the attention cost as the time and energy consumed in reading credit reports, scrutinizing the applicant's application forms, and so forth.

The interest rate $r > 0$ is fixed exogenously.[8] If the loan officer approves the application, the expected profit (before considering attention cost) is

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

where $\text{distaste}_G \geq 0$ captures group-specific *preference-based* attributes and p is the default rate. For the sake of simplicity, equation (1) assumes a zero recovery rate upon default. We also assume risk neutrality and no time discounting. To ensure that lending can happen in equilibrium, we assume that $r > \text{distaste}_G$, so an applicant for whom the default probability is zero is worth lending to.

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

$$(2) \qquad\qquad p = \bar{p}_G + p_I,$$

where $\bar{p}_G$ is a group-specific average observable at no cost, and $p_I \sim N(0, \sigma^2)$ is an

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

9

applicant-specific component that can be learned by paying the attention cost c.[9] As such,

differences in distaste$_G$ capture taste-based discrimination and differences in $\bar{p}_G$ capture statistical

discrimination.

Optimal loan officer behavior. We explain the solution intuitively and refer the reader to

Appendix A for formal proofs. As illustrated in Panel A of Figure 2, loan officers can adopt any of

three strategies. The optimal strategy falls into three regions and depends on the ex-ante SES status

of the group:

1. Applicants from *extremely high-SES groups* (low $\bar{p}_G$ or distaste$_G$) are *immediately approved*

   without information acquisition. While paying attention to them can enable the loan officer to

   screen out the occasional bad borrower, the probability that this occurs is sufficiently low that

   the cost of attention outweighs the benefit.

   - In our empirical setting, this should apply to only a very small subset of borrowers. The

     average approval rate over the full sample is only 34%, indicating that most applicants

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[9]Technically, using normal distributions for p_I can lead to default rates above 1 or below 0. The results are

qualitatively unchanged if we use modified zero-mean distributions with bounded support such as truncated normal

distributions.

are not considered worthy borrowers. A simple back-of-the-envelope analysis suggests that the occurrence of such extremely high-SES groups should be rare.[10]

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

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

The two cutoffs between these three regions are graphically illustrated in Panel (b) of Figure 2. We plot the loan officer's expected utility when employing each of the three strategies as a function of the group-specific average default rate $\bar{p}_G$.[11] Finding the optimal strategy in each region amounts to simply choosing the strategy with the highest expected utility.

[**Figure** 2 about here.]

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[10]How good does an applicant group have to be for it to be worth approving without information acquisition? The average interest rate in our data is approximately 8.6%. If the bank's cost of capital is equal to China's central bank rate of 3.25% in our sample period, this would mean the bank can earn a cost-adjusted annual return of only 5.35% if the applicant does not default. In contrast, if the application defaults and we assume a 40% recovery rate as the loan is uncollateralized, the bank stands to lose 60%. Therefore, as long as the average application default rate is higher than $\frac{5.35\%}{5.35\%+60\%} \approx 8\%$, the default loan officer's action without information acquisition is rejection.

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

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

Therefore, increases in attention costs lead to *asymmetric* consequences for applicants from different groups. When loan officers are busier, applicants from low-SES groups will be rejected more often; applicants from extremely high-SES groups may even be accepted more often.[12] This discussion is formalized into the testable predictions presented below.

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

1. (Average effect) G_1 will receive weakly less attention and be approved less often.

2. (Comparative statics) If loan officer attention cost c increases, then:

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

(a) In the *base case* where the more favorable group (G_2) is in the intermediate region, both groups will receive weakly less attention, and the *gaps* between their attention and approval rates will weakly widen.

(b) In the *special case* where the favorable group (G_2) is in the extremely high-SES region, then its approval rate will in fact increase.

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

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

III. Data and Institutional Background

In this section, we describe the data and provide background information on the retail loan-screening process. We also compare the basic statistics between high- versus low-SES applicants. The main empirical results based on loan officer attention variation are reported in Section IV.

A. Data Source

We obtain internal retail-lending screening records from one of the largest national banks in China. The sample data cover approximately 146,000 loan applications screened by 92 loan officers working at the bank's headquarters office from April 2013 through April 2014. Borrowers include both wage/salary workers and self-employed individuals running small/micro-scale businesses. The loan terms and targeted borrowers are comparable to those associated with retail financing products in the United States. Loan maturity is one to three years; the median (mean) loan amount is 60,000 (66,461) Chinese RMB, which is equivalent to $9,787 ($10,841) U.S. dollars and comparable to the average personal installment loan of around $16,000 in the U.S.[13] 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.[14] Summary statistics are presented in Table I and variable definitions are listed in Appendix Table B1.

[**Table** 1 about here.]

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

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[13]Source:

https://www.experian.com/blogs/ask-experian/research/personal-loan-study/.

[14]Source:

https://www.federalreserve.gov/releases/g19/hist/cc_hist_tc_levels.html.

used metrics for creditworthiness, 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.

B.   The Loan-Screening Process

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

[**Figure** 3 about here.]

Stage 1. Application submission.   Loan applications are sourced from local bank branches all over the country. Each applicant submits an application for a specific maturity and loan amount. The local bank branch manager ensures that the application materials are complete, determines the appropriate interest rate and terms for each application, but approval decisions need to be made by loan officers at bank headquarters in stage three.

Stage 2. Assignment of applications to headquarters loan officers.   After an application is completed in stage one, it is stored electronically in the bank's systems and then distributed to the headquarters loan officers by a central workload-dispatcher algorithm over which loan officers have

no control. As for how exactly the algorithm assigns applications, see Section D for an in-depth discussion.

Stage 3. 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.[15] Our sample comprises 92 officers. Of a total of 145,982 applications, only 34.2% are approved, so the process is relatively selective. Our data include precise timestamps when applications are assigned to officers and when officers make decisions, enabling us to measure officers' attention allocation to each application by calculating the length of time they spend reviewing the application.

Key premise: loan officers are attention constrained.   A key premise of this attention-based mechanism is that decision-makers face attention constraints. In our sample, loan officers have to read lengthy documents within short periods of time. First, each application package includes an application form that spans 10 to 20 pages long, which includes the borrower's demographic information, personal wealth and income, the purpose of borrowing, etc. It 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 can run into hundreds of pages. In addition, A credit report issued by the central credit bureau, which is about 10 pages long, is also attached. Meanwhile, we find that loan officers only spend a meager median (mean) of 18 (31) minutes per application.[16] Needless to say, this is not

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[15]This is the only decision she needs to make. Loan terms are already determined at stage 1.

[16]We discuss in detail how we measure the review time in the next section.

enough time to go over all application materials carefully.[17] Overall, our evidence suggests that loan officers are indeed facing attention constraints.

C.   Applicant Socioeconomic Status (SES)

Loan officers use socioeconomic labels to guide attention allocation.   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. In private conversations, loan officers explain that they rely on a few easily observable socioeconomic labels as signals for guiding time allocation. Some of these labels are related to applicants' social statuses while others are related to applicants' economic statuses, and we call them "socioeconomic labels" collectively in subsequent discussions. These are zero-or-one indicator labels that can be easily observed on application forms that are verified by the branch officers in stage one.

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

1. *PublicEmployee*: whether the applicant works for the public sector. Chinese society treats public employees, including those working in the government, public schools or hospitals,

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[17]In private conversations, loan officers also told us that they are under time pressure and feel rather rushed in the loan screening process. Besides, the per-application review time in our sample is shorter than in similar loan review processes in the U.S. To mention a crude comparison, when examining a U.S. commercial bank, Agarwal and Ben-David (2018) find that 133 loan officers screened 30,268 loan applications over two years (see their Table 1). In our data, 92 loan officers screened 145,982 applications over two years. This implies that the average review time in the U.S. is $\frac{133 \times 2/30,268}{92 \times 1/145,982} \approx 13.9$ times longer than that in our data. In addition, Wei and Zhao (2022) show that the median processing time is 8–29 days in the U.S. mortgage market. However, this number includes processing time across all steps, from the submission of an application to the final origination of a loan, not just the review time spent by loan officers, and thus is not directly comparable to our review time measure.

state-owned firms, or any other government-sponsored institutions, as meriting higher social status.[18] Insofar as an applicant needs to fill in her position on the first page of the application form, this is a salient and easily observable signal for loan officers.

2. *LocalResident*: whether the applicant is a local city resident rather than a migrant worker. Local residents are typically thought to be of higher status than migrant workers (i.e., people who grow up in rural areas and migrate to work in a city) as the former generally have access to better public services such as education and healthcare because of local policy restrictions.[19] The Chinese "Hukou" (household registration) system makes it easy to distinguish local residents from migrant workers, making this another salient signal that loan officers use.

There are also four labels that reflect an applicant's *economic status*:

1. *EmploymentCert*: whether the applicant has an official certificate that verifies her position of employment. Such a certificate is considered acceptable to the bank only when 1) the employer's official stamp and a top manager's signature are on the certificate, and 2) the employer's identity can be recognized and verified by the bank. This depends on whether the applicant works for a large employer. In contrast, employees of microscale businesses and self-employed entrepreneurs cannot. Thus, loan officers generally consider the availability of an employment certificate as a signal of superior economic status.

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[18]Public employees are colloquially described as "the insiders of the system" in China, and public positions are considered as high social status in Chinese society. For example, in 2019, 1.4 million applicants competed for around 24,000 government positions, suggesting that on average about one out of 60 candidates can land a job "inside the system".

[19]In fact, discrimination against migrant workers has been a long concern in China.

2. *IncomeCert*: whether the applicant's employer can provide an employer-issued income certificate. In practice, this depends on whether the applicant is in a long-term position with high job security. Short-term contractors or paid interns cannot provide this certificate.

3. *RegularPay*: whether the income of the applicant is stable in terms of both timing and amount. This depends on the type of employment. For instance, salespeople usually have commission-based income which can be volatile and would not have this label.[20]

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

While the social labels might (but do not have to) potentially relate to some taste-based prejudice by loan officers and the general society, it is not surprising that the economic labels are correlated with applicants' fundamental credit risk and thus can lead to cross-sectional differences in borrower financial access. However, when these socioeconomic signals are used by loan officers to determine attention allocation, our attention-driven mechanism suggests that the associated inclusion gap could be further widened, no matter which kind of motivation drives the differential perception among applicants. This difference-in-difference implication cannot be simply driven by fundamental credit risk differentials and is unique under this attention-based mechanism.

Applicants cannot change these labels. It is important to note that, under our institutional setting, the availability of those salient SES labels is determined by borrowers' *ability* to provide

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

the corresponding documentation, rather than their *willingness*. At the time of loan application, the SES labels are exogenous to the applicant's discretion, as they are determined by the applicant's ex-ante occupation type, migration status, etc. For instance, if a borrower is self-employed or works in a micro/small business, she typically cannot provide an employment certificate that can be considered "valid" by the bank. Instead, a certificate officially issued by a large public company or government entity is considered valid and indicates higher socioeconomic status. Also, applicants who work in the public sector (PublicEmployee = 1) are treated better by loan offices. While it is possible that people are well aware of this, it is too difficult to switch jobs to the public sector just for the sake of obtaining a loan.

Defining applicants from high and low SES backgrounds. Our attention-based mechanism, which is formally analyzed in Section II, suggests that applicants with fewer socioeconomic status labels may be considered having lower SES 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 higher socioeconomic backgrounds. We test this prediction formally in Section IV.

Given that loan officers are considering multiple social- and economic-status labels, we use a data-driven approach to summarize the combined effects of the aforementioned status indicators into two variables, "Social Status" and "Economic Status," to classify how applicants' socioeconomic status are perceived by loan officers. Specifically, we fit a linear probability model by regressing the approval probability on those SES labels in Table II, and we compute the regression-predicted value of application approval for the two social-status labels and four

20

economic-status labels, separately:[21]

$$\text{SocialStatus}_i \equiv \widehat{\text{Approval}}_i | \{\text{PublicEmployee}_i, \text{LocalResident}_i\}$$

$$(3) \qquad = \hat{b}_{\text{PublicEmployee}} \cdot \text{PublicEmployee}_i + \hat{b}_{\text{LocalResident}} \cdot \text{LocalResident}_i$$

$$\text{EconomicStatus}_i \equiv \widehat{\text{Approval}}_i | \{\text{EmploymentCert}_i, \text{RegularPay}_i, \text{IncomeCert}_i, \text{HomeOwner}_i\}$$

$$= \hat{b}_{\text{EmploymentCert}} \cdot \text{EmploymentCert}_i + \hat{b}_{\text{RegularPay}} \cdot \text{RegularPay}_i +$$

$$(4) \qquad \hat{b}_{\text{IncomeCert}} \cdot \text{IncomeCert}_i + \hat{b}_{\text{HomeOwner}} \cdot \text{HomeOwner}_i$$

[**Table** 2 about here.]

In other words, these two variables are single-dimensional summaries of the multiple social and economic labels in a given application. For simplicity, in subsequent analyses, we create two indicator variables, High-SES(Social)$_i$ and High-SES(Economic)$_i$, which equal one for applicants whose SocialStatus$_i$ and EconomicStatus$_i$ values, respectively, are above the sample median.[22] The correlation between the two High SES indicators is -0.133, suggesting they capture different information about the borrowers' profiles.

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

[22]In our baseline analyses, we fit the above-mentioned linear probability models using the full sample. In the Internet Appendix Section A, we show that our empirical results remain robust when using out-of-sample fitting.

Credit quality distribution largely overlaps between the two borrower groups. As we can see from the definitions of the SES labels, borrowers from the low-SES group likely have lower credit quality and thus lower credit access on average. However, a pure cross-sectional difference in credit quality cannot explain the main implication of our paper, which is a difference-in-difference effect suggesting that the gap in attention allocation and financial inclusion between high- and low-SES borrower groups widen as loan officers' attention constraints get tighter. Also, even the average difference in approval rates across the high- versus low-SES borrower groups (18% versus 51% by social status and 25% versus 66% by economic status, as shown in Panel B of Table I) seems too large to be fully justified by differences in credit risk. Comparing the credit quality distributions of the two borrower groups, we find substantial overlap between the high- and low-SES borrowers as shown in Figure IA2. In fact, we see a large share of rejected borrowers in the low-SES group actually have higher credit quality than the median high-SES borrowers who are approved. We discuss more details about the borrowers' credit quality distributions in the appendix Section B.

IV.   The Impacts of Loan Officer Attention Constraints

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

A. Measuring Loan Officer Attention-Constraints and Attention Allocation

Measuring variations in attention constraints. To proxy for loan officer attention constraints, we compute an officer-day level variable 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 I, the median officer processes 19 applications on a given day, and the 10th and 90th percentiles are 10 and 27 applications, respectively. Therefore, there are substantial variations in officer busyness and the concomitant time constraint on each application. In other words, while loan officers are always busy (time spent on each application is always low), they sometimes become even busier.[23]

[**Figure** 4 about here.]

We argue that loan officer busyness is relevant to attention constraints. First, as shown in Figure 4, when officers are busier, they work longer hours and the probability that officers work overtime rises from approximately 20% on the least busy days to over 60% on the busiest days.[24] Second, when officers are busier, they spend less time reviewing each application. This is reflected in both Panels (a) and (b) of Figure 1, as well as in the subsequent analyses presented in this and the

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

[24]Appendix Figure IB1 and Table IB2 also indicate that the longer an officer works on a given day, the less time she spends reviewing each individual application.

next section. Overall, these findings are consistent with our view that officers are more severely attention constrained when they are busy.

Instrumented Variations in Attention Constraints   Using *realized* loan officer busyness raises an endogeneity concern: loan officers can set their own pace at work, which may lead to omitted variable problems. For instance, a loan officer who wants to relax on a particular day may choose to quickly reject most applications perfunctorily, leading to a spurious negative correlation between busyness and the officer's loan-approval rate. To be clear, such situations *per se* cannot lead to our difference-in-differences result, which shows the *differential* impact of attention constraints on loan officer decisions for applicants from high- and low-SES groups. To obtain these differential results, one needs to explain why a careless officer would rashly reject the low-SES borrowers but not the high-SES ones. That said, we take this endogeneity concern seriously.

To resolve this endogeneity concern, we need to find a source of busyness variation that is external: i.e. *not controlled* by loan officers. As described in Section B, loan applications are assigned to officers by a central dispatcher algorithm over which officers have no control. Apart from assurances from the bank we study, we also confirm that the assignment algorithm is external to loan officers by verifying that the number of assignments has no relationship with current or previous loan officer backlogs (Appendix Table IA8).[25]

Using the number of assignments as an instrument, we capture the external variation in

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

officer busyness through a first-stage regression at the officer–day level,

$$\text{(5)} \qquad \text{Busyness}_{j,d} = a + \sum_{\tau=0}^{3} b_\tau \cdot \text{Assignment}_{j,d-\tau} + \epsilon_{j,d},$$

where $\text{Assignment}_{j,d}$ is the number of applications assigned to loan officer j on working day d. We include three lagged working days because some applications are processed a few days after assignments are allotted. In Panel A of Table III, we present details associated with this first-stage regression using a number of different specifications, such as with/without lagged assignment terms, and with/without fixed effects. The main specification we use in our later instrumental variable analyses is in column (4).[26] The instrument is strong and can explain more than 40% of the variation in realized officer busyness. As will be shown later, the F statistic for this first-stage regression is well above the Staiger-Stock rule-of-thumb threshold of ten or the Stock-Yogo threshold of 16.38, confirming the strength of this instrument. Hereafter, we call the value predicted in regression (5) "predicted busyness."

We then consider a second instrument which can be thought of as a further refinement of the previous one. Even though we find no correlation between assignments and loan characteristics (explained in Section D), one might still worry about correlations between assignments and unobservable loan quality. We argue that this concern is unlikely to explain our findings, for three reasons. First, we obtain the entire set of administrative records for these loan applications and control for a comprehensive list of group fixed effects and loan characteristics, and control for all the characteristics that are commonly considered in the screening practice. Second, to explain our difference-in-differences results, the confounding driver of assignments has to be negatively

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[26]Our results are robust if we use those alternative specifications for the first-stage estimation.

correlated with the credit quality of low-SES borrowers but uncorrelated, or even positively correlated, with the credit quality of high-SES borrowers. Third, in all our specifications, we control for week, branch, and loan-officer-year-month fixed effects, which enable us to control for all aggregate time-series variations in loan application volume or loan officer habits or preferences. Therefore, we are effectively capturing the idiosyncratic variations which are very unlikely to have any systematic correlation with the credit quality gap between borrower groups.

Although this concern is not very realistic, we address it by constructing a loan-level, leave-one-out (LOO) instrument that is based on variations on loan officer workload from non-local markets which are not affected by local market conditions. The intuition is, since the loan officers we study work at the headquarters office, while applications are sourced from bank branches all over the country, if many assignments from province A make a given loan officer busy, this could affect her decision-making regarding applications from province B even when neither the quantity nor the quality of applications from province B changes. Specifically, when examining a loan officer's decision-making process on a loan application from a province, we construct a "Bartik-type measure as the weighted average assignments to the same loan officer from all other provinces. By using this measure as our instrument *and directly control for the number of assignments from the source province*, we tease out the effect of loan officer attention constraints that is driven by *external* workload variations that are orthogonal to the local market conditions. As shown in Panel B of Table III, this LOO instrument is also very strong and it explains a similar share of variations in loan officer busyness as the first instrument.

[**Table** 3 about here.]

Measuring attention allocation. With internal timestamps for each action, we can directly measure loan officer attention allocation by estimating how much time is spent reviewing each application.[27] To remove variations in application review times that are unlikely to reflect active loan officer choices,[28] 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

(6)
$$\text{StandardizedReviewTime} = \log\left(\frac{\text{ReviewTime}}{\text{Median ReviewTime by group}}\right) + \underbrace{\text{Median log(ReviewTime)}}_{\text{full sample}}$$

where the groups in the denominator of the first term are Officer × Month-Year × Loan-Type × Bank-Branch buckets. In other words, we remove review-time variations that are explained by interactions of 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 IB1. The second term in equation (6) simply adds back the overall sample median of log review time. As reported in Table I, the interquartile range of this attention measure (standardized review time) runs from 0.488 to 1.476.

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[27]We measure the time spent reviewing each as the number of minutes that elapses between two consecutive decisions rendered by the same loan officer. We 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.

[28]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.

B.   The Impact on Attention Allocation

Having defined measures of loan officer attention constraints and attention allocation in the previous section, we now examine the impact of tighter attention constraints on attention allocation and approval rates.

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

[**Table** 4 about here.]

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

28

similar tests for column (2), measuring SES based on the applicant's economic status. Consistent with the visual patterns displayed in Figure 1, when officers are busier, the attention they pay to applicants decreases, but the decrease is disproportionately larger for low-SES applicants. For instance, the results reported in column (1) indicate that, when officer busyness varies from the lowest to the highest decile, the attention paid to low-SES applicants declines by $(10-1) \times -0.059 \approx 53\%$. While it is unavoidable that officers will spend less time on each application when they are busier, the attention gap between high- and low-SES applicants increases by $(10-1) \times 0.017 \approx 15.3\%$, and these effects are statistically significant at the 1% level. In column (3), we show that the effects remain statistically and economically similar when both social and economic status are considered simultaneously.

We then re-examine these results using the two above-mentioned instruments to capture variations in loan officer busyness. In columns (4) through (9) of Table IV, we use *Predicted Busyness* and *LOO-Predicted Busyness* to estimate how idiosyncratic variations in loan officer attention constraints affect their allocation of review time. The instrumented busyness measures are estimated in an earlier stage, and the F statistics are reported at the end of the corresponding columns. As shown in the table, the F statistics are very high, confirming our earlier argument that the two instruments are strong. For these 2SLS regressions, we estimate standard errors using the bootstrap method. Under these instrumented analyses, the effects are qualitatively and quantitatively similar to those estimated in OLS analyses.

Using an auxiliary attention measure to provide complementary evidence. In Appendix C, we use another loan officer action—conducting further due diligence when screening

29

applicants—to proxy officer attention allocation.[29] This indirect measure yields the same conclusion, as officers are less likely to conduct due diligence for low-SES applicants when they are attention constrained. In particular, by comparing the reasons loan officers cite when rejecting applications, we find that, when a loan officer rejects a high-SES 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 a low-SES applicant based on boilerplate reasons such as "leverage is too high." More importantly, such differences in rejection reasons become more prominent when loan officers are busier. In sum, this suggestive result complements our main finding, suggesting that low-SES applicants receive less attention allocation when loan officers face tighter attention constraints.

C.   The Impact on Lending Decisions

In Table V, we use similar specifications to estimate the impact of officer busyness on approval decisions. The results reported in column (1) indicate that, for applicants with low social status, increasing from the lowest to the highest busyness decile reduces approval probability by $(10 - 1) \times -0.009 \approx 8.1$ percentage points. This reduction is about 45% of the average approval rate for this group of applicants. Similarly, the results reported in column (2) show a decline in the

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[29]At the bank we study, a loan officer must select from a list of reasons when she renders a rejection. While some reasons for rejection indicate that the officer makes rejection decisions based on information already in hand (e.g., high leverage or a bad credit history), some others indicate that the loan officer, before rejecting the application, engaged in additional due diligence to gain information beyond what was readily available in the application package. For example, the loan officer can indicate that she called one of the applicant's references but was given inconsistent information during the call.

approval rate by $(10 - 1) \times -0.011 \approx 9.9$ percentage points, which is about 39% of the group average. In contrast, the approval probability is roughly unchanged or even slightly increased for the high-SES groups. The results remain broadly similar when both SES measures are considered jointly for column (3).

We then use the instrumented busyness measures to estimate the effects of loan officer attention constraints on approval decisions. The results reported in columns (4) through (9) of Table V are robust when using both Predicted Busyness and LOO-Predicted Busyness. Overall, these results are consistent with our main prediction that, when loan officers face tighter attention constraints, low-SES applicants receive disproportionately less attention and are rejected more frequently. In some specifications, we even find evidence that high-SES groups experience higher approval rates, suggesting that the special-case model predictions may have some bite.

In Appendix Table IB4, we further show that our main results hold up when we examine each of the six social or economic status labels separately.[30]

To further confirm that we are indeed utilizing the idiosyncratic variations in loan officer workload as instruments for their attention constraints, we also conduct an additional robustness check for all our instrumental variable analyses. Specifically, we use an alternative "residual" measure of the instrument by first regressing the assignment or LOO assignment on week and branch fixed effects, which fully control for time-series or locational fundamentals, and then we take the residual component for each of those two variables and use it as the instrument in our

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[30]Using these two instrumented measures of busyness, we reproduce Figure 1 in Figures IB3 and IB4, and reproduce Figure IB2 in Figures IB5 and IB6. We find qualitatively similar results in all cases.

analyses. As shown in Appendix Tables IA10 and IA11, our results are robust to using "residual" variation in instruments.[31]

[**Table** 5 about here.]

It is worth noting that, in our regressions, we control for officer × month-year, week, bank branch, and loan-type fixed effects. Therefore, our findings do not stem from any differences regarding officer-specific preferences, branch-specific risk-management styles, or aggregate time trends. We also control for a comprehensive list of features that could be related to borrower creditworthiness; in unreported robustness checks, we also find that our results are not sensitive to the choice of controls. Appendix Figure IB2 further shows that, conditional on all loan characteristics and fixed effects, the gaps between the high- and low-SES applicant groups in terms of both attention allocation and approval rate widen almost monotonically when loan officers get busier.

In addition, we also show that our results are similar under additional robustness checks. Specifically, we use propensity score matching to focus on comparable borrowers in the low- versus high-SES groups, and find the results to be largely unchanged (Appendix Tables IA5 and IA6).

D.   Loan officer work patterns and the assignment algorithm

By using assignments as the instrumental variable and controlling for week, branch, loan-type, and officer × month-year fixed effects, we end up identifying off *idiosyncratic* variations

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[31]We also show in the appendix Table III that, after controlling for week and loan officer fixed effects, the within-group R-squared is still as high as about 20%, suggesting that our instrument is strong even when focusing on idiosyncratic variations.

in loan officer busyness. What drives the remaining variation? Here, we provide more background information about the assignment algorithm.

Although the bank we study does not disclose the exact implementation details of the algorithm, we can catch a glimpse from informal discussions with bank employees. According to the employees, the algorithm groups loan applications based on a variety of factors such as the branch where the application is submitted, the loan type, size categories, etc. Every day, a loan officer is randomly matched to one or several groups of applications.[32] The officer-group matching changes randomly over time, and as a consequence, the law of large numbers ensures that different loan officers' workloads are on average similar over a longer horizon, but they experience idiosyncratic variations in their workloads on a day-by-day basis as a result of the randomness of the assignments. While the bank does not disclose the basis of the officer-to-group matching, bank employees affirm that loan officers have no influence over the matching criteria and that the matching does not take into account the quality of applications. Therefore, this assignment algorithm generates idiosyncratic variations in officer attention constraints that are orthogonal to loan officer preferences and loan quality.

To test the claims of bank employees, we conducted tests to confirm that assignments are indeed uncorrelated with credit quality. We examined the relationship between assignments and a comprehensive list of observable loan characteristics and reported the results in Appendix Table IA9. Consistent with our discussion with bank employees, the results provide no indication of a relationship between assignment volume and loan characteristics.

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

Assignment volume is a valid instrument for loan officer busyness because loan officers have an incentive to finish their backlogs. Although loan officers face no "hard constraints" in completing all assigned workloads within the same day, they do face "soft constraints" such that if the backlogs are not processed within 2-3 days, their supervisors may "have a conversation with them".[33] Consistent with this, we find that when loan officers are assigned heavier workloads, they work longer hours (Figure IA3 and Table IB2) and spend less time reviewing each application (Figure IB1).

Lastly, we note that the headquarters loan officers we study have incentives that are generally aligned with the bank. They are paid fixed salaries plus bonuses, and their bonuses are determined by metrics that take into account both the volume of applications they process and the realized default rate relative to the bank's target rate. We are not aware of any significant agency problems that might distort loan officer incentives.[34]

V. Conclusion

Insufficient financial inclusion of individuals from low SES backgrounds is a concern on both equity and efficiency grounds. Motivated by Bartoš et al. (2016), we propose that financial inclusion can be hindered by attention constraints on financial decision-makers. In the selection process, attention-constrained decision-makers may ration their attention allocation using ex-ante

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[33] Also, severe delay in the loan processing may lead the applicants to complain, given that the expected processing time (including all other steps that we are not looking at) for a loan application is about two weeks.

[34] Also, unlike loan officers from the branch offices who usually also play "sales" roles (e.g., Giacoletti et al., 2021), our sample loan officers do not face any quota pressure. Meanwhile, they also do not face any "upper limits" regarding how many loans to process in a day.

socioeconomic labels. As a result, low-SES applicants may be given insufficient attention and be rejected more often. For applicants from very high-SES backgrounds, the reverse often applies: they may be quickly approved without careful review. As a result, this attention-based mechanism can lead to an inclusion gap between high- and low-SES borrowers.

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

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

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

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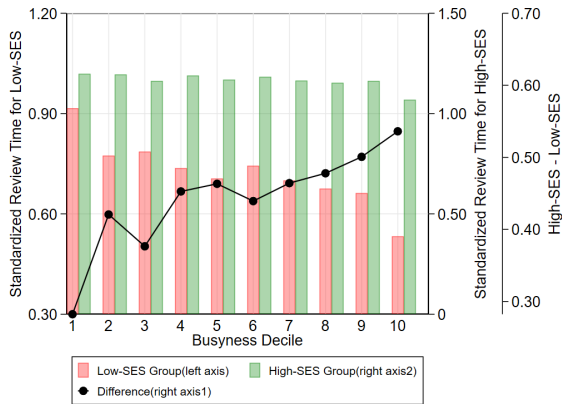
(a) Officer attention allocation by applicant social status
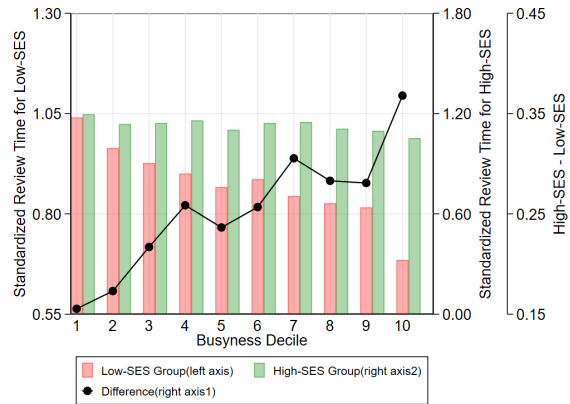
(b) Officer attention allocation by applicant economic status
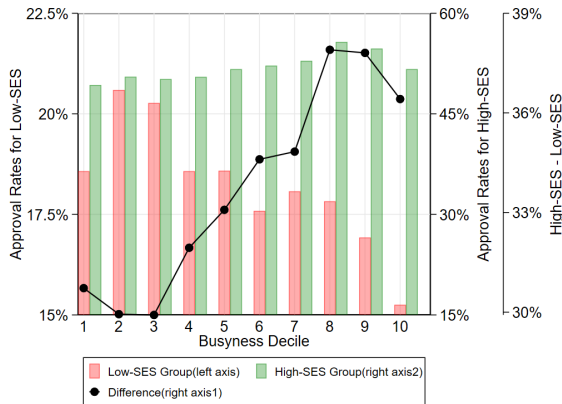
(c) Officer approval decisions by applicant social status
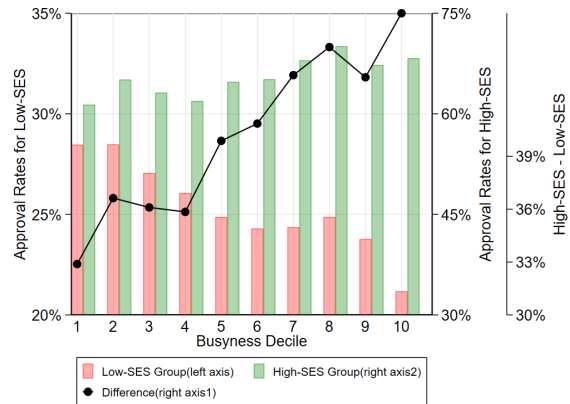
(d) Officer approval decision by applicant economic status

Figure 2. Illustration of The Model

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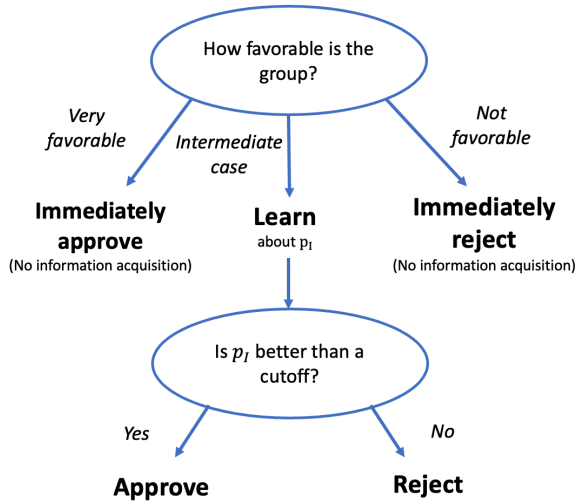
(a) Optimal loan officer decisions
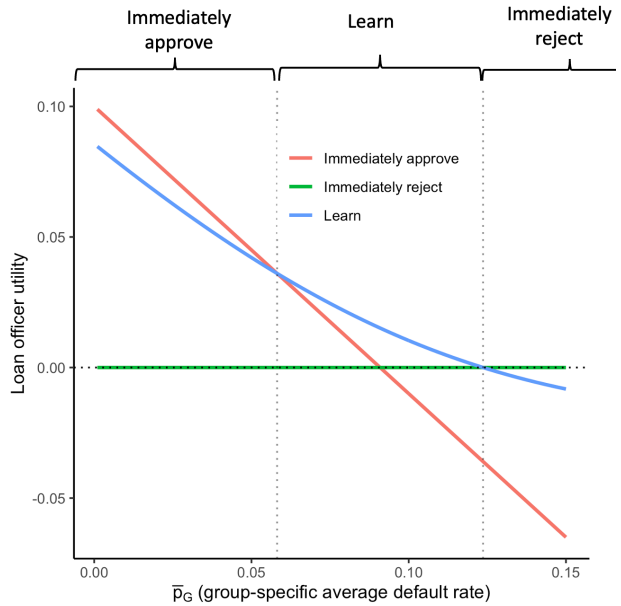
(b) Solving for the optimal strategy across groups

Figure 3. **Flow Chart of Loan Origination and Screening**

In stage one, loan applications are submitted at regional bank branches across the country. Loan amounts, maturities, and interest rates are already determined at this stage. In stage two, a central dispatcher algorithm assigns applications to headquarters loan officers. In stage three, loan officers read each application and decide whether to approve or reject it.
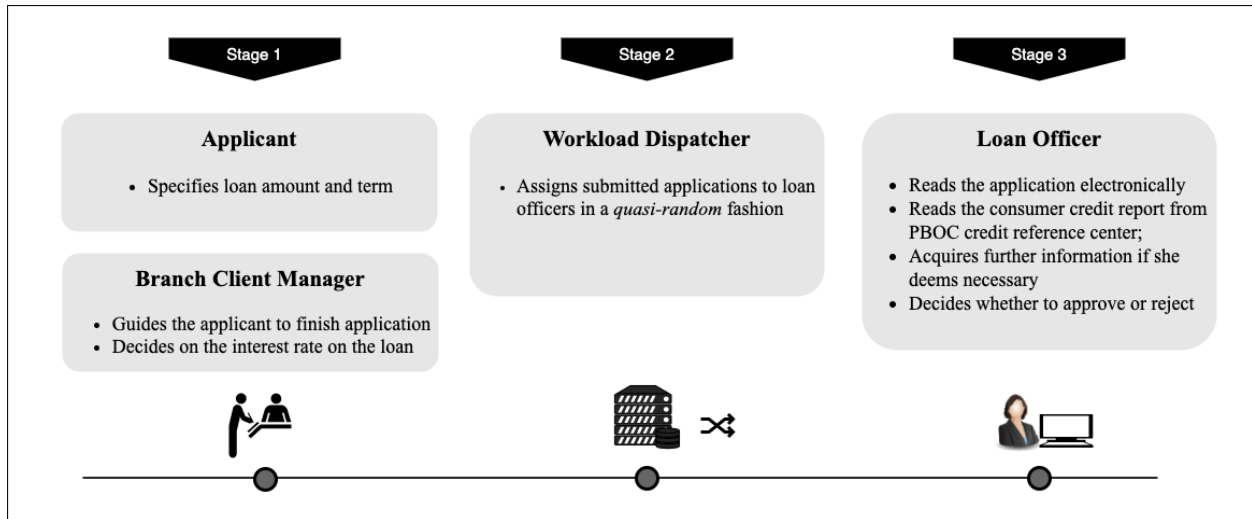
Figure 4. Officer Busyness and Work Schedules

We sort the sample into deciles differentiated by officer busyness, which is defined as the number of applications an officer processes on a given day. Panel (a) plots the average time of a workday 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)).
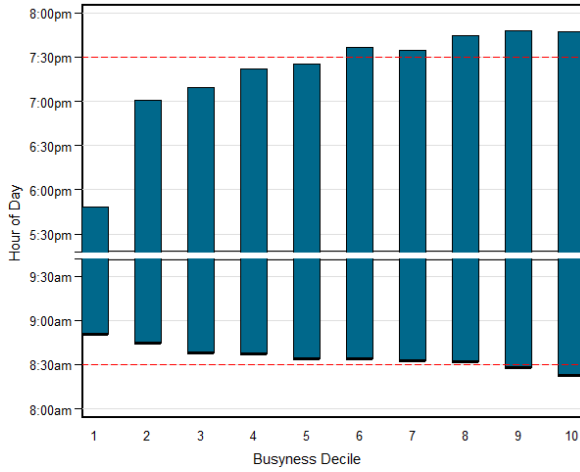
(a) Officer work schedule
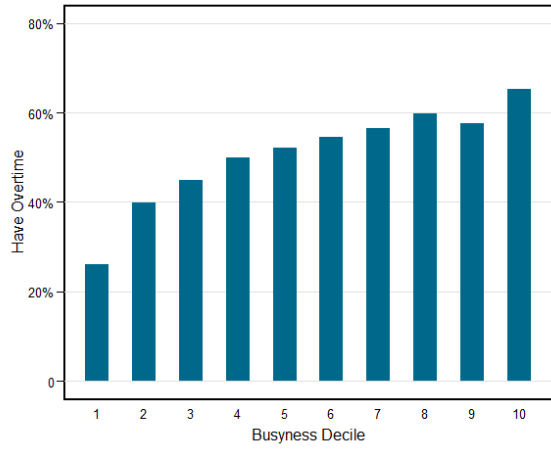
(b) Officer overtime

Table I. Summary Statistics

This table presents summary statistics. In Panel A we report the summary statistics for the full sample. In Panel B we compare the means of applicants in groups with high versus low social/economic status. See Appendix Table B1 for variable definitions.

Panel A. Summary statistics for the full sample

	N	Mean	SD	10%	25%	50%	75%	90%
Officer screening activities								
Approval	145,982	0.342	0.474	0	0	0	1	1
ReviewTime (*min*)	145,977	30.674	40.615	2.433	6.712	18.354	36.536	72.392
StandardizedReviewTime	145,977	0.933	1.082	−0.552	0.488	1.068	1.476	2.113
Busyness	145,982	19.150	6.979	10	15	19	24	27
Predicted Busyness	145,982	17.323	5.241	10.408	13.866	17.531	20.756	23.873
LOO-Predicted Busyness	145,982	16.406	4.951	9.843	13.041	16.534	19.786	22.636
Assignment	145,982	17.621	9.410	5	11	18	24	30
Borrower characteristics								
PublicEmployee	145,982	0.081	0.273	0	0	0	0	0
LocalResident	145,982	0.455	0.498	0	0	0	1	1
EmploymentCert	145,982	0.620	0.486	0	0	1	1	1
IncomeCert	145,982	0.342	0.474	0	0	0	1	1
RegularPay	145,982	0.117	0.321	0	0	0	1	1
HomeOwner	145,982	0.223	0.417	0	0	0	0	1
NoCreditHistory	145,982	0.173	0.379	0	0	0	0	1
LeverageRatio	145,982	0.268	0.850	0	0.017	0.103	0.276	0.543
OverdueMonth	145,982	1.073	1.829	0	0	0	1	3
CreditInqury	145,982	3.274	5.907	0	0	1	4	9
HasInvestmentAcc	145,982	0.007	0.081	0	0	0	0	0
SocialSecurity	145,982	0.406	0.491	0	0	0	1	1
Litigation	145,982	0.002	0.043	0	0	0	0	0
Peasant	145,982	0.114	0.317	0	0	0	0	1
NonCollege	145,982	0.296	0.457	0	0	0	1	1
Female	145,982	0.240	0.427	0	0	0	0	1
Age	145,982	35.767	8.258	25.458	28.951	34.723	42.145	47.866
Income (*RMB*)	145,982	57,131	112,254	8,000	12,000	22,000	50,000	150,000
Loan characteristics								
LoanSize (*RMB*)	145,982	66,461	28,057	40,000	50,000	60,000	80,000	100,000
LoanToIncome	145,982	3.285	2.733	0.600	1.286	2.609	4.444	6.667
ShortTerm	145,982	0.279	0.449	0	0	0	1	1
InterestRate (%)	145,982	8.558	0.208	8.400	8.400	8.610	8.610	8.610

Panel B. Comparison between the high- versus low-SES groups

SES measure:	SocialStatus		EconomicsStatus	
	High-SES	Low-SES	High-SES	Low-SES
Approval	0.519	0.181	0.655	0.254
StandardizedReviewTime	1.169	0.719	1.131	0.877

Table II. **Higher Approval Probability for Applicants with More 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 C, *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 B1 for variable definitions. Standard errors are double-clustered at the week and officer levels. ***$p < 1\%$, **$p < 5\%$, *$p < 10\%$.

	Approval					
	(1)	(2)	(3)	(4)	(5)	(6)
PublicEmployee	0.246***					0.027***
	(17.062)					(3.985)
ResidentCert		0.467***				0.029
		(28.719)				(1.041)
StandardPay			0.419***			0.188***
			(22.675)			(10.223)
EmploymentCert				0.527***		0.459***
				(30.703)		(17.641)
IncomeCert					0.395***	0.020
					(23.722)	(1.123)
Application 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	0.140	0.265	0.170	0.354	0.222	0.361

Table III. 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 at officer-day level, 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 A. 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	7	8	9
$Assignment_{j,d}$	0.519***	0.418***	0.392***	0.367***	0.332***	0.239***	0.358***	0.329***	0.243***
	(11.070)	(11.813)	(12.118)	(11.163)	(10.267)	(8.564)	(10.659)	(10.334)	(8.151)
$Assignment_{j,d-1}$		0.216***	0.174***	0.163***	0.143***	0.088***	0.162***	0.144***	0.095***
		(5.929)	(5.284)	(5.441)	(4.622)	(3.489)	(6.102)	(5.132)	(3.730)
$Assignment_{j,d-2}$			0.125***	0.080***	0.064**	0.015	0.082***	0.067***	0.022
			(5.796)	(3.827)	(2.792)	(0.769)	(4.499)	(3.319)	(1.157)
$Assignment_{j,d-3}$				0.140***	0.119***	0.054***	0.142***	0.122***	0.061***
				(10.255)	(8.287)	(5.197)	(12.005)	(9.126)	(5.766)
Officer FE	N	N	N	N	Y	N	N	Y	N
Officer-Month-Yr FE	N	N	N	N	N	Y	N	N	Y
Week FE	N	N	N	N	N	N	Y	Y	Y
Observation	9,498	9,498	9,498	9,498	9,498	9,498	9,498	9,498	9,498
Within R-squared					0.422	0.197	0.508	0.408	0.200
Adjusted R-squared	0.420	0.482	0.502	0.527	0.555	0.638	0.596	0.615	0.669

Panel B. Using LOO-assignments to predict busyness

Dependent Variable:	$Busyness_{j,d}$								
	1	2	3	4	5	6	7	8	9
$LOO\text{-}Assignment_{j,d}$	0.452***	0.395***	0.379***	0.363***	0.323***	0.201***	0.336***	0.293***	0.200***
	(8.275)	(8.551)	(9.391)	(9.124)	(8.281)	(9.347)	(9.354)	(8.744)	(9.214)
$LOO\text{-}Assignment_{j,d-1}$		0.157***	0.128***	0.126***	0.109***	0.060***	0.119***	0.099***	0.061***
		(4.716)	(4.302)	(4.536)	(3.985)	(3.065)	(4.705)	(4.038)	(3.218)
$LOO\text{-}Assignment_{j,d-2}$			0.106***	0.077***	0.063**	0.018	0.074***	0.057**	0.025
			(4.114)	(3.126)	(2.484)	(0.805)	(3.354)	(2.708)	(1.256)
$LOO\text{-}Assignment_{j,d-3}$				0.111***	0.093***	0.034***	0.108***	0.086***	0.042***
				(8.700)	(7.544)	(3.542)	(9.872)	(8.281)	(4.394)
Officer FE	N	N	N	N	Y	N	N	Y	N
Officer-Month-Yr FE	N	N	N	N	N	Y	N	N	Y
Week FE	N	N	N	N	N	N	Y	Y	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982	145,982	145,982	145,982
Within R-squared					0.320	0.122	0.344	0.259	0.119
Adjusted R-squared	0.317	0.363	0.384	0.406	0.450	0.595	0.514	0.555	0.640

Table IV. **Effects of Officer Attention Constraints on Review Time**

For this table, we estimate how loan office attention constraints affect the time they spend on reviewing each loan application by applicants from high and low 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 (6)). *High-SES(Social)* and *High-SES(Economic)* are dummy variables indicating whether the applicant has above-median *SocialStatus* and *EconomicStatus*, respectively, and the definition is explained in Section C. For columns (1) through (3), *BusynessDecile* is the officer's daily busyness, defined as the number of applications processed on a given day, sorted into deciles. For columns (4) through (9), *BusynessDecile* is the officer's instrumented daily busyness, defined as the number of applications processed on a given day sorted into deciles and instrumented by the total or leave-one-out (LOO) number of applications assigned to the loan officer over the preceding three working days. For columns (4) through (6), we use assignment-predicted busyness; for columns (7) through (9), we use LOO assignment-predicted busyness. For the overall effect of loan office attention constraints on groups with high social or economic status, we calculate the sum of two groups of coefficients $(\beta_1 + \beta_3)$ and $(\beta_1 + \beta_5)$, and report the P-values of their T-tests. The regressions include officer × month-year fixed effects, week fixed effects, origination-bank-branch fixed effects, and loan-type fixed effects. Application controls include log(*Income*), log(*Loan/Income*), log(1+*LeverageRatio*), log(1+*OverdueMonth*), log(1+*CreditInqury*), *HasInvestmentAcc*, *Female*, log(*Age*), *Peasant*, *NonCollege*, *SocialSecurity*, *Litigation*, *ShortTerm*, and log(*InterestRate*). See Table B1 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								
Busyness measure:	Actual Busyness			Predicted Busyness			LOO-Predicted Busyness		
	1	2	3	4	5	6	7	8	9
β_1BusynessDecile	-0.059***	-0.058***	-0.061***	-0.025***	-0.024***	-0.029***	-0.020***	-0.016***	-0.022***
	(-17.248)	(-19.538)	(-16.167)	(-8.297)	(-9.248)	(-8.999)	(-6.347)	(-5.970)	(-6.395)
β_2High-SES(Social)	0.439***		0.413***	0.461***		0.434***	0.469***		0.444***
	(13.854)		(12.801)	(23.833)		(21.608)	(23.566)		(21.385)
β_3High-SES(Social) × BusynessDecile	0.017***		0.017***	0.013***		0.015***	0.013***		0.013***
	(3.949)		(3.922)	(4.722)		(5.152)	(4.783)		(4.484)
β_4High-SES(Economic)		0.249***	0.188***		0.285***	0.215***		0.291***	0.222***
		(13.496)	(9.599)		(13.311)	(10.031)		(14.021)	(10.912)
β_5High-SES(Economic)× BusynessDecile		0.017***	0.014***		0.013***	0.012***		0.012***	0.011***
		(6.639)	(5.117)		(4.139)	(3.645)		(3.817)	(3.740)
Application Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Local Busyness Controls	N	N	N	N	N	N	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observation	145,977	145,977	145,977	145,977	145,977	145,977	145,977	145,977	145,977
Adjusted R-squared	0.076	0.046	0.082	0.074	0.044	0.082	0.075	0.045	0.082
$\beta_1 + \beta_3$	-0.042***		-0.044***	-0.011***		-0.014***	-0.006***		-0.009***
P-value of $(\beta_1 + \beta_3)$	(0.000)		(0.000)	(0.000)		(0.000)	(0.001)		(0.000)
$\beta_1 + \beta_5$		-0.041***	-0.047***		-0.011***	-0.017***		-0.005**	-0.011***
P-value of $(\beta_1 + \beta_5)$		(0.000)	(0.000)		(0.000)	(0.000)		(0.048)	(0.000)
First-stage F-Statistics				99.5	99.5	99.5	41.7	41.7	41.7

Table V. Effects of Attention Constraints on Approval Decisions

For this table, we estimate how loan office attention constraints affect their approval decisions on loan applications by high- and low-SES applicants. The dependent variable is a dummy variable indicating whether the officer approves the application. *High-SES(Social)* and *High-SES(Economic)* are dummy variables indicating whether the applicant's *SocialStatus* and *EconomicStatus* are above the median, respectively, and the definition is explained in Section C. For columns (1) through (3), *BusynessDecile* is the officer's daily busyness, defined as the number of applications processed on a given day, sorted into deciles. For columns (4) through (9), *BusynessDecile* is the officer's instrumented daily busyness, defined as the number of applications processed on a given day sorted into deciles and instrumented by the total or leave-one-out (LOO) number of applications assigned to the loan officer over the preceding three working days. For columns (4) through (6), we use assignment-predicted busyness; for columns (7) through (9), we use LOO assignment-predicted busyness. For the overall effect of loan office attention constraints on groups with high social or economic status, we calculate the sum of two groups of coefficients $(\beta_1 + \beta_3)$ and $(\beta_1 + \beta_5)$, and report the P-values of their T-tests. The regressions include officer $\times$ 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 B1 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								
Busyness measure:	Actual Busyness			Predicted Busyness			LOO-Predicted Busyness		
	1	2	3	4	5	6	7	8	9
β_1BusynessDecile	-0.009***	-0.011***	-0.010***	-0.004***	-0.003***	-0.006***	-0.004***	-0.003***	-0.006***
	(-6.415)	(-9.395)	(-6.964)	(-4.380)	(-4.046)	(-8.048)	(-5.144)	(-4.700)	(-9.396)
β_2High-SES(Social)	0.408***		0.375***	0.399***		0.367***	0.403***		0.371***
	(26.896)		(23.928)	(56.706)		(50.568)	(57.625)		(53.533)
β_3High-SES(Social) $\times$ BusynessDecile	0.007***		0.006***	0.009***		0.008***	0.008***		0.008***
	(3.326)		(3.289)	(7.241)		(7.018)	(6.688)		(7.141)
β_4High-SES(Economic)		0.373***	0.331***		0.383***	0.331***		0.385***	0.333***
		(36.447)	(31.948)		(37.182)	(35.370)			
β_5High-SES(Economic)$\times$ BusynessDecile		0.015***	0.011***		0.013***	0.012***		0.012***	0.011***
		(7.014)	(5.286)		(8.564)	(7.725)		(8.402)	(7.876)
Application Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Local Busyness Controls	N	N	N	N	N	N	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.269	0.217	0.338	0.272	0.219	0.342	0.272	0.219	0.342
$\beta_1 + \beta_3$	-0.002		-0.004**	0.005***		0.002***	0.004***		0.001*
P-value of $(\beta_1 + \beta_3)$	(0.251)		(0.012)	(0.000)		(0.000)	(0.000)		(0.055)
$\beta_1 + \beta_5$		0.004*	0.002		0.010***	0.006***		0.009***	0.005***
P-value of $(\beta_1 + \beta_5)$		(0.067)	(0.300)		(0.000)	(0.000)		(0.000)	(0.000)
First-stage F-Statistics				99.5	99.5	99.5	41.7	41.7	41.7

A. Analytical Results

A. Solving the model

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

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

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

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

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

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

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

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

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

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

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

- <u>Immediately accept region.</u> For sufficiently small $\bar{p}_G$, $U_A > U_R$ because $\lim_{\bar{p}_G \downarrow 0} \Pi(\bar{p}_G) = r - \text{distaste}_G > 0 = U_R$. Further, as long as $c > 0$, as $\bar{p}_G$ decreases there exists sufficiently small $\bar{p}_G$ such that $U_A > U_L$. Intuitively, because the probability of

51

rejection after information acquisition is sufficiently low, it is not worth paying the cost to acquire information.[35]

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

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

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

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

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

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

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

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

Note that it is possible for the first two regions to have zero length under certain parameters.[36]

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

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

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

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

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

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

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

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

B.   Uneven distribution of workloads is suboptimal for lender profits

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

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

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

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

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

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

B. Variable Definitions

Table B1 provides the definitions of the key variables used in our analyses.

[**Table** B1 about here.]

Table B1. **Variable Definitions.**

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

Peasant	Equals one if the applicant reports holding a permanent agricultural residence registration in an application and zero otherwise.
NonCollege	Equals one if the applicant has a non-college degree and zero otherwise.
Female	Equals one if the applicant is female and zero otherwise.
Age	The applicant's age.
Income	The applicant's total income.

Loan characteristics

Loan/Income	The ratio of the amount of the loan for which the applicant has applied to the applicant's total income.
ShortTerm	Equals one if the term of the loan for which the application has applied is less than 3 years.
InterestRate	The interest rate of the loan for which the application has applied at origination.

Attention Constraints and Financial Inclusion

INTERNET APPENDIX

IA.   Additional Empirical Results

A.   Robustness to high- and low-SES definitions

In our main analyses, we summarize the combined effects of applicant socioeconomic status (SES) by fitting a linear probability model using the full sample, and then we define high- and low-SES status based on whether the fitted value is above or below the sample median.

In this section, we show that this data-driven approach that defines high- and low-SES status is robust when using out-of-sample fitting, and thus our approach is not subject to in-sample bias. Specifically, instead of regressing the approval probability on the six SES labels using the full sample, we fit this linear probability model using only the subsample that includes the first 50% (25%) of the sample period, or a subsample of 50% (25%) of the randomly selected observations. As shown in Table IA1, the estimated coefficients using these alternative subsamples are very similar to those estimated using the full sample, and the fitted values of "Social Status" and "Economic Status" are also very similar. In fact, no matter which sample we use, the high- and low-SES dummy indicators based on whether the fitted "Social Status" and "Economic Status" values are above or below median are always consistent for each loan applicant.

Moreover, we show that our main results remain robust when using such out-of-sample analyses. First, we use the first 50% of the sample to define the high- and low-SES groups, and repeat the main regression analyses using the remaining 50% of the sample. The results are robust, as shown in Tables IA2 and IA3. Moreover, the results are also robust when we apply out-of-sample fitting based on randomly drawn samples. Specifically, after drawing a 50% random subsample to fit the linear probability model and using the fitted values to define the high- and low-SES groups, we run our main regression analyses using only the remaining 50% subsample. We repeat this random-draw procedure 100 times and in Figure IA1 present the empirical distribution of the key regression coefficients estimated over these 100 iterations. As shown in the figure, the coefficients for **BusynessDecile**, $High - SES(Social) \times BusynessDecile$, and $High - SES(Economic) \times BusynessDecile$ are all qualitatively and quantitatively similar to the baseline estimations. In particular, consistent with the prediction based on our attention-driven mechanism, the values of the two interaction terms are significantly greater than zero, with p-values under 0.001. We also note

that all these results remain similar if we use a 25% subsample to fit the linear probability model and the remaining observations for the regression analyses. Space limitations prevent us from reporting those additional results.

[**Table** IA1 about here.]

[**Table** IA2 about here.]

[**Table** IA3 about here.]

[**Figure** IA1 about here.]

B.   Credit Quality of Applicants by Social/Economic Statuses

Under the state when loan officers are *not* attention constrained, a lower approval rate faced by borrowers in the low-SES group could simply be driven by their higher average credit risk. However, not only this pure risk-driven effect cannot explain the difference-in-difference results we presented earlier in this section, but also even the average difference in attention allocation and approval rates across the high- versus low-SES borrower groups seems too large to be fully justified by differences in credit risk.

Regarding attention allocation, the median (average) time that officers spend reviewing an application with low social status is only 12.17 (24.53) minutes, which is approximately 50% (33%) lower than that for high status applicants who receive 24.86 (37.42) minutes. Similarly, the median (average) time that officers spend reviewing an application with low economic status is 16.12 (28.76) minutes as opposed to 25.16 (37.41) minutes for applicants accorded high economic status. Regarding the lending decision, when we compare the approval rates reported in Panel B of Table I, we can see that on average the gaps between high- and low-SES groups are large. Specifically, the low social (economic) status groups experience average approval rates of only 18.1% (25.4%), while the high social (economic) status groups experience much higher approval rates of 51.9% (65.5%).

These cross-sectional differences are so large such that they cannot be easily explained alone by the limited difference in average credit quality across borrower groups. In Figure IA2, we plot the distribution of each major credit risk metric for borrowers in the high- versus low-SES groups respectively. These credit quality distributions mask substantial overlap. In addition, the appendix Table IA4 present further numerical details about the extent of the overlap: among the

2

applicants with low social (economic) status who are rejected, 47% (44%) earn income higher than the median high-status applicant who are approved, and 32% (35%) exhibit lower leverage ratios. The fact that these numbers are only slightly below 50% implies that the low-SES group demonstrates comparable credit quality as the high-SES group based on the key metrics.

[**Figure** IA2 about here.]

[**Table** IA4 about here.]

To verify that our findings are not driven by the variation in borrower credit risk, we utilize propensity score matching to identify the most closely-matched borrowers in the low- and high-SES groups and test whether our difference-in-difference results remain robust even after accounting for the potential influence of borrower credit risk. Tables IA5 and IA6 result resemble those of our main analyses, except that we match applicants from high- and low-SES groups that have similar backgrounds. Specifically, we use the full set of application controls applied before as matching variables to pair the high-SES application with the single nearest neighbor low-SES application and rerun the main analyses by using the matched sample.

[**Table** IA5 about here.]

[**Table** IA6 about here.]

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

This section provides additional suggestive evidence of differential officer attention allocation to high- and low-SES 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 officer makes rejection decisions based on information already in hand (e.g., high leverage or bad credit history), while some others indicate that the loan officer, before rejecting, attempted *further due diligence* to gain information beyond that readily available in the application package. For example, the loan officer can indicate that she also called the applicant's reference but found inconsistent information. We use this as another indicator for loan officer attention allocation in addition to their review time.

In Table IA7, we find that loan officers are more likely to conduct extra due diligence on applications with more SES labels. More importantly, the effect of social and economic statuses on

officer due diligence is more pronounced when loan officers are busier. As discussed in Section A, we measure loan officer business by the number of applications she processes in a day. As in Table IV, we sort officer busyness into deciles and estimate a regression of an officer due diligence indicator on social and economic status indicators and busyness deciles as well as their interactions. When loan officers are busier, applicants from groups with lower social or economic status receive significantly less due diligence, but the effect is minor or non-existent for the high-socioeconomic-status applicants. From columns (4) to (9), we further verify that the results are robust to using the two loan officer busyness instruments in Section A. Overall, these results are consistent with the parallel findings where we measure attention allocation using loan officer review time (Table IV). One caveat is that the due diligence measure is indirect and imperfect, as it is based on short commented quotes by loan officers only on rejected loans. Thus, we should only consider these additional evidence as suggestive.

[**Table** IA7 about here.]

D. Additional Details Regarding the Instrumented Busyness Measures

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

1. Figure IA3 replicates the patterns shown in Figure 4 by using each of the two instrumented busyness measures instead of raw busyness. We show that loan officers work longer hours and are more likely to work overtime when they are more attention-constrained, as measured by the two instrumented busyness measures.

2. With Table IA8, 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 IA9, we verify that the instrumented busyness measures are not correlated with applicant and loan characteristics.

4. Tables IA10 and IA11 resemble those of our main analyses, except that we use the demeaned assignment to capture only residual variations after controlling for the week, bank branch, and loan-type fixed effects.

[**Figure** IA3 about here.]

[**Table** IA8 about here.]

[**Table** IA9 about here.]

[**Table** IA10 about here.]

[**Table** IA11 about here.]

Figure IA1. Coefficients using Out-of-Sample Fitted SES

This figure presents the results of robustness checks of the key regression coefficients reported in Tables IV and V. We first employ a linear probability model on a 50% randomly selected subsample to fit each applicant's SES. We then use the non-selected 50% of the subsample for the regression analyses. This random-draw process is repeated 100 times. The distribution of each key coefficient over 100 iterations is presented. In Panel A we reports the effects of officer attention constraints on review time. In Panel B we report the effects of officer attention constraints on approval decisions. For the sake of brevity, we present the results based on LOO-predicted busyness. The results are very similar when we use actual or predicted busyness.

Panel A. Effects of officer attention constraints on review time

(a) $BusynessDecile$ **(b)** $High^-SES(Social) \times BusynessDecile$ **(c)** $High^-SES(Economic) \times BusynessDecile$
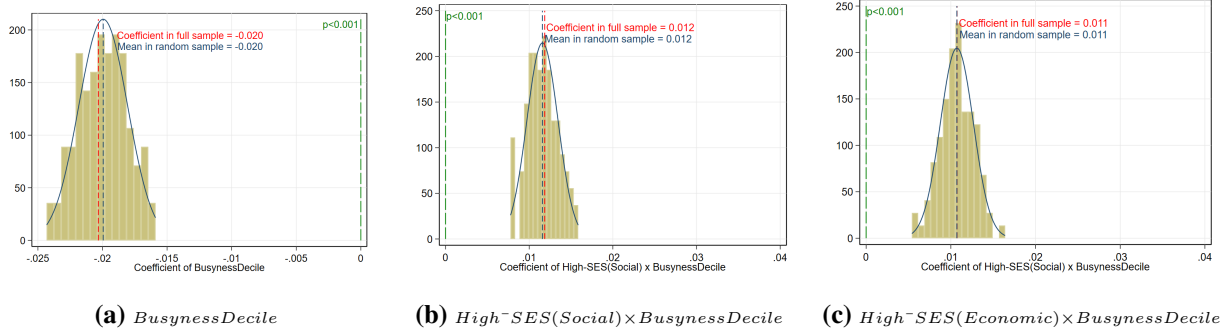
Panel B. Effects of officer attention constraints on approval decisions

(d) $BusynessDecile$ **(e)** $High^-SES(Social) \times BusynessDecile$ **(f)** $High^-SES(Economic) \times BusynessDecile$

6
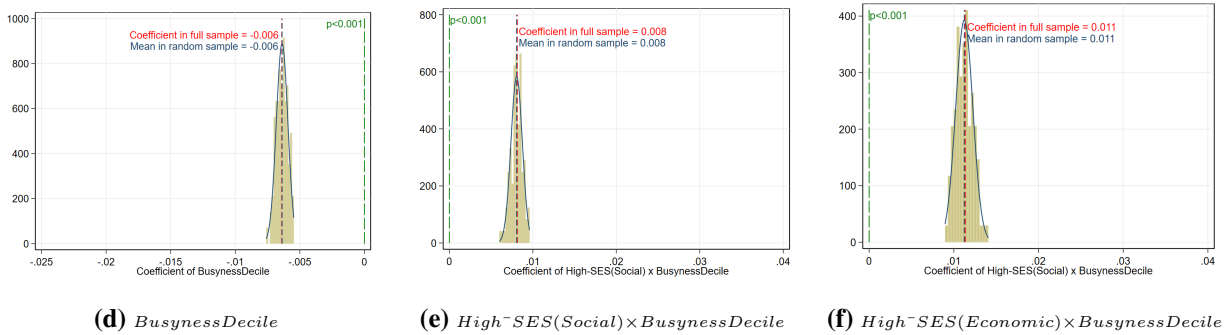
Figure IA2. **Distribution of Credit Quality: high- and low-SES Applicants**

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

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

(a) **log(1+LeverageRatio)**   (b) **log(Income)**   (c) **log(LoanToIncome)**

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

(d) **log(1+LeverageRatio)**   (e) **log(Income)**   (f) **log(LoanToIncome)**
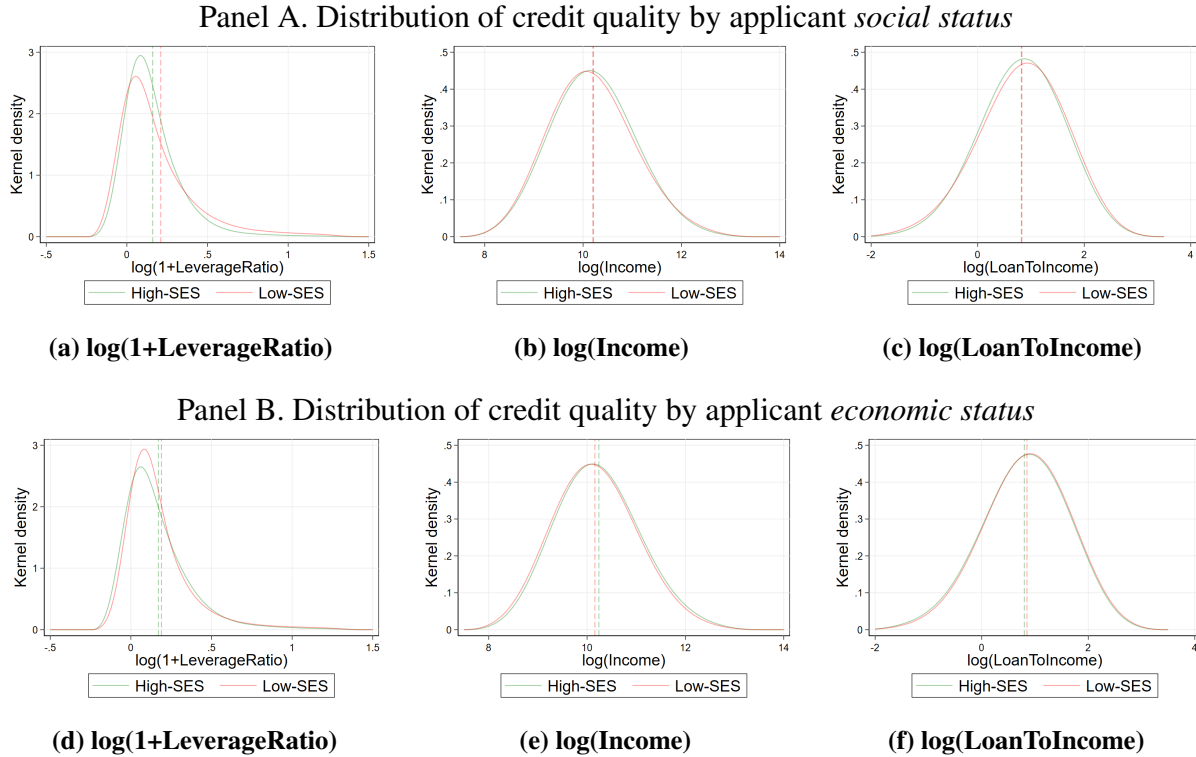
Figure IA3. **Robustness: Loan Officer Busyness and Work Schedule**

This figure replicates Figure 4, except that we sort loan officer busyness by each of the two instrumented measures. For 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 A. 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).
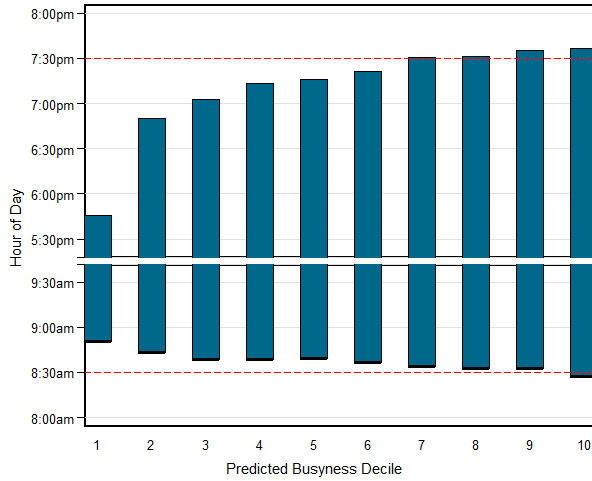
(a) **Work Schedule by Predicted Busyness**
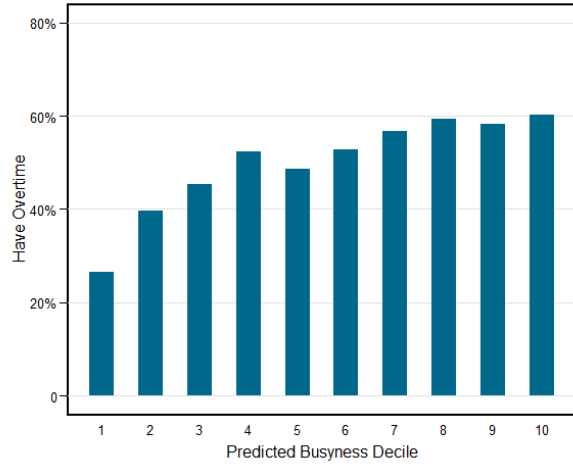
(b) **Overtime by Predicted Busyness**
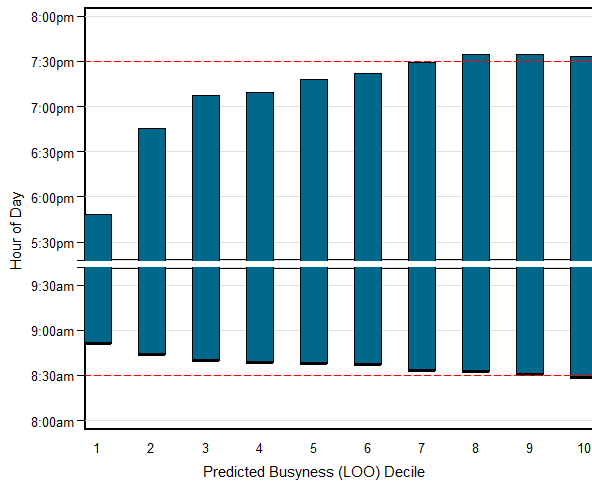
(c) **Work Schedule by LOO-Predicted Busyness**
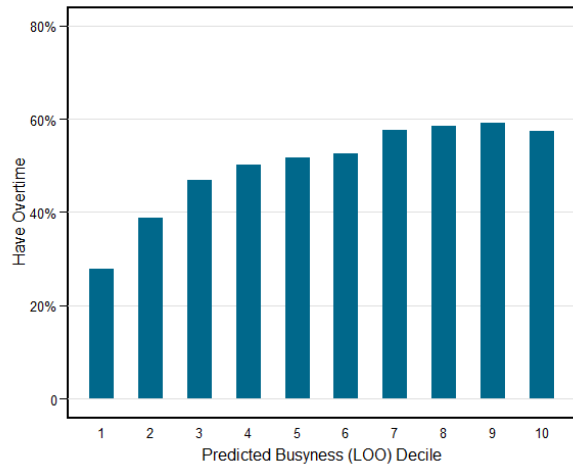
(d) **Overtime by LOO-Predicted Busyness**

Table IA1. **Out-of-sample Fitting for Socioeconomic Status**

In this table, we report the results obtained after adopting multuple approaches to regressing approval probability on socioeconomic labels. In addition to using the full sample to fit the linear probability model as in our main analyses, we also consider fitting the model using only a subsample from an earlier part of the sample period, and a randomly selected subsample. In Panels A and C we report the fitted coefficients using social status and economic status labels, respectively. In Panels B and D we report summary statistics for the fitted values of "Social Status" and "Economic Status". T-statistics are reported in the parentheses. ***$p < 1\%$, **$p < 5\%$, *$p < 10\%$

Panel A: Estimated coefficients by social status

Sample:	Approval				
	Full	Time		Random	
	100%	50%	25%	50%	25%
	1	2	3	4	5
PublicEmployee	0.098***	0.087***	0.056***	0.089***	0.091***
	(12.828)	(8.595)	(4.962)	(10.171)	(7.862)
LocalResident	0.452***	0.421***	0.369***	0.449***	0.451***
	(28.729)	(22.007)	(19.376)	(96.931)	(77.851)
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	72,997	36,890	72,997	36,890
Adjusted R-squared	0.268	0.249	0.255	0.270	0.272

Panel B: Predicted approval rates by social status

	N	Mean	SD	10%	25%	50%	75%	90%
Predicted Approval (Full sample)	145,982	0.342	0.159	0.195	0.195	0.195	0.495	0.495
Predicted Approval (First half of the sample)	145,982	0.323	0.146	0.188	0.188	0.188	0.464	0.464
Predicted Approval (First 25% of the sample)	145,982	0.291	0.139	0.162	0.162	0.162	0.430	0.430
Predicted Approval (Randomly chosen half of the sample)	145,982	0.343	0.159	0.197	0.197	0.197	0.496	0.496
Predicted Approval (Randomly chosen 25% of the sample)	145,982	0.341	0.161	0.193	0.193	0.193	0.491	0.491

Panel C: Estimated coefficients by economic status

Sample:	Full	Time		Random	
	100%	50%	25%	50%	25%
	1	2	3	4	5
EmploymentCert	0.399***	0.359***	0.304***	0.385***	0.393***
	(22.789)	(16.531)	(12.532)	(52.979)	(41.129)
IncomeCert	0.088***	0.094***	0.091***	0.102***	0.092***
	(5.712)	(4.644)	(3.755)	(13.634)	(9.122)
RegularPay	0.113***	0.138***	0.202***	0.112***	0.110***
	(9.521)	(7.507)	(9.275)	(10.268)	(8.457)
HomeOwner	0.179***	0.165***	0.157***	0.188***	0.182***
	(17.394)	(12.266)	(11.459)	(22.780)	(18.768)
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	72,997	36,890	72,997	36,890
Adjusted R-squared	0.369	0.331	0.328	0.372	0.372

Panel D: Predicted approval rates by economic status

	N	Mean	SD	10%	25%	50%	75%	90%
Predicted Approval (Full sample)	145,982	0.342	0.269	0.009	0.009	0.489	0.489	0.690
Predicted Approval (First half of the sample)	145,982	0.323	0.253	0.011	0.011	0.465	0.465	0.668
Predicted Approval (First 25% of the sample)	145,982	0.303	0.243	0.010	0.010	0.423	0.423	0.682
Predicted Approval (Randomly chosen half of the sample)	145,982	0.344	0.270	0.010	0.010	0.489	0.489	0.695
Predicted Approval (Randomly chosen 25% of the sample)	145,982	0.341	0.268	0.008	0.008	0.490	0.490	0.677

Table IA2. *Robustness using Out-of-Sample Fitted SES:* **Effects on Review Time**

For this table, we report the robustness of Table IV, where we report results indicating how loan officer attention constraints affect the time they spend on reviewing each loan application. All the specifications are the same, except that we use the first half of the sample to fit applicant SES by regressing approval probability on socioeconomic labels and the remaining half to run the regression analysis as in Table IV. *BusynessDecile* is the officer's daily busyness measure, defined as the number of applications processed on a given day, sorted into deciles. Application controls are similar to those included in earlier regressions. 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								
Busyness measure:	Actual Busyness			Predicted Busyness			LOO-Predicted Busyness		
	1	2	3	4	5	6	7	8	9
β_1BusynessDecile	-0.059***	-0.052***	-0.064***	-0.026***	-0.017***	-0.025***	-0.015***	-0.011***	-0.019***
	(-14.757)	(-17.857)	(-13.662)	(-7.918)	(-6.036)	(-7.006)	(-4.151)	(-3.281)	(-6.274)
β_2High-SES(Social)	0.277***		0.242***	0.375***		0.343***	0.378***		0.347***
	(6.686)		(5.735)	(12.613)		(11.437)	(12.447)		(12.742)
β_3High-SES(Social) $\times$ BusynessDecile	0.030***		0.032***	0.022***		0.019***	0.017***		0.018***
	(4.822)		(5.032)	(5.402)		(4.490)	(4.018)		(4.711)
β_4High-SES(Economic)		0.204***	0.129***		0.266***	0.190***		0.270***	0.195***
		(8.602)	(5.980)		(9.345)	(6.558)		(9.582)	(7.083)
β_5High-SES(Economic)$\times$ BusynessDecile		0.019***	0.021***		0.012***	0.014***		0.011***	0.013***
		(5.640)	(5.829)		(2.991)	(3.193)		(2.684)	(3.387)
Application Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Local Busyness Controls	N	N	N	N	N	N	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observation	72,983	72,983	72,983	72,983	72,983	72,983	72,983	72,983	72,983
Adjusted R-squared	0.067	0.042	0.074	0.067	0.040	0.071	0.064	0.040	0.071
$\beta_1 + \beta_3$	-0.028***		-0.032***	-0.003		-0.006***	0.002		-0.001
P-value of $(\beta_1 + \beta_3)$	(0.000)		(0.000)	(0.128)		(0.008)	(0.392)		(0.827)
$\beta_1 + \beta_5$		-0.032***	-0.043***		-0.005*	-0.012***		0.000	-0.006*
P-value of $(\beta_1 + \beta_5)$		(0.000)	(0.000)		(0.072)	(0.000)		(0.874)	(0.058)
First-stage F-Statistics				39.1	39.1	39.1	15.6	15.6	15.6

Table IA3. *Robustness Using Out-of-Sample Fitted SES:* **Effects on Approval Decisions**

In this table, we report results that confirm the robustness of Table V, where we report results indicating how loan officer attention constraints affect approval decisions on loan applications. All the specifications are the same, except that we use the first half of the sample to fit applicant SES by regressing approval probability on socioeconomic labels and the remaining half to run the regression analysis as in Table V. *BusynessDecile* is the officer's daily busyness measure, defined as the number of applications processed on a given day, sorted into deciles. Application controls are similar to those included in earlier regressions. 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								
Busyness measure:	Actual Busyness			Predicted Busyness			LOO-Predicted Busyness		
	1	2	3	4	5	6	7	8	9
β_1BusynessDecile	-0.006***	-0.009***	-0.005***	-0.000	-0.002**	-0.002**	-0.001	-0.002	-0.002**
	(-3.090)	(-5.109)	(-3.061)	(-0.357)	(-1.979)	(-2.292)	(-0.383)	(-1.612)	(-1.976)
β_2High-SES(Social)	0.463***		0.431***	0.468***		0.425***	0.474***		0.431***
	(18.267)		(19.156)	(39.197)		(41.976)	(38.601)		(46.805)
β_3High-SES(Social) $\times$ BusynessDecile	0.002		0.001	0.002		0.002	0.001		0.001
	(0.588)		(0.229)	(0.803)		(1.203)	(0.278)		(0.659)
β_4High-SES(Economic)		0.444***	0.406***		0.459***	0.398***		0.463***	0.402***
		(20.328)	(21.247)		(32.628)	(30.142)		(32.851)	(29.979)
β_5High-SES(Economic)$\times$ BusynessDecile		0.007***	0.003*		0.006***	0.006***		0.005***	0.005***
		(3.395)	(2.029)		(3.172)	(2.956)		(2.859)	(2.961)
Application Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Local Busyness Controls	N	N	N	N	N	N	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observation	72,983	72,983	72,983	72,983	72,983	72,983	72,983	72,983	72,983
Adjusted R-squared	0.294	0.244	0.377	0.301	0.251	0.385	0.301	0.251	0.385
$\beta_1 + \beta_3$	-0.004*		-0.005**	0.001		-0.000	0.000		-0.001
P-value of ($\beta_1 + \beta_3$)	(0.066)		(0.029)	(0.204)		(0.785)	(0.952)		(0.173)
$\beta_1 + \beta_5$		-0.002	-0.002		0.004***	0.003***		0.003***	0.003**
P-value of ($\beta_1 + \beta_5$)		(0.389)	(0.336)		(0.002)	(0.003)		(0.007)	(0.021)
First-stage F-Statistics				39.1	39.1	39.1	15.6	15.6	15.6

Table IA4. **Credit Quality of high- and low-SES Applicants**

For this table, we compare the credit quality of applicants with high versus low social or economic status. As explained in Section C, the high-SES group is defined as applicants whose level of *SocialStatus* (equation (3)), or *EconomicStatus* (equation (4)) is above the sample median. *LeverageRatio* is defined as the debt-to-income ratio in the applicant's credit report, and *NoCreditHistory* is a dummy indicator that equals one for those without credit histories. *LoanToIncome* is the loan-amount-to-income ratio. We report, by applicant SES group and approcal decision, 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 low-SES applicants that are rejected with higher credit quality than the median high-SES applicant that is approved.

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

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

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

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

Table IA5. *Robustness Using Propensity Score Matching:* **Effects of Officer Attention Constraints on Review Time**

For this table, we report results pertaining to the propensity score analysis of how loan office attention constraints affect their approval decisions on loan applications by applicants from high and low socioeconomic backgrounds. The regression specification is the same as in Table IV, except that we utilize the matched sample for high- and low-SES applicants. The propensity matching is calculated by the single nearest neighbor method applied to the full set of application controls. *BusynessDecile* is the officer's daily busyness measure, defined as the number of applications processed on a given day, sorted into deciles. Application controls are similar to before. 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								
Busyness measure:	Actual Busyness			Predicted Busyness			LOO-Predicted Busyness		
	1	2	3	4	5	6	7	8	9
β_1BusynessDecile	-0.057***	-0.057***	-0.064***	-0.019***	-0.029***	-0.036***	-0.020***	-0.020***	-0.028***
	(-12.720)	(-15.349)	(-10.216)	(-4.059)	(-5.598)	(-5.051)	(-4.759)	(-4.001)	(-3.821)
β_2High-SES(Social)	0.426***		0.230***	0.463***		0.271***	0.488***		0.277***
	(11.938)		(7.741)	(17.986)		(6.183)	(18.934)		(5.079)
β_3High-SES(Social)× BusynessDecile	0.015***		0.019***	0.007*		0.014**	0.009**		0.013*
	(3.067)		(3.222)	(1.853)		(2.332)	(2.303)		(1.789)
β_4High-SES(Economic)		0.245***	0.123***		0.245***	0.144***		0.245***	0.146***
		(11.823)	(5.802)		(7.923)	(4.796)		(7.617)	(4.341)
β_5High-SES(Economic)× BusynessDecile		0.014***	0.015***		0.014***	0.011**		0.014***	0.011**
		(4.689)	(4.399)		(3.107)	(2.244)		(3.052)	(2.250)
Application Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Local Busyness Controls	N	N	N	N	N	N	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observation	105,195	57,201	40,953	105,195	57,201	40,953	105,195	57,201	40,953
Adjusted R-squared	0.066	0.038	0.047	0.062	0.042	0.056	0.071	0.042	0.056
$\beta_1 + \beta_3$	-0.042***		-0.046***	-0.012***		-0.021***	-0.011***		-0.015***
P-value of ($\beta_1 + \beta_3$)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)
$\beta_1 + \beta_5$		-0.043***	-0.050***		-0.014***	-0.025***		-0.006**	-0.017***
P-value of ($\beta_1 + \beta_5$)		(0.000)	(0.000)		(0.000)	(0.000)		(0.021)	(0.000)
First-stage F-Statistics				99.3	99.3	99.3	41.7	41.7	41.7

Table IA6. *Robustness Using Propensity Score Matching:* **Effects of Attention Constraints on Approval Decisions**

For this table, we report results pertaining to the propensity score analysis of how loan office attention constraints affect the time they spend on reviewing each loan application by high- and low-SES applicants. The regression specification is the same as in Table V, except that we utilize the matched sample for high- and low-SES applicants. The propensity matching is calculated by the single nearest neighbor method applied to the full set of application controls. *BusynessDecile* is the officer's daily busyness measure, defined as the number of applications processed on a given day, sorted into deciles. Application controls are similar to before. 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								
Busyness measure:	Actual Busyness			Predicted Busyness			LOO-Predicted Busyness		
	1	2	3	4	5	6	7	8	9
β_1BusynessDecile	-0.008***	-0.013***	-0.015***	-0.003***	-0.006***	-0.009***	-0.004***	-0.008***	-0.012***
	(-6.357)	(-9.564)	(-8.572)	(-2.818)	(-4.339)	(-5.172)	(-3.809)	(-4.652)	(-6.788)
β_2High-SES(Social)	0.451***		0.301***	0.437***		0.299***	0.446***		0.297***
	(-28.180)		(-17.883)	(48.230)		(21.537)	(50.278)		(21.158)
β_3High-SES(Social) $\times$ BusynessDecile	0.006***		0.006***	0.009***		0.005**	0.007***		0.005***
	(-2.871)		(-2.751)	(6.283)		(2.223)	(5.127)		(2.661)
β_4High-SES(Economic)		0.355***	0.260***		0.359***	0.254***		0.358***	0.256***
		(-21.076)	(-19.318)		(21.224)	(15.306)		(20.827)	(15.369)
β_5High-SES(Economic)$\times$ BusynessDecile		0.014***	0.011***		0.013***	0.012***		0.013***	0.012***
		(-6.554)	(-7.624)		(5.644)	(5.465)		(5.792)	(5.346)
Application Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Local Busyness Controls	N	N	N	N	N	N	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observation	105,195	57,201	40,953	105,195	57,201	40,953	105,195	57,201	40,953
Adjusted R-squared	0.271	0.227	0.259	0.277	0.235	0.265	0.275	0.235	0.265
$\beta_1 + \beta_3$	-0.002		-0.008***	0.006***		-0.004**	0.003***		-0.007***
P-value of ($\beta_1 + \beta_3$)	(-0.188)		(0.000)	(0.000)		(0.012)	(0.000)		(0.000)
$\beta_1 + \beta_5$		0.000	-0.003***		0.006***	0.003**		0.005***	-0.000
P-value of ($\beta_1 + \beta_5$)		(-0.809)	(-0.037)		(0.000)	(0.046)		(0.000)	(0.994)
First-stage F-Statistics				99.3	99.3	99.3	41.7	41.7	41.7

Table IA7. Effects of Attention Constraints on Due Diligence

For this table, we estimate how loan officer attention constraints affect their extra due diligence efforts on loan applications by high- versus low-SES 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, and zero otherwise. *High-SES(Social)* and *High-SES(Economic)* are dummy variables indicating whether *SocialStatus* and *EconomicStatus* are above the median, respectively. For columns (1) through (3), *BusynessDecile* is the officer's daily busyness, defined as the number of applications processed on a given day, sorted into deciles. For columns (4) through (9), *BusynessDecile* is the officer's instrumented daily busyness, defined as the number of applications processed on a given day sorted into deciles and instrumented by the total or leave-one-out (LOO) number of applications assigned to the loan officer over the preceding three working days. For columns (4) through (6), we use assignment-predicted busyness; for columns (7) through (9), we use LOO assignment-predicted busyness. As in Table V, 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								
Busyness measure:	Actual Busyness			Predicted Busyness			LOO-Predicted Busyness		
	1	2	3	4	5	6	7	8	9
β_1BusynessDecile	-0.002*	-0.002*	-0.003***	-0.005***	-0.005***	-0.006***	-0.002*	-0.002*	-0.003***
	(-1.693)	(-1.655)	(-2.755)	(-4.188)	(-4.250)	(-5.326)	(-1.693)	(-1.655)	(-2.755)
β_2High-SES(Social)	0.144***		0.134***	0.152***		0.133***	0.144***		0.134***
	-13.447		-12.774	-13.898		-12.191	-13.447		(12.774)
β_3High-SES(Social) $\times$ BusynessDecile	0.004**		0.003**	0.003*		0.004**	0.004**		0.003**
	-2.348		-2.052	-1.886		-2.217	-2.348		(2.052)
β_4High-SES(Economic)		0.197***	0.182***		0.194***	0.179***		0.197***	0.182***
		-12.477	-10.442		-11.756	-10.513		-12.477	(10.442)
β_5High-SES(Economic)$\times$ BusynessDecile		0.009***	0.008***		0.009***	0.009***		0.009***	0.008***
		-3.774	-3.357		-3.658	-3.372		-3.774	(3.357)
Application Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Local Busyness Controls	N	N	N	N	N	N	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	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	96,009
Adjusted R-squared	0.130	0.130	0.149	0.133	0.130	0.149	0.131	0.130	0.150
$\beta_1 + \beta_3$	-0.006***		-0.007***	-0.002*		-0.002**	0.002*		0.000
P-value of $(\beta_1 + \beta_3)$	(-0.005)		(-0.001)	(-0.070)		(-0.015)	(-0.079)		(0.710)
$\beta_1 + \beta_5$		-0.001	-0.002		0.004**	0.003*		0.006***	0.005***
P-value of $(\beta_1 + \beta_5)$		(-0.841)	(-0.505)		(-0.011)	(-0.090)		(0.000)	(0.001)
First-stage F-Statistics				95.6	95.6	95.6	38.2	38.2	38.2

Table IA8. 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:	$Assignment_{j,d}$			
	1	2	3	4
$Backlog_{j,d}$	−0.016	−0.016	−0.016	−0.016
	(−1.133)	(−1.138)	(−1.139)	(−1.136)
$Backlog_{j,d-1}$		0.005	0.005	0.005
		(1.613)	(1.627)	(1.634)
$Backlog_{j,d-2}$			0.000	0.000
			(0.123)	(0.113)
$Backlog_{j,d-3}$				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 IA9. **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 A, we use the total or leave-one-out number of applications assigned to officers to create instrumented versions of busyness, which we call *predicted busyness* and *leave-one-out (LOO) predicted busyness*. In each of the two panels, we regress each applicant or loan characteristic on deciles (1 through 10) of predicted and LOO-predicted busyness. As with the regression results reported in Tables IV and V, 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 B1. ***$p < 1\%$, **$p < 5\%$, *$p < 10\%$.

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	0.518	0.042	0.396	−0.055	−0.207
	(−1.111)	(1.207)	(0.239)	(0.308)	(0.840)	(−0.640)	(−0.471)
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.061	0.031	0.114	0.010	0.082	0.011	0.459

Dependent variable:	NonCollege	Female	log(Age)	log(Income)	log(LoanTo Income)	ShortTerm	log(Interest Rate)
	1	2	3	4	5	6	7
PredictBusynessDecile	0.479	0.522	−0.159	−0.717	0.481	0.141	−0.008
	(0.879)	(0.965)	(−0.506)	(−0.526)	(0.424)	(0.492)	(−0.728)
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.117	0.010	0.056	0.489	0.412	0.785	0.868

Panel B. Applicant characteristics by leave-one-out (LOO) predicted busyness

Dependent variable:	StateOfficial	LocalResident	Employment Cert	IncomeCert	RegularPay	HomeOwner	log(1+Lever ageRatio)
	1	2	3	4	5	6	7
LOOPredictBusynessDecile	−0.179	−0.705	−0.650	−0.094	0.767*	−0.184	0.247
	(−0.487)	(−0.489)	(−0.364)	(−0.080)	(1.785)	(−0.240)	(0.575)
Local Busyness Controls	Y	Y	Y	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.045	0.346	0.091	0.317	0.392	0.387	0.042

Dependent variable:	NoCredit History	log(1+Over dueMonth)	log(1+Cred itInqury)	HasInvest mentAcc	SocialSecurity	Litigation	Peasant
	1	2	3	4	5	6	7
LOOPredictBusynessDecile	−1.176	−0.300	0.498	0.022	−0.019	−0.083	−0.180
	(−1.619)	(−0.351)	(0.255)	(0.170)	(−0.036)	(−0.863)	(−0.372)
Local Busyness Controls	Y	Y	Y	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.061	0.031	0.114	0.010	0.082	0.011	0.459

Dependent variable:	NonCollege	Female	log(Age)	log(Income)	log(LoanTo Income)	ShortTerm	log(Interest Rate)
	1	2	3	4	5	6	7
LOOPredictBusynessDecile	0.293	0.244	−0.270	−0.350	0.268	0.256	−0.012
	(0.513)	(0.396)	(−0.755)	(−0.286)	(0.263)	(0.758)	(−0.952)
Local Busyness Controls	Y	Y	Y	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.117	0.010	0.056	0.489	0.412	0.785	0.868

Table IA10. Robustness Using Demeaned Assignment: Effects of *Instrumented* Attention Constraints on Review Time

For this table, we estimate how instrumented loan officer attention constraints affect the time they spend reviewing loan applications submitted by high- and low-SES applicants. These results resemble our main analyses in Table IV, except that we use the residual assignment as the instrument after demeaning for the week, bank branch, and loan-type fixed effects. The dependent variable is the standardized application review time, defined as the logarithm of the excess time an officer spends reviewing each application (equation (6)). *High-SES(Social)* and *High-SES(Economic)* are dummy variables indicating, separately, whether *SocialStatus* and *EconomicStatus* are above the median. *BusynessDecile* is the officer's instrumented daily busyness, defined as the number of applications processed on a given day sorted into deciles and instrumented by the residual of the total or leave-one-out (LOO) number of applications. For columns (1) to (3), we use demeaned-assignment-predicted busyness; for columns (4) to (6), we use demeaned-LOO assignment-predicted busyness. For the effect of loan office attention constraints on groups with high social or economic status, we calculate the sum of two groups of coefficients $(\beta_1 + \beta_3)$ and $(\beta_1 + \beta_5)$, and report the P-values of their T-tests. The regressions include officer $\times$ 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*). Local busyness controls include loan officer assignments from the same province. See Table B1 for the variable definitions. T-statistics are reported in parentheses. Bootstrapped standard errors are double-clustered at the week and officer levels. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Dependent variable:	StandardizedReviewTime					
Busyness measure:	Predicted Busyness			LOO-Predicted Busyness		
	1	2	3	4	5	6
β_1BusynessDecile	-0.020***	-0.016***	-0.022***	-0.013***	-0.009***	-0.015***
	(-8.592)	(-8.627)	(-8.903)	(-5.923)	(-4.992)	(-6.256)
β_2High-SES(Social)	0.468***		0.442***	0.477***		0.451***
	(30.676)		(29.648)	(31.201)		(31.216)
β_3High-SES(Social) $\times$ BusynessDecile	0.014***		0.014***	0.012***		0.012***
	(5.796)		(5.920)	(5.343)		(5.544)
β_4High-SES(Economic)		0.305***	0.231***		0.309***	0.236***
		(14.618)	(10.782)		(14.048)	(11.019)
β_5High-SES(Economic)$\times$ BusynessDecile		0.009***	0.009***		0.008***	0.008***
		(3.158)	(2.928)		(2.682)	(2.896)
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	0.081	0.075	0.044	0.081
$\beta_1 + \beta_3$	-0.006***		-0.013***	-0.001		-0.007***
P-value of $(\beta_1 + \beta_3)$	(0.000)		(0.000)	(0.671)		(0.004)
$\beta_1 + \beta_5$		-0.007***	-0.008***		-0.001	-0.003*
P-value of $(\beta_1 + \beta_5)$		(0.001)	(0.000)		(0.453)	(0.065)
First-stage F-Statistics	156.4	156.4	156.4	122.9	122.9	122.9

Table IA11. Robustness Using Demeaned Assignment: Effects of *Instrumented* Attention Constraints on Approval Decisions

For this table, we estimate how instrumented loan officer attention constraints affect their approval decisions for loan applications submitted by high- and low-SES applicants. These results resemble our main analyses in Table V, except that we use the residual assignment as the instrument after demeaning for the week, bank branch, and loan-type fixed effects. The dependent variable is a dummy indicating whether the officer approves the application. *High-SES(Social)* and *High-SES(Economic)* are dummy variables indicating, separately, whether *SocialStatus* and *EconomicStatus* are above the median. *BusynessDecile* is the officer's instrumented daily busyness, defined as the number of applications processed on a given day sorted into deciles and instrumented by the residual of total or leave-one-out (LOO) number of applications. For columns (1) to (3), we use demeaned-assignment-predicted busyness; for columns (4) to (6), we use demeaned-LOO assignment-predicted busyness. For the effect of loan officer attention constraints on groups with high social or economic status, we calculate the sum of two groups of coefficients $(\beta_1 + \beta_3)$ and $(\beta_1 + \beta_5)$, and report the P-values of their T-tests. The regressions include officer $\times$ 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*). Local busyness controls include loan officer assignments from the same province. See Table B1 for the variable definitions. T-statistics are reported in parentheses. Bootstrapped standard errors are double-clustered at the week and officer levels. $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Dependent variable:	Approval					
Busyness measure:	Predicted Busyness			LOO-Predicted Busyness		
	1	2	3	4	5	6
β_1BusynessDecile	-0.001**	-0.001**	-0.002***	-0.002***	-0.001	-0.002***
	(-2.014)	(-2.009)	(-2.712)	(-2.869)	(-1.642)	(-3.674)
β_2High-SES(Social)	0.428***		0.398***	0.428***		0.398***
	(65.296)		(60.452)	(67.947)		(60.394)
β_3High-SES(Social) $\times$ BusynessDecile	0.003***		0.003***	0.003***		0.003***
	(3.369)		(2.649)	(3.398)		(2.906)
β_4High-SES(Economic)		0.429***	0.378***		0.430***	0.377***
		(36.592)	(35.389)		(36.838)	(36.318)
β_5High-SES(Economic)$\times$ BusynessDecile		0.005***	0.003**		0.004***	0.003**
		(2.661)	(1.981)		(2.614)	(2.073)
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	0.218	0.341	0.272	0.218	0.341
$\beta_1 + \beta_3$	0.002***		0.002*	0.002***		0.001
P-value of $(\beta_1 + \beta_3)$	(0.000)		(0.064)	(0.008)		(0.187)
$\beta_1 + \beta_5$		0.003***	0.001*		0.003***	0.000
P-value of $(\beta_1 + \beta_5)$		(0.000)	(0.085)		(0.000)	(0.408)
First-stage F-Statistics	156.4	156.4	156.4	122.9	122.9	122.9

IB. Supplemental Empirical Results

In this section, we report supplemental empirical results.

1. Figure IB1 shows that, when officers work longer hours in a day, the average review time for each application is shorter.

2. Figure IB2 plots the estimated conditional difference between the high- versus low-SES applicants under each realized busyness decile.[37] For both review time and approval rate, the gap between the high- versus low-SES applicant groups keeps widening almost monotonically when loan officer gets busier and busier.

3. Figures IB3 and IB4 replicate Figure 1 using predicted and leave-one-out (LOO) predicted busyness instead of the actual busyness.

4. Figures IB5 and IB6 are similar to Figure IB2 but based on predicted and LOO-predicted busyness measures rather than realized busyness.

5. In Table IB1 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 A.

6. In Table IB2 we report results pertaining to the relationship between officer attention constraints and work patterns. When officers are busier, they begin working earlier and/or work late. That is, when officers are busier, they face longer working hours and work more overtime hours.

7. Table IB3 results resemble those of our main analyses reported in Tables II.

8. Table IB4 results resemble those of our main analyses reported in Tables IV and V, except that we estimate the effect of each individual social or economic status label instead of the overall social or economic status measure. For the sake of brevity, we present results using only LOO-predicted busyness. The results obtained using raw or predicted busyness are similar.

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[37]That is, we modify regressions in Section B using ten dummy variables to indicate each busyness decile and regress standardized review time or approval on the ten decile dummies, the High-SESindicator, and interaction with each decile dummy. The conditional difference between the high- versus low-SES groups for each busyness decile is then plotted in the figure.

[**Figure** IB1 about here.]

[**Figure** IB2 about here.]

[**Figure** IB3 about here.]

[**Figure** IB4 about here.]

[**Figure** IB5 about here.]

[**Figure** IB6 about here.]

[**Table** IB1 about here.]

[**Table** IB2 about here.]

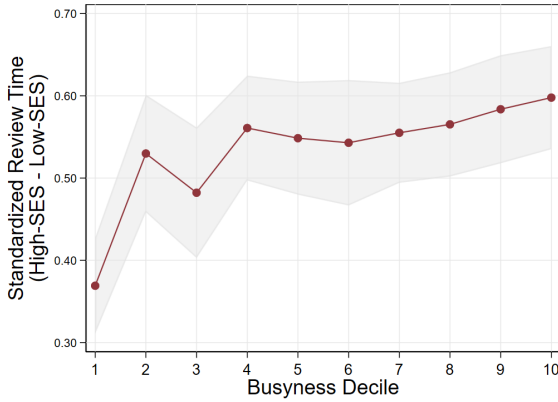[**Table** IB3 about here.]

[**Table** IB4 about here.]

Figure IB1. **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 A.
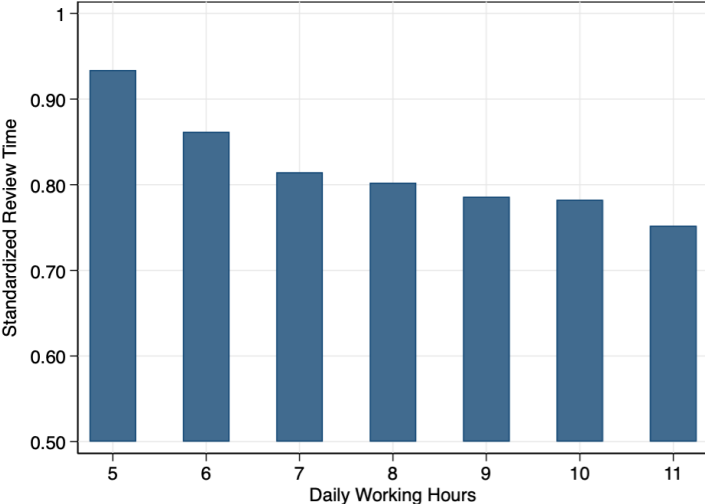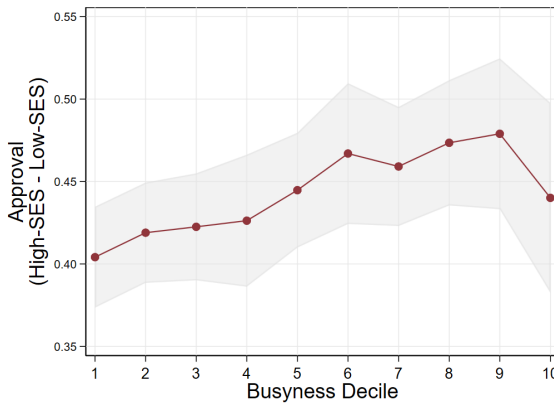
Figure IB2. Difference-in-Differences Effects of Loan Officer Attention Constraints

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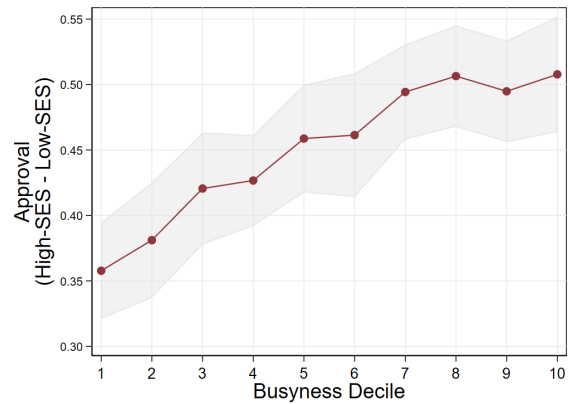

(a) Attention gap across social status
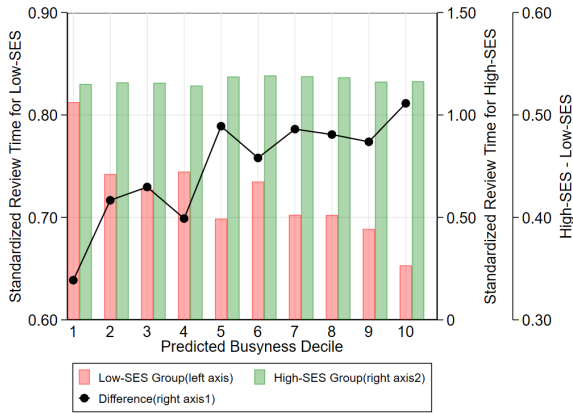
(b) Attention gap across economic status
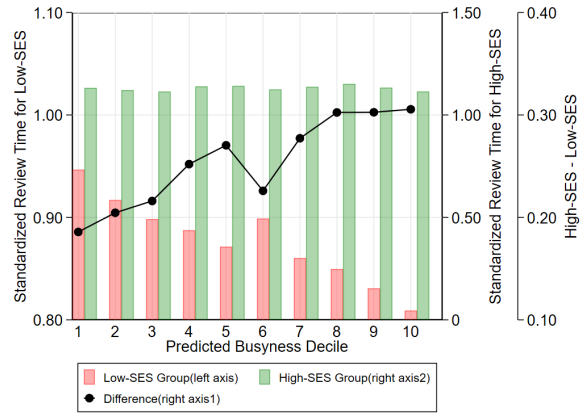
(c) Approval gap across social status

(d) Approval gap across economic status

25

Figure IB3. **Robustness Test of Figure 1: Attention and Approval Rates by Officer Attention Constraints, Instrumented Estimation**
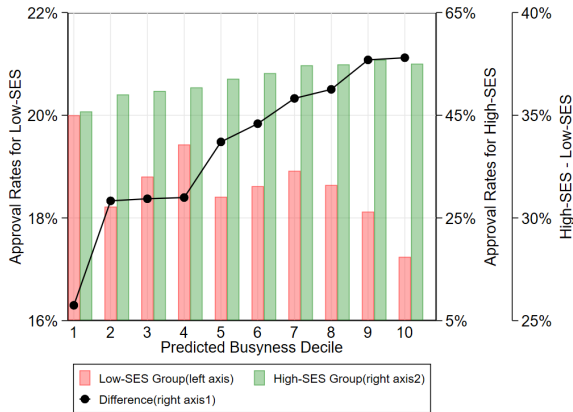
This figure is similar to Figure 1, except that we use loan officers' predicted busyness instrumented by the number of assignments as discussed in Section A. As explained in Section C, we use the possession (or not) of various labels to classify applicants into high- and low-SES groups based on social status (Panels (a) and (c)) or economic status (Panels (b) and (d)). In all panels, we sort the sample into deciles by officer attention constraints measured by their *busyness*, which is defined as the number of applications processed per day. Panels (a) and (b) plot the average officer attention allocation, measured as the standardized review time on each loan in the screening process, by busyness decile. Panels (c) and (d) plot the average loan approval rate by busyness decile. The measurement of standardized review time is explained in Section A. Each red (green) bar graphs the average for the low- (high-) SES group of applicants. The black line plots the differences between the two groups.
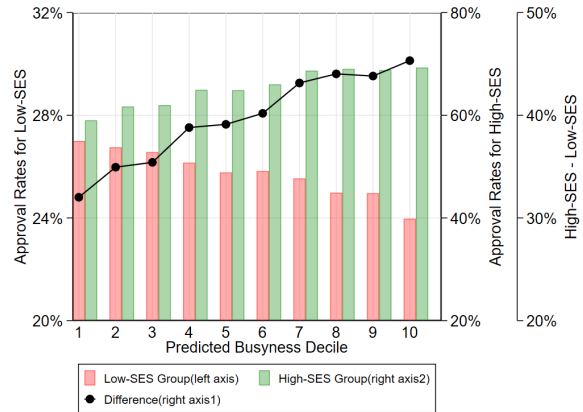

(a) Officer attention allocation by applicant social status

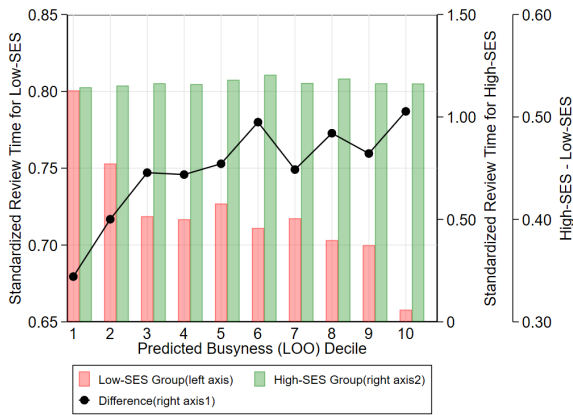**(b) Officer attention allocation by applicant economics status**

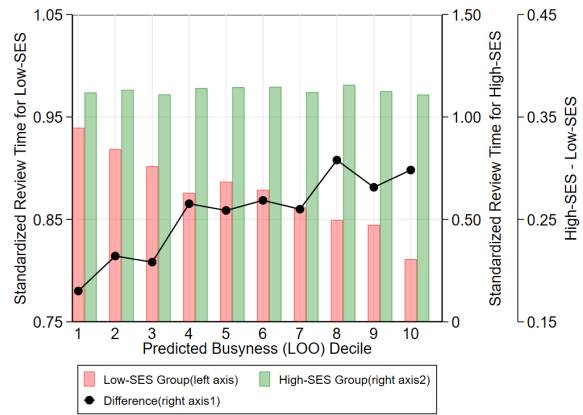**(c) Officer approval decision by applicant social status**

(d) Officer approval decision by applicant economics status

Figure IB4. **Robustness Test of Figure 1: Attention and Approval Rates by Officer Attention Constraints, LOO Instrumented Estimation**
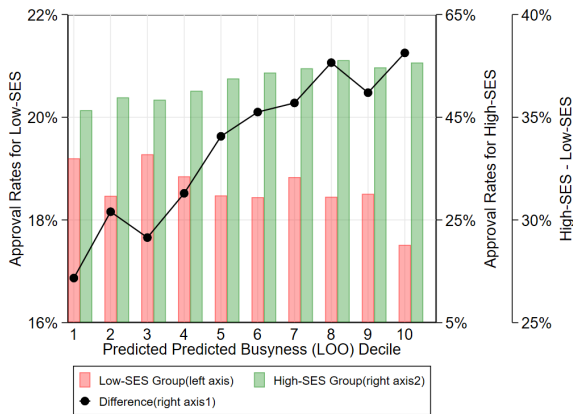
This figure is similar to Figure 1, except that we use loan officers' LOO predicted busyness instrumented by the number of assignments as discussed in Section A. As explained in Section C, we use the possession (or not) of various labels to classify applicants into high- and low-SES groups based on social status (Panels (a) and (c)) or economic status (Panels (b) and (d)). In all panels, we sort the sample into deciles by officer attention constraints measured by their *busyness*, which is defined as the number of applications processed per day. Panels (a) and (b) plot the average officer attention allocation, measured as the standardized review time on each loan in the screening process, by busyness decile. Panels (c) and (d) plot the average loan approval rate by busyness decile. The measurement of standardized review time is explained in Section A. Each red (green) bar graphs the average for the low- (high-) SES group of applicants. The black line plots the differences between the two groups.

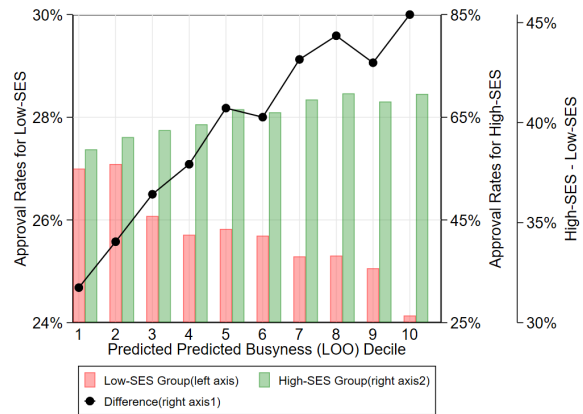**(a) Officer attention allocation by applicant social status**

(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 IB5. **Difference-in-Differences Effects of Loan Officer Attention Constraints, Instrumented Estimations**

This Figure replicates Figure IB2 except that we use the assignment-predicted busyness to measure loan officer attention constraints. The top panels plot the results for officer attention, measured as the standardized review time the loan officer spent on each application. The bottom panels plot the estimations for loan approval. For Panels (a) and (c), applicant SES is measured by their social status. For Panels (b) and (d), applicant SES is measured by their economic status. Fixed effects, controls, and standard error clustering are the same as those in Tables IV and V. 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 IB6. **Difference-in-Differences Effects of Loan Officer Attention Constraints, LOO Instrumented Estimations**
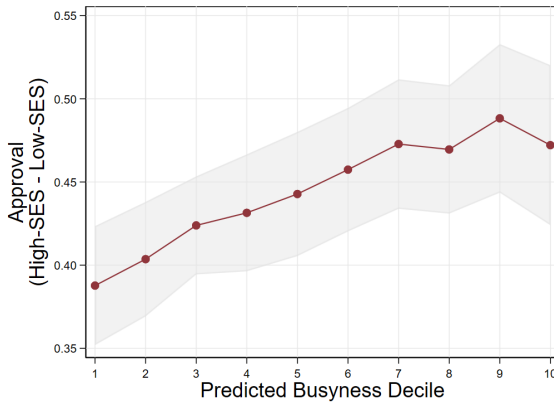
This Figure replicates Figure IB2 except that we use the leave-one-out (LOO) assignment-predicted busyness to measure loan officer attention constraints. The top panels plot the results for officer attention, measured as the standardized review time the loan officer spent on each application. The bottom panels plot the estimations for loan approval. For Panels (a) and (c), applicant SES is measured by their social status. For Panels (b) and (d), applicant SES is measured by their economic status. Fixed effects, controls, and standard error clustering are the same as those in Tables IV and V. The shaded areas represent the 95% confidence intervals for the corresponding regression coefficients.
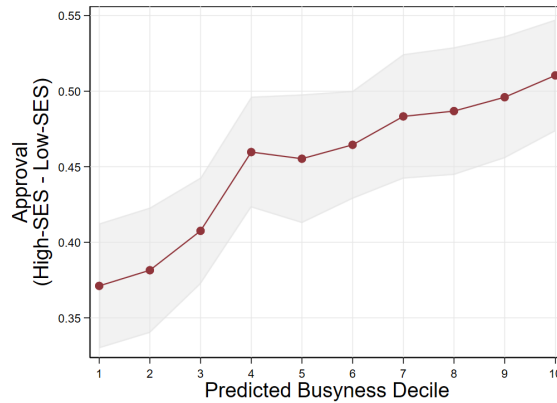
(a) Attention gap across social status

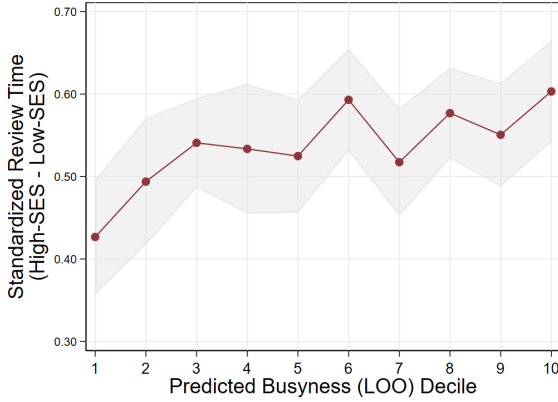**(b) Attention gap across economic status**

(c) Approval gap across social status

(d) Approval gap across economic status

Table IB1. 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 IB2. **The Relationship between Officer Busyness and Work Hour Patterns**

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

Dependent variable:	PunchInHour	PunchOutHour	DailyWorkingHours	HaveOvertime
	1	2	3	4
BusynessDecile	-0.046***	0.355***	0.404***	0.041***
	(-11.767)	(12.261)	(14.339)	(13.759)
Application Controls	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y
Week FE	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y
Observation	9,235	9,235	9,235	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***	0.197***	0.232***	0.030***
	(-7.444)	(5.480)	(6.461)	(6.580)
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	0.275	0.278	0.293	0.259

Table IB3. Higher Approval Probability for Applicants with More 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 C, *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 B1 for variable definitions. Standard errors are double-clustered at the week and officer levels. $***p < 1\%$, $**p < 5\%$, $*p < 10\%$.

Dependent variable:	Approval										
	1	2	3	4	5	6	7	8	9	10	11
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)	
log(1+LeverageRatio)	-0.265***	-0.185***	-0.133***	-0.211***	-0.254***	-0.239***	-0.186***	-0.139***	-0.141***	-0.145***	-0.267***
	(-36.742)	(-22.642)	(-13.175)	(-26.171)	(-34.237)	(-29.286)	(-22.489)	(-13.045)	(-13.255)	(-12.365)	(-37.740)
NoCreditHistory	-0.267***	-0.131***	-0.055***	-0.174***	-0.240***	-0.216***	-0.130***	-0.051***	-0.049***	-0.059***	-0.280***
	(-22.899)	(-17.220)	(-8.751)	(-18.105)	(-20.400)	(-21.334)	(-17.290)	(-8.288)	(-8.204)	(-10.379)	(-22.940)
log(1+OverdueMonth)	-0.050***	-0.018***	0.001	-0.030***	-0.041***	-0.036***	-0.019***	0.001	0.000	-0.001	-0.049***
	(-17.593)	(-7.701)	(0.464)	(-11.750)	(-16.738)	(-15.057)	(-8.042)	(0.303)	(0.122)	(-0.614)	(-17.610)
log(1+CreditInqury)	-0.000	-0.007***	-0.009***	-0.002	0.002	-0.007***	-0.007***	-0.010***	-0.011***	-0.010***	0.001
	(-0.113)	(-2.865)	(-4.170)	(-0.909)	(0.957)	(-3.042)	(-2.931)	(-4.602)	(-4.899)	(-5.099)	(0.204)
HasInvestmentAcc	-0.037***	-0.034***	-0.029**	-0.031**	-0.029**	-0.038***	-0.036***	-0.031***	-0.033***	-0.035***	-0.032**
	(-2.729)	(-2.784)	(-2.608)	(-2.500)	(-2.068)	(-2.869)	(-2.988)	(-2.737)	(-2.868)	(-2.920)	(-2.274)
SocialSecurity	0.029***	0.049***	0.041***	0.053***	0.059***	0.042***	0.037***	0.037***	0.034***	0.035***	0.060***
	(8.607)	(15.401)	(12.385)	(16.513)	(17.137)	(11.853)	(12.355)	(10.842)	(11.264)	(11.986)	(16.875)
Litigation	-0.090***	-0.056**	-0.030	-0.070***	-0.076***	-0.062**	-0.055**	-0.021	-0.019	-0.042*	-0.097***
	(-3.594)	(-2.522)	(-1.372)	(-3.232)	(-3.191)	(-2.540)	(-2.432)	(-0.948)	(-0.834)	(-1.765)	(-3.962)
Peasant	-0.014***	-0.016***	-0.014***	-0.015***	-0.012**	-0.013***	-0.016***	-0.013***	-0.014***	-0.025***	-0.013***
	(-3.092)	(-4.603)	(-4.630)	(-3.354)	(-2.631)	(-3.103)	(-4.656)	(-4.487)	(-4.819)	(-3.644)	(-2.830)
NonCollege	-0.003	-0.008***	-0.006**	-0.008***	-0.010***	-0.005*	-0.005**	-0.005*	-0.004	-0.002	-0.010***
	(-1.142)	(-3.179)	(-2.598)	(-3.099)	(-3.815)	(-1.855)	(-2.076)	(-1.915)	(-1.597)	(-0.719)	(-3.895)
Female	0.024***	0.016***	0.013***	0.018***	0.023***	0.014***	0.017***	0.012***	0.012***	0.013***	0.021***
	(9.090)	(6.262)	(5.105)	(7.582)	(8.743)	(5.052)	(6.662)	(4.503)	(4.440)	(4.517)	(8.270)
log(Age)	0.018***	0.003	-0.011**	0.009*	0.047***	0.009*	-0.001	-0.008*	-0.007	-0.003	0.029***
	(3.395)	(0.624)	(-2.132)	(1.875)	(9.662)	(1.789)	(-0.175)	(-1.714)	(-1.444)	(-0.678)	(5.977)
log(Income)	0.103***	0.088***	0.086***	0.091***	0.095***	0.043***	0.090***	0.066***	0.061***	0.048***	0.097***
	(16.979)	(19.584)	(18.008)	(16.441)	(14.710)	(8.312)	(20.338)	(14.184)	(13.546)	(10.079)	(15.540)
log(LoanToIncome)	0.067***	0.057***	0.056***	0.061***	0.075***	0.027***	0.056***	0.042***	0.038***	0.020***	0.071***
	(13.259)	(14.241)	(13.369)	(12.445)	(13.471)	(6.201)	(14.095)	(10.539)	(9.704)	(4.871)	(13.448)
ShortTerm	-0.231***	-0.198***	-0.173***	-0.212***	-0.223***	-0.213***	-0.198***	-0.171***	-0.171***	-0.036***	-0.235***
	(-13.106)	(-12.721)	(-13.109)	(-13.298)	(-13.083)	(-14.949)	(-12.861)	(-13.826)	(-13.884)	(-4.629)	(-12.792)
log(InterestRate)	-8.799***	-7.645***	-6.788***	-8.165***	-8.684***	-8.185***	-7.602***	-6.730***	-6.712***	-0.616***	-9.012***
	(-19.628)	(-19.613)	(-20.398)	(-19.757)	(-19.418)	(-22.634)	(-19.749)	(-21.010)	(-21.039)	(-2.085)	(-19.218)
Application Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y
Week FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y
Observation	145,982	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	0.123

Table IB4. The Effects of Officer Attention Constraints by Individual Socioeconomic Labels

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

Panel A: Officer attention by LOO-predicted busyness

Dependent variable:	StandardizedReviewTime					
	1	2	3	4	5	6
BusynessDecile	-0.016***	-0.020***	-0.022***	-0.019***	-0.017***	-0.018***
	(-4.940)	(-7.212)	(-5.945)	(-6.911)	(-4.745)	(-5.300)
PublicEmployee	0.141***					
	(3.916)					
PublicEmployee× BusynessDecile	0.016***					
	(4.309)					
LocalResident		0.512***				
		(39.224)				
LocalResident× BusynessDecile		0.012***				
		(209.026)				
EmploymentCert			0.514***			
			(207.519)			
EmploymentCert× BusynessDecile			0.013***			
			(20.005)			
IncomeCert				0.438***		
				(63.367)		
IncomeCert× BusynessDecile				0.013***		
				(52.386)		
RegularPay					0.194***	
					(33.758)	
RegularPay× BusynessDecile					0.015***	
					(20.066)	
HomeOwner						0.270***
						(80.159)
HomeOwner× BusynessDecile						0.016***
						(10.917)
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	0.036	0.075	0.087	0.064	0.037	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**	-0.003***
	(-1.476)	(-5.361)	(-8.133)	(-5.009)	(-2.120)	(-4.756)
PublicEmployee	0.209***					
	(12.698)					
PublicEmployee× BusynessDecile	0.005**					
	(2.253)					
LocalResident		0.423***				
		(56.485)				
LocalResident× BusynessDecile		0.008***				
		(6.909)				
EmploymentCert			0.472***			
			(64.066)			
EmploymentCert× BusynessDecile			0.010***			
			(8.324)			
IncomeCert				0.345***		
				(40.196)		
IncomeCert× BusynessDecile				0.010***		
				(7.022)		
RegularPay					0.376***	
					(27.183)	
RegularPay× BusynessDecile					0.007***	
					(4.164)	
HomeOwner						0.390***
						(40.462)
HomeOwner× BusynessDecile						0.013***
						(9.031)
Application Controls	Y	Y	Y	Y	Y	Y
Local Busyness Controls	Y	Y	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.143	0.270	0.359	0.229	0.174	0.221