# Data Regulation in Credit Markets *

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**Abstract**

We study a credit market in which the lender bases its lending decisions on a borrower's digital profile, and the borrower can manipulate its digital profile at a cost. We show that when the extent of data collected by the lender is observable, as the lender utilizes more data in its underwriting models, the borrower is more likely to manipulate their digital profile, which impairs the quality of the lender's data and its lending decisions. Therefore, even if obtaining and analyzing additional data is costless, the lender will voluntarily limit its own data coverage. In contrast, when the data coverage is unobservable, the lender tends to use all available data. Thus, disclosure policy can play a valuable role in allowing the lender to credibly commit to limiting its data coverage. Moreover, in the aggregate, borrowers too prefer that some digital data be collected.

**Keywords**: Data regulation, FinTech lending, Digital profiles, Alternative data, Manipulation

**JEL**: G21, G23

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# 1 Introduction

The increasing digitization of individuals' lives has led to the generation of a substantial amount of valuable data, derived from activities like app usage and social media engagement. These big data are increasingly utilized by lending companies to assess and evaluate borrowers in the credit market. In fact, one notable characteristic of FinTech lenders, as opposed to traditional banks, is their reliance on algorithms and alternative data as a substitute for face-to-face interactions between lenders and borrowers.

Once the digital profile information is widely used for lending decisions, it is natural that, as implied by the Lucas critique (Lucas, 1976), in response borrowers may change their behavior. In fact, borrowers may consciously attempt to manipulate their digital profile. While some variables in such a profile may be hard to manipulate, or may require a borrower to change her intrinsic habits (e.g., transaction records for utility bills), others can be manipulated more easily. For instance, a consumer may switch to an iOS device when applying for loans through an online lending platform, understanding that from the lender's point of view, iOS users imply higher income and lower default rates than Android users (Berg et al., 2020). Such manipulation adversely affects the quality of the data collected by a lender.

Moreover, given the extensive availability of digital data, regulators worldwide have implemented regulations pertaining to the utilization of alternative data in credit markets. For example, in 2019, the federal banking regulators in the United States issued an interagency statement that outlined the advantages and risks associated with the use of alternative data in assessing consumers' creditworthiness. Similarly, in 2021, the European Commission put forth proposed revisions to the Consumer Credit Directive, which aimed to tackle specific concerns pertaining to the processing of personal data within the consumer credit market. These revisions placed a strong emphasis on principles such as transparency, fairness, data minimization, and purpose limitation.

In this paper, we develop a theoretical model to examine the impact of lenders' utilization of big data technology on borrowers' manipulation behavior, as well as the reciprocal influence of borrowers' manipulation on the lenders' decisions. Our study sheds new light on the regulatory considerations surrounding the use of big data in credit markets. Our model features a single lender and a borrower. The borrower has a project for which she seeks funding from the lender. There are two types of borrowers, high and low, based on the probability the project will succeed. The type is privately known to the borrower.

The borrower has a digital profile connected to her underlying type. The lender chooses how much data to collect about the borrower's digital profile. The collected data generate a noisy signal about borrower creditworthiness, and the lender can base its credit decisions on this signal. Importantly, the borrower can manipulate their digital profile at some cost, in order to fool the lender about their type.

We consider two regulatory regimes: the transparent regime and the non-transparent regime. In the transparent regime, the extent of data used by the lender is observed to the borrower, whereas in the non-transparent regime, this data coverage remains unobservable. The transition from the non-transparent regime to the transparent one thus represents a regulatory change that enhances transparency regarding the utilization of big data in the credit market.

In the transparent regime, our key insight is that the low type borrower's incentive to manipulate their information increases rather than decreases in the extent of data collected by the lender. The better the data that the lender has, the more likely that those who generate high signals are indeed high types. As a result, the interest rate offered to borrowers who generate high signals is lower. This feature, in turn, implies that low types have a greater incentive to manipulate their data.

As a result of this increased manipulation, an increase in the data coverage in the lender's underwriting model can give rise to a non-monotonic effect on its expected lending profit in the transparent regime. On the one hand, better data coverage leads to more informed lending. On the other hand, increased data coverage can induce low-type borrowers to manipulate their digital profiles more often. That is, understanding that the lender would rely more on the collected data, the low-type borrowers have a greater incentive to disguise themselves as high types. This manipulation lowers the quality of the lender's data and impairs its lending decisions.

The latter negative force is more salient when the manipulation cost for borrowers is low and low-type projects have negative net present value (NPV). We show that in the transparent regime, the lender optimally chooses to limit its own coverage of big data in equilibrium. To establish our result as starkly as possible, in our model we assume there is no direct cost to acquiring more data.[1] By restricting its own data collection, the lender limits manipulation by borrowers, thus sustaining its data quality and its overall profit.

Our results imply there is an endogenous limit on the value of big data to a lender in the transparent regime. Acquiring additional data beyond this optimal limit results in the data itself being less useful for predicting default. As information becomes cheap in the digital age, in the spirit of Holmström informativeness (Holmström, 1979), it seems a lender should acquire and use unlimited amounts of information on borrowers. In our model, the lender has no direct cost to acquiring information. Rather, borrower manipulation renders the information less valuable, generating an endogenous cost to acquiring more of it.

In contrast, in the non-transparent regime, the lender chooses to maximize data usage. Essentially, the lender always has an incentive to deviate and increase its data coverage beyond what the borrower believes it is doing. Thus, when data coverage is unobserved by the borrower, the lender cannot credibly commit to limiting it.

Interestingly, we find that in the aggregate borrowers too may prefer that the lender acquire some digital information, rather than completely abstain from it. In particular, a lender who has more information can more easily discern between the types. In this scenario, high-type borrowers obtain better terms, and are initially better off with a better informed lender. Low-type borrowers, on the other hand, are worse off. Aggregate borrower payoff increases, because the improvement in the welfare of the high types initially dominates the reduction in welfare of the low types. If the lender continues to acquire digital data, however, manipulation by the low type increases to the point that the welfare of high-type borrowers also declines.

[1] It is immediate that if there were a large direct cost to increasing its data coverage, the lender would limit the amount of data acquired.

Our model can offer insights into the ongoing regulatory debate about the use of big data in the credit market.

Firstly, there is concern that transparency regarding the use of alternative data is inadequate. In the U.S., lenders are required by the Fair Credit Reporting Act (FCRA) and the Equal Credit Opportunity Act (ECOA) to disclose the sources and types of information used for credit decisions. However, the extent to which these regulations apply specifically to alternative data requires further clarification. In the EU, the 2021 proposal for the Consumer Credit Directive explicitly emphasizes that consumers should have the right to obtain a meaningful explanation of the credit assessment, including the main variables, logic, and associated risks involved.

In our framework, transparency is enhanced when the lender's data coverage becomes observable to the borrower. By comparing the transparent regime to the non-transparent one, we find that enhanced transparency regarding the use of alternative data grants the lender the power to commit to limiting its data coverage. This restrains borrower manipulation, preserves data quality, and maintains profitability. Therefore, rather than imposing additional restrictions that harm profitability, increased transparency actually benefits the lender.

Secondly, regulations may impose limitations on the use of data in credit lending. In the U.S., the Equal Credit Opportunity Act (1974) prohibits discrimination based on race, ethnicity, gender, and other factors in any aspect of credit. The Gramm-Leach-Bliley Act (GLBA) of 1999 establishes basic requirements for financial institutions to safeguard the privacy and security of consumer financial information. However, the EU has taken a more proactive approach. The 2021 proposal for the Consumer Credit Directive explicitly states that certain types of personal data, such as data from social media platforms or health data including cancer-related information, should not be used to assess creditworthiness. The European Data Protection Supervisor even suggests the prohibition of using search query data or online browsing activities, based on principles like purpose limitation, fairness, and transparency.

In our framework, we demonstrate that if the restriction on data usage is moderate, it might not impact the equilibrium or the mechanism highlighted in our paper. However, if the limit becomes highly restrictive, it can have adverse consequences for both the lender and the borrower.

More broadly, our framework allows us to understand the effects of different factors on borrower manipulation and on credit market outcomes. For example, as financial literacy improves, i.e., individuals gain better knowledge about the data used in credit underwriting and actions they can take to enhance their creditworthiness, the manipulation cost for borrowers may decrease. According to our model, this increase in financial literacy, coupled with the resulting lower manipulation cost, can potentially induce more manipulation, ultimately diminishing borrower payoff. On the other hand, anti-fraud measures implemented by lenders may actually benefit borrowers by deterring manipulation.

Our paper builds on the literature on manipulation in contracting settings, in which the agent can manipulate the observed performance measure. In such a setting, the multi-tasking model of Holmström and Milgrom (1991) implies that when manipulation of a particular variable is easy, the contract should not depend on that variable. In a moral hazard setting, Goldman and Slezak (2006) show that manipulation is more likely when managers have high-powered incentives. Lacker and Weinberg (1989) consider a situation with hidden information, and show the optimal contract may involve the agent falsifying the reported state. When both adverse selection and moral hazard are present, Beyer et al. (2014) find that in the presence of manipulation, the optimal contract is less steep than otherwise.

Recent work on agent manipulation in financial settings includes Barbalau and Zeni (2022) in the context of green bonds. Cohn, Rajan, and Strobl (2022) examine an issuer manipulating information provided to a credit rating agency, and tie the incentives to manipulate to the quality of the rating process. With respect to mortgage loans, Rajan, Seru, and Vig (2015) show that the interest rate on a loan becomes a worse predictor of default as securitization increases during the subprime crisis. Our manipulation mechanism provides one potential explanation for this documented failure of default models.

The general idea that an agent's endogenous action can induce information loss has many broad implications. For instance, Perez-Richet and Skreta (2022) study the optimal design of tests with manipulable inputs and find the optimal tests must induce productive falsification. Frankel and Kartik (2022) also show that data-based decision making should account for the manipulation of data by agents. Our application to the credit lending market allows us to determine normative implications and study the effects of different regulations on borrower and lender welfare.

Our paper is also related to the growing literature on FinTech lending and the use of big data in the lending business. Berg, Fuster, and Puri (2021) offer an excellent survey on this literature. Berg et al. (2020) and Agarwal et al. (2020) show that digital footprint variables can be important predictors of default, and usefully complement credit bureau information. Di Maggio and Yao (2021) note FinTech lenders' reliance on information provided in credit reports to automate their lending decisions fully, and Di Maggio, Ratnadiwakara, and Carmichael (2022) find that alternative data used by a major FinTech platform exhibit substantially more predictive power with respect to the likelihood of default than traditional credit scores. Jansen et al. (2022) analyze the welfare effects of increased data availability in the credit market. Theory wise, Parlour, Rajan, and Zhu (2022) examine the impact of FinTech competition with banks in payment services, He, Huang, and Zhou (2023) study the effect of open banking on lending market competition, and Li and Pegoraro (2022) model competition between banks and a bigtech platform. We contribute to this literature by focusing on borrowers' manipulation behavior and exploring its implications for the lender's decisions and the overall credit market.

# 2 The Model

We consider a credit market with a lender and a borrower. The borrower has a project that requires a financial investment of 1 unit at time 0. The project may either succeed or fail. If it succeeds, it generates a payoff at time 2 that is specified below. If it fails, the payoff is zero. The risk-free rate is zero, and both agents are risk-neutral.

The borrower is penniless and seeks external financing for the entire investment of 1. As is standard with limited liability, both parties receive zero when the project fails. Thus, without loss of generality, we can refer to the external financing contract as debt and the financier as a lender.

## 2.1 The Borrower

**The borrower's project:** There are two types of borrowers, high ($H$) and low ($L$), who differ in the likelihood that their project will be successful. Let $q_\theta$ denote the probability that the project of the borrower of type $\theta$ is successful, where $0 < q_L < q_H < 1$. The borrower privately knows her own type. The prior probability that the borrower has the high type is $\alpha \in (0, 1)$, and this fraction is common knowledge.

If the borrower accepts a loan from the lender, she undertakes the project. If the project fails, the borrower defaults. Otherwise, if the project succeeds, it generates a gross payoff of $1 + v$, where $v$ captures the profitability of a successful project. We assume that $v$ has an atomless distribution $F(\cdot)$ with support $[0, R]$ and density $f(\cdot)$. The distribution $F(\cdot)$ has an increasing hazard rate, that is, $\frac{f(v)}{1-F(v)}$ is increasing in $v$.

We assume that the borrower's outside option is zero. In other words, if the borrower does not secure the loan for the project, their payoff is zero. Further, we assume that $q_H(1 + R) > 1$, that is, the most profitable project (with profitability $R$) is positive-NPV for the high type.

**The borrower's digital profile:** In addition to her project type, the borrower has a digital profile denoted by $t \in \{H, L\}$. We use the term "digital profile" to include all "alternative data" about the borrower, that is, information other than traditional financial information that is considered when evaluating a loan applicant. As noted by Kona (2020), for individuals such alternative data includes information such as whether the borrower has been paying rent and utility bills on time (i.e., cash flow data), their academic background, and their employment history. In our usage, it also includes variables highlighted by Berg et al. (2020), such as the electronic device the borrower uses (e.g., desktop, tablet, or mobile), the operating system of the device (e.g., Windows, iOS, or Android), the channel through which a customer has visited a website, and the time at which a customer applies for a loan. In addition, there may be information gleaned from the number and types of apps installed, metrics of social connectivity, and their social media presence (Agarwal et al., 2020). For small and medium-sized businesses (SMBs), the digital profile can include their business ratings and reviews on social media and other sites like Yelp, website data such as traffic and global traffic rank, online presence, and engagement data.

Of course, in deciding whether to make a loan, the lender also considers traditional financial information such as the credit score, income, and wealth of the borrower, as well as their history with respect to debt (such as types of loans, outstanding balances, and length of credit history). These variables are factored into the success probabilities $q_H$ and $q_L$, as well as the probability $\alpha$ of the borrower being the high type. Our focus is on the *additional* information a lender may have from alternative data obtained from the user's online presence.

**Manipulation:** A key feature of our model is that the borrower can manipulate their digital profile. Manipulation increases the probability that the digital profile provides incorrect information about the borrower's type. Denote the borrower's manipulation decision as $m \in [0, 1]$. With probability $m$, the manipulation is successful, and a borrower of type $\theta$ presents a digital profile similar to someone of type $\tilde{\theta} \neq \theta$. With probability $1 - m$, the manipulation is unsuccessful, and their digital profile reveals them to be of type $\theta$. To manipulate, a borrower incurs a cost $C(m)$, where $C(0) = C'(0) = 0$ and $C'(m), C''(m) > 0$ for all $m > 0$.[2] The borrower's manipulation decision is unobserved by the lender.

There can be several ways to interpret the manipulation cost. First, it includes the expenditure of time, effort, and money for borrowers to manipulate their digital profiles. For example, an individual may intentionally switch from an Android phone to an iPhone when applying for a loan online, or a restaurant seeking more funding may engage in inflating Google reviews to enhance its social presence.

Second, manipulation can potentially have legal consequences and damage the borrower's reputation. For instance, in the case of the restaurant inflating its reviews, once the deception is

[2] In Section 6.1, we consider an extension in which the manipulation cost is affected by the lender's data technology as well, demonstrating the robustness of our insights.

uncovered, it can negatively impact the restaurant's reputation. Therefore, the potential loss of reputation can be considered as a form of manipulation cost.

## 2.2 The Lender

**Data technology:** The lender can leverage the power of alternative data in its lending business. It chooses a data technology $\rho \in [0, 1]$ in its underwriting model, where $\rho$ represents the probability that the lender successfully observes the digital profile of the borrower. The more advanced the data technology (i.e,, the higher the value of $\rho$), the more informative is the lender's signal about the borrower's digital profile.[3]

Specifically, the lender observes a signal about the borrower $s \in \{s_H, s_L, s_0\}$. With probability $1 - \rho$, the lender does not learn anything extra from the borrower's digital profile, and we say it observes the uninformative signal $s_0$. Conversely, the signals $s_H$ and $s_L$ allow the lender to update its priors over borrower type, as specified below. Because the signal obtained by the lender is directly informative only about the borrower's digital profile rather than the true type, the probability of receiving signal $s_H$ and signal $s_L$ depend on the extent of manipulation by the borrower.

To focus on the effect that manipulation by the borrower has on the lender, we assume that the lender faces no direct technological cost. That is, increasing $\rho$ has no cost for the lender, such as the cost of acquiring and processing the data and the risk of privacy violations. Thus, the only reason that the lender may not choose the most informative technology, $\rho = 1$, is due to the fact that manipulation by the borrower may lead to a reduction in signal quality.[4]

In practice, data technology used in underwriting models encompasses various aspects, including data coverage (that is, the amount and types of digital data obtained) and the quality of the algorithms used to extract relevant information from the data. For example, lenders may

[3]We didn't consider the lender's information collection about the borrower's project profitability $v$ because compared with the borrower type $\theta$ (and their digital profile), $v$ could reflect more transient or personal borrower characteristics which are hard to be captured by any data, e.g., the transient liquidity needs and the personal value of the loan to the individual borrower.

[4]In Section 6.2, we consider an extension in which the lender incurs costs to acquire and process data. We demonstrate the enduring validity of our insight in this context.

choose to incorporate more alternative data into their underwriting models to paint a more complete picture of a borrower's digital profile. Furthermore, even with the same set of alternative data collected in a loan application proposal, lenders can enhance their algorithms to generate more insightful and useful information. For convenience, going forward we interpret $\rho$ as the extent of coverage about the borrower's digital behavior.

**Regulatory regimes:** Depending on the regulatory regimes, the lender's data coverage $\rho$ can be observable to the borrower or not. In the transparent regime, where the lender is required to disclose "the main variables, the logic, and risks involved" in the credit underwriting model, $\rho$ is observable to the borrower. In contrast, in the non-transparent regime, the lender's data coverage $\rho$ remains opaque to the borrower.

**Loan pricing:** We assume the lender has deep pockets and can raise an arbitrary amount of funds at an interest rate normalized to zero. The lender's data collection facilitates personalized loan pricing. Specifically, the lender decision on whether to offer a loan to the borrower, and the interest rate if it does so, is contingent on the digital signal $s$ obtained from the borrower. The interest rate offered to the borrower is denoted as $r$. Thus, if a loan is accepted and the project succeeds, the lender obtains a net payoff $r$, whereas its net payoff is $-1$ when the project fails. Since no borrower will accept a loan offer at an interest rate strictly higher than the project's maximum profitability rate $R$, when the lender does not want to make a loan, it can simply offer the interest rate $R$.

## 2.3 Sequence of Moves

The sequence of moves in the game is illustrated in Figure 1. At time 0, the lender chooses its data coverage $\rho$ to maximize the expected profit from lending. In the transparent regime, the borrower can observe the data coverage, while in the non-transparent regime, the borrower cannot. The borrower then decides manipulation intensity $m$ after learning their type. At time 1, the borrower observes the profitability rate $v$ of their project. Then, the lender receives signals about the borrower and offers a personalized loan contract at the interest rate $r$. Based on the contract offer $r$ and the project profitability rate $v$, the borrower decides whether or not to accept the lender's loan offer. Finally, at time 2, the project's outcome is revealed, and both agents' payoffs are realized.

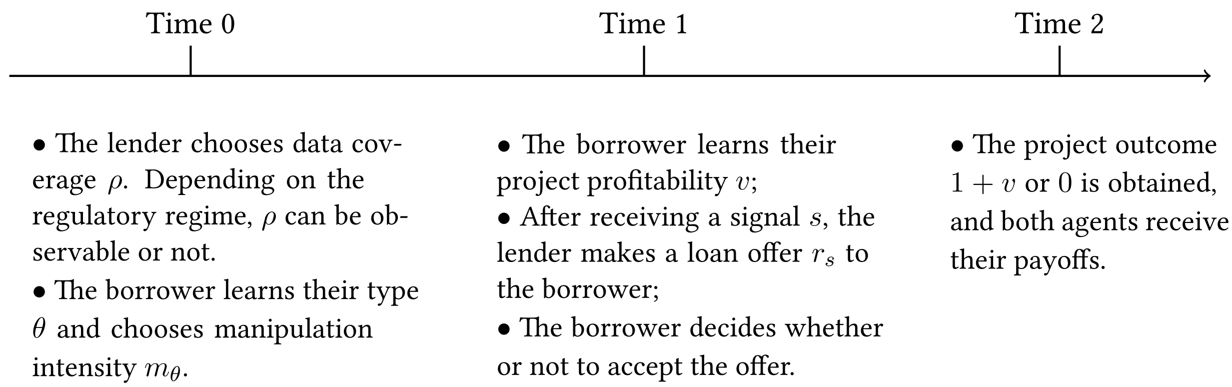



Figure 1: Timeline

## 2.4 Equilibrium Definition

We consider perfect Bayesian equilibria of the model. The lender chooses the extent of data coverage $\rho$ at time 0. At time 1, after receiving the digital signal $s$ it updates its belief over the borrower type and chooses the interest rate to offer to the borrower, $r_s$. The borrower knows their own type $\theta$ and chooses the extent of manipulation at time 0. Finally, at time 1, the borrower observes the project profitability and the offered interest rate $r_s$, and decides whether to accept or reject the loan.

**Definition 1** (Equilibrium)**.** *A* perfect Bayesian equilibrium *is characterized by the lender actions $\rho^* \in [0,1]$ and $r_s^*$ for each $s \in \{s_H, s_L, s_0\}$, borrower actions $m_\theta^* \in [0,1]$ for each $\theta \in \{H, L\}$ and a loan acceptance decision, and lender's posterior belief $\mu_s$ that the borrower has the high type given signal $s$, such that:*

(i) *The data coverage $\rho^*$ maximizes the lender's expected profit.*

(ii) *The manipulation intensity $m_\theta^*$ maximizes the expected payoff of a borrower with type $\theta$ given the borrower's belief about the data coverage.*

(iii) *The lender's interest rate offer $r_s^*$ maximizes its expected payoff given the digital signal it observes, $s$.*

(iv) *The lender's posterior belief $\mu_s$ given its digital signal $s$ satisfies Bayes' rule wherever possible.*

(v) *The borrower's loan acceptance decision maximizes their expected payoff given their type $\theta$ and project profitability $v$.*

The lender does not observe the manipulation decisions of each type of borrower. Rather, the lender forms a belief $\hat{m}_\theta$ about the extent of manipulation by each type, $m_\theta$. In equilibrium, of course, the lender's beliefs have to be correct. Similarly, in making their manipulation decisions, the borrower forms beliefs $\hat{\rho}$ regarding the lender's data coverage. When computing the equilibrium, we must specify a belief function $\hat{\rho}$, which stipulates how the borrower updates their belief $\hat{\rho}$ about the lender's data coverage. Specifically, in the transparent regime where the borrower observes the data coverage, the belief function is perfectly aligned with the lender's actual data coverage, i.e., $\hat{\rho} = \rho$. In contrast, in the non-transparent regime, the borrower cannot observe the lender's data coverage and the equilibrium belief consistency requires that $\hat{\rho} = \rho^*$, where $\rho^*$ is the equilibrium level of data coverage.

## 3 Borrower Behavior and Optimal Interest Rates

We now characterize the equilibrium in the main model. We begin the analysis by examining the borrower's decision to accept or reject a loan offer at time 1 and then proceed to move backward to time 0 in our analysis.

## 3.1 Optimal Loan Acceptance Decisions by the Borrower

Suppose that the borrower accepts a loan at interest rate $r$ and undertakes the project. If the project succeeds, the borrower repays the loan plus the interest rate, obtaining a net payoff $v - r$. Otherwise, if the project fails, the borrower defaults and receives $0$. As such, for $\theta \in \{H, L\}$, the borrower's expected payoff if they accept the loan is

$$w(\theta, r) = q_\theta \left[ v - r \right]. \tag{1}$$

The borrower has an outside option of zero. Thus, the borrower accepts the loan if $r < v$, is indifferent if $r = v$, and rejects if $r > v$. Going forward, we assume that an indifferent borrower accepts the loan, so that the borrower accepts if and only if

$$r \leq v. \tag{2}$$

Thus, at time 0, the lender believes that the probability that the borrower will accept a loan at rate $r$ is $1 - F(r)$, which characterizes the demand function faced by the lender.[5]

## 3.2 Optimal Interest Rates Offer by the Lender

Consider the lender's choice of the interest rate to offer the borrower. After observing signal $s \in \{s_H, s_L, s_0\}$, which may be contaminated by the borrower manipulation, the lender updates its posterior beliefs about the borrower type. Let $\mu_s$ denote the lender's posterior belief that the borrower has the high type given signal $s$, that is, $\mu_s \equiv \Pr(\theta = H|s)$. Let $\bar{q}_s = \mu_s q_H + (1 - \mu_s) q_L$ denote the average success rate of the project given signal $s$.

The lender understands that if it makes a loan offer at interest rate $r$, the borrower accepts the offer with probability $1 - F(r)$. Conditional on the borrower accepting the offer, the lender obtains a net payoff $r$ if the project succeeds and $-1$ if the project fails. Therefore, the lender's

[5] For simplicity, we do not explicitly incorporate limited liability for the borrower in our analysis. With limited liability, one could argue that a borrower with $v < r$ may also accept the loan and accept a net payoff of zero. Formally, one could introduce an arbitrarily small cost to the borrower from undertaking the project. In this case, the borrower will strictly prefer to reject the loan if $v \leq r$. Hence, our analysis may be interpreted as focusing on the limiting case in which the cost to the borrower of undertaking a project approaches zero.

expected payoff is

$$\pi_s(r) = (1 - F(r))\left[\bar{q}_s \cdot r \,-\, (1 - \bar{q}_s)\right]. \tag{3}$$

The offered interest rate $r_s$ maximizes this expected payoff.

Given signal $s$, the lender's posterior belief $\mu_s$ depends on its beliefs over the borrower's manipulation intensity. In equilibrium, of course, the lender's beliefs about manipulation must match the borrower's actual manipulation intensity.

**Lemma 1.** *Suppose the lender obtains signal $s \in \{s_H, s_L, s_0\}$. Then,*

(i) *If $\bar{q}_s(1+R) \geq 1$, the optimal interest rate $r_s$ satisfies the equation*

$$r - \frac{1 - F(r)}{f(r)} = \frac{1}{\bar{q}_s} - 1. \tag{4}$$

(ii) *If $\bar{q}_s(1+R) < 1$, the optimal interest rate is $r_s = R$.*

Equation (4) is the first-order condition that emerges from the lender's maximization problem. Given signal $s$, if some projects have a weakly positive NPV (i.e., $\bar{q}_s(1+R) \geq 1$), the lender sets an interest rate according to equation (4). As in auction theory, the left-hand side can be interpreted as the virtual interest rate. Rewriting the equation as $r_s = \frac{1}{\bar{q}_s} - 1 + \frac{1-F(r_s)}{f(r_s)}$, the lender charges a markup over the zero-profit interest rate $\frac{1}{\bar{q}_s} - 1$.

Of course, if given signal $s$, all projects have negative NPV (i.e., $\bar{q}_s(1+R) < 1$), the lender simply rejects the loan application by setting $r_s = R$.

## 3.3 The Borrower's Manipulation Decision

Next, consider the manipulation decision of the borrower. When making manipulation decisions, the borrower holds a belief $\hat{\rho}$ about the lender's data coverage. As discussed above, the specification of the belief function depends on the regulatory regime. Suppose the borrower of type $\theta \in \{H, L\}$ manipulates with probability $m_\theta$. Since the borrower's manipulation decision is not observable to the lender, the lender only holds a belief about her manipulation intensity, denoted as $\hat{m}_\theta$ for each $\theta$. The lender's belief about borrower manipulation in turn affects its posterior belief about borrower type given signal $s$. Finally, the lender's posterior beliefs determine the interest rates offered after each signal, as in Lemma 1.

Taking this belief $\hat{m}_\theta$ as given, each type of borrower determines their actual manipulation intensity $m_\theta$ accounting for the following scenarios. With probability $1-\hat{\rho}$, the digital signal is $s_0$. With probability $\hat{\rho}$, the digital signal about the borrower is either $s_H$ or $s_L$. In this case, the digital signal equals the underlying borrower type $\theta$ with further probability $1-m_\theta$, and the other type $\tilde{\theta}$ with probability $m_\theta$.

Putting all this together, the expected payoff of the borrower of type $\theta$ is

$$u(\theta, m_\theta; \hat{m}_\theta, \hat{\rho}) = -C(m_\theta) + \hat{\rho}\, m_\theta \cdot \underbrace{q_\theta \int_{r_{\tilde{\theta}}}^{R} (v - r_{\tilde{\theta}}) dF(v)}_{\text{payoff when mistaken for the other type}}$$

$$+ \hat{\rho}\,(1-m_\theta) \cdot \underbrace{q_\theta \int_{r_\theta}^{R} (v - r_\theta) dF(v)}_{\text{payoff when type is correctly recognized}} + (1-\hat{\rho}) \cdot \underbrace{q_\theta \int_{r_0}^{R} (v - r_0) dF(v)}_{\text{payoff when digital signal is uninformative}} . \quad (5)$$

Note that when type $\theta$ generates signal $s_\theta$, we say it has been "correctly recognized," whereas when it generates signal $s_{\tilde{\theta}} \neq s_\theta$, we say it has been "mistaken for the other type." We show below in Proposition 1 that type $H$ never generates signal $s_L$ in equilibrium, and that type $L$ may generate either signal $s_H$ or signal $s_L$.

There are three cases to consider in equation (5). First, given the borrower's belief $\hat{\rho}$ about the lender's data technology, with probability $\hat{\rho} \cdot m_\theta$ the borrower will successfully pretend to be a different type $\tilde{\theta} \neq \theta$ and be offered the interest rate $r_{\tilde{\theta}}$. As discussed in Section 3.1, if the realized project profitability rate $v$ exceeds $r_{\tilde{\theta}}$, the borrower accepts the offer, obtaining an expected payoff $q_\theta(v - r_{\tilde{\theta}})$. Otherwise, the borrower goes for the outside option and obtains a payoff of zero. Therefore, when the borrower manipulates successfully, her expected payoff is $q_\theta \int_{r_{\tilde{\theta}}}^{R} (v - r_{\tilde{\theta}}) dF(v)$.

Second, with probability $\hat{\rho}(1-m_\theta)$, the borrower's digital profile will be correctly recognized as belonging to type $\theta$. The offered interest rate is $r_\theta$. Again, she accepts the loan offer $r_\theta$ if $v \geq r_\theta$, and settles for the outside option otherwise. Thus, the expected payoff in this case is

$q_\theta \int_{r_\theta}^{R}(v - r_\theta)dF(v)$.

Finally, with the remaining probability $1-\hat{\rho}$, the lender's digital signal is uninformative about borrower type, and the borrower will be offered the interest rate $r_0$. Again, the borrower needs to make a choice between the loan offered by the lender featured with interest rate $r_0$ and the outside option. The resulting expected payoff for the borrower is $q_\theta \int_{r_0}^{R}(v - r_0)dF(v)$.

We show that the high-type borrower never manipulates and the low-type borrower manipulates with positive probability (i.e., $m_H^* = 0$ and $m_L^* > 0$) if they believe that lender's data coverage is strictly positive: $\hat{\rho} > 0$. Let $r_j$ denote the optimal interest rate offered by the lender following signal $s_j$.

**Proposition 1.** *Suppose that the borrower's belief about the lender's data coverage $\hat{\rho} > 0$. Define the marginal payoff of a low-type borrower who manipulates with intensity $m$ and succeeds as the following:*

$$B(m \,|\, \hat{\rho}) = \hat{\rho}\, q_L \left( \int_{r_H(m)}^{R} (v - r_H(m))dF(v) - \int_{r_L}^{R} (v - r_L)dF(v) \right). \tag{6}$$

*Then, in the equilibrium that emerges in the subsequent subgame,*

(i) *The high-type borrower does not manipulate their digital profile, i.e., $m_H^* = 0$.*

(ii) *The low-type borrower manipulates with positive probability, and the equilibrium manipulation intensity $m_L^*$ is either equal to 1, or satisfies the equation*

$$B(m_L \,|\, \hat{\rho}) = C'(m_L), \tag{7}$$

*where $B(\cdot)$ is given by equation (6).*

(iii) *The interest rates offered by the lender satisfy $r_H < r_0 < r_L$.*

Whenever the borrower believes that the lender acquires some digital data (i.e., $\hat{\rho} > 0$), the subsequent equilibrium sees no manipulation by the high-type borrower, but some manipulation by the low-type borrower. Going forward, for the rest of the paper, we set $m_H = 0$, and use the subscript-less variable $m$ to indicate $m_L$, optimal manipulation by the low type. The signal structure implied by Proposition 1 is then shown in Figure 2.

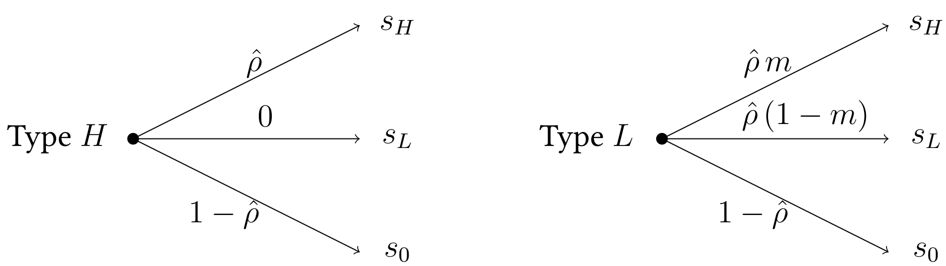



Figure 2: Structure of digital signal when the high-type borrower does not manipulate, and the low type manipulates with intensity $m$

Part (ii) of Proposition 1 analyzes the manipulation intensity of a low-type borrower. For a low-type borrower, a marginal increase in manipulation intensity would enable her to secure a loan with an interest rate of $r_H$, resulting in an expected payoff increase of $q_L \left( \int_{r_H(m)}^{R} (v - r_H(m)) dF(v) - \int_{r_L}^{R} (v - r_L) dF(v) \right)$. This scenario occurs when the borrower's digital profile is detected by the lender, which happens with a probability of $\hat{\rho}$. Equation (6) thus summarizes the marginal benefit for such a low-type borrower. Moreover, taking into account the manipulation cost, we can express the net benefit of manipulation for the low-type borrower as $B(m \,|\, \hat{\rho}) - C'(m)$.

As part (ii) of Proposition 1 shows, if the net benefit of manipulation at $m = 1$ is still positive for the low-type borrower, the equilibrium manipulation intensity is $m = 1$. Otherwise, the equilibrium manipulation intensity takes an interior solution, determined by $B(m \,|\, \hat{\rho}) = C'(m)$, as given by equation (7). In equation (7), we write the interest rate charged for the borrower with high-type digital profiles as $r_H(m)$ to emphasize that the interest rate is a function of the manipulation intensity $m$.

Given the manipulation strategies of each type of borrower, and using the fact that in equilibrium the lender's beliefs must match the actual manipulation strategies, the lender's posterior beliefs after each signal may be written as follows. Let $\mu_j$ denote the posterior probability of the high-type borrower after signal $s_j$. Then, $\mu_L = 0$, $\mu_0 = \alpha$, and $\mu_H = \frac{\alpha}{\alpha + (1-\alpha)m} \in (0, \alpha)$. As part (iii) of the proposition says, it follows that the interest rate is lowest after signal $s_H$ and highest after signal $s_L$.

As noted earlier, the borrower's manipulation intensity depends on the interest rates offered by the lender. The lender's optimal interest rate offers, in turn, depend on the lender's beliefs about the manipulation intensity. In equilibrium, the lender's beliefs must be correct.

The following corollary summarizes the equilibrium relationship between the manipulation intensity and the lender's interest rate offers.

**Corollary 1** (Manipulation and optimal interest rates)**.** *In equilibrium, when the low-type borrower's manipulation intensity* $m$ *increases,*

(i) *the interest rate charged for the borrower with a high-type digital profile increases, i.e.,* $\frac{\partial r_H}{\partial m} > 0$*;*

(ii) *the interest rate charged for the borrower that is unrecognized and that for the borrower with a low-type digital profile does not change, i.e.,* $\frac{\partial r_0}{\partial m} = 0$ *and* $\frac{\partial r_L}{\partial m} = 0$.

Part (i) of Corollary 1 states that when the low-type borrower is more likely to manipulate their digital profile, the lender will set higher interest rates upon receiving the high-type signal. A higher manipulation intensity by the low-type borrower lowers the posterior belief that the borrower is truly high-type, hence the average success rate of the borrower's project (i.e., $\frac{\partial \mu_H}{\partial m} < 0$ and $\frac{\partial \bar{q}_H}{\partial m} < 0$). As a result, the lender raises the interest rate when offering the loan as compensation for the lower likelihood of retrieving the initial funding.

By contrast, as long as the signal does not reveal anything about the borrower type, the lender always charges the interest rate $r_0$ as given by Lemma 1, regardless of the low-type borrower's manipulation intensity $m$. This result is intuitive because $m$ does not affect the lender's posterior belief when the signal is uninformative. Likewise, the lender knows that the borrower is a low type with certainty upon signal $s = L$, and again, the resulting interest rate $r_L$ is not affected by $m$.

Furthermore, equation (7) clearly shows that the low-type borrower's manipulation intensity is affected by their belief about the lender's data coverage. The following corollary formally presents the result. Let $m^*(\hat{\rho})$ be the equilibrium manipulation intensity given the belief $\hat{\rho}$ about data coverage.

**Corollary 2.** *Suppose $m^*(\hat{\rho}) < 1$. Then, the higher the belief about the data coverage chosen by the lender, the more intensively the low-type borrower manipulates their digital profile. That is, $\frac{\partial m^*}{\partial \hat{\rho}} > 0$.*

When the borrower believes that the lender adopts higher data coverage in its underwriting process (i.e., $\hat{\rho}$ increases), a borrower's digital profile is more likely to be revealed. Understanding this, a low-type borrower will have a greater incentive to manipulate their data, and to pretend to be a high-type borrower. The resulting positive relationship between the belief about the lender's choice of data coverage and the low-type borrower's manipulation intensity, as summarized in Corollary 2, underlies the key mechanism in our paper, driving the main insight in Section 4.

# 4 Optimal Data Coverage by the Lender

We now turn to the lender's choice of data coverage, $\rho$. At the beginning of time 0, the lender chooses data coverage to maximize its unconditional expected profit in the lending business, understanding how borrowers form belief about its data coverage in different regulatory regimes. Recall from equation (3) that the profit after signal $s$ and interest rate offer $r$ is $\pi_s(r) = (1 - F(r))[\bar{q}_s r - (1 - \bar{q}_s)]$, where $\bar{q}_s = \mu_s q_H + (1 - \mu_s) q_L$ is the average quality of the project given signal $s$. The optimal interest rate offer $r_s$ also varies by signal, and is given by equation (4) in Lemma 1.

The low-type borrower manipulates with intensity $m$. Overall, therefore, the borrower presents a high-type digital profile with probability $\alpha + (1 - \alpha)m$. With a further probability $\rho$, the borrower will generate signal $s_H$ from the lender's data technology and receive the interest rate $r_H$. The lender in turn makes an expected profit of $\pi_H(r_H)$.

Next, with probability $(1 - \alpha)(1 - m)$ the low-type borrower continues to have the digital profile of a low type. It is recognized as the low type by the lender with a further probability $\rho$. In this case, the lender makes an expected profit of $\pi_L(r_L)$.

Finally, with probability $1 - \rho$, the lender's data technology does not work, and the borrower will be unrecognized regardless of her underlying type. In this case, the lender sets interest rate

$r_0$ and makes profit $\pi_0(r_0)$. Overall, the lender's unconditional expected profit at time 0 may be written as:

$$\Pi(\rho;\hat{\rho}) = \rho\Big(\{\alpha + (1-\alpha)m\}\pi_H(r_H) + (1-\alpha)(1-m)\pi_L(r_L)\Big) + (1-\rho)\pi_0(r_0). \qquad (8)$$

Note that in equation (8) data coverage $\rho$ affects the unconditional expected profit $\Pi$ directly. As implied by equations (4) and (7), the low-type borrower's manipulation intensity $m$ and the lender's optimal interest rate $r_H$ are affected by the borrower's belief $\hat{\rho}$ about the data coverage. Thus, the lender's actual data coverage $\rho$ also indirectly affects $\Pi$ through $m$ and $r_H$ in the transparent regime since $\hat{\rho} = \rho$ there.

To highlight the effects of borrower manipulation on the lender's choice of data coverage, we first consider a benchmark case in which the borrower cannot manipulate. We will then discuss the equilibrium data coverage in both the transparent and non-transparent regimes.

## 4.1 Benchmark: No Manipulation

Consider first a benchmark economy in which the borrower is unable to manipulate their digital profile, that is, $m_\theta = 0$ for each $\theta \in \{H, L\}$.[6] Consequently, the borrower's digital profile accurately reflects their true type.

In this scenario, if the lender's signal provides any information, it directly reveals the borrower's type. That is,

$$s = \begin{cases} s_\theta & \text{with probability } \rho, \text{ for each } \theta \in \{H, L\} \\ s_0 & \text{with probability } 1-\rho. \end{cases} \qquad (9)$$

In particular, the quality of the signal strictly improves with digital data coverage $\rho$. Given that increasing $\rho$ incurs no additional costs, it is evident that the lender prefers maximum data coverage.

**Proposition 2** (No-manipulation benchmark)**.** *Suppose the borrower cannot manipulate their digital profile. Then, regardless of the regulatory regimes, in equilibrium the lender chooses maximal*

[6] Alternatively, we can assume the borrower's marginal cost of manipulation is infinite for any positive $m$, i.e., $C'(m) = \infty$ for any value of $m > 0$.

*data coverage, i.e., $\rho^* = 1$. Hence, the digital signal is fully informative about borrower type.*

In the absence of borrower manipulation, the lender will actively pursue all accessible digital data prior to granting a loan. This finding is intuitive because, in such a scenario, gathering more data unequivocally leads to improved borrower screening, yielding only benefits.

## 4.2 The Transparent Regime: Endogenous Limits on Data Coverage

We now return to our base model, in which the borrower may manipulate their digital profile. In this section, we study the equilibrium in the transparent regime. When the lender's data coverage is observable to the borrower, their belief about the data coverage is always consistent with the lender's actual data coverage, i.e., $\hat{\rho} = \rho$.

In the transparent regime, we are particularly interested in understanding under what circumstance the lender's optimal choice of data coverage is strictly below 1, that is, $\rho^* < 1$. The key insight builds on Corollary 2. Manipulation by the low-type borrower reduces the lender's profit. Suppose that if the lender chooses full data coverage (i.e., sets $\rho = 1$), the low-type borrower optimally manipulates with less than full intensity (i.e., chooses $m < 1$). Then, by reducing its data coverage slightly, the lender can induce the low-type borrower to reduce the extent of manipulation. The direct effect of reducing data coverage is to reduce lender profit, whereas the indirect effect of thereby reducing borrower manipulation increases lender profit.

We identify sufficient conditions under which the indirect effect outweights the direct effect, and overall lender profit is greater at some $\rho < 1$ than at $\rho = 1$. Recall that the interest rate charged after signal $s_H$ depends on the manipulation intensity of the low-type borrower, $m$. If the borrower manipulates fully (i.e., sets $m = 1$), the belief after signal $H$ is $\mu_H = \alpha$, that is, it is equal to the prior and to the belief after signal $r_0$. Thus, the optimal interest rate set by the lender in this case is $r_0$.

**Proposition 3** (Optimal data coverage in the transparent regime)**.** *Suppose the lender's choice of digital data coverage, $\rho$, is observable to the borrower. In equilibrium,*

(i) *The lender chooses a strictly positive data coverage, i.e.,* $\rho^* > 0$.

(ii) *If* $q_L < \frac{1}{1+R}$ *(i.e., low-type projects are all negative NPV) and* $C'(1) \leq B(1 \,|\, 1)$ *(i.e., manipulation cost is sufficiently low), where* $B(\cdot)$ *is given by equation (6), the lender chooses less than full data coverage (i.e.,* $\rho^* < 1$*).*

Proposition 3 shows that, in the transparent regime, despite the data technology having no direct cost in our model, the lender may choose to adopt less than full data coverage. This result sharply contrasts with the benchmark economy without manipulation.

The conditions in part (ii) of the proposition include: (a) projects of low-type borrowers all have negative NPV, or $q_L(1+R) < 1$, and (b) the borrower's manipulation cost is sufficiently low. More specifically, Condition (b) states that the highest manipulation cost $C'(1)$ should be lower than a threshold denoted by $B(1 \,|\, 1)$. Based on equation (6), the low-type borrower's marginal manipulation benefit monotonically decreases in the manipulation intensity. Thus, when the low-type borrower manipulates with full intensity, the marginal payoff becomes the lowest. In this case, the lender's signal $s_H$ becomes completely uninformative, leading to the same level of interest rates under the high signal and no signal, that is, $r_H(1) = r_0$. We thus can rewrite the threshold $B(1 \,|\, 1)$ as

$$B(1 \,|\, 1) = q_L \left( \int_{r_0}^{R} (v - r_0) dF(v) - \int_{r_L}^{R} (v - r_L) dF(v) \right). \tag{10}$$

Taken together, the second condition implies that the digital profile is easily manipulable, and the first ensures that such manipulation by the low type leads to a significant deterioration in lender profit. In such a case, the lender endogenously avoids full data coverage in order to maintain data quality. Note that these are sufficient conditions, and the result on the lender choosing less than full data coverage can continue to hold if the conditions are violated in a minor way.

We will show in the next section that the borrower being able to observe the extent of data coverage chosen by the lender is critical to the result in Proposition 3.

## 4.3 The Non-Transparent Regime

In the non-transparent regime, the lender's choice of data coverage remains opaque to the borrower. The equilibrium consistency requires that the borrower's belief about the data coverage must match the lender's actual choice in equilibrium, i.e., $\hat{\rho} = \rho^*$.

**Proposition 4** (Optimal data coverage in the non-transparent regime)**.** *Suppose the lender's choice of digital data coverage, $\rho$, is not observable to the borrower. Then,*

(i) *If $C'(1) < B(1 \mid 1)$, where $B(1 \mid 1)$ is given by equation (10), there is an equilibrium the lender chooses maximal data coverage, i.e., $\rho^* = 1$, and the low-type borrower manipulates with probability 1 (i.e., $m^* = 1$).*

(ii) *If $C'(1) \geq B(1 \mid 1)$, there is a unique equilibrium in which the lender chooses maximal data coverage, i.e., $\rho^* = 1$, and the low-type borrower manipulates with strictly positive probability (i.e., $m^* > 0$).*

Proposition 4 shows that when the lender's credit underwriting model remains opaque to the borrower, the maximal data coverage can always be sustained in equilibrium, i.e., $\rho^* = 1$. Notably, the borrower will choose to manipulate their digital profile, so here the lender's signal is not fully informative about borrower type.

Why does the lender choose maximal data coverage? Suppose, instead, the borrower believes the lender limits the scope of alternative data it acquires ($\hat{\rho} < 1$). In response to this belief about the data coverage, the borrower will restrict their manipulation of their digital profile. However, the lender now has an incentive to deviate and increase its data coverage. In other words, the lender cannot credibly commit to acquiring limited information about the borrower.

Importantly, since the borrower cannot observe the actual increase in data coverage, she only makes her manipulation decision based on her belief about the data coverage. Therefore, for any belief $\hat{\rho}$ the borrower may have about the lender's data coverage such that $m(\hat{\rho}) < 1$, the lender strictly prefers acquiring more data. In equilibrium, this force drives the lender towards achieving the highest possible data coverage.

In Section 5, we will examine the implications of regulations that impose transparency on the use of alternative data in credit markets. We will compare the equilibria in the transparent and non-transparent regimes to gain insights into these implications.

### 4.4 Borrower Surplus and Total Surplus

Having examined the optimal data coverage for the lender in both the transparent and non-transparent regimes, in this section, we explore the effects of the equilibrium data coverage on the borrower and the social planner. To simplify notations, we denote the equilibrium data coverage as $\rho$.

First, consider the borrower. Let $u_\theta(\rho)$ be the expected utility of the type $\theta$ borrower when the data coverage is $\rho$. Here,

$$u_H(\rho) = q_H\Big\{\rho\int_{r_H(m)}^{R}(v-r_H(m))dF(v)+(1-\rho)\int_{r_0}^{R}(v-r_0)dF(v)\Big\}, \tag{11}$$

$$\begin{aligned} u_L(\rho) = q_L\Big\{&\rho m\int_{r_H(m)}^{R}(v-r_H(m))dF(v)+\rho(1-m)\int_{r_L}^{R}(v-r_L)dF(v) \\ &+(1-\rho)\int_{r_0}^{R}(v-r_0)dF(v)\Big\}-C(m). \end{aligned} \tag{12}$$

Note that $m$, the equilibrium manipulation intensity of the low-type borrower, depends on $\rho$.

The borrower's ex ante expected payoff is

$$\mathcal{U}=\alpha\, u_H+(1-\alpha)\, u_L. \tag{13}$$

The social planner cares about the total surplus, which is defined as the sum of the lender profit and the borrower surplus:

$$\mathcal{S}=\Pi+\mathcal{U}, \tag{14}$$

where the lender profit $\Pi$ and the borrower surplus $\mathcal{U}$ are given by equations (8) and (13), respectively.

We show that there are conditions under which both the borrower and the social planner have a higher utility when the data coverage is strictly positive. It is unsurprising that the lender's profit would be higher when data coverage is strictly positive than when it is zero. What might be surprising is that in ex ante terms the borrower too is strictly better off.

Intuitively, the low type is hurt as data coverage increases from zero, for two reasons. First, when $\rho > 0$, in equilibrium the low type is sometimes revealed to be the low type, and obtains a low payoff. Second, the increase in $\rho$ induces the low type to increase their manipulation, which incurs a cost. Conversely, the high type benefits when data coverage is increased above zero, because when the digital signal is high, they obtain a better interest rate (i.e., they sometimes obtain the rate $r_H$ rather than $r_0$). The trade-off between these two effects will depend on how much manipulation by the low type ($m$) and the interest rates offered by the lender ($r_H, r_L$, and $r_0$) change as $\rho$ increases. The sizes of these effects, in turn, depend on the distribution of project profitability, $v$.

We show that if $v$ has the uniform distribution, both the borrower and the social planner are better off with strictly positive data coverage.

**Proposition 5** (Borrower surplus and total surplus)**.** *Comparing strictly positive data coverage (i.e., some $\rho > 0$) to no data coverage (i.e., $\rho = 0$),*

(i) *The high-type borrower is better off and the low-type borrower is worse off with strictly positive data coverage. That is, $\frac{\partial u_H}{\partial \rho} \mid_{\rho=0} > 0$ and $\frac{\partial u_L}{\partial \rho} \mid_{\rho=0} < 0$.*

(ii) *Suppose that the project profitability $v$ is uniformly distributed, that is, $v \sim U[0, R]$. Then, ex ante both the borrower and the social planner are better off with strictly positive data coverage. That is, $\frac{\partial \mathcal{U}}{\partial \rho} \mid_{\rho=0} > 0$ and $\frac{\partial \mathcal{S}}{\partial \rho} \mid_{\rho=0} > 0$.*

Proposition 5 reveals an interesting finding that counters the common belief that the borrower is fearful of data collection. In fact, the borrower actually prefers the lender to have access to some digital data. The collection of such data enables personalized loan pricing, which can potentially be detrimental to the low-type borrower. However, the high-type borrower benefits from more extensive screening and personalized pricing. Surprisingly, the latter effect can outweigh the former, resulting in an optimally positive data coverage for the borrower.

Finally, while the borrower prefers a low (yet positive) level of data coverage and the lender prefers a high (but not full) level of data coverage, the social planner aims to strike a balance between the two. Consequently, the social planner favors a moderately positive data coverage that satisfies the interests of both parties.

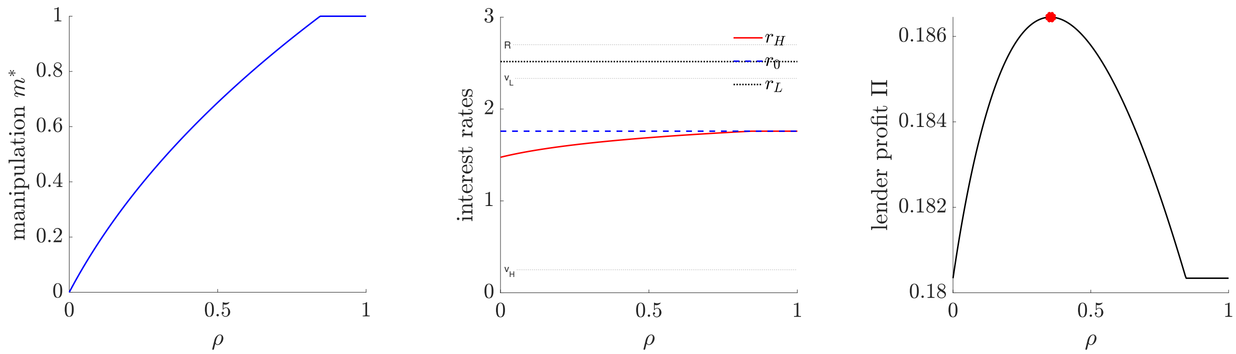
## 4.5 A Numerical Example

Sections 4.2 and 4.3 demonstrate that the lender restricts data coverage in the transparent regime, while utilizing the complete data coverage in the non-transparent regime. In this section, we present a numerical example to illustrate this crucial finding of our paper. Figure 3 plots the impact of data coverage on the equilibrium variables in the transparent regime, while $\rho = 1$ can always be sustained in equilibrium in the non-transparent regime.

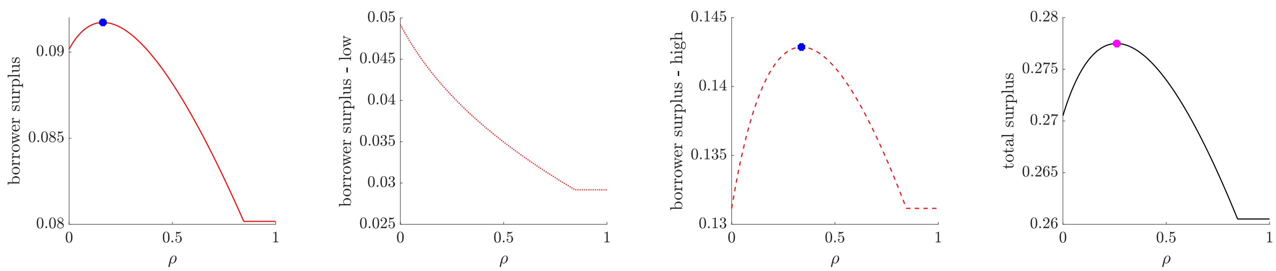
In this numerical example, we suppose the project profitability follows a uniform distribution; that is, $v \sim U[0, R]$. The manipulation cost is assumed to be $C(m) = c \cdot m^2$. The parameters are $q_H = 0.8, q_L = 0.3, \alpha = 0.5, R = 2.7$, and $c = 0.02$.

To begin with, consistent with Corollary 2, Panel (a) of Figure 3 demonstrates that in the transparent regime, more data coverage $\rho$ can induce (weakly) more manipulation from the low-type borrower. That is, when $\rho < 0.85$, the equilibrium manipulation intensity $m^*$ by the low-type borrower strictly increases in $\rho$. After $\rho$ continues to grow and exceeds $0.85$, the low-type borrower fully manipulate their digital profile, i.e., $m^* = 1$.

As the low-type borrower manipulates their digital profile more intensively, the lender's posterior belief about the borrower being the high type after receiving the high signal $s_H$ decreases. In response, the lender charges a higher interest, as shown in Corollary 1 and Panel (b) of Figure 3. By contrast, since only the low-type borrower manipulates and their manipulation does not affect the lender's posterior belief when the signal is uninformative, the interest rates the lender charges for the unrecognized and the low type do not change. Note that in Panel (b) of Figure 3, we also plot several auxiliary horizontal lines at the level of $R$ (the maximum project profitability), and $v_\theta \equiv \frac{1}{q_\theta} - 1$ (the zero-profit interest rate for type $\theta$, as discussed in Lemma 1). Panel




(a) Manipulation intensity (b) Interest rates (c) Lender profit




(d1) Borrower surplus (d2) $u_L$ (d3) $u_H$ (e) Total surplus

This figure plots the effect of data coverage $\rho$ on the low-type borrower's manipulation intensity in Panel (a), equilibrium interest rates in Panel (b), the lender's profit in Panel (c), borrower surplus in Panels (d1)-(d3), and total surplus in Panel (e). The manipulation cost function is assumed to be $C(m) = c \cdot m^2$. The parameters are $\alpha = 0.5$, $q_H = 0.8$, $q_L = 0.3$, $R = 2.7$, and $c = 0.02$.

Figure 3: The effect of data coverage

(b) confirms that the interest rate $r_s$ charged for the borrower of digital profile $\theta$ has always a markup over the zero-profit interest rate, that is, $r_s > v_s$, where $s \in \{s_H, s_L\}$.

With more intensive manipulation, the lender's unconditional expected profit can decrease in the data coverage when $\rho$ takes a large value, as shown in Panel (c) of Figure 3. Therefore, the lender may not choose the maximum data coverage even though it is free. In this numerical example, the lender optimally chooses $\rho^* \approx 0.35$ to maximize its lending profit in the transparent regime (as indicated by the red dot), which strictly falls below 1. This is consistent with Proposition 3. In contrast, Proposition 4 shows that the lender always tends to choose the maximal data coverage in the non-transparent regime, $\rho^* = 1$.

Next, we study the normative implications of the data coverage for borrower surplus and total surplus, as examined in Section 4.4. Panel (d) plots the effect of data coverage on the ex ante borrower surplus $\mathcal{U}$, the high-type borrower surplus $u_H$, and low-type borrower surplus $u_L$. Like the lender profit, the expected borrower surplus also exhibits a hump-shape pattern with respect to the data coverage. Thus, consistent with Proposition 5, the borrower also favors a strictly positive data coverage. In this example, ex ante borrower payoff is maximized at $\rho \approx 0.16$. For a low-type borrower, higher data coverage makes it hard for her to pretend a high type, leading to unfavorable interest rate. Moreover, the low-type borrower engages in more manipulation, incurs higher cost, and becomes even more worse off, resulting in a (weakly) decreasing line as shown in Panel (d2). For a high-type borrower, higher data coverage implies that she is more likely to be identified by the lender and receives a favorable interest rate. However, when the low-type borrower manipulates intensively, the lender's signal has very low quality, making it more difficult for the high-type borrower to separate themselves from the low-type one and thus leading to the unfavorable interest rates. Thus, as shown in Panel (d3), the borrower surplus for the high type can exhibit a hump-shape pattern, with the maximum point at $\rho \approx 0.33$.

Finally, panel (e) of Figure 3 confirms Proposition 5 that the social planner desires a positive data coverage from the lender. Total welfare is maximized at $\rho \approx 0.26$ in this numerical example.

# 5 Implications

In this section, we examine the implications of our framework for the credit market. We begin by discussing how our model provides new insights into regulations surrounding the utilization of alternative data in credit underwriting. Specifically, we focus on two regulatory aspects: transparency regarding the use of alternative data and limitations on its usage. Subsequently, we delve into the impact of manipulation costs.

## 5.1 Regulating the Use of Alternative Data in Underwriting Credit

Motivated by the widespread availability of digital data, many countries in the world have regulations related to the use of data, which are often quite heterogeneous across different countries.

Consider the U.S., for example. On July 25, 2019, in a U.S. House hearing entitled "Examining the Use of Alternative Data in Underwriting and Credit Scoring to Expand Access to Credit," Stephen Lynch, Chairman of the Task Force on Financial Technology, commented that "oversight of the use of alternative data is either highly fragmented or completely nonexistent, leading to uncertainty for lenders and potential harm for consumers."[7] On December 3, 2019, U.S. federal banking regulators issued an interagency statement discussing the benefits and risks of alternative data in assessing consumers' creditworthiness.[8] The agencies recognize that use of alternative data in a manner consistent with applicable consumer protection laws may improve the speed and accuracy of credit decisions and may help firms evaluate the creditworthiness of consumers who currently may not obtain credit in the mainstream credit system.

The European Union (EU) has taken a significant step in regulating data usage through the General Data Protection Regulation (GDPR). In response to the growth of digital lenders and the increasing online distribution of consumer credit, the European Commission proposed a revision to the Consumer Credit Directive in June 2021. This proposal aligns with the GDPR and aims to address specific concerns related to personal data processing within the consumer credit market. These concerns include the use of alternative data sources for creditworthiness assessments and the transparency of assessments conducted using machine learning techniques.[9] The European Data Protection Supervisor (EDPS) emphasizes the importance of complying with data protection legislation, particularly regarding creditworthiness assessments. This includes upholding principles such as transparency, fairness, data minimization, and purpose limitation.[10]

Regulators are therefore aware of some of the trade-offs with the use of data in the context of creditworthiness assessment. We here discuss two possible aspects of regulations that our model can shed light on: transparency on the use of alternative data, and limits on its use.

[7] See https://www.congress.gov/event/116th-congress/house-event/LC65599/text?s=1&r=3.

[8] See https://www.fdic.gov/news/financial-institution-letters/2019/fil19082.html.

[9] EC (2021), 'The Proposal for a Directive of the European Parliament and of the Council on Consumer Credits,' European Commission Brussels COM(2021) 347 final.

[10] See https://edps.europa.eu/system/files/2021-08/EDPS-2021-15-Consumer_Credits_fin_EN.pdf.

### 5.1.1 Transparency on the use of alternative data

There is concern that there is insufficient transparency about the types of alternative data being used and their impact on credit decisions. To ensure transparency, the Fair Credit Reporting Act (FCRA) and the Equal Credit Opportunity Act (ECOA) in the U.S. require lenders to disclose the sources and types of information used, so that consumers are aware of the reasons for credit decisions. However, as noted by Johnson (2019), the broad applicability of these regulations needs to be reaffirmed, especially in the context of alternative data.

In the EU, the European Commission's proposal for the Consumer Credit Directive has already included provisions to enhance transparency. For instance, it explicitly states that "the consumer should also have the right to obtain a meaningful explanation of the assessment made and of the functioning of the automated processing used, including among others the main variables, the logic and risks involved, as well as a right to express his or her point of view and to contest the assessment of the creditworthiness and the decision."

Now, suppose a regulatory authority formally implements rules requiring transparency of lender behavior. In the model, that translates to an economy switching from the non-transparent regime to the transparent regime. Proposition 4 shows that in the non-transparent regime, the lender tends to adopt the maximal data coverage in its underwriting model. However, when we transition to the transparent regime, Proposition 3 illustrates that when the manipulation cost is low, the equilibrium exhibits less than full data coverage (i.e., $\rho^* < 1$); that is, the lender deliberately limits its use of available data. In other words, compared to when the data coverage is unobservable, the lender consistently chooses lower data usage when the data coverage becomes observable.

Interestingly, rather than decreasing profit, transparency regarding the use of alternative data in credit underwriting (weakly) benefits the lender. Opacity harms the lender because, for a given level of borrower belief about the data coverage, the lender can always opportunistically raise it, which increases profit without triggering more borrower manipulation. When the data collection is transparent, the lender can credibly commit to limited data acquisition, i.e., a lower

$\rho$. Thus, the observability of data coverage imposed by the regulation effectively grants the lender commitment power to restrict data usage.

**Corollary 3** (Lender prefers transparency)**.** *The lender's data coverage is (weakly) lower, while the expected profit is (weakly) higher when the data coverage is observable compared to when it is unobservable.*

In addition to increasing lending profit, Figure 3 demonstrates that transparency on the use of alternative data can also benefit the borrower. In our framework, this improvement arises from the reduction of manipulation cost and a more favorable interest rate received by the high-type borrower.

#### 5.1.2 Limits on the use of alternative data

Regulators may seek to limit the kinds of alternative data that a lender can use. Within our model, we can interpret such a limit as an upper bound on the extent of data coverage a lender can choose. That is, the maximum amount of data allowed by regulation may be $\bar{\rho}$, where $\bar{\rho} \in [0, 1]$.

The specific level of $\bar{\rho}$ will be determined by the legal and regulatory landscape governing consumer financial data. For instance, the 1999 Gramm-Leach-Bliley Act (GLBA) in the U.S. establishes baseline requirements for financial institutions to protect the privacy and security of consumer financial information. The Equal Credit Opportunity Act (1974) prohibits discrimination on the basis of race, ethnicity, gender, and some other factors in any aspect of a credit transaction. Privacy and fairness considerations can therefore limit the types of alternative data that can be used in credit underwriting, ultimately determining the level of $\bar{\rho}$.

In the EU, Recital 47 of the Proposal for the Consumer Credit Directive offers clear indications on the types of information which should not be used to assess creditworthiness. Specifically, it states that "personal data, such as personal data found on social media platforms or health data, including cancer data, should not be used when conducting a creditworthiness assessment." Furthermore, the EDPS explicitly recommends extending the prohibition to search query data or online browsing activities. The EDPS argues that the utilization of such data is incompatible with the principles of purpose limitation, fairness, transparency, as well as the relevance, adequacy, and proportionality of data processing.

Our baseline model assumes that the maximum possible value of $\rho$ is 1, meaning that $\bar{\rho} = 1$. This represents an economy without any constraint on data coverage, and the equilibrium level of data coverage in this case is denoted as $\rho^*$, regardless of the regulatory regime.

We can extend our baseline model to a more general scenario where $\bar{\rho}$ can range between 0 and 1. In this extended economy, if the constraint is not binding, meaning that $\bar{\rho} > \rho^*$, the equilibrium will feature the same level of data coverage as $\rho^*$. However, if $\bar{\rho}$ is less than $\rho^*$, the equilibrium data coverage might differ.

The status quo can be understood as an economy where $\bar{\rho}$ is close to 1, enabling the lender to utilize all available alternative data given the existing technology. As regulations become more specific regarding the permissible types of alternative data, the upper limit $\bar{\rho}$ may decrease. In both the transparent and non-transparent regimes, if the regulation moderately restricts the use of alternative data based on privacy or fairness concerns, the equilibrium level of data coverage should remain unaffected. However, if regulators impose highly restrictive regulations (i.e., setting a very low $\bar{\rho}$), it can have negative consequences not only for the lender but also for the borrower.

## 5.2 The Effect of Manipulation Costs

One crucial parameter in our model is the cost of manipulation. In practice, several factors can influence this cost. For example, if financial literacy improves (i.e., individuals become knowledgeable about the data used in credit underwriting and the actions they can take to enhance their creditworthiness), it may result in a decrease in the manipulation cost within our model.

Furthermore, many lenders are adopting more sophisticated algorithms and techniques to detect and prevent borrower manipulation. In our framework, this would result in an increase in the manipulation cost for the borrower. As lenders become better equipped to identify and mitigate manipulation attempts, borrowers would likely face higher costs and challenges in successfully manipulating their digital profiles.

These factors contribute to the dynamic nature of the manipulation cost within our model, reflecting the evolving landscape of financial literacy and technological advancements in credit underwriting practices.

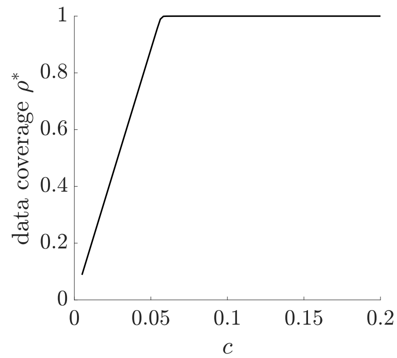
We consider the impact of the manipulation cost through a numerical comparative statics analysis in the transparent regime, depicted in Figure 4. Note that in the non-transparent regime, as shown in Proposition 4, the lender always adopts the maximal data coverage. Thus, the effect of the manipulation cost in the non-transparent regime can be examined in the same comparative statics analysis when $\rho^* = 1$. In Figure 4, we fix the parameters to be $q_H = 0.8$, $q_L = 0.3$, $\alpha = 0.5$, and $R = 2.7$, the same as those for Figure 3. The manipulation cost is set to $c \cdot m^2$, where $c$ varies between 0.01 and 0.2. For each value of $c$, we first determine $\rho^*$, the optimal data coverage for the lenders in the transparent regime, and then the equilibrium values of the other variables.

As Panel (a) of Figure 4 shows, when the manipulation cost increases, the lender generally increases it data coverage, knowing that the borrower's actions are now less likely to compromise the quality of data it receives. Panel (b) shows that as a result of the increase in $c$, even though data coverage is increasing, the low-type borrower does indeed reduce its manipulation.

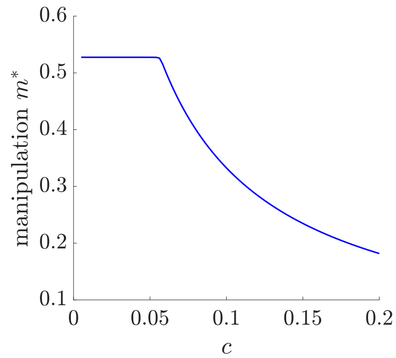
Consequently, in Panel (c) of Figure 4, when the lender receives signal $s_H$ indicating high-type digital profile, it can exhibit greater confidence in the borrower being of high type. This increased certainty enables the lender to offer a lower interest rate. As a result of its superior information (both due to increased data coverage and reduced manipulation), the lender can generate higher expected profits from the lending business, as illustrated in Panel (d) of Figure 4.

In Panels (e1) of Figure 4, it is evident that the reduced manipulation by the borrower benefits them in an ex ante sense. Upon closer examination in Panel (e2), a greater manipulation cost can have adverse effects on the low-type borrower. Additionally, the inability of the low type to mimic the high type means they consistently receive unfavorable interest rates, resulting in lower surplus.

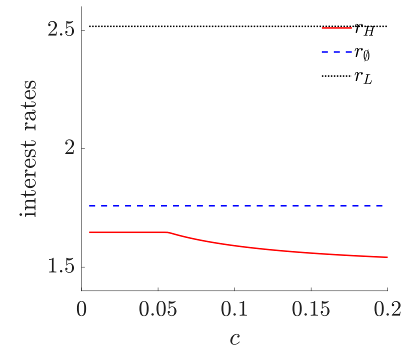
In contrast, Panel (e3) of the figure demonstrates that the high-type borrower consistently



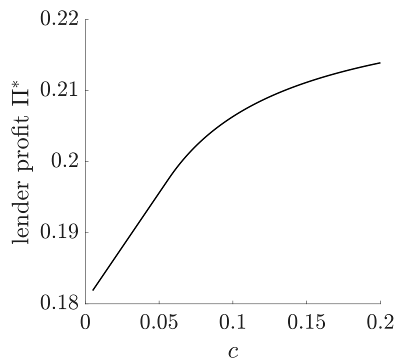

(a) Data coverage



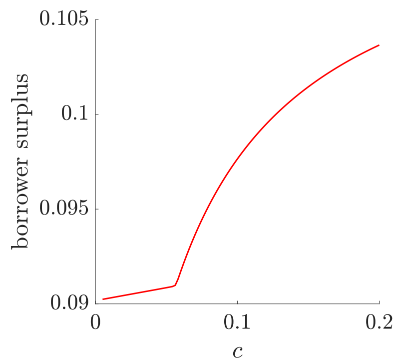

(b) Manipulation



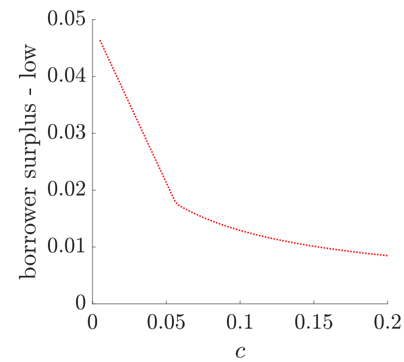

(c) Interest rates



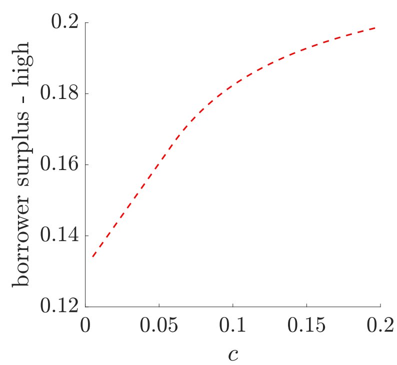

(d) Lender profit



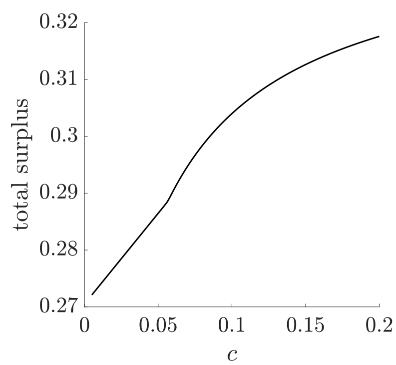

(e1) Borrower surplus




(e2) Borrower surplus: low type




(e3) Borrower surplus: high type




(f) Total surplus

This figure plots the effect of the manipulation cost on borrowers' manipulation intensity, the lender's data coverage, lender profit, and borrower surplus. The reservation interest rate $v$ is assumed to follow a uniform distribution $U(0, R)$, and the manipulation cost function is $C(m) = c \cdot m^2$. The parameters are $q_H = 0.8$, $q_L = 0.3$, $\alpha = 0.5$, and $R = 2.7$, which are the same as in Figure 3. For each value of $c$, we first find the optimal $\rho$ for the lender, and then compute the equilibrium values of the other variables.

Figure 4: The effect of the manipulation cost

experiences higher payoffs as the manipulation cost increases. This is because they are more likely to distinguish themselves from the low type and enjoy the advantageous low interest rates. Overall, total surplus increases in the manipulation cost.

Revisiting the discussions at the beginning of the section, our results shed new light on the implications of financial literacy and technological advancements in credit underwriting. Firstly, an increase in financial literacy can potentially have negative implications for consumers. As depicted in Figure 4, a decrease in the manipulation cost associated with these factors may lead to a rise in manipulation, thereby compromising the lender's data quality and its ability to accurately screen borrowers. Consequently, the high-type borrower may receive inferior loan terms and experience lower payoffs, ultimately reducing ex ante borrower surplus.

On the other hand, anti-fraud measures implemented by lenders may actually prove beneficial to borrowers on average. The resulting higher manipulation cost acts as a deterrent for low-type borrowers, discouraging them from manipulating their digital profile. This allows the lender to offer low interest rates to borrowers who appear highly creditworthy (i.e., those that generate high signals). These borrowers benefit, and indeed the ex ante borrower surplus also increases.

It is worth noting that the current analysis of comparative statics reveals that total surplus increases monotonically with the manipulation cost. This suggests that, if feasible, the regulator should set the manipulation cost as high as possible. However, if we expand the model by explicitly incorporating borrowers' privacy concerns, there may be an optimal choice for the manipulation cost that lies within a range. Specifically, the privacy cost can be seen as a function that increases as the lender acquires more data, resulting in a decrease in borrower surplus. Since a higher manipulation cost reduces the lender's worry about borrower manipulation and is associated with higher data coverage, an increasing manipulation cost might ultimately reduce borrower surplus and total surplus, leading to an interior optimal choice of the manipulation cost for the regulator.

# 6 Extensions

We finally discuss several extensions of our baseline model to demonstrate the robustness of our key insights.

## 6.1 When Data Coverage Affects Manipulation Costs

As the data technology employed by the lender becomes more advanced, one may conjecture that it becomes increasingly challenging for the borrower to manipulate their digital profile. For instance, the machine learning algorithm can be designed to be highly opaque, making it difficult for borrowers to understand how each factor affects their creditworthiness as evaluated by the lender. Additionally, when thousands of variables are incorporated into the underwriting models, diminishing the individual significance of each variable in determining creditworthiness, it becomes more arduous to manipulate multiple variables simultaneously.

In this section, we consider this possibility by augmenting the manipulation cost from $C(m)$ to $C(m,\rho)$, where $C(0,\rho) = C'(0,\rho) = 0$, $\frac{\partial C(m,\rho)}{\partial m} > 0$, $\frac{\partial^2 C(m,\rho)}{\partial m^2} > 0$, and $\frac{\partial C(m,\rho)}{\partial \rho} > 0$. This means that, not only does more intensive manipulation incur higher costs, similar to the baseline model, but also a higher level of data coverage in the lender's underwriting model induces additional manipulation costs.

The following Proposition 6 demonstrates the robustness of our main results. Specifically, as in Proposition 3, Part (i) of Proposition 6 characterizes the sufficient conditions under which the equilibrium in the transparent regime exhibits data coverage that is strictly lower than one. Similarly, the lender avoids full data coverage if funding a project of the low-type borrowers only results in a loss (i.e., $q_L(1+R) < 1$) and the borrower's manipulation cost is sufficiently low.

Part (ii) of Proposition 6, similar to Proposition 4, characterizes the equilibrium in the non-transparent regime. In this case, when data coverage is unobservable to the borrower, the maximal data coverage can always be sustained in equilibrium. Finally, Part (iii) of the proposition demonstrates that in the extended model, the lender benefits from the transparency imposed by the regulation.

**Proposition 6** (Augmented Manipulation Cost)**.** *Suppose that the manipulation cost is also affected by the lender's data coverage, i.e.,* $C(m,\rho)$*, where* $C(0,\rho) = C'(0,\rho) = 0$*,* $\frac{\partial C(m,\rho)}{\partial m} > 0$*,* $\frac{\partial^2 C(m,\rho)}{\partial m^2} > 0$*, and* $\frac{\partial C(m,\rho)}{\partial \rho} > 0$*.*

(i) *Suppose that the data coverage is observable to the borrower. In equilibrium, the lender chooses a strictly positive data coverage, i.e.,* $\rho^* > 0$*. Moreover, if* $q_L < \frac{1}{1+R}$ *(i.e., low-type projects are all negative NPV) and* $\frac{\partial C(m,\rho)}{\partial m} \mid_{m=1} \leq B(1 \mid 1)$ *(i.e., manipulation cost is sufficiently low), where* $B(1 \mid 1)$ *is given by equation (10), the lender chooses less than full data coverage (i.e.,* $\rho^* < 1$*).*

(ii) *Suppose that the data coverage is unobservable to the borrower.*

- *If* $\frac{\partial C(m,\rho)}{\partial m} \mid_{m=1} < B(1 \mid 1)$*, there is an equilibrium the lender chooses maximal data coverage, i.e.,* $\rho^* = 1$*, and the low-type borrower manipulates with probability 1 (i.e.,* $m^* = 1$*).*
- *If* $\frac{\partial C(m,\rho)}{\partial m} \mid_{m=1} \geq B(1 \mid 1)$*, there is a unique equilibrium in which the lender chooses maximal data coverage, i.e.,* $\rho^* = 1$*, and the low-type borrower manipulates with strictly positive probability (i.e.,* $m^* > 0$*).*

(iii) *As in Corollary 3, the lender's data coverage is (weakly) lower, while its expected profit is (weakly) higher when the data coverage is observable compared to when it is unobservable.*

## 6.2 Costly Data Coverage

In the baseline model, we exclude the direct data-collection cost and show that, despite the availability of free data technology, under certain sufficient conditions, the lender may choose to adopt less than full data technology. While it is easy to define the bound $\rho = 1$ as full data coverage in the model, it could be challenging to conceptualize its real-world equivalent.

In this section, we propose an alternative approach to model the bound. Specifically, we consider that as the lender collects more data, the associated cost increases. Let's assume that collecting data with an extent of $\rho$ incurs a cost for the lender, denoted as $K(\rho)$. Here, we assume that $K'(\rho) > 0$ and $K''(\rho) > 0$, indicating that the cost increases with the extent of data collection.

The following proposition summarizes equilibrium data coverage under observable and unobservable data coverage and demonstrate the robustness of our insights.

**Proposition 7** (Data collection cost)**.** *Suppose that to acquire and process the data with data coverage $\rho$ costs the lender $K(\rho)$, where $K'(\rho) > 0$ and $K^{''}(\rho) > 0$.*

(i) *Suppose that the data coverage is observable to the borrower. Then the same conditions in Proposition 3 identify the sufficient conditions for $\rho^* < 1$. That is, $q_L < \frac{1}{1+R}$ (i.e., low-type projects are all negative NPV) and $C'(1) \leq B(1 \,|\, 1)$ (i.e., manipulation cost is sufficiently low), where $B(1 \,|\, 1)$ is given by equation (10).*

(ii) *Suppose that the data coverage is unobservable to the borrower. Unlike Proposition 4, even if $C'(1) \leq B(1 \,|\, 1)$, the lender will not choose the optimal data coverage such that the low-type manipulates with probability 1. If $C'(1) > B(1 \,|\, 1)$ and the marginal data collection cost $K'(\rho)$ is not that steep, like Proposition 4, there is a unique equilibrium in which the lender chooses maximal data coverage, i.e., $\rho^* = 1$, and the low-type borrower manipulates with strictly positive probability (i.e., $m^* > 0$).*

(iii) *As in Corollary 3, the lender's data coverage is (weakly) lower, while its expected profit is (weakly) higher when the data coverage is observable compared to when it is unobservable.*

Part (i) of Proposition 7 demonstrates that, under the same sufficient conditions as characterized in the baseline model (see Proposition 3), the lender does not fully utilize all available data in credit underwriting. Given that this extended economy is more restricted than the baseline economy, it is intuitive to observe non-full data coverage under the same sufficient conditions.

Part (ii) of Proposition 7 examines the scenario when data coverage is unobservable. Taking into account the costs associated with acquiring and processing data, even if the borrower's manipulation cost is low, the lender's optimal choice of data coverage will not result in 100% manipulation intensity from the low-type borrower. This contrasts with Part (i) of Proposition 7. The reason is that full manipulation by the low-type borrower would render the lender's signal completely useless, thereby undermining any initial investment in data technology by the lender. Only when the borrower's manipulation cost is high and the cost of data collection for the lender is relatively low can we observe the lender employing full data coverage.

Finally, similar to Corollary 3 in the baseline model, Part (iii) of Proposition 7 demonstrates that the regulatory authority's request for transparency can assist the lender in committing to limit its data usage in credit underwriting, thereby enhancing profitability.

# 7 Conclusion

FinTech lenders often base their lending decisions on alternative data, including the online or digital profiles of borrowers. Some components of alternative data may be easier for borrowers to manipulate than traditional credit metrics. In this paper, we study a credit model in which the lender collects signals about the borrower's digital profiles, but the digital profiles can be manipulated by the borrower at a cost.

We consider two regulatory regimes: the transparent regime in which the lender's use of alternative data is observable to the borrower and the non-transparent regime in which the usage is unobservable. In the non-transparent regime, the lender tends to use full data coverage. In contrast, in the transparent regime, when the lender's signal is improved by higher data coverage, the borrower is more likely to manipulate their digital profile, which reduces the lender's signal quality and impairs its lending decisions. Thus, even if it is costless to include more data in the underwriting model, in equilibrium, the lender chooses to avoid exploiting the full potential of its data in the transparent regime.

The comparison of the two regulatory regimes reveals that disclosure policy can play an important role; by making the extent of the lender's data coverage transparent, it may allow the lender to credibly signal that their data collection efforts are limited, reducing the incentive of the borrower to manipulate their digital profile and sustaining the lender profit.

Interestingly, we also find that in the aggregate borrowers are better off if the lender does collect some alternative data, as opposed to not acquiring it at all. Better data leads to the high type in expectation obtaining better credit terms. Even though the low-type borrower has a reduced payoff, aggregate borrower surplus initially improves when the lender acquires some alternative data. Thus, when the manipulation cost is relatively low, both the lender and the borrower strictly prefer that the lender acquire some alternative data, rather than limit the amount of data they collect.

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# Appendix: Proofs

## Proof of Lemma 1

Suppose the lender obtains signal $s \in \{s_H, s_L, s_0\}$. Recall that $\mu_s = \text{Prob}(\theta = H \mid s)$, and $\bar{q}_s = \mu_s q_H + (1-\mu_s)q_L$.

(i) Suppose the lender offers the interest rate $r$. Borrowers of either type $\theta \in \{H, L\}$ accept the offer if $v \geq r$. If the borrower has type $\theta$, the lender earns $q_\theta(1+r)$ when the project is successful and zero when it is not. The expected profit of the lender given signal $s$ and interest rate offer $r$ is therefore

$$\begin{aligned} \pi_s(r) &= (1-F(r))[\mu_s\{q_H(1+r)-1\} + (1-\mu_s)\{q_L(1+r)-1\}] \\ &= (1-F(r))[\bar{q}_s(1+r)-1]. \end{aligned} \tag{A15}$$

The first-order condition is:

$$-f(r)[\bar{q}_s r - (1-\bar{q}_s)] + (1-F(r))\bar{q}_s = 0,$$

which can be simplified to

$$r - \frac{1-F(r)}{f(r)} = \frac{1}{\bar{q}_s} - 1, \tag{A16}$$

which is equation (4) in the lemma.

Now, the first-order condition provides a solution to the lender's problem only if there exists an interest rate $r \in (0, R)$ at which the lender earns a strictly positive profit. A necessary and sufficient condition for the latter is that $\bar{q}_s(1+R) > 1$.

The second-order condition is

$$-2\bar{q}_s f(r) - f'(r_s)[\bar{q}_s r - (1-\bar{q}_s)] < 0. \tag{A17}$$

By assumption, the hazard rate $\frac{f(r)}{1-F(r)}$ is strictly increasing in $r$. Therefore, the inverse hazard rate $\frac{1-F(r)}{f(r)}$ is strictly decreasing in $r$, and the left-hand side of the first-order condition, equation (4) is strictly increasing in $r$. Thus, the first-order condition provides a unique maximum to the lender's problem.

(ii) Suppose that $\bar{q}_s(1+R) \leq 1$. Then, there is no interest rate $r$ at which the lender can earn a positive profit. Therefore, it is optimal to set $r_s = R$. ■

## Proof of Proposition 1

Suppose that $\hat{\rho} > 0$. We first show that, in any equilibrium of the subsequent game, the lender charges a strictly lower interest rate when it observes the signal $s = s_H$ rather than when it observes the signal $s = s_L$. Let $r_j$ denote the optimal interest rate offer after signal $s_j$.

**Claim**: $r_H < r_L$.

**Proof of Claim** We prove the claim by contradiction. Suppose instead that $r_H > r_L$, that is, borrowers who generate signal $s_H$ are charged higher interest rates than those who generate signal $s_L$.

As shown in equation (5), the expected utility of a type $\theta$ borrower who chooses manipulation intensity $m$ is

$$\begin{aligned} u(\theta, m; \hat{m}_\theta, \hat{\rho}) \quad = \quad & q_\theta \Big\{ \hat{\rho} \Big( m \int_{r_{\tilde{\theta}}}^{R} (v - r_{\tilde{\theta}}) dF(v) + (1-m) \int_{r_\theta}^{R} (v - r_\theta) dF(v) \Big) \\ & + (1-\hat{\rho}) \int_{r_0}^{R} (v - r_0) dF(v) \Big\} - C(m_\theta). \end{aligned} \tag{A18}$$

Observe that the interest rates $r_\theta$ and $r_{\tilde{\theta}}$ are not directly dependent on $m$, but instead depend on the lender's beliefs $\hat{m}_\theta$. The borrower takes these interest rates as given (even though the offers themselves will only materialize at date 1). In equilibrium, manipulation is strictly positive if and only if $\frac{\partial u(\theta, m; \hat{m}_\theta, \hat{\rho})}{\partial m} \mid_{m=0} > 0$. As $C'(0) = 0$, this condition reduces to

$$\hat{\rho}\, q_\theta \Big\{ \int_{r_{\tilde{\theta}}}^{R} (v - r_{\tilde{\theta}})) dF(v) - \int_{r_\theta}^{R} (v - r_\theta)) dF(v) \Big\} > 0. \tag{A19}$$

That is, for $m > 0$, it must be that (i) $\hat{\rho} > 0$ and (ii) $\int_{r_{\tilde{\theta}}}^{R} (v - r_{\tilde{\theta}})) dF(v) > \int_{r_\theta}^{R} (v - r_\theta)) dF(v)$. The latter condition immediately implies that $r_{\tilde{\theta}} < r_\theta$ because $\int_{r}^{R} (v - r)) dF(v)$ is decreasing in $r$. Thus, to have $m > 0$ in equilibrium, it must be that $\hat{\rho} > 0$ and $r_{\tilde{\theta}} < r_\theta$.

Now, suppose that $r_H \geq r_L$. Then, it must be that the low-type borrowers do not manipulate, i.e., $m_L = 0$. Therefore, on receiving an $H$ signal, the lender knows the borrower must have the high type. On receiving signal $L$, at best the borrower is the high type with probability $\alpha$ (and this can only happen if the high type manipulates with probability 1; else the probability of the high type is strictly less than 1 when signal $L$ is received). Therefore, it must be that $r_H < r_L$, which is a contradiction.

(i) Given that $r_H < r_L$, following similar arguments as above, it follows that the high-type borrower will never manipulate their data, i.e., $m_H = 0$. The low-type borrower will manipulate with positive intensity, i.e., $m_L > 0$, when $\hat{\rho} > 0$.

(ii) Suppose $\hat{\rho} > 0$. Following arguments in the proof of the Claim, the low-type borrower will manipulate with positive probability if $r_H < r_L$, which is true. For simplicity, we denote the low-type borrower's manipulation intensity $m_L$ as $m$. Thus, the equilibrium manipulation intensity $m^*$ satisfies the first-order condition

$$\hat{\rho} q_L \left( \int_{r_H}^{R} (v - r_H) dF(v) - \int_{r_L}^{R} (v - r_L) dF(v) \right) = C'(m). \tag{A20}$$

Since $C(\cdot)$ is convex, the second-order condition is immediately satisfied. As the lender must hold consistent beliefs in equilibrium, we impose $\hat{m} = m$ in the first-order condition (A20), which yields equation (7), where we write $r_H(m)$ to emphasize the $r_H$ is a function of $m$.

(iii) We have shown above that $r_H < r_L$. It remains to show that $r_0 \in (r_H, r_L)$. In equilibrium, the lender's posterior beliefs must match the actual manipulation strategies of the borrower. Observe that when $m_H = 0$ and $m_L = m > 0$, the lender's posterior beliefs after each signal $s$ therefore satisfy $\mu_H = \frac{\alpha}{\alpha + (1-\alpha)m}$, $\mu_L = 0$, and $\mu_0 = \alpha$. That is, we have $\mu_L < \mu_0 < \mu_H$. It follows immediately that $r_H < r_0 < r_L$. ■

## Proof of Corollary 1

As mentioned in the proof of Proposition 1 part (iii), the lender's equilibrium beliefs are $\mu_H = \frac{\alpha}{\alpha + (1-\alpha)m}$, $\mu_L = 0$, and $\mu_0 = \alpha$. Observe that the posterior beliefs after signals $s_L$ and $s_0$ are therefore independent of the actual manipulation $m$. Thus, based on Lemma 1, the optimal interest rates $r_0$ and $r_L$ are also independent of $m$. This proves part (ii) of the Corollary.

Consider part (i) of the Corollary. It is immediate that $\frac{\partial \mu_H}{\partial m} < 0$ in equilibrium. Given that $\bar{q}_H = \mu_H q_H + (1-\mu_H) q_L$, we have $\frac{\partial \bar{q}_H}{\partial m} < 0$. Therefore, based on Lemma 1, $r_H$ must increase when $m$ increases. ■

## Proof of Corollary 2

In what follows, for notational convenience we write $m = m^*$. When $m < 1$, it satisfies the first-order condition for optimal manipulation, equation (7).

Denote $I_H = \int_{r_H(m)}^{R} (v - r_H(m)) dF(v)$, and $I_L = \int_{r_L}^{R} (v - r_L) dF(v)$. Then, this first-order condition may be written as $\hat{\rho} q_L (I_H - I_L) = C'(m)$.

Applying the implicit function theorem, we have

$$\frac{dm}{d\hat{\rho}} = -\frac{q_L(I_H(m) - I_L)}{-C''(m) + \hat{\rho} q_L \frac{\partial I_H(m)}{\partial m}} = \frac{q_L(I_H(m) - I_L)}{C''(m) - \hat{\rho} q_L \frac{\partial I_H(m)}{\partial m}}. \tag{A21}$$

In the last expression, $I_H(m) > I_L$ because $r_H(m) < r_L$, so the numerator is strictly positive. Further, $\frac{\partial I_H(m)}{\partial m} = -(1 - F(r_H)) r'_H(m) > 0$. Now, an increase in $m$ implies a reduction in $\mu_H$, the posterior probability of the high type after signal $s_H$. In turn, through Lemma 1 part (i), it implies an increase in $r_H$. That is, $r'_H(m) > 0$. Therefore, the denominator in the last expression in equation (A21) is strictly positive. Hence, $\frac{dm}{d\hat{\rho}} > 0$. ■

## Proof of Proposition 2

Suppose the borrower cannot manipulate their signal. Then, for any positive value of $\rho$, the lender's beliefs after each signal $s$ are $\mu_H = 1$, $\mu_L = 0$, and $\mu_0 = \alpha$. The corresponding optimal interest rates are as in Lemma 1, and it follows that $r_H < r_0 < r_L$.

Recall that the lending profit after signal $s$ and interest rate $r$ is $\pi_s = (1 - F(r))[\bar{q}_s r - (1 - \bar{q}_s)]$, where $\bar{q}_s = \mu_s q_H + (1 - \mu_s) q_L$ is the average quality of the project given signal $s$. Then, at date 0, given the data coverage $\rho$ the lender's expected profit may be written as

$$\Pi = \rho \left\{ \alpha \pi_H(r_H) + (1-\alpha) \pi_L(r_L) \right\} + (1-\rho) \pi_0(r_0). \tag{A22}$$

To prove that the lender optimally chooses $\rho^* = 1$, we show that the lender's expected profit $\Pi$ is monotonically increasing in $\rho$. Observe that as the borrower is taking no action with respect to manipulation, the offers $r_H$, $r_L$, and $r_0$ do not depend on $\rho$. Thus, taking the derivative of the expected profit in (A22) with respect to $\rho$ yields

$$\frac{d\Pi}{d\rho} = \alpha\pi_H(r_H) + (1-\alpha)\pi_L(r_L) - \pi_0(r_0).$$

Thus, $\frac{d\Pi}{d\rho} > 0$ is equivalent to

$$\begin{aligned}
\frac{d\Pi}{d\rho} > 0 \iff & \alpha\pi_H(r_H) + (1-\alpha)\pi_L(r_L) > \pi_0(r_0) \\
\iff & \alpha \max_r \pi_H(r) + (1-\alpha) \max_r \pi_L(r) > \max_r \pi_0(r) \\
\iff & \alpha \max_r \pi_H(r) + (1-\alpha) \max_r \pi_L(r) > \max_r \left[\alpha\pi_H(r) + (1-\alpha)\pi_L(r)\right]. \qquad \text{(A23)}
\end{aligned}$$

As $r_H \neq r_L$, it is straightforward that the last inequality must hold. Therefore, the lender's expected profit is monotonically increasing in $\rho$ and it thus chooses the maximum $\rho$ in equilibrium.

■

## Proof of Proposition 3

In the transparent regime, $\hat{\rho} = \rho$.

(i) Recall from equation (8) that the lender's profit is

$$\Pi(\rho) = \rho\Big(\{\alpha + (1-\alpha)m\}\pi_H(r_H) + (1-\alpha)(1-m)\pi_L(r_L)\Big) + (1-\rho)\pi_0(r_0), \qquad \text{(A24)}$$

where $m$ is the manipulation intensity of the low-type borrower.

Thus,

$$\begin{aligned}
\frac{d\Pi}{d\rho} = \frac{\partial\Pi}{\partial\rho} + \frac{\partial\Pi}{\partial m}\frac{dm}{d\rho} \quad = \quad & \{\alpha + (1-\alpha)m\}\pi_H + (1-\alpha)(1-m)\pi_L - \pi_0 \\
& +\rho\{(1-\alpha)(\pi_H - \pi_L) + \{\alpha + (1-\alpha)m\}\pi'_H(r_H)r'_H(m)\}\frac{dm}{d\rho} \qquad \text{(A25)}
\end{aligned}$$

Thus,

$$\frac{d\Pi}{d\rho}\Big|_{\rho=0} \quad = \quad \{\alpha + (1-\alpha)m\}\pi_H + (1-\alpha)(1-m)\pi_L - \pi_0. \qquad \text{(A26)}$$

Observe that when $\rho = 0$, $m = 0$. Together with what we have already shown in the proof of

Proposition 2 that $\alpha\pi_H + (1-\alpha)\pi_L - \pi_0 > 0$ (see equation (A23) and the related arguments), we can derive that $\frac{d\Pi}{d\rho} \mid_{\rho=0} > 0$, so that $\rho^* > 0$.

(ii) For part (ii), we invert the mapping between $\rho$ and $m$ and think of $\rho$ as a function of the $m$ in equilibrium, that is, we consider the $\rho$ that gives rise to a particular equilibrium $m$.

First, we show that $\Pi$ is decreasing in $m$ at the point $m = 1$; that is, $\frac{\partial\Pi}{\partial m} \mid_{m=1} < 0$. Based on equation (A24),

$$\begin{aligned}\frac{d\Pi}{dm} &= \frac{\partial\Pi}{\partial m} + \frac{\partial\Pi}{\partial\rho}\frac{d\rho}{dm} \\ &= \rho\Big\{(1-\alpha)\pi_H(r_H(m)) + (\alpha + (1-\alpha)m)\frac{\partial\pi_H(r_H(m))}{\partial m} - (1-\alpha)\pi_L(r_L)\Big\} \\ &+ \Big\{\{\alpha + (1-\alpha)m\}\pi_H(r_H(m)) + (1-\alpha)(1-m)\pi_L(r_L) - \pi_0(r_0)\Big\}\frac{d\rho}{dm}. \end{aligned} \tag{A27}$$

Observe that when $m = 1$, we have $\pi_H(r_H(m)) = \pi_0(r_0)$. That is, when all low-type borrowers manipulate their data, signal $s_H$ becomes completely uninformative and is hence equivalent to signal $s_0$. Therefore, when we substitute $m = 1$ into equation (A27), the second row drops out, and we have

$$\frac{d\Pi}{dm} \mid_{m=1} = \rho\Big\{(1-\alpha)\{\pi_H(r_H(m)) - \pi_L(r_L)\} + \frac{\partial\pi_H(r_H(m))}{\partial m} \mid_{m=1} \Big\}. \tag{A28}$$

Recall that

$$\pi_H(r_H(m)) = \{1 - F(r_H(m))\}\left[\bar{q}_H(1 + r_H(m)) - 1\right], \tag{A29}$$

where $\bar{q}_H = \mu_H q_H + (1-\mu_H)q_L$. Thus,

$$\begin{aligned}\frac{\partial\pi_H(r_H(m))}{\partial m} &= -f(r_H(m))\frac{\partial r_H(m)}{\partial m}[\bar{q}_H(1 + r_H(m)) - 1] \\ &+ (1 - F(r_H(m)))\left(\frac{\partial\bar{q}_H}{\partial m}(1 + r_H(m)) + \bar{q}_H\frac{\partial r_H}{\partial m}\right)\end{aligned} \tag{A30}$$

Now, from Lemma 1, we have $\bar{q}_H(1 + r_H) - 1 = \frac{1-F(r_H(m))}{f(r_H(m))}\bar{q}_H$. Substituting into equation (A30) and simplifying,

$$\frac{\partial\pi_H(r_H(m))}{\partial m} = \{1 - F(r_H(m))\}(1 + r_H(m))\frac{\partial\bar{q}_H}{\partial m}. \tag{A31}$$

Further, we can write $\bar{q}_H = q_L + \frac{\alpha}{\alpha+(1-\alpha)m}(q_H - q_L)$, so that $\frac{\partial\bar{q}_H}{\partial m} = -\frac{\alpha(1-\alpha)}{\{\alpha+(1-\alpha)m\}^2}(q_H - q_L)$.

Substituting this expression into equation (A31) and setting $m = 1$, we have

$$\frac{\partial \pi_H(r_H(m))}{\partial m} \mid_{m=1} = -\{1 - F(r_H(1))\} (1 + r_H(1)) \alpha(1-\alpha)(q_H - q_L). \tag{A32}$$

In addition, when $m = 1$, $\bar{q}_H = \alpha q_H + (1-\alpha) q_L$. Using this expression and equation (A32), and making the appropriate substitutions into equation (A28), we obtain

$$\frac{\partial \Pi}{\partial m} \mid_{m=1} = \rho(1-\alpha)\Big\{\{1 - F(r_H(m))\}\{(1 + r_H(m)) q_L - 1\} - \pi_L(r_L)\Big\}. \tag{A33}$$

Observe that $\pi_L(r_L) \geq 0$. Therefore, a sufficient condition to ensure that $\frac{\partial \Pi}{\partial m} \mid_{m=1} < 0$ is

$$q_L(1 + R) < 1, \quad \text{or} \quad q_L < \frac{1}{1+R}, \tag{A34}$$

which has been assumed in the statement of the proposition.

Second, we ensure that when $\rho = 1$, the low-type borrower optimally chooses $m = 1$. Based on the first-order condition for optimal manipulation by the low type, equation (7) in Proposition 1, we know that if that condition is satisfied at $m = 1$, we must have:

$$\rho q_L \left( \int_{r_H(1)}^{R} (v - r_H(1)) dF(v) - \int_{r_L}^{R} (v - r_L) dF(v) \right) = C'(1).$$

Therefore, when $\rho = 1$, the low-type borrower optimally choose $m = 1$ whenever the cost is overshadowed by the benefit

$$C'(1) \leq q_L \left( \int_{r_H(1)}^{R} (v - r_H(1)) dF(v) - \int_{r_L}^{R} (v - r_L) dF(v) \right). \tag{A35}$$

Now, observe that when $m = 1$, we have $\mu_H = \alpha = \mu_0$. Thus, the optimal interest rate set by the lender is $r_0$, that is, $r_H(1) = r_0$. We can therefore rewrite equation (A35) as

$$C'(1) \leq q_L \left( \int_{r_0}^{R} (v - r_0) dF(v) - \int_{r_L}^{R} (v - r_L) dF(v) \right). \tag{A36}$$

If the condition (A36) holds with equality, then the fact that $\frac{\partial \Pi}{\partial m} \mid_{m=1} < 0$ is enough to show that the lender does not choose full data coverage.

If the condition (A36) holds as a strict inequality, then a small reduction in $\rho$ from $\rho = 1$ has no effect on manipulation (i.e., we continue to have $m = 1$). Note that the profit of the lender is flat in this region, because as commented earlier, when $m = 1$, signals $s_H$ and $s_0$ are equivalent, so changing the probabilities across these signals cannot affect the profit. Further, in this case there exists some $\rho_1 < 1$ such that

$$\rho_1 q_L \left( \int_{r_H(1)}^{R} (v - r_H(1)) dF(v) - \int_{r_L}^{R} (v - r_L) dF(v) \right) = C'(1). \tag{A37}$$

At $\rho_1$, we again have $\frac{\partial \Pi}{\partial m} \mid_{m=1} < 0$, so that the data coverage chosen by the lender is strictly less than $\rho_1$, and hence strictly less than 1. ∎

## Proof of Proposition 4

Recall that $\hat{\rho}$ denotes the borrower's belief about the extent of data coverage and $\rho$ denotes the actual choice of data coverage. Then, the low-type borrower's equilibrium manipulation intensity $m$ is a function of $\hat{\rho}$. Thus, the offered interest rate after signal $s_H$ depends on $\hat{\rho}$ rather than $\rho$.

The lender's payoff function may be written as:

$$\begin{aligned} \Pi(\rho, \hat{\rho}) &= \rho \Big( \{\alpha + (1-\alpha) m(\hat{\rho})\} \pi_H(r_H(m(\hat{\rho}))) + (1-\alpha)(1 - m(\hat{\rho})) \pi_L \Big\} \\ &\quad + (1-\rho) \pi_0(r_0). \end{aligned} \tag{A38}$$

The derivative with respect to $\rho$ is

$$\frac{\partial \Pi}{\partial \rho} = \{\alpha + (1-\alpha) m(\hat{\rho})\} \pi_H(r_H) + (1-\alpha)(1 - m(\hat{\rho})) \pi_L(r_L) - \pi_0(r_0).$$

Noting that $\pi_H(r_H) > \pi_L(r_L)$ and $0 \leq m(\hat{\rho}) < 1$ we have

$$\begin{aligned} \{\alpha + (1-\alpha) m(\hat{\rho})\} \pi_H(r_H) + (1-\alpha)(1 - m(\hat{\rho})) \pi_L(r_L) &\geq \alpha \pi_H(r_H) + (1-\alpha) \pi_L(r_L) \\ &> \pi_0(r_0), \end{aligned}$$

where the last inequality was proved toward the end of the proof of Proposition 2.

Therefore, whenever $m(\hat{\rho}) < 1$, we have $\frac{\partial \Pi}{\partial \rho} > 0$, and the lender has an incentive to increase $\rho$. If $m(\hat{\rho}) = 1$, then the posterior beliefs after signal $s_H$ and signal $s_0$ are the same and equal to the prior $\alpha$. Thus, at this point, setting $\rho = \hat{\rho}$ is a best response, and any $\rho \geq \hat{\rho}$ represents an equilibrium (because $m$ is weakly increasing in $\rho$, it follows that $m(y) = 1$ for any $y \geq \hat{\rho}$).

Finally, note that following the arguments in the proof of Proposition 3, when $C'(1) \geq q_L \left( \int_{r_0}^{R} (v - r_0) dF(v) - \int_{r_L}^{R} (v - r_L) dF(v) \right)$, we have $m(\hat{\rho}) < 1$ for any $\hat{\rho} < 1$.

Both parts of the Proposition now follow. ∎

## Proof of Proposition 5

(i) Denote $I_j = \int_{r_j}^{R}(v - r_j)dF(v)$. Specifically, $I_H(m) = \int_{r_H(m)}^{R}(v - r_H)dF(v)$, $I_L = \int_{r_L}^{R}(v - r_L)dF(v)$ and $I_0 = \int_{r_0}^{R}(v - r_0)dF(v)$.

Then, the payoff of the high-type borrower may be written as

$$u_H(\rho, m(\rho)) = \rho q_H I_H(m) + (1 - \rho)q_H I_0.$$

Hence,

$$\frac{du_H}{d\rho} = \frac{\partial u_H}{\partial \rho} + \frac{\partial u_H}{\partial m}\frac{dm}{d\rho} = q_H(I_H - I_0) + \rho q_H \frac{\partial I_H}{\partial m}\frac{dm}{d\rho}. \tag{A39}$$

Here, $\frac{\partial I_H}{\partial m} = -(1 - F(r_H(m)))\, r'_H(m)$, and $\frac{dm}{d\rho}$ is as in equation (A21).

Now, observe that when $\rho = 0$ we obtain

$$\frac{du_H}{d\rho}\,|_{\rho=0} = q_H(I_H - I_0). \tag{A40}$$

Note that when $\rho = 0$, the low-type optimally sets $m = 0$. Further $I_H(0) > I_0$. Thus, $\frac{du_H}{d\rho}\,|_{\rho=0} > 0$.

Similarly, we can write the payoff of the low-type borrower as

$$u_L(\rho, m(\rho)) = -C(m) + \rho m q_L I_H + \rho(1 - m)q_L I_L + (1 - \rho)q_L I_0.$$

Therefore,

$$\frac{du_L}{d\rho} = \frac{\partial u_L}{\partial \rho} + \frac{\partial u_L}{\partial m}\frac{dm}{d\rho}. \tag{A41}$$

Here, $\frac{\partial u_L}{\partial \rho} = q_L\{mI_H + (1 - m)I_L - I_0\}$. Further, $\frac{\partial u_L}{\partial m} = -C'(m) + \rho(q_H - q_L) + \rho m q_L \frac{\partial I_H}{\partial m}$. Observe that the low-type's first-order condition for optimal manipulation (equation (7)) specifies that $C'(m) = \rho(q_H - q_L)$. Therefore, we have $\frac{\partial u_L}{\partial m} = \rho m q_L \frac{\partial I_H}{\partial m}$.

Substituting these expressions into equation (A41), we obtain

$$\frac{du_L}{d\rho} = q_L\{mI_H + (1 - m)I_L - I_0\} + \rho m q_L \frac{\partial I_H}{\partial m}\frac{dm}{d\rho}. \tag{A42}$$

Noting again that when $\rho = 0$ we also have $m = 0$,

$$\frac{du_L}{d\rho}\,|_{\rho=0} = q_L\{I_L - I_0\} < 0, \tag{A43}$$

as $I_L < I_0$.

(ii) The ex ante borrower payoff is

$$\mathcal{U} \quad = \quad \alpha u_H + (1-\alpha) u_L. \tag{A44}$$

Using the expressions for $\frac{du_H}{d\rho}\mid_{\rho=0}$ and $\frac{du_L}{d\rho}\mid_{\rho=0}$ in equations (A40) and (A43) respectively, we obtain

$$\frac{d\mathcal{U}}{d\rho}\mid_{\rho=0} \quad = \quad \alpha q_H (I_H - I_0) + (1-\alpha) q_L (I_L - I_0). \tag{A45}$$

Now, denote a function $G(q) \equiv q \int_{r(q)}^{R} (v - r(q)) dF(v)$, where $r(q)$ is implicitly determined by equation (4) in Lemma 1. Assume that $r_s < R$ for $s \in \{s_H, s_L, s_0\}$.

Then, we can write equation (A45) as

$$\frac{d\mathcal{U}}{d\rho}\mid_{\rho=0} \quad = \quad \alpha G(q_H) + (1-\alpha) G(q_L) - G(\alpha q_H + (1-\alpha) q_L). \tag{A46}$$

Hence, $\frac{d\mathcal{U}}{d\rho}\mid_{\rho=0} > 0$ if and only if $G$ is convex, that is, $G''(q) > 0$.

Now,

$$G'(q) \quad = \quad \int_{r(q)}^{R} (v - r(q)) dF(v) - q \int_{r(q)}^{R} r'(q) dF(v) \tag{A47}$$

$$G''(q) \quad = \quad -(1 - F(r))\{2r'(q) + q r''(q)\} + q\, f(r(q))\, (r'(q))^2. \tag{A48}$$

Define the inverse hazard rate as $H(r) = \frac{1-F(r)}{f(r)}$. Applying the implicit function theorem to the implicit equation that sets the optimal interest rate, equation (4) in Lemma 1, we show that

$$r'(q) = -\frac{1}{q^2(1 - H'(r))} < 0, \tag{A49}$$

$$r''(q) = \frac{2q(1-H'(r)) + q^2 H''(r) r'(q)}{q^4 (1 - H'(r))^2} = \Big( -\frac{2}{q} - \frac{H''(r) r'(q)}{1 - H'(r)} \Big) r'(q). \tag{A50}$$

Substituting into the right-hand side of equation (A48), we have

$$\begin{aligned} G''(q) \quad &= \quad -(1 - F(r))\{2r'(q) - 2r'(q) - \frac{q H''(r) (r'(q))^2}{1 - H'(r)} + q\, f(r(q))\, (r'(q))^2 \\ &= \quad \Big( \frac{H(r) H''(r)}{1 - H'(r)} + 1 \Big)\, q\, f(r(q)\, (r'(q))^2. \end{aligned} \tag{A51}$$

Therefore, $G''(q) > 0$ whenever

$$H(r)\, H''(r) \quad < \quad 1 - H'(r). \tag{A52}$$

The right-hand side is strictly positive, as $H'(r)$ is strictly decreasing (recall that we have assumed

$F(\cdot)$ has an increasing hazard rate).

Now, when $v \sim U[0, R]$, we have $f(r) = \frac{1}{R}$ and $F(r) = \frac{r}{R}$. Thus $H(r) = R - r$, so that $H'(r) = -1$ and $H''(r) = 0$. It is immediate that equation (A52) holds, and hence in this case $G''(q) > 0$. It follows that $\frac{d\mathcal{U}}{d\rho} |_{\rho=0} > 0$.

Finally, observe that $\mathcal{S} = \mathcal{U} + \Pi$. In Proposition 3, we have shown that $\frac{d\Pi}{d\rho} |_{\rho=0} > 0$. Therefore, it follows immediately that $\frac{d\mathcal{S}}{d\rho} |_{\rho=0} > 0$. ∎

## Proof of Corollary 3

The proof follows Propositions 3 and 4. Specifically, when the manipulation cost is low, i.e., $C'(1) \leq q_L \left( \int_{r_0}^{R} (v - r_0) dF(v) - \int_{r_L}^{R} (v - r_L) dF(v) \right)$, as discussed around equation (A36), there exists some $\rho_1$ such that equation (A37) holds and the lender achieves the same profit when $\rho \in (\rho_1, 1)$. Since $\frac{\partial \Pi}{\partial m} |_{m=1} < 0$, the lender's optimal data coverage $\rho^*$ must be strictly less than $\rho_1$. In contrast, when the data coverage is unobservable, the lender is indifferent between $\rho \in [\rho_1, 1]$. Consequently, the lender's data coverage is strictly lower when the data coverage is observable compared to when it is unobservable. Furthermore, the lender earns a higher profit in the former case.

Otherwise, when $C'(1) > q_L \left( \int_{r_0}^{R} (v - r_0) dF(v) - \int_{r_L}^{R} (v - r_L) dF(v) \right)$, even at $\rho = 1$ the low-type borrower manipulates with probability less than 1. Here, the lender might choose full data coverage under even when data coverage is observable data. If so, the lender chooses the same extent of data coverage and it earns the same profit as under unobservable data coverage.

∎

## Proof of Proposition 6

In the transparent regime, the derivation follows similar procedures in the baseline model. The extended manipulation cost function only affects the characterization of the equilibrium manipulation intensity for the low-type borrower when $\rho > 0$. Specifically, equation (7) becomes the following:

$$\rho q_L \left( \int_{r_H(m)}^{R} (v - r_H(m))dF(v) - \int_{r_L}^{R} (v - r_L)dF(v) \right) = \frac{\partial C(m, \rho)}{\partial m}. \tag{A53}$$

Thus, the sufficient conditions for $\rho^* < 1$, as characterized in equations (A35) or (A36), change accordingly.

The proof of part (ii) of the proposition is similar to the proof of Proposition 4 with only replacing $C'(1)$ with $\frac{\partial C(m,\rho)}{\partial m}|_{m=1}$. Finally, the proof of part (iii) of the proposition is similar to that of Corollary 3. ■

## Proof of Proposition 7

(i) Consider the scenario in which the data coverage is observable to the borrower. Given a data coverage $\rho$, the subsequent game will be characterized in the same way as in the baseline model. Thus, the only change occurs at the beginning of the game when determining the optimal data coverage. The proof here follows that of Proposition 3. The lender's expected profit function is

$$\Pi(\rho) = \rho\Big(\{\alpha + (1-\alpha)m\}\pi_H(r_H) + (1-\alpha)(1-m)\pi_L(r_L)\Big) + (1-\rho)\pi_0(r_0) - K(\rho). \tag{A54}$$

Compared with equation (A24), there is an extra cost term $-K(\rho)$ here. Taking the partial derivative with respect to $\rho$ yields

$$\begin{aligned} \frac{d\Pi}{d\rho} &= \{\alpha + (1-\alpha)m\}\pi_H + (1-\alpha)(1-m)\pi_L - \pi_0 \\ &\quad + \rho\{(1-\alpha)(\pi_H - \pi_L) + \{\alpha + (1-\alpha)m\}\pi'_H(r_H)r'_H(m)\}\frac{dm}{d\rho} - K'(\rho). \end{aligned}$$

Setting it to zero implicitly determines the equilibrium $\rho$:

$$\begin{aligned} 0 &= \{\alpha + (1-\alpha)m\}\pi_H + (1-\alpha)(1-m)\pi_L - \pi_0 \\ &\quad + \rho\{(1-\alpha)(\pi_H - \pi_L) + \{\alpha + (1-\alpha)m\}\pi'_H(r_H)r'_H(m)\}\frac{dm}{d\rho} - K'(\rho). \end{aligned} \tag{A55}$$

Next, as in the proof of Proposition 3, we can show that $\rho^* > 0$. Furthermore, to characterize the sufficient conditions for $\rho^* < 1$, we follow the same procedure as in the proof of Proposition

3, expressing $\rho$ as a function of $m$, and obtain

$$\frac{\partial \Pi}{\partial m}\mid_{m=1}= \rho(1-\alpha)\Big\{\{1-F(r_H(m))\}\{(1+r_H(m))q_L-1\}-\pi_L(r_L)\Big\}-\frac{\partial K(\rho)}{\partial \rho}\frac{d\rho}{dm},$$

which is the counterpart of equation (A33). Note that we've shown that $\frac{d\rho}{dm}>0$ and assumed that $\frac{\partial K(\rho)}{\partial \rho}>0$. Thus, as in the baseline model, a sufficient condition to ensure that $\frac{\partial \Pi}{\partial m}\mid_{m=1}<0$ is

$$q_L(1+R)<1, \quad \text{or} \quad q_L<\frac{1}{1+R}.$$

Moreover, as the lender's data-collection cost does not enter directly into the borrower's manipulation function, the other sufficient condition does not change, which is equation (A36), or

$$C'(1)\le q_L\left(\int_{r_0}^{R}(v-r_0)dF(v)-\int_{r_L}^{R}(v-r_L)dF(v)\right).$$

(ii) Consider the scenario in which the data coverage is unobservable to the borrower. Again, given the borrower's belief about the data coverage $\hat{\rho}$, the borrower determines the manipulation intensity. The lender's optimal interest rates are also set in accordance with the borrower manipulation behavior. So the characterization of the subsequent game after $\hat{\rho}$ remains the same as in the baseline model.

We then move back to the beginning of the game to determine the lender's optimal data coverage, following similar procedures as in Proposition 4. The lender's expected profit function (A38) can be augmented as the following:

$$\begin{aligned}\Pi(\rho,\hat{\rho}) \quad &= \quad \rho\Big(\{\alpha+(1-\alpha)m(\hat{\rho})\}\pi_H(r_H(m(\hat{\rho})))+(1-\alpha)(1-m(\hat{\rho}))\pi_L\Big\}\\ &\quad\; +(1-\rho)\pi_0(r_0)-K(\rho).\end{aligned}$$

The derivative with respect to $\rho$ is

$$\frac{\partial \Pi}{\partial \rho} \quad = \quad \{\alpha+(1-\alpha)m(\hat{\rho})\}\pi_H(r_H)+(1-\alpha)(1-m(\hat{\rho}))\pi_L(r_L)-\pi_0(r_0)-K'(\rho). \tag{A56}$$

Denote $\Delta(\hat{\rho})=\{\alpha+(1-\alpha)m(\hat{\rho})\}\pi_H(r_H)+(1-\alpha)(1-m(\hat{\rho}))\pi_L(r_L)-\pi_0(r_0)$. Then

$$\frac{\partial \Pi}{\partial \rho} \quad = \quad \Delta(\hat{\rho})-K'(\rho). \tag{A57}$$

When $m(\hat{\rho})=1$ so that $\Delta(\hat{\rho})=0$, we know that $\frac{\partial \Pi}{\partial \rho}<0$ for any $\rho>0$. Therefore, unlike the baseline model, the lender will never allow $m^* = 1$ in equilibrium.

When $m(\hat{\rho}) < 1$, we've shown $\Delta(\hat{\rho}) > 0$ in the baseline model. Inserting $\hat{\rho} = \rho$ in equation (A56) and setting it to zero yields the optimal data coverage $\rho$, which is the solution implicitly determined by: $\Delta(\rho) = K'(\rho)$. Only when the marginal data-collection cost is not steep, i.e., $K'(\rho)$ is low for any $\rho$, do we have $\frac{\partial \Pi}{\partial \rho} > 0$ so that the equilibrium $\rho^* = 1$.

(iii) Since the newly added data-collection cost $K(\rho)$ affects the lender by only reducing their expected profit by $K(\rho)$, under both observable and unobservable data coverage, the comparison between the two scenarios should resemble that in the baseline model where $K(\rho) = 0$. Therefore, Corollary 3 remains valid in this extension. ∎