The Limits of Big Data: Data Manipulation in Credit Lending Markets *

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Abstract

We study a credit lending market in which the lender bases its lending decisions on borrowers' digital profiles, and borrowers can manipulate their digital profiles at a cost. We find that as the lender utilizes higher data coverage in its underwriting models, the borrowers are more likely to manipulate their digital profiles, which impairs the quality of the lender's data and its lending decisions. Therefore, even if the data technology is costless, the lender may not exploit the full potential of its data. Our model sheds new light on FinTech lending and the related regulations.

Keywords: FinTech lending, Digital profiles, Alternative data, Manipulation

JEL: G21, G23

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1 Introduction

The increasing digitization of people's lives has left behind a trace of valuable data such as app usage and social media activity. The data helps paint various digital profiles and has been increasingly used by FinTech companies to screen and score borrowers in the credit market. As important players in this market, a distinct feature of FinTech lenders is the substitution of algorithms and alternative data for in-person interactions between the lender and the borrower (Di Maggio, Ratnadiwakara, and Carmichael, 2022).

Once digital profile information is widely used for lending decisions, it is natural that borrowers may change their behavior, thereby affecting the data collected by the FinTech lenders, as would be implied by the Lucas critique (Lucas, 1976). While some of the digital-profile variables are hard to manipulate or require a borrower to change her intrinsic habits (e.g., transaction records for utility bills), some 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 iOS users imply higher income and lower default rates than Android users (Berg, Burg, Gombović, and Puri, 2020).

The increasing prominence of algorithms and alternative data in the credit market elevates the importance of understanding their adoption, borrowers' responses, and implications for the aggregate economy. In this paper, we build a theoretical model to study how lenders' use of data technology affects borrowers' manipulation behavior and how borrowers' manipulation in turn affects lenders' data usage and lending decisions.

Our model features a single lender and a continuum of borrowers. Each borrower has a project for which they seek funding from the lender. There are two types of borrowers, high and low, based on the probability their project will succed. The type is the private knowledge of the borrower. The low-type borrower's project has negative NPV, and the high-type borrower's project has positive NPV. Thus, the lender wishes to weed out low-type borrowers.

Each 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.

The 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 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. On the one hand, a higher data coverage improves the quality of the lender's data, better informing its lending decisions. On the other hand, a higher data coverage can induce low-type borrowers to manipulate their digital profiles. Understanding that the lender would rely more on the collected data, the low-type borrowers have greater incentives to disguise themselves as high types, which lowers the quality of the lender's data and impairs its lending decisions.

When the manipulation cost is low for borrowers, the latter negative force becomes salient. Our main result is that, in equilibrium, the lender optimally chooses to limit its own data coverage—even if it is costless to acquire more data for its underwriting models, the lender would not do so. In this way, the lender limits the borrowers' manipulation, sustaining its data quality and lending profit.

Our results imply there is an endogenous limit on the value of big data to a lender. Acquiring additional data beyond this optimal limit results in the data itself being less useful for predicting default. In turn, there is an endogenous limit on how much information the lender will acquire. If information acquisition were costless, in the spirit of Holmström informativeness (Holmström, 1979), the lender should acquire unlimited amounts of information on the borrower, and then use it in making a prediction of borrower creditworthiness. In our model, the lender has no exogenous cost to acquiring information. Rather, borrower manipulation renders the information less valuable, generating an endogenous cost to acquiring more of it.

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 contractual settings includes Barbalau and Zeni (2022) in the context of green bonds. Cohn et al. (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.

Our paper is also related to the growing literature on FinTech lending and the use of big data in the lending business. Berg et al. (2021) offer an excellent survey on this literature. Berg et al. (2020) show digital footprint variables (e.g., computer type, distribution channel) to 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. Di Maggio et al. (2022) find that alternative data used by a major FinTech platform exhibits substantially more predictive power with respect to the likelihood of default than traditional credit scores and helps broaden credit access. Jansen et al. (2022) analyze the welfare effects of increased data availability in the credit market. We contribute to this literature by focusing on borrowers' manipulation behavior and exploring its implications for the lender's lending decisions and the credit market.

2 The Model

We consider a credit market with a lender and a continuum $[0, 1]$ of borrowers. Each borrower seeks unit funding for a project. If the project succeeds, it generates cash flow R; if it fails, the cash flow is zero. The risk-free rate is zero, and all agents are risk-neutral.

2.1 Borrowers

There are two types of borrowers, high-type (H) and low-type (L). Let $t_i \in \{H, L\}$ denote borrower i's type. A fraction $\alpha \in (0, 1)$ of the borrowers are high-type borrowers, and the success rate of their project is $q_H \in (0, 1)$. The remaining fraction $1 - \alpha$ of borrowers are low-type, and their project success rate is $q_L \in (0, 1)$. We assume that $q_H R > 1 > q_L R$. That is, the high type has a positive net present value (NPV) project, and the low type has a negative NPV one. Denote the average project success rate as $\bar{q} \equiv \alpha q_H + (1 - \alpha) q_L$. We assume that $\bar{q} R > 1$ so that without additional information, an average project has positive NPV and is thus worth funding. Each borrower knows their own type, and the fraction α is common knowledge. If the borrower i accepts a loan from the lender and undertakes the project, she repays the loan plus the interest rate when the project succeeds. Otherwise, if the project fails, the borrower defaults.

To ensure that the borrowers retain some surplus from a successful project when dealing with the monopolistic lender, we assume that borrower i has an outside loan offer at an interest rate v_i. The outside offer is independent across borrowers and has an atomless distribution $F(\cdot)$ with density $f(\cdot)$. The support of the outside offer v_i is $[0, R - 1]$, with the upper bound being the maximum net payoff from the project investment. We assume that the hazard rate is increasing, that is, $\frac{f(v_i)}{1-F(v_i)}$ is increasing in v_i. The outside option serves as the borrower's reservation interest rate, and its realization is privately known to borrower i. One can think of v_i as a reduced-form way to model an alternative loan offered by another lender.

In addition to her project type, a borrower has a digital profile denoted by $\theta_i \in \{H, L\}$. As shown by Berg et al. (2020), digital profiles of customers include variables such as the device type (e.g., desktop, tablet, mobile), operating system (e.g., Windows, iOS, Android), the channel through which a customer has visited the website and the time at which a customer makes the purchase. For small and medium-sized businesses (SMBs), digital profiles can include their business ratings and reviews on social media and other sites like Yelp, website data such as traffic and global traffic rank, social media presence, and engagement data.

A key feature of our model is that borrowers can manipulate their digital profile. Denote borrower i's manipulation decision as $m_i \in [0, 1]$, where $m_i = 0$ indicates no manipulation and $m_i = 1$ means complete manipulation. Manipulation increases the probability that the digital profile is dissociated from the type. Specifically, a borrower's manipulation decision affects her digital profile as follows:

$$\theta_i = \begin{cases} t_{-i}, & \text{with probability } m_i, \\ t_i, & \text{with probability } 1 - m_i, \end{cases} \tag{1}$$

where $-i \neq i$. To manipulate, a borrower incurs a cost $C(m_i)$, where $C(0) = C'(0) = 0$ and $C'(m_i), C''(m_i) > 0$ when $m_i > 0$.

2.2 The Lender

The lender can leverage the power of alternative data in its lending business. Specifically, the lender chooses a data technology $\rho \in [0, 1]$ in its underwriting model. The technology and the collected data yield a signal s_i about the borrower i's digital profile, where

$$s_i = \begin{cases} \theta_i, & \text{with probability } \rho, \\ \varnothing, & \text{with probability } 1 - \rho. \end{cases} \tag{2}$$

The empty set $\varnothing$ denotes that the lender does not receive any information about the borrower.[1] One can interpret ρ as the data coverage in the lender's underwriting algorithm. The higher the

[1] Our key insights remain valid if we consider an alternative data structure in which the signal s_i correctly reveals the underlying borrower type with probability ρ; that is, $\Pr(s_i = H|\theta_i = H) = \Pr(s_i = L|\theta_i = L) = \rho$, where $\rho \in [\frac{1}{2}, 1]$.

data coverage, the more likely the lender's signal is informative.

Different alternative data read together can be effective in evaluating financial credibility. For instance, paying rent and utility bills on time demonstrates responsible behavior, and good academic background may show employment potential. A steady job for a reasonable length of time indicates reliability and a regular source of income. Asset ownership, such as purchasing a retail item on installments and making timely payments, proves respect for financial commitments. While none of them may make a strong case individually, aggregation of such innocuous details can present a responsible individual who might otherwise be dismissed as risky and unqualified (see, for example, Kona (2020)).

To convey our insight most transparently, we assume that increasing the extent of data coverage, ρ, has no cost for the lender. Note also that because the signal obtained by the lender is informative only about the borrower's digital profile, the signal depends on the extent of manipulation by the borrower.

Personalized loan pricing adopted by the lender is facilitated by its data collection. We assume that standard information about the borrower (i.e., information such as income, wealth, and credit score) is already incorporated into the prior α, and focus on the collection of alternative data, i.e., digital signals. Specifically, the lender observes a digital signal $s_i \in \{H, L, \varnothing\}$ from borrower i and decides whether to offer the borrower a loan and if so, at what interest rate. The interest rate is denoted as r_i. Thus, when the project succeeds, the lender obtains a net payoff r_i, whereas the lender's payoff is -1 when the project fails. Note that given the borrower's reservation interest rate, no borrower will accept a loan offer at an interest rate strictly higher than $R-1$. Thus, when the lender does not want to make a loan, it can simply offer such an interest rate. Without loss of generality, we set the interest rate offer to R in this case. We assume the lender has deep pockets and can raise an arbitrary amount of funds at an interest rate normalized to zero.

2.3 Sequence of Moves

The sequence of moves in the economy is illustrated in Figure 1. At date 0, the lender chooses its data coverage ρ to maximize the expected profit from lending. After observing the data coverage, each borrower decides their manipulation intensity m_i. At date 1, each borrower observes their outside loan offer v_i.[2] Then, the lender receives signals from the borrowers and offers a personalized loan contract at the interest rate r_i. Based on the contract offer r_i and the outside option v_i, each borrower decides whether or not to accept the lender's offer. Finally, at date 2, the project's outcome is revealed, and all agents' payoffs are realized.

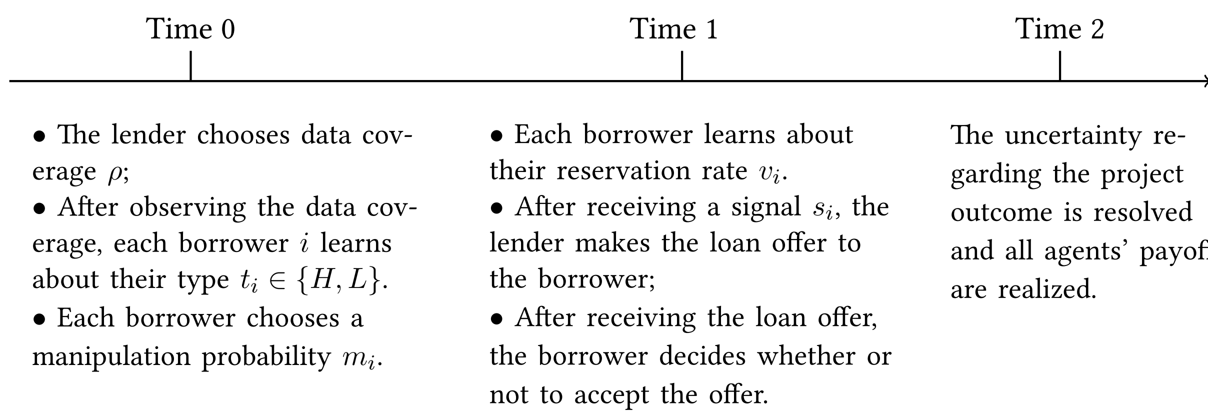


Figure 1: Timeline

2.4 Equilibrium Definition

We consider the perfect Bayesian equilibria of the model.

Definition 1 (Equilibrium definition). *A perfect Bayesian equilibrium is characterized by the lender's data coverage $\rho \in [0, 1]$, the lender's loan offers r_i, and each borrower's manipulation decision $m_i \in [0, 1]$ and loan acceptance decisions such that:*

(i) *At date 0, the lender chooses data coverage ρ to maximize its expected profit.*

[2] An alternative timing would be that each borrower makes manipulation decisions after observing their outside loan offer v_i. We consider this possibility in Section 4 and demonstrate the robustness of our key insight.

(ii) *At date 0, upon observing the lender's data coverage ρ, borrower i chooses the manipulation intensity m_i that maximizes her expected payoff.*

(iii) *At date 1, upon observing the digital signal $s_i \in \{H, L, \varnothing\}$ about borrower i, the lender chooses interest rate r_i to maximize its expected profit, given its posterior belief over types. The posterior belief, in turn, is given by Bayes rule wherever possible.*

(iv) *At date 1, given the loan offer r_i and data coverage ρ, her type t_i, and the reservation interest rate v_i, the borrower i's acceptance decision maximizes her expected payoff.*

3 Data Coverage and Data Manipulation

We first consider a benchmark where borrowers cannot manipulate their digital profiles. We then characterize the equilibrium outcome.

3.1 A No-Manipulation Benchmark

Consider first a benchmark economy in which the borrowers cannot manipulate their digital profiles, that is, $m_i = 0$ for all $i \in [0, 1]$. Then, based on equation (1), a borrower's digital profile is always consistent with her underlying type: $\theta_i = t_i$ for any $i \in [0, 1]$. Therefore, if the lender's signal reveals any information, the borrower's type is revealed. As expanding digital data coverage is costless, it is immediate that the lender prefers maximal data coverage.

Lemma 1 (No-manipulation benchmark)**.** *When borrowers cannot manipulate their digital profiles, the lender optimally sets data coverage to be one, i.e., $\rho^* = 1$.*

Lemma 1 shows that when borrowers' digital profiles are not subject to manipulation, the lender will choose maximal data coverage. That is, the lender will fully use all available digital data in its underwriting models. This result is very intuitive since, in this circumstance, acquiring more data unambiguously results in a better screening of borrowers, and thus only has a benefit.

This finding stands in stark contrast to what we will show in the next section in which borrowers can manipulate their digital profiles.

3.2 Data Collection and Manipulation

We now consider the case in which borrowers can manipulate their digital profiles to influence the lender's underwriting process. We begin with the borrower's acceptance/rejection decision of a loan offer.

3.2.1 Optimal Loan Acceptance Decisions by Borrowers

Suppose that borrower i 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 $R-(1+r)$. Otherwise, if the project fails, the borrower defaults and receives 0. As such, for $t \in \{H, L\}$, the borrower's expected payoff is

$$w(t,r) = q_t \left[R-(1+r)\right]. \tag{3}$$

The borrower has an outside offer at interest rate v_i, which serves as her reservation interest rate. If the borrower accepts the outside offer, her expected payoff is $w(t, v_i) = q_t \left[R-(1+v_i)\right]$. Thus, the borrower accepts the loan if and only if

$$r \leq \min\{v_i, R-1\} = v_i, \tag{4}$$

where the equality follows because the support of the random variable v_i is $[0, R-1]$. Thus, at time 0, the borrower believes that the probability they will accept a loan at rate r is $1-F(r)$.

3.2.2 Optimal Interest Rates and Manipulation Intensity

Borrowers' manipulation behavior m_i affects the lender's optimal choice of interest rate. Specifically, after observing signal $s_i \in \{H, L, \varnothing\}$, which the borrowers' manipulation might contaminate, the lender updates its posterior beliefs about the borrower type and determines the optimal interest rate for its loan offer. Let μ_s denote the lender's posterior belief that the borrower is of the high type after observing signal s; that is, $\mu_s \equiv \Pr(t_i = H|s)$. Based on borrowers' optimal loan acceptance strategy (4), the lender understands that if it makes a loan offer at interest rate r, borrower i 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 its payoff becomes -1 if it fails. Therefore, given the loan offer at interest rate r, the lender's expected payoff is

$$\pi_{s_i}(r) = (1 - F(r)) \left[\bar{q}_s \cdot r \, - \, (1 - \bar{q}_s)\right], \tag{5}$$

where $\bar{q}_s \equiv \mu_s q_H + (1 - \mu_s) q_L$ indicates the average success rate of the project after receiving the signal s. Maximizing the expected payoff (5) thus yields the lender's optimal interest rate r_s, for $s \in \{H, L, \varnothing\}$.

In the meantime, borrowers' equilibrium manipulation intensity m_i is affected by the lender's choice of interest rate. Given the lender's interest rate for borrowers with high digital profile r_H and that for those with low digital profile r_L, all borrowers of a given type face the same trade-off when deciding whether to manipulate. Thus, they must adopt the same manipulation intensity; that is, $m_i = m_t$ for $t \in \{H, L\}$.

If a borrower of type $t \in \{H, L\}$ with reservation rate v_i manipulates with probability m_i, their expected payoff at date 0 is

$$\begin{aligned} u(t, m_i) = -C(m_i) + \rho \cdot m_i \cdot & \underbrace{\left(w(t, r_{\tilde{t}})(1 - F(r_{\tilde{t}})) + \int_0^{r_{\tilde{t}}} w(t, v_i) dF(v_i) \right)}_{\text{expected payoff when incorrectly recognized}} \\ + \rho \cdot (1 - m_i) \cdot & \underbrace{\left(w(t, r_t)(1 - F(r_t)) + \int_0^{r_t} w(t, v_i) dF(v_i) \right)}_{\text{expected payoff when correctly recognized}} \\ + (1 - \rho) \cdot & \underbrace{\left(w(t, r_\varnothing)(1 - F(r_\varnothing)) + \int_0^{r_\varnothing} w(t, v_i) dF(v_i) \right)}_{\text{expected payoff when unrecognized}}. \end{aligned} \tag{6}$$

There are three cases to consider in equation (6). First, given the lender's data technology ρ, with probability $\rho \cdot m_i$ the borrower will successfully pretend to be a different type $\tilde{t}$ and receive the according interest rate $r_{\tilde{t}}$. As discussed in Section 3.2.1, if the realized reservation interest rate v_i exceeds $r_{\tilde{t}}$, the borrower accepts the offer, obtaining an expected payoff $w(t, r_{\tilde{t}})$.

Otherwise, the borrower goes for the outside option with reservation interest rate v_i, and her expected payoff is $w(t, v_i)$. Therefore, when the borrower manipulates successfully, her expected payoff is $w(t, r_{\tilde{t}})(1 - F(r_{\tilde{t}})) + \int_0^{r_{\tilde{t}}} w(t, v_i)dF(v_i)$.

Second, with probability $\rho \cdot (1 - m_i)$, the borrower will remain in the original profile t. Similar to the first case, she either accepts the loan offer r_t or goes for the outside option, leading to an expected payoff of $w(t, r_{\tilde{t}})(1 - F(r_t)) + \int_0^{r_t} w(t, v_i)dF(v_i)$. Finally, with the remaining probability $1 - \rho$, the borrower will not be recognized as any type since the lender's signal is not informative. Again, the borrower needs to make a choice between the loan offered by the lender featured with interest rate $r_\varnothing$ and the outside offer with reservation interest rate v_i. The resulting expected payoff for the borrower is $w(t, r_\varnothing)(1 - F(r_\varnothing)) + \int_0^{r_\varnothing} w(t, v_i)dF(v_i)$.

To proceed, we conjecture and verify later that only low-type borrowers manipulate their digital profiles in equilibrium, namely, $m_L > 0$ whereas $m_H = 0$. We thus only focus on the manipulation incentive of the low-type borrowers hereafter and characterize the equilibrium interest rates and manipulation intensity. Denote the manipulation intensity of the low-type borrowers as m, i.e., $m_L = m$. Given the low-type borrowers' manipulation intensity m, upon receiving a signal $s_i = H$, the lender's posterior belief about the borrower being the high-type is:

$$\mu_H = \frac{\alpha}{\alpha + (1 - \alpha)m}. \tag{7}$$

Then, the lender chooses interest rate r to maximize the expected profit as given by (5), where $\bar{q}_H = \mu_H q_H + (1 - \mu_H)q_L$, which yields the optimal interest rate r_H as determined implicitly in the following equation:

$$\frac{f(r_H)}{1 - F(r_H)} = \frac{\bar{q}_H}{\bar{q}_H(1 + r_H) - 1}. \tag{8}$$

The second-order condition for the maximization is $-f'(r_H)(\bar{q}_H(1 + r_H) - 1) - 2f(r_H)\bar{q}_H < 0$.

When observing signal $s_i = L$, since in equilibrium, high-type borrowers never manipulate their data, the lender knows that the borrower must be low-type and the project is not worth funding. So the lender does not make a loan offer, and as discussed in Section 2, we simply let the optimal interest rate $r_L = R$ in this case. The resulting payoff for the lender is $\pi_L = 0$. Note that we have characterized $r_H \leq r_L$, which is consistent with the conjecture that only low-type borrowers manipulate their digital profiles in equilibrium.

When the signal does not contain any information, i.e., $s_i = \varnothing$, the lender's posterior about the probability of the borrower being high type does not change, i.e., $\mu_\varnothing = \alpha$. Inserting $\mu_\varnothing = \alpha$ into equation (5) and maximizing yields the optimal interest rate $r_\varnothing$ as determined implicitly in the following equation:

$$\frac{f(r_\varnothing)}{1 - F(r_\varnothing)} = \frac{\bar{q}}{\bar{q}(1 + r_\varnothing) - 1}. \tag{9}$$

The second-order condition for the maximization is $-f'(r_\varnothing)(\bar{q}(1 + r_\varnothing) - 1) - 2f(r_\varnothing)\bar{q} < 0$. Part (1) of Proposition 1 summarizes the optimal interest rates set by the lender.

Proposition 1. *Suppose that the lender chooses data coverage ρ.*

(1) *When receiving signal $s_i = H$, the lender offers the loan with interest rate r_H^*, where r_H^* is determined by equation (7); when receiving signal $s_i = L$, the lender offers the loan with interest rate $r_L^* = R$; and when receiving uninformative signal, i.e., $s_i = \varnothing$, the lender offers the loan with interest rate $r_\varnothing^*$, where $r_\varnothing^*$ is determined by equation (9).*

(2) *The high-type borrowers never manipulate their digital profiles in equilibrium. The low-type borrowers manipulate with positive probability if and only if $\rho > 0$. In this case, the equilibrium manipulation intensity m^* is determined by equation (10).*

The following corollary summarizes how the manipulation intensity by low-type borrowers affects the lender's loan decisions.

Corollary 1 (Manipulation and optimal interest rates)**.** *When the low-type borrowers' manipulation intensity increases,*

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

(2) *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., $\frac{\partial r_\varnothing}{\partial m} = 0$ and $\frac{\partial r_L}{\partial m} = 0$.*

Part (1) of Corollary 1 states that when the low-type borrowers are more likely to manipulate their digital profiles, the lender will set higher interest rates upon receiving the high-type signal. As shown in equation (7), a higher manipulation intensity by the low-type borrowers 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 $r_\varnothing$ as given by (9), regardless of the borrowers' 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 $s_i = L$, and again, the resulting interest rate r_L is not affected by m.

Finally, we characterize the optimal manipulation decision by the low-type borrowers. Given all other low-type borrowers' manipulation decision m, a low-type borrower i's expected payoff $u(L, m_i)$ is given by equation (6). Taking the partial derivative of $u(L, m_i)$ with respect to m_i, setting it equal to zero, and replacing $m_i = m$ yields the following equation that determines the equilibrium manipulation intensity m^* by the low-type borrowers:

$$\rho q_L \int_{r_H(m)}^{R-1} (v_i - r_H(m)) dF(v_i) = C'(m). \tag{10}$$

If the net benefit of manipulation at $m = 1$ is still positive, the equilibrium manipulation intensity is $m^* = 1$. In equation (10), we write the interest rate charged for the borrowers with high-type digital profiles as $r_H(m)$ to emphasize that the interest rate is a function of the manipulation intensity m. Thus, equation (10) clearly shows that the low-type borrowers' manipulation intensity is affected by the data coverage. The following corollary formally presents the result.

Corollary 2. *The higher the data coverage chosen by the lender, the more intensively the low-type borrowers manipulate their digital profiles. That is,* $\frac{\partial m}{\partial \rho} \geq 0$.

As suggested by the signal structure (2), when the lender adopts higher data coverage in its underwriting process (i.e., ρ increases), a borrower's digital profile is more likely to be revealed and in turn influences the lender's lending decision. Understanding this, a low-type borrower will have greater incentives to manipulate her data, pretending to be a high-type borrower. The resulting positive relationship between the lender's choice of data coverage and the low-type borrowers' manipulation intensity, as summarized in Lemma 2, underlies the key mechanism in our paper, driving the main insight as will be provided in Section 3.2.3.

3.2.3 Optimal Data Coverage by the Lender

Finally, at the beginning of date 0, the lender chooses data coverage to maximize its unconditional expected profit in the lending business. Specifically, given the low-type borrowers' manipulation intensity m, a fraction $\alpha + (1-\alpha)m$ of borrowers own the high-type digital profile. With probability ρ, these borrowers will be recognized as high type by the lender's data technology and offered the interest rate r_H, where r_H is given by equation (8). The lender in turn makes an expected profit of $\pi_H(r_H)$, where $\pi_H(\cdot)$ is given by (5). Next, a fraction $(1-\alpha)(1-m)$ of borrowers remain with the low-type digital profile and are recognized as the low type by the lender with probability ρ. In this case, the lender effectively declines to lend to the borrowers by charging prohibitively high interest rates, thereby making zero expected profit, i.e., $\pi_L(r_L) = 0$. 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 $r_\varnothing$ and makes profit $\pi_\varnothing(r_\varnothing)$ accordingly, where $r_\varnothing$ is implicitly determined by (9), and $\pi_\varnothing(\cdot)$ is given by equation (5). Overall, the lender's unconditional expected profit at the beginning of the economy is as follows:

$$\Pi(\rho) = \rho \cdot (\alpha + (1-\alpha)m) \cdot \pi_H(r_H) + (1-\rho) \cdot \pi_\varnothing(r_\varnothing). \tag{11}$$

Note that the unconditional expected profit Π is a function of the data coverage ρ because the low-type borrowers' manipulation intensity m and the lender's optimal interest rate r_H are both functions of ρ, as implied by equations (8) and (10).

We are particularly interested in understanding what circumstance the lender's optimal choice of data coverage is strictly below 1, that is, $\rho^* < 1$. The following proposition summarizes the finding.

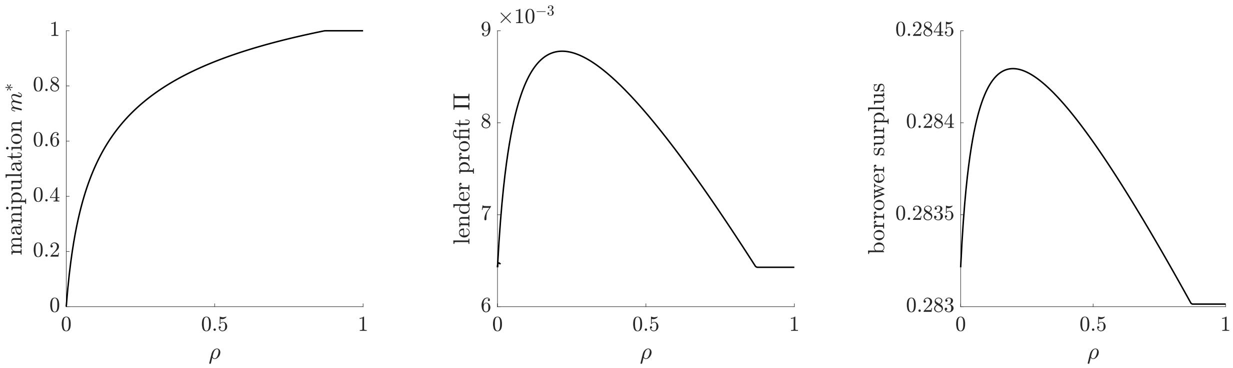
Proposition 2 (Optimal data coverage). *Define* $\hat{\rho} \equiv \frac{C(1)}{q_L \int_{r_H(1)}^{R-1}(v-r_H(1))\mathrm{d}F(v)}$, *where* $r_H(\cdot)$ *is implicitly determined by equation (8). Suppose that* $\hat{\rho} < 1$, *or alternatively,* $C(1) < q_L \int_{r_H(1)}^{R-1}(v-r_H(1))\mathrm{d}F(v)$. *Then, in equilibrium, the lender chooses non-full data coverage, i.e.,* $\rho^* < 1$.

Proposition 2 shows that despite the free data technology, in equilibrium, the lender may optimally select the one that features non-full data coverage. This result stands in stark contrast with the full data coverage in the no-manipulation benchmark economy as characterized by Lemma 1. On the one hand, when the lender adopts more advanced data technology in the underwriting process, its signal is more likely to be informative, leading to better lending decisions. On the other hand, as shown in Lemma 2, more advanced data technology can induce more intensive manipulation by the borrowers, which lowers the quality of the lender's signal. When the manipulation cost is low (e.g., $C(1) < q_L \int_{r_H(1)}^{R-1}(v - r_H(1))\mathrm{d}F(v)$) so that the digital profile is easily manipulated, the lender's signal quality deteriorates severely for a large and increasing ρ. In this case, the latter effect dominates, leading the lender to avoid the full data coverage to retain the data quality.

3.2.4 A Numerical Example

In this section, we examine a numerical example to illustrate the key insights of our paper. Consider that the reservation interest rate follows a uniform distribution; that is, $v_i \sim U(0, R-1)$. The manipulation cost is assumed to be $C(m_i) = c \cdot m_i^2$. The parameters are $q_H = 0.8, q_L = 0.2, \alpha = 0.6, R = 2$, and $c = 0.0005$. We plot the low-type borrowers' equilibrium manipulation intensity and the lender's unconditional expected profit against its data coverage in Figure 2.

Consistent with Corollary 2, Panel (a) of Figure 2 demonstrates that more data coverage ρ can induce (weakly) more manipulation from low-type borrowers. Specifically, when $\rho < 0.87$, the equilibrium manipulation intensity m^* strictly increases in ρ. After ρ continues to grow and exceeds 0.87, the low-type borrowers fully manipulate their data, i.e., $m^* = 1$. Due to this more intensive manipulation, the lender's unconditional expected profit can decrease in the data



(a) Manipulation intensity (b) Lender profit (c) Borrower surplus

Figure 2: The effect of data coverage

coverage when ρ takes a large value, as shown in Panel (b) of this figure. Therefore, the lender may not choose the maximum data coverage even though it is free. In this numerical example, the lender optimally chooses $\rho^* = 0.21$ to maximize its lending profit, which strictly falls below 1. This is consistent with Proposition 2.

In addition, we also examine the effect of data coverage on the borrower surplus, which is defined to be the ex ante expected payoff of a borrower:

$$u = \alpha \cdot u(H, 0) + (1 - \alpha) \cdot u(L, m), \tag{12}$$

where $u(t, m_i)$ is given by equation (6). Panel (c) of Figure 2 shows that, like the lender profit, borrower surplus also exhibits a hump-shape pattern with respect to the data coverage. Several forces drive such a non-monotone pattern. For a low-type borrower, higher data coverage incentivizes her to engage in more manipulation, which incurs higher costs. 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, more manipulation by the low-type borrowers contaminates the lender's signal, making it more difficult for the high-type borrower to separate from the low-type one and thus leading to the unfavorable interest rates for the high-type borrower.

4 Variation: If Borrowers Learn the Outside Option First

In the main model, we assume that the borrowers make manipulation decisions before learning about their reservation interest rate v_i, which suggests that the borrowers receive their loan offer from the lender and the outside unmodeled lender simultaneously. An alternative timeline would be that the borrowers learn about their outside interest rate v_i first, engage in manipulation and then seek a loan offer from the lender.

Denote the equilibrium interest rate set by the lender upon signals $s_i = H$, $s_i = \varnothing$, and $s_i = L$ as r_H^*, $r_\varnothing^*$, and r_L^* respectively. As in the main model, we conjecture and verify that in equilibrium $r_H^* < r_\varnothing^* < r_L^*$ and thus only the low-type borrowers have incentives to manipulate. Therefore, upon signal $s_i = L$, the lender knows that the borrower type with certainty and refuses to lend to her, under which case we simply set $r_L^* = R$ as in the main model. Moreover, since the interest rate upon the uninformative signal is not affected by borrowers' manipulation, we follow the same procedure as in the baseline model to compute the equilibrium interest rate $r_\varnothing^*$, as given by equation (9). We next determine the low-type borrowers' manipulation and the interest rate r_H^* upon signal $s_i = H$.

We can express a low-type borrower's payoff from manipulation as follows:

$$\begin{aligned} u(L, m_i) = -C(m_i) + \rho \cdot m_i \cdot & \underbrace{w(L, \min\{r_H^*, v_i\})}_{\text{expected payoff when misrecognized as high type}} \\ + \rho \cdot (1 - m_i) \cdot & \underbrace{w(L, \min\{r_L^*, v_i\})}_{\text{expected payoff when recognized as low type}} \\ + (1 - \rho) \cdot & \underbrace{w(L, \min\{r_\varnothing^*, v_i\})}_{\text{expected payoff when unrecognized}} . \end{aligned} \tag{13}$$

The low-type borrower payoff is only affected by the equilibrium interest rates r_H^*, r_L^*, and $r_\varnothing^*$, but not the actual interest rates, because when considering manipulation, borrowers don't know the actual interest rates offered by the lender and only hold beliefs about these rates. In other words, the manipulation decisions do not respond to the actual interest rates.

Maximizing the expected profit (13) with respect to the manipulation yields the optimal manipulation m_i^* as determined as following: if $v_i > r_H^*$, m_i^* is the unique root to the following equation:

$$C'(m_i) = \rho \left(w(L, r_H^*) - w(L, v_i) \right), \tag{14}$$

and otherwise $m_i^* = 0$.

Upon observing the high-type signal $s_i = H$, the lender chooses r_H to maximize the expected lending profit $\pi_H(r_H)$, where

$$\pi_H(r_H) = \alpha(1 - F(r_H)) \left(q_H r_H - (1 - q_H) \right) \\ + (1 - \alpha) \int_{r_H}^{R-1} \left(q_L r_H - (1 - q_L) \right) m_i(v_i; r_H^*, r_L^*, r_\varnothing^*) dF(v_i). \tag{15}$$

Taking the derivative of (15) with respect to r_H and setting it to zero at $r_H = r_H^*$ yields

$$\alpha(1 - F(r_H^*))q_H - \alpha f(r_H^*)(q_H r_H^* - (1 - q_H)) \\ + (1 - \alpha) q_L \int_{r_H^*}^{R-1} m_i(v_i; r_H^*, r_L^*, r_\varnothing^*) dF(v_i) = 0, \tag{16}$$

which determines the optimal interest rate r_H^*. The following lemma summarizes the equilibrium interest rates and manipulation for a given data coverage ρ.

Lemma 2. *Suppose that the borrowers learn about their reservation interest rate before manipulation. Given the data coverage ρ,*

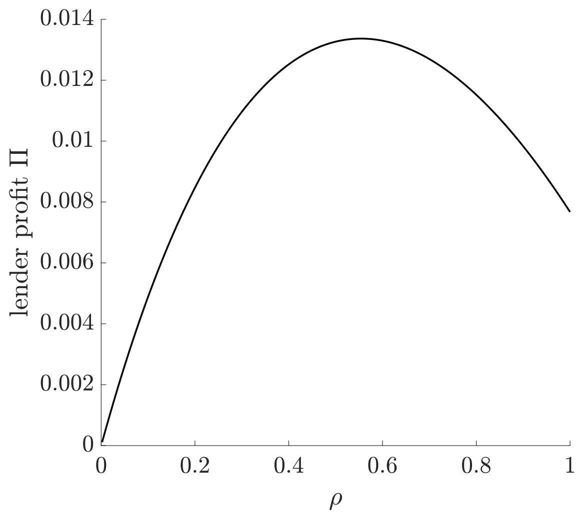
(1) *When receiving signal $s_i = H$, the lender offers interest rate r_H^*, where r_H^* is determined by equation (16). Moreover, if v_i follows a uniform distribution, r_H^* is uniquely determined. In addition, the lender's optimal interest rates r_L^* and $r_\varnothing^*$ upon the respective signals $s_i = L$ and $s_i = \varnothing$ are the same as those in the baseline model, i.e., $r_L^* = R$ and $r_\varnothing^*$ is determined by equation (9).*

(2) *The high-type borrowers and the low-type borrowers with reservation interest rate $v_i > r_H^*$ never manipulate their digital profiles. Given the equilibrium interest rate r_H^*, the manipulation intensity m_i of the low-type borrowers with reservation interest rate v_i is determined by equation (14).*

Finally, at the beginning of the game, the lender chooses the data coverage to maximize the expected profit:

$$\begin{aligned}\Pi(\rho) = &\rho \cdot \alpha(1 - F(r_H^*)) \left(q_H r_H^* - (1 - q_H)\right) \\ &+ \rho \cdot (1 - \alpha) \left(q_L r_H^* - (1 - q_L)\right) \int_{r_H^*}^{R-1} m_i(v_i; r_H^*, r_L^*, r_\varnothing^*) dF(v_i) \\ &+ (1 - \rho)(1 - F(r_\varnothing^*)) \left(\bar{q} r_\varnothing^* - (1 - \bar{q})\right).\end{aligned}$$

We use numerical analysis to examine the lender's optimal choice of data coverage. Figure 3 shows that the lender's profit exhibits a hump-shape pattern against the data coverage. Thus, in equilibrium the lender can still choose non-full data coverage despite the free data technology.



This figure plots the effect of the data coverage ρ on the lender's profit when borrowers learn about their reservation interest rates before manipulation. The parameters are $q_L = 0.2, q_H = 0.8, \alpha = 0.5, R = 2$, and $c = 0.03$.

Figure 3: When borrowers learn their reservation interest rates first: the lender profit

5 Implications

In this section, we explore the implications of our model for the credit lending market.

5.1 Regulations on the Use of Alternative Data

Using alternative data in credit underwriting models has drawn significant attention from regulators. For instance, in December 2019 Federal regulators issued a joint statement on the use of alternative data in credit underwriting, focusing on the consumer protection implications of the use of alternative data, highlighting potential benefits and risks.[3] The regulators believe that using valid alternative data may not be any riskier than financial data used in conventional credit evaluation and underwriting process. They also add that forbidding or tightly reining the use of alternative data may turn out counterproductive by hurting the chances of the underserved.

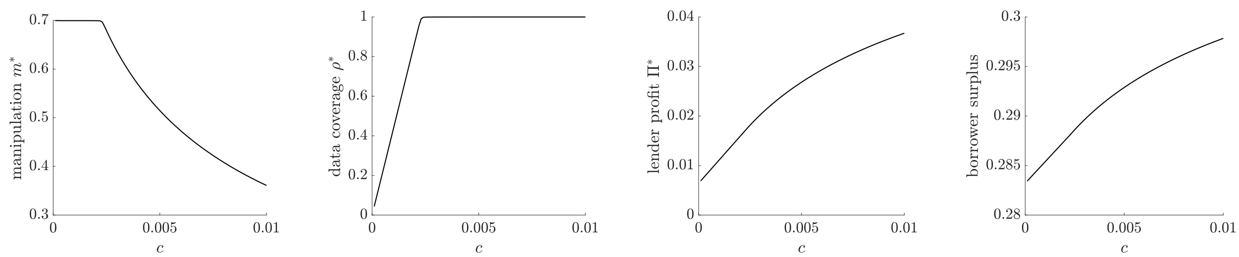
Our model sheds new light on this debate through the perspective of data manipulation. As shown in Figure 2, forbidding the use of alternative data limits the borrowers' manipulation behavior (see Panel (a)). The prohibition can have ambiguous effects on the lender's expected profit and the borrower surplus, as shown in Panels (b) and (c). Specifically, when only a handful of alternative data variables are used in the underwriting models, limiting the lender's data usage will impair its informed lending decisions and lower the profit. The borrower surplus also decreases. By contrast, if the lender has already adopted a large amount of alternative data in its underwriting models, limiting the use of alternative data instead improves the lender's profit because the reduction in borrower manipulation sustains the quality of the data collected by the lender. In this case, borrower surplus also improves since the better screening helps the high-type borrowers separate from the low-type ones.

5.2 The Effect of Manipulation Costs

We then examine the effect of the manipulation cost by conducting a comparative statics analysis. This exercise helps shed light on the development of FinTech lending. Figure 4 numerically illustrates it. As manipulation costs increase, low-type borrowers manipulate their digital profiles less intensively. Due to the less manipulation, borrowers' digital profiles are more closely connected to their underlying type, which suggests high-quality signals observed by the lender.

[3]See https://www.federalreserve.gov/newsevents/pressreleases/bcreg20191203b.htm.

Therefore, the lender increases its data coverage without worrying much about induced manipulation from borrowers and lower signal quality. The lender in turn makes a higher expected profit from the lending business. Meanwhile, borrowers enjoy a higher expected payoff when the manipulation cost increases. Although the low-type borrowers become worse off as manipulation becomes more costly, the high-type borrowers benefit as the high cost prevents low-type borrowers' manipulation. Overall, the latter effect dominates, and the borrower surplus increases with the manipulation cost.



(a) Manipulation (b) Data coverage (c) Lender profit (d) Borrower payoff

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_i is assumed to follow a uniform distribution $U[0, R-1]$, and the manipulation cost function is $C(m_i) = c \cdot m_i^2$. The parameters are $q_H = 0.8$, $q_L = 0.2$, $\alpha = 0.6$, and $R = 2$.

Figure 4: The effect of manipulation cost

The development of FinTech lending features heavier reliance on alternative data in making fast lending decisions. This can be viewed as a reduction in the manipulation cost because compared with traditional credit metrics such as tax reports and fixed assets, alternative data such as social media activity is more likely to derive from borrowers' digital footprints, which are subject to their manipulation. Our model thus predicts that in the era of FinTech lending, low-type borrowers are more likely to engage in manipulation, and the lender should optimally respond by lowering the data coverage. Still, the lender can suffer from a decrease in lending profit. And the borrower surplus will decrease as well.

6 Conclusion

FinTech lenders often base their lending decisions on alternative data, which is more likely to be manipulated by borrowers than the traditional credit metrics. In this paper, we study a credit lending 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 show that as the lender's signal is strengthened by higher data coverage, the borrower is more likely to manipulate her digital profile, which lowers the lender's signal quality and impairs its lending decisions. As such, even if it is costless to cover more data in the underwriting model, in equilibrium, the lender chooses to avoid exploiting the full potential of its data. In this way, the lender limits the borrower's manipulation intensity, thereby sustaining its signal quality and achieving optimal profits.

Appendix: Proofs

Proof of Lemma 1

Denote the lender's expected profit as $\pi_{s_i}(r)$ when it observes signal $s_i \in \{H, L, \varnothing\}$ about borrower i and makes a loan offer at interest rate r. Because signals H and L are fully revealing, $\pi_H(r) = q_H(1+r) - (1-q_H)$ and $\pi_L = q_L(1+r) - (1-q_L)$. Similarly, in the case that the lender learns nothing from the borrower's digital profile (i.e., $s_i = \varnothing$), the lender believes that the borrower is type H with probability α. Thus, $\pi_\varnothing(r) = \alpha\pi_H(r) + (1-\alpha)\pi_L(r)$.

The optimal interest rate that maximizes $\pi_{s_i}(r)$ is denoted as r_{s_i}; that is, $r_{s_i} = \operatorname{argmax}_r \pi_{s_i}(r)$. Then, at date 0, given the data coverage ρ the lender's expected profit is

$$\Pi = \rho\left\{\alpha\pi_H(r_H) + (1-\alpha)\pi_L(r_L)\right\} + (1-\rho)\pi_\varnothing(r_\varnothing). \tag{A1}$$

To prove that the lender optimally chooses $\rho^* = 1$, we show that the lender's expected profit Π is monotonically increasing in ρ. Observe that as the borrower is taking no action with respect to manipulation, the offers r_H, r_L, and $r_\varnothing$ do not depend on ρ. Thus, taking the derivative of the expected profit in (A1) with respect to ρ yields

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

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

$$\begin{aligned}
& \alpha\pi_H(r_H) + (1-\alpha)\pi_L(r_L) > \pi_\varnothing(r_\varnothing) \\
\Leftrightarrow\ & \alpha \max_r \pi_H(r) + (1-\alpha)\max_r \pi_L(r) > \max_r \pi_\varnothing(r) \\
\Leftrightarrow\ & \alpha \max_r \pi_H(r) + (1-\alpha)\max_r \pi_L(r) > \max_r \left[\alpha\pi_H(r) + (1-\alpha)\pi_L(r)\right].
\end{aligned}$$

It is straightforward that the last inequality must hold. As such, the lender's expected profit is monotonically increasing in ρ and it thus chooses the maximum ρ in equilibrium. ■

Proof of Proposition 1

To characterize the optimal interest rates by the lender and the optimal manipulation intensity by borrowers, we first note that in equilibrium, the lender must charge a (weakly) lower interest rate for borrowers with a high-type digital profile than those with a low-type digital profile, and thus only low-type borrowers manipulate their digital profile. Suppose not, i.e., suppose that the lender sets a higher interest rate for borrowers with a high-type digital profile (i.e., if $r_H \geq r_L$). It is the high-type borrowers that have the incentives to manipulate their data. Then, upon observing signal $s = H$, the lender assures that the borrower must be high type and in turn charges a lower, rather than a higher, interest rate for the borrower, which is a contradiction.

The following proposition summarizes these discussions.

Proposition A1. *In any equilibrium:*

(i) *The lender charges a strictly lower interest rate for borrowers with high-type digital profiles than those with low-type digital profiles, i.e.,* $r_H < r_L$*;*

(ii) *High-type borrowers never manipulate their digital profiles. A low-type borrower will manipulate with positive probability if and only if* $\rho > 0$ *and* $v_i > r_H$.

Proof. (i) We prove this part by contradiction. Suppose instead that $r_H > r_L$, that is, borrowers with high-type digital profile are charged higher interest rates. Denote the expected utility of a borrower of type t with reservation value v who manipulates with probability m as

$$\begin{aligned} u(t, m \mid v) &= \rho(m\, w(t, r_{\tilde{t}})(1 - F(r_{\tilde{t}})) + (1 - m)\, w(t, r_t))(1 - F(r_t)) \\ &\quad + (1 - \rho)\, w(t, r_\varnothing)(1 - F(r_\varnothing)) - C(m), \end{aligned} \tag{A2}$$

where $\tilde{t} \neq t$. That is, with probability m the manipulation is successful and with probability $1 - m$ the manipulation fails. The borrower incurs the manipulation cost $C(m)$.

Observe that $w(t, r_\varnothing)$ is not affected by the choice of m. The borrower takes r_H and r_L as given (even though the offers themselves will only materialize at date 1). In equilibrium, manipulation is strictly positive if and only if $\frac{\partial u}{\partial m}\mid_{m=0} > 0$. As $C'(0) = 0$, this condition reduces to

$$\rho\{w(t, r_{\tilde{t}})(1 - F(r_{\tilde{t}})) - w(t, r_t))(1 - F(r_t))\} > 0. \tag{A3}$$

That is, for $m > 0$, it must be that (i) $\rho > 0$ and (ii) $\psi \equiv w(t, r_{\tilde{t}})(1 - F(r_{\tilde{t}})) - w(t, r_t))(1 - F(r_t)) > 0$. The latter condition immediately implies that $r_{\tilde{t}} < r_t$. To see this, suppose that $r_{\tilde{t}} \geq r_t$. As $w(t, r)$ is strictly decreasing in r, we have $w(t, r_{\tilde{t}}) \leq w(r_t)$. Further, $1 - F(r_{\tilde{t}}) \leq 1 - F(r_t)$. It is therefore immediate that $\psi < 0$ and it is optimal to set $m = 0$. Thus, to have $m > 0$ in equilibrium, it must be that $r_{\tilde{t}} < r_t$.

Now, suppose that $r_H \geq r_L$. Then, it must be that $m_L = 0$. Therefore, on receiving an H signal, the lender knows the borrower must have the H type. On receiving signal L, at best the borrower is the high type with probability α (and this can only happen if the H type manipulates with probability 1; else the probability of the high type is strictly less than 1 when signal L is received).

Now, as we show later, the interest rate offered at a given signal is strictly decreasing in the proportion of H types given that signal. Thus it follows that when the L type does not manipulate, it must be that $r_H < r_L$. This contradicts the assumption that $r_H \geq r_L$.

(ii) Given that $r_H < r_L$, following similar arguments as above, it follows that the high-type borrowers will never manipulate their data, i.e., $m_H = 0$. The low-type borrowers will manipulate with positive intensity, whenever $\rho > 0$ and $v_i \geq r_H$, and with zero intensity otherwise. □

■

Proof of Corollary 1

Part (2) of the lemma is straightforward: Since $\bar{q}_\varnothing$ in equation (9) is independent of m, the optimal interest rate $r_\varnothing$ is independent of m as well. In addition, r_L is set to be R, which is again independent of m. We next only examine Part (1). Based on equation (7), $\frac{\partial \mu_H}{\partial m} < 0$. Given that $\bar{q}_H = \mu_H q_H + (1 - \mu_H) q_L$, we have $\frac{\partial \bar{q}_H}{\partial m} < 0$. Meanwhile, for a given r_H, when m increases, the right-hand side (RHS) of equation (8) increases, i.e., $\frac{\partial}{\partial \bar{q}_H}\left(\frac{\bar{q}_H}{\bar{q}_H(1+r_H)-1}\right) < 0$. As such, we must have $\frac{\partial}{\partial m}\left(\frac{\bar{q}_H}{\bar{q}_H(1+r_H)-1}\right) > 0$.

We then argue that when m increases r_H increases by contradiction. Suppose instead that r_H decreases. Then, by assumption, the left-hand side (LHS) of equation (8) decreases. However, as argued above, the RHS of equation (8) is increasing in m for a given r_H. Now, a decreasing r_H would further increase the RHS of equation (8). A contradiction. Therefore, we must have r_H increase in m.

Proof of Corollary 2

To simplify analysis, we view ρ as a function of m. By equation (10), when $m < 1$ we can express ρ as following:

$$\rho = \frac{C(m)}{q_L \int_{r_H(m)}^{R-1} (v_i - r_H(m))dF(v_i)}. \tag{A4}$$

Let's define $G(m) \equiv \int_{r_H(m)}^{R-1} (v_i - r_H(m))dF(v_i)$ so that $\rho = \frac{C(m)}{q_L G(m)}$. Then,

$$\begin{aligned} G(m) &= (v_i - r_H)F(v_i) \mid_{r_H}^{R-1} - \int_{r_H}^{R-1} F(v_i)dv_i \\ &= (R - 1 - r_H) + \int_{R-1}^{r_H} F(v)dv. \end{aligned}$$

Taking derivative of G with respect to m yields

$$\frac{\partial G}{\partial m} = -(1 - F(r_H))\frac{\partial r_H}{\partial m} < 0,$$

where the inequality follows Lemma 1. Therefore, based on equation (A4) we must have

$$\frac{\partial \log(\rho)}{\partial m} = \frac{1}{C(m)}\frac{\partial C(m)}{\partial m} - \frac{1}{G(m)}\frac{\partial G(m)}{\partial m} > 0,$$

which suggests that $\frac{\partial \rho}{\partial m} > 0$. Therefore, when $m < 1$, we obtain $\frac{\partial m}{\partial \rho} > 0$. Finally, when $m = 1$, it immediately follows that $\frac{\partial m}{\partial \rho} = 0$.

Proof of Proposition 2

As in the proof of Lemma 2, the analysis is easier if we view ρ and hence the lender's unconditional expected profit Π, as a function m. First, we want to show that Π is decreasing in m at the local of $m = 1$; that is, $\frac{\partial \Pi}{\partial m} \mid_{m=1} < 0$. Based on equation (11),

$$\begin{aligned} \frac{\partial \Pi}{\partial m} &= \frac{\partial \Pi}{\partial m} + \frac{\partial \Pi}{\partial \rho}\frac{\partial \rho}{\partial m} \\ &= \rho(1-\alpha)\frac{\partial \pi_H(r_H(m))}{\partial m} + ((\alpha + (1-\alpha)m)\pi_H(r_H(m)) - \pi_\varnothing(r_\varnothing))\frac{\partial \rho}{\partial m}. \end{aligned}$$

When $m = 1$, $\pi_H(r_H(m)) = \pi_\varnothing(r_\varnothing)$. This is because when all low-type borrowers manipulate their data, the lender's signal will become completely uninformative, leading to the same expected profit under signal $s_i = H$ and under uninformative signal $s_i = \varnothing$. We thus have

$$\frac{\partial \Pi}{\partial m} \mid_{m=1} = \rho(1-\alpha)\frac{\partial \pi_H(r_H(m))}{\partial m}.$$

Note that based on equation (**??**),

$$\pi_H(r_H(m)) = (1 - F(r_H(m)))[\bar{q}_H(1 + r_H(m)) - 1].$$

Following Lemma 1, we know that when m increases, r_H increases and thus $1 - F(r_H)$ decreases. When m increases, the LHS of equation (8) increases and the numerator of its RHS decreases. Thus, the denominator of the RHS $\bar{q}_H(1 + r_H) - 1$ must decrease. Taken together, when m increases, the lender's expected profit $\pi_H(r_H(m))$ must decrease; that is, $\frac{\partial \Pi}{\partial m} \mid_{m=1} < 0$.

Second, based on equation (10) we know that when $m = 1$,

$$\rho = \hat{\rho} \equiv \frac{C(1)}{q_L \int_{r_H(1)}^{R-1} (v - r_H(1)) dF(v)}.$$

Finally, combining $\frac{\partial \Pi}{\partial m} \mid_{m=1} < 0$ and $\frac{\partial \rho}{\partial m} > 0$, we know that $\frac{\partial \Pi}{\partial \rho} \mid_{\rho=\hat{\rho}} < 0$. Therefore, as long as $\hat{\rho} < 1$, the lender will choose the optimal data coverage $\rho^* < \hat{\rho} < 1$ to avoid the worst case in which every low-type borrower manipulates her type and the signal becomes completely uninformative.

Proof of Lemma 2

The majority of the proof is given in the main text. We now prove that the solution to equation (16) exists and when $v_i \sim U[0, R-1]$, the solution is unique.

When $r_H^* = 0$, the left-hand side (LHS) of equation (16) is

$$\alpha q_H + \alpha f(0)(1-q_H) + (1-\alpha)q_L \int_0^{R-1} m_i(v_i; 0, r_L^*, r_\varnothing^*) dF(v_i) > 0.$$

When $r_H^* = R-1$, the LHS of equation (16) is $-\alpha f(R-1)(Rq_H - 1) < 0$. Therefore, by intermediate value theorem, there must exist solutions to equation (16).

If $v_i \sim U[0, R-1]$, the derivative in r_H of the LHS of equation (16) is less than zero, or

$$\alpha\left\{\frac{-2q_H}{R-1}\right\} + (1-\alpha)\frac{\rho q_L}{2c}\left\{-1 + \frac{r_H}{R-1}\right\} \quad < \quad 0. \tag{A5}$$

The first term is strictly negative, and the second term is strictly negative for all $r_H < R-1$, and zero at $r_H = R-1$. Thus, the FOC is strictly decreasing in r_H, and hence in conjunction with it being positive at $r_H = 0$ and negative at $r_H = R-1$, we know there is a unique r_H at which it is satisfied. That is, there is a unique equilibrium r_H^*.

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