Data Regulation in Credit Markets *

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Keywords: FinTech lending, Digital data, Manipulation, Regulation

JEL: G21, G23

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Abstract

We study a credit market in which the lender makes decisions based on a borrower's digital profile, and the borrower can manipulate the digital profile. We show that when the extent of data collected by the lender is observable, borrower manipulation increases when the lender utilizes more data in its underwriting models. Such manipulation worsens both the quality of the lender's data and its lending decisions. Therefore, even if obtaining and analyzing additional data is costless, the lender will endogenously limit its own data coverage. Disclosure regulations can play a valuable role in allowing the lender to credibly commit to limiting its data coverage, and privacy regulations can benefit all borrowers, including those who choose to share their data with the lender.

1 Introduction

The online activities of people generate substantial amounts of valuable data. These big data are increasingly utilized by lending companies to assess and evaluate borrowers. In fact, a 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. At the same time, regulators across the world have considered the proper use of alternative data in credit markets. For example, in 2019, federal banking regulators in the U.S. issued an inter-agency statement that outlined the advantages and risks associated with the use of alternative data in assessing consumers' creditworthiness.[1] Similarly, in 2021, the European Commission put forth proposed revisions to its directive on consumer credit, to tackle concerns related to the use of personal data.[2]

When digital information is widely used for lending decisions, it is natural that (as implied by the Lucas critique (Lucas, 1976)) borrowers may change their behavior to mask their online activities. Some variables in a digital profile (e.g., utility bill transactions) may be hard to manipulate because they require a borrower to change their intrinsic habits; conversely, others (such as which device to use to access the lender's site) can be manipulated more easily. In fact, the same set of technologies such as generative artificial intelligence that are being used by lenders can also be employed by borrowers to manipulate their digital profile.[3] Such manipulation in turn adversely affects the usefulness of the data collected by a lender.

To examine the equilibrium effects of such behavior, we develop a theoretical model in which a lender chooses the amount of digital data to acquire on a borrower, and the borrower in turn can manipulate the data. We establish three main results. First, borrower manipulation acts as an endogenous factor that limits the usefulness of data, and induces a lender to voluntarily restrict its data coverage. Second, regulations related to transparency and disclosure of how a lender uses different kinds of data can benefit both borrowers and lenders. In particular, such regulations allow a lender to credibly commit to restricting its data coverage. Third, privacy regulations that give borrowers the right to share or withhold data from a lender can benefit both privacy-conscious borrowers and borrowers who choose to share their data. Essentially, they allow a borrower who would otherwise have manipulated their information to a new way to hide themselves, by pooling with borrowers who refuse to

[1] See https://www.federalreserve.gov/supervisionreg/caletters/caltr1911.htm.

[2] See https://commission.europa.eu/document/download/ed2bb667-04b4-4bae-b990-277e3da7c2c9_en.

[3] For example, FraudGPT, the dark web counterpart of ChatGPT, can generate realistic counterfeit IDs, fabricated identities, and financial statements. See "Generative AI financial scammers are getting very good at duping work email," CNBC, February 2024.

share their data for privacy reasons.

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 also has a digital profile connected to her underlying type. The lender chooses how much data to collect about the borrower's digital profile. The data generate a noisy signal about the borrower's creditworthiness, and the lender bases 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, transparent (in which the lender's data coverage is observed by the borrower) and opaque (in which the lender's data coverage remains unobserved). In the transparent regime, we show that the low-type borrower's incentive to manipulate their information increases 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, borrowers who generate high signals obtain credit on better terms (i.e., at a lower interest rate), which implies that low types have a greater incentive to manipulate their data.

Thus, if the lender increases the amount of data it collects, there are two countervailing effects. On the one hand, better data coverage leads to more informed lending. On the other hand, increased data coverage induces low-type borrowers to manipulate their digital profiles more often. This manipulation lowers the quality of the lender's data and impairs its lending decisions. The latter force is more salient when the manipulation cost for borrowers is low. We show that in equilibrium in the transparent regime, the lender may optimally choose to limit its own data coverage. To establish our result as starkly as possible, in our model we assume there is no direct cost to acquiring more data.[4]

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 data on borrowers. Instead, 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.

In contrast, in the opaque regime, the lender chooses to maximize data usage. Essentially, when data coverage is unobserved by the borrower, the lender cannot credibly commit to limiting it. Whatever a borrower believes about what data the lender is using, the lender has an incentive to deviate and acquire more data.

[4] 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.

We find that in the aggregate borrowers too may prefer that the lender acquire some digital information. A lender who has more information can more easily discern between the types. High-type borrowers obtain loans with 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 when high types gain more than low types lose.

Our model offers several insights into the ongoing regulatory discussion about the use of big data in the credit market. First, 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 is unclear. In the E.U., the 2021 proposal for a new directive on consumer credit 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 opaque one, we find that enhanced transparency grants the lender the ability to commit to limiting its data coverage. This restrains borrower manipulation, preserves data quality, and maintains profitability. Therefore, increased transparency actually benefits the lender.

Second, regulations may impose limitations on the use of data in lending. For example, the 2021 E.U. proposal 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. We show 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.

Third, recent regulations such as the California Consumer Privacy Act and the revised Payment Services Directive 2 (PSD2) in Europe have emphasized granting consumers control over their own data. We expand on our base model to allow borrowers to provide access to their own data or withhold it from lenders. Borrowers who share their data can in turn choose to manipulate these data. We find that such regulations can benefit all borrowers, including both privacy-conscious borrowers and those who are unconcerned about privacy and choose to share their data with the lender. Essentially, such regulations provide low types with an additional tool to disguise themselves, by pooling with privacy-conscious borrowers who withhold their data, reducing their expected manipulation cost. Further, high-type borrowers who do share their data now obtain improved credit terms.

Overall, our findings highlight the intriguing dynamics between privacy protection, data sharing, and borrower manipulation behavior within the context of credit lending. More broadly, our framework allows us to understand the effects of different factors on borrower manipulation and credit market outcomes. For example, as financial literacy improves, individuals will gain better knowledge of both the data used in credit underwriting and the actions they can take to enhance their creditworthiness. In our model, this would be equivalent to the manipulation cost decreasing for borrowers. Borrower manipulation will increase, making lending less efficient overall. Along a similar vein, anti-fraud measures implemented by lenders that deter manipulation may benefit borrowers in the aggregate, because the loss to low-type borrowers may be outweighed by the gain to high-type borrowers.

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. Liang and Madsen (2024) build on the career concerns framework of Holmström (1999) and study how the acquisition of new data impacts the agent effort and aggregate welfare. 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, Guttman, and Marinovic (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 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. In addition, there is a line of research in econometrics and computer science that explicitly considers the strategic manipulation behavior within data (e.g., Dekel et al., 2010; Chen et al., 2018; Björkegren et al., 2020; Hennessy and Goodhart, 2023; Gamba and Hennessy, 2024).

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) consider a more abstract setting and 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. Goldman, Martel, and Schneemeier (2022) show that media coverage can increase manipulation of corporate disclosures.

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, Burg, Gombović, and Puri (2020) and Agarwal, Alok, Ghosh, and Gupta (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, Nagel, Yannelis, and Zhang (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. Although the specific types of alternative data we are considering – those that are easily manipulable – are likely more relevant for smaller, unsecured loans, our model applies to both collateralized and uncollateralized loans. For example, (Buchak, Matvos, Piskorski, and Seru, 2018) demonstrate that FinTech mortgage lenders in the US rely on different sources of information that non-FinTech lenders.

Privacy and the impact of related regulations have been the subject of increasing research interest (e.g., Tang, 2019; Chen, Huang, Ouyang, and Xiong, 2021; Agur, Ari, and Dell'Ariccia, 2023; Aridor, Che, and Salz, 2023; Doerr, Gambacorta, Guiso, and Sanchez del Villar, 2023); see Johnson (2022) for a survey on this topic. Our paper contributes to this literature by introducing the concept of non-sharing of data with the lender and manipulation of digital data as complementary strategies employed by borrowers to safeguard their privacy.

2 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 Borrower

Borrower's project: Each borrower has a project that requires an investment of 1 unit at time 0, and generates a random payoff at time 1. If the project succeeds, at time 1 it generates a cash flow of $1 + v$, where v captures the profitability of a successful project. This profitability is privately known to the borrower. 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. If the project fails, the cash flow at time 1 is zero.

There are two types of borrowers, high (H) and low (L), who differ in the likelihood that their project will be successful. Let q_θ denote the probability that the project of the borrower of type θ is successful, where $0 < q_L < q_H < 1$. The borrower privately knows her own creditworthiness. The prior probability that the borrower has a high success probability is $\alpha \in (0, 1)$, and this fraction is common knowledge. Both success probability q and project profitability v are private information for the borrower. For brevity, we refer to the success profitability as the "type" of the borrower, so that the high-type (low-type) borrower succeeds with probability q_H (q_L).

We assume that the borrower's reservation utility is zero, that is, if they do not accept the loan for the project, they obtain a zero payoff. Further, we assume that $q_H(1 + R) > 1$, that is, the most profitable project of the high-type borrower has positive NPV.

Borrower's digital profile: Each borrower has a digital profile. If this profile is uncovered by the lender, the latter obtains a digital signal $d \in \{d_h, d_\ell\}$ about the borrower's type. 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 about cash flows (such as whether the borrower has been paying rent and utility bills on time), their educational background, and their employment history. In our usage, it also includes the digital variables highlighted by Berg et al. (2020), such as the electronic device the borrower uses (e.g., desktop, tablet, or mobile), the operating system (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, reviews on social media and on sites like Yelp, web traffic data such as the global traffic rank, online presence, and use 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 α of the borrower being the high type. Our focus is on the *additional* information a lender may obtain 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 $m \in [0, 1]$, where m represents the probability that manipulation is successful. The manipulation is relevant only if the lender succeeds in uncovering the borrower's digital profile. In this case, if the manipulation is unsuccessful, which happens with probability $1 - m$, the high-type borrower generates signal d_h and the low-type borrower generates signal d_ℓ. Conversely, if the manipulation is successful, the high-type generates signal d_ℓ and the low-type signal d_h. To manipulate, a borrower incurs a cost $C(m)$, where $C(0) = C'(0) = 0$ and $C'(m), C''(m) > 0$ for all $m > 0$. 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 a borrowers to manipulate their digital profile. 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 a restaurant inflating its reviews, once the deception is uncovered, it can negatively impact the restaurant's reputation. Therefore, the expected reputational damage is included in the manipulation cost.

2.2 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 ρ 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 ρ), the more informative is the lender's signal about the borrower's digital profile.

Specifically, the lender observes a signal from the borrower's digital profile. We denote this digital signal as $d \in \{d_h, d_\ell, d_0\}$. 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 d_0. Conversely, the signals d_h and d_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 d_h and signal d_ℓ depends on the extent of manipulation by the borrower.

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 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 useful information. For convenience, going forward we refer to ρ as the extent of coverage about the borrower's digital behavior.

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 ρ has no cost for the lender. 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.[5]

Regulatory regimes: Depending on the regulatory regimes, the lender's data coverage ρ may be observed by the borrower or may remain unobservable. In a transparent regime, the lender is required to disclose the main variables used in the credit underwriting model and to describe the algorithm in some way, so ρ is observed by the borrower. In contrast, in the opaque regime, the lender's data coverage ρ remains unobserved by the borrower.

[5] In Section 5.2, 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.

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 d 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 ρ to maximize the expected profit from lending. The borrower observes ρ in the transparent regime, but not in the opaque regime. The borrower then learns their success probability q_θ, and chooses manipulation intensity m_θ. At time 1, the borrower observes the profitability v of their project. Next, the lender receives a digital signal d about the borrower and offers a personalized loan contract at the interest rate r_d. The borrower then decides whether or not to accept the lender's loan offer. If the borrower accepts, the project is undertaken with the outcome being realized at time 2.

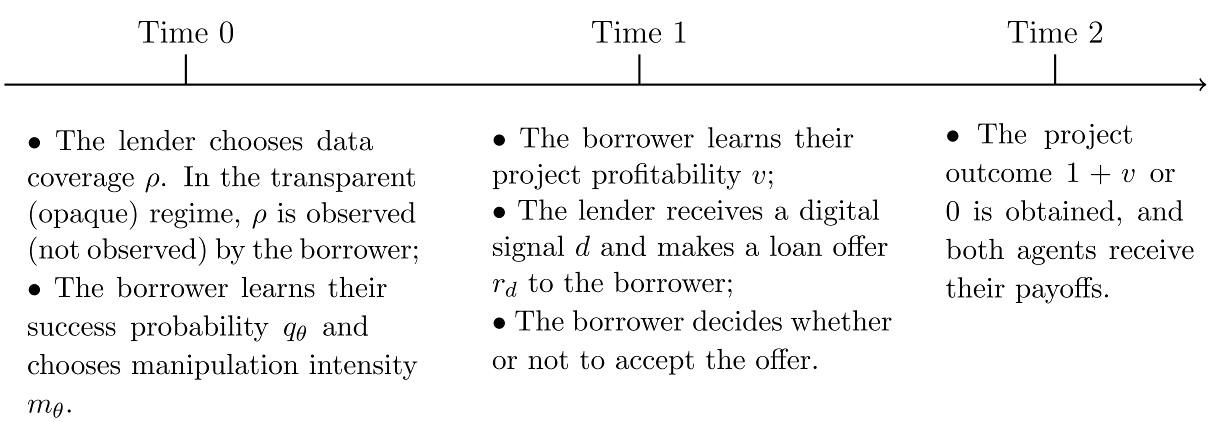


Figure 1: Timeline

We consider perfect Bayesian equilibria of the model.

Definition 1 (Equilibrium)**.** *A* perfect Bayesian equilibrium *is characterized by the lender's choice of data coverage* $\rho^* \in [0, 1]$ *and interest rate offer* r_d^* *for each* $d \in \{d_h, d_\ell, d_0\}$*, the borrower's manipulation intensity* $m_\theta^* \in [0, 1]$ *for each* $\theta \in \{H, L\}$ *and a loan acceptance* *decision, and the lender's posterior belief μ_d that the borrower has the high success probability given digital signal d, such that:*

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

(ii) *The manipulation intensity m_θ^* maximizes the expected payoff of a borrower with success probability q_θ, given the borrower's belief about the lender's data coverage.*

(iii) *The lender's interest rate offer r_d^* maximizes its expected payoff given the digital signal d.*

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

(v) *The borrower's loan acceptance decision maximizes their expected payoff given their success probability q_θ and profitability v.*

The lender does not observe the manipulation decision of each type of borrower. Rather, the lender forms a belief $\hat{m}_\theta$ about the extent of manipulation by each creditworthiness type, m_θ. In equilibrium, of course, the lender's beliefs have to be correct.

Similarly, in the opaque data regime, the borrower has a belief $\hat{\rho}$ regarding the lender's data coverage, and in equilibrium the belief must match the actual choice of ρ by the lender; i.e., $\hat{\rho} = \rho^*$. In the transparent regime, the borrower directly observes the extent of data coverage.

3 Equilibrium in the Transparent and Opaque Regimes

We now characterize the equilibrium in the main model. We first examine the borrower's decision to accept or reject a loan offer at time 1 and then turn to time 0.

3.1 Borrower's Loan Acceptance Decision

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 $v - r$. If the project fails, the borrower defaults and receives 0. Hence, for $\theta \in \{H, L\}$, the borrower's expected payoff if they accept the loan is $q_\theta [v - r]$.

The borrower has a reservation utility 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 $r \leq v$.

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.[6]

3.2 Lender's Interest Rate Offers

Consider the lender's choice of the interest rate to offer the borrower. After observing digital signal $d \in \{d_h, d_\ell, d_0\}$, the lender updates its posterior beliefs about the borrower type. Let μ_d denote the lender's posterior belief that the borrower has the high type given signal d, that is, $\mu_d \equiv \Pr(\theta = H|d)$. Let $\bar{q}_d = \mu_d q_H + (1 - \mu_d) q_L$ denote the average success rate of the project given signal d.

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 expected payoff is

$$\pi_d(r) = (1 - F(r)) \left[\bar{q}_d \cdot r \; - \; (1 - \bar{q}_d) \right]. \tag{1}$$

The offered interest rate r_d maximizes this expected payoff.

Lemma 1 (Optimal interest rates)**.** *Suppose the lender obtains signal $d \in \{d_h, d_\ell, d_0\}$. Then,*

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

$$r - \frac{1 - F(r)}{f(r)} = \frac{1}{\bar{q}_d} - 1. \tag{2}$$

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

Equation (2) is the first-order condition that emerges from the lender's maximization problem. Given signal d, if some projects have a weakly positive NPV (i.e., $\bar{q}_d(1+R) \geq 1$), the lender sets an interest rate according to equation (2). As in auction theory, the left-hand side can be interpreted as the virtual interest rate. Rewriting the equation as $r_d = \frac{1}{\bar{q}_d} - 1 + \frac{1-F(r_d)}{f(r_d)}$, the lender charges a markup over the zero-profit interest rate $\frac{1}{\bar{q}_d} - 1$.

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

[6]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.

3.3 Borrower's Manipulation Decision

Next, consider the manipulation decision of the borrower. When choosing their manipulation intensity, the borrower holds a belief $\hat{\rho}$ about the lender's data coverage. Suppose the borrower of type $\theta \in \{H, L\}$ manipulates with probability m_θ. Since the borrower's manipulation decision is not observable to the lender, the lender's interest rate offer for a given digital signal depends only on its belief about the manipulation intensity of each type, $\hat{m}_\theta$.

Taking this belief $\hat{m}_\theta$ as given, each type of borrower determines their actual manipulation intensity m_θ accounting for the following scenarios. With probability $1-\hat{\rho}$, the digital signal is d_0. With probability $\hat{\rho}$, the digital signal about the borrower is either d_h or d_ℓ. With a minor abuse of notation, we define $d_\theta = d_h$ (d_ℓ) and $d_{\tilde{\theta}} = d_\ell$ (d_h) when $\theta = H$ (L). When type θ generates signal d_θ, we say it has been "correctly recognized," whereas when it generates signal $d_{\tilde{\theta}} \neq d_\theta$, we say it has been "mistaken for the other type."

Then, the digital signal equals the underlying borrower type θ with further probability $1 - m_\theta$, and the other type $\tilde{\theta}$ with probability m_θ. Putting all this together, the expected payoff of the borrower of type θ is

$$u_\theta(m_\theta; \hat{m}_\theta, \hat{\rho}) = -C(m_\theta) + \hat{\rho}\, m_\theta \cdot \underbrace{q_\theta \int_{r_{\tilde{\theta}}}^{R} (v - r_{\tilde{\theta}}) dF(v)}_{\text{payoff when mistaken for the other type}}$$
$$+ \hat{\rho}\,(1 - m_\theta) \cdot \underbrace{q_\theta \int_{r_\theta}^{R} (v - r_\theta) dF(v)}_{\text{payoff when type is correctly recognized}} + (1 - \hat{\rho}) \cdot \underbrace{q_\theta \int_{r_0}^{R} (v - r_0) dF(v)}_{\text{payoff when digital signal is uninformative}}. \tag{3}$$

There are three cases to consider in equation (3). 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 rejects the loan and settles for the reservation utility 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 θ. The offered interest rate is r_θ. Again, she accepts the loan offer r_θ 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 in equilibrium the high-type borrower never manipulates, that is, $m_H^* = 0$. If the low-type borrower believes that the lender's data coverage is positive (i.e., $\hat{\rho} > 0$), they manipulate with positive probability (i.e., $m_L^* > 0$). An immediate implication is that the low digital signal d_ℓ reveals the borrower to have low success probability, so that the offered interest rate increases to $r_\ell > r_0$, where r_0 is offered to borrowers generating the uninformative signal d_0. Conversely, as long as $m_L^* < 1$, the offered interest rate after the high digital signal falls to $r_h < r_0$.

Let m denote the manipulation intensity of a low-type borrower, and $\hat{m}$ the lender's belief about this intensity. The interest rate offered after signal d_h will depend on $\hat{m}$, and may be written as $r_h(\hat{m})$. With probability $1 - \hat{\rho}$, regardless of how much they manipulate, the borrower generates the digital signal d_0. If the lender obtains an informative signal and the borrower succeeds in manipulating, they generate digital signal d_h and are offered a loan at interest rate $r_h(\hat{m})$, whereas if they fail they generate digital signal d_ℓ and are offered the interest rate r_ℓ. Noting that in equilibrium $\hat{m} = m$, the change in the low-type borrower's expected equilibrium payoff from succeeding versus failing at manipulation may be written as

$$\hat{\rho}\, q_L \left(\int_{r_h(m)}^{R} (v - r_h(m))dF(v) - \int_{r_\ell}^{R} (v - r_\ell)dF(v) \right). \tag{4}$$

Now suppose the low-type borrower manipulates with probability 1, that is, $m = 1$. Observe that when $m = 1$, the lender's belief after the high digital signal d_h is equal to their belief after the uninformative signal d_0. Thus, the interest rate offered, $r_h(1)$, equals r_0. Denote

$$\Delta_B(\hat{\rho}) \;=\; \hat{\rho} q_L \left(\int_{r_0}^{R} (v - r_0)dF(v) - \int_{r_\ell}^{R} (v - r_\ell)dF(v) \right). \tag{5}$$

Observe that, for a given $\hat{\rho}$, Δ_B depends only on the exogenous variables in the model.

We now characterize the borrower's manipulation decision. Suppose that, in either the transparent or the opaque regime, the lender chooses data coverage ρ. A best response on the part of the borrower is characterized by (i) an optimal manipulation intensity for each of the high and low type borrowers and (ii) an optimal loan acceptance decision; i.e., accepting a loan if the interest rate r is weakly lower than the project profitability v. We say that a best response of the borrower is *consistent* if the lender's posterior beliefs after each of the digital signals d_h, d_ℓ, and d_0 satisfy Bayes' rule given the borrower's strategy, and the offered interest rates r_h, r_ℓ, and r_0 are determined from Lemma 1 given the lender's posterior beliefs.

In the special case that $m_L^* = 1$, the signal d_ℓ represents a zero-probability event, and we assign the belief that the borrower is the low-type.

Proposition 1. *Suppose that, in either the transparent or opaque regimes, the lender chooses data coverage ρ. Then, in any consistent best response of the borrower,*

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

(ii) The low-type borrower manipulates with strictly positive probability. Further, if $\Delta_B(\hat{\rho}) < C'(1)$, the equilibrium manipulation intensity is strictly between 0 and 1, that is, $m_L^* \in (0,1)$, whereas if $\Delta_B(\hat{\rho}) \geq C'(1)$, then $m_L^* = 1$.

(iii) The interest rates offered by the lender satisfy $r_h \leq r_0 < r_\ell$, with strict inequality whenever $m_L^* < 1$.

Going forward, for the rest of the paper, we set $m_H = 0$, and use the subscript-less variable m to indicate m_L, the extent of manipulation by the low type. The signal structure implied by Proposition 1 is shown in Figure 2.

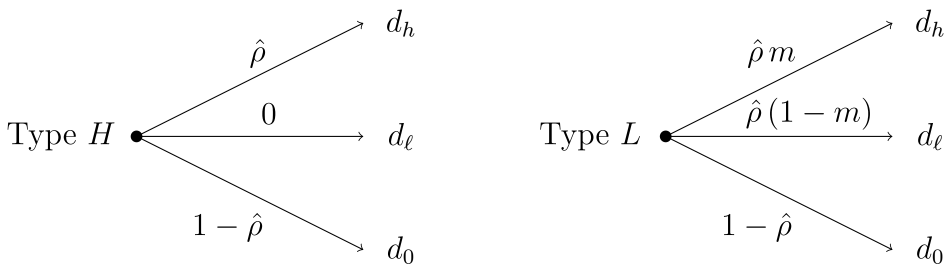


Figure 2: Structure of digital signal when the high-type borrower does not manipulate, and the low type manipulates with intensity m

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 μ_j denote the posterior probability of the high-type borrower after signal d_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 d_h and highest after signal d_ℓ.

As we show in the proof of the Proposition, when $C'(1) > \Delta_B(\hat{\rho})$, the equilibrium manipulation intensity of the low-type borrower, m^*, satisfies the equation

$$C'(\hat{\rho}) \quad = \quad \hat{\rho} q_L \left(\int_{r_h(m)}^{R} (v - r_h(m)) dF(v) - \int_{r_\ell}^{R} (v - r_\ell) dF(v) \right). \qquad (6)$$

We show that in this case, the manipulation intensity is increasing in $\hat{\rho}$, the borrower's belief about the lender's data coverage.

Lemma 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, $\frac{dm^*}{d\hat{\rho}} > 0$.*

Proofs of all results in the main text are provided in Appendix A.

When $\hat{\rho}$ is higher, the borrower believes that their digital profile is more likely to be revealed. Thus, a low-type borrower has a greater incentive to manipulate their data. The resulting positive relationship between the lender's choice of data coverage and the low-type borrower's manipulation intensity underlies the key mechanism in our paper.

3.4 Lender's Data Coverage

We now turn to the lender's choice of data coverage, ρ, at the start of the game. The lender chooses its data coverage to maximize its expected profit from lending. Recall from equation (1) that the profit after signal d and interest rate offer r is $\pi_d(r) = (1 - F(r))[\bar{q}_d r - (1 - \bar{q}_d)]$, where $\bar{q}_d = \mu_d q_H + (1 - \mu_d) q_L$ is the average quality of the project given digital signal d. The optimal interest rate offer r_d also varies by signal, and is given by Lemma 1.

With probability ρ, the lender obtains an informative signal (d_h or d_ℓ) from the borrower's digital profile. The low-type borrower manipulates with intensity m. Overall, therefore, the lender obtains digital signal d_h with probability $\rho\{\alpha + (1 - \alpha)m\}$. The lender offers the interest rate r_h when it obtains signal d_h. Let $\pi_h(r_h)$, as characterized in equation (1), denote the lender's expected profit after signal d_h.

With probability $\rho(1-\alpha)(1-m)$ the lender obtains the digital signal d_ℓ and offers interest rate r_ℓ. In this case, the lender makes an expected profit of $\pi_\ell(r_\ell)$. Finally, with probability $1 - \rho$, the lender obtains an uninformative digital signal. In this case, the lender sets interest rate r_0 and earns a profit $\pi_0(r_0)$.

Overall, the lender's expected profit at the start of the game may be written as:

$$\Pi(\rho) = \rho\Big(\{\alpha + (1 - \alpha)m\}\pi_h(r_h) + (1 - \alpha)(1 - m)\pi_\ell(r_\ell)\Big) + (1 - \rho)\pi_0(r_0). \tag{7}$$

Note that in equation (7), the low-type borrower's manipulation intensity m is a function of the borrower's belief over data coverage, $\hat{\rho}$. In the transparent data regime, the borrower directly observes ρ. In the opaque data regime, the borrower has a belief over ρ, and in equilibrium the belief matches the actual choice of data coverage by the lender.

In turn, the lender's optimal interest rate r_h depends on the lender's belief over the low-type borrower's manipulation intensity, $\hat{m}$. Thus, the lender's choice of data coverage ρ

affects its profit both directly as shown in equation (7) and also indirectly through m and r_h.

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 then discuss the equilibrium choice of data coverage in both the transparent and opaque regimes.

3.4.1 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 $\theta \in \{H, L\}$.[7] Recall that $d_\theta = d_h$ (d_ℓ) and $d_{\tilde{\theta}} = d_\ell$ (d_h) when $\theta = H$ (L). In the no-manipulation case, the digital signal fully reveals the borrower's success probability. That is,

$$d = \begin{cases} d_\theta & \text{with probability } \rho, \text{ for each } \theta \in \{H, L\} \\ d_0 & \text{with probability } 1 - \rho. \end{cases} \tag{8}$$

In particular, the quality of the signal strictly improves with digital data coverage ρ. Given that increasing ρ incurs no additional costs, it is immediate that the lender prefers maximal data coverage.

Lemma 3 (No-manipulation benchmark)**.** *Suppose the borrower cannot manipulate their digital profile. Then, regardless of the regulatory regimes, in equilibrium the lender chooses maximal data coverage, i.e., $\rho^* = 1$. Hence, the digital signal is fully informative about borrower type.*

3.4.2 The Transparent Regime: Endogenous Limit on Data Coverage

We now turn to our base model, in which the borrower can manipulate their digital profile. In this section, we study the equilibrium in the transparent regime. In this regime, the borrower directly observes the lender's choice of data coverage ρ.

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 Lemma 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.

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

We identify a sufficient condition under which the indirect effect outweighs the direct effect, and overall lender profit is greater at some $\rho < 1$ than at $\rho = 1$. Recall the definition of Δ_B in equation (5), and set $\hat{\rho} = 1$. We have

$$\Delta_B(1) \;\; = \;\; q_L \left(\int_{r_0}^{R} (v - r_0) dF(v) - \int_{r_\ell}^{R} (v - r_\ell) dF(v) \right). \tag{9}$$

We show that if the marginal cost of manipulation is low, specifically if $C'(1) \leq \Delta_B(1)$, the lender endogenously limits its own data coverage.

Proposition 2 (Optimal data coverage in the transparent regime)**.** *In equilibrium in the transparent regime:*

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

(ii) *The lender chooses less than maximal data coverage (i.e.,* $\rho^* < 1$*) if and only if* $C'(1) \leq \Delta_B(1)$*, (i.e., the manipulation cost is sufficiently low),*

Proposition 2 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 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 d_h becomes completely uninformative, leading to the same level of interest rates under the high signal and no signal, that is, $r_h(1) = r_0$.

The condition in part (ii) of the proposition requires the marginal cost of manipulation when $m = 1$ to be sufficiently low. Essentially, it implies that the digital profile is easily manipulable by the borrower. In such a case, the lender endogenously avoids full data coverage in order to maintain data quality. Note that the condition is a sufficient condition, and the result on the lender choosing less than full data coverage will sometimes continue to hold even when it is violated.[8]

3.5 The Opaque Regime

In the opaque regime, the borrower does not observe the lender's data coverage. We show that in this case there is always an equilibrium which features full data coverage, i.e., $\rho^* = 1$. Further, if the manipulation cost is not too high, the equilibrium is unique. Notably, in equilibrium the low-type borrower manipulates their their digital profile, so digital signal is not fully informative about borrower type.

[8] In Section 3.7, we illustrate this point in a numerical example.

Proposition 3 (Optimal data coverage in the opaque regime)**.** *Suppose the lender's choice of digital data coverage, ρ, is not observable to the borrower. Then,*

(i) *In any equilibrium, the low-type borrower manipulates fully, i.e., $m^* = 1$.*

(ii) *There is always an equilibrium in which the lender chooses maximal data coverage, i.e., $\rho^* = 1$.*

(iii) *The equilibrium with maximal data coverage is unique if and only if $C'(1) \geq \Delta_B(1)$ (i.e., the manipulation cost is sufficiently high),*

Why does the lender choose maximal data coverage in this scenario? Suppose, instead, the borrower believes that the lender limits the scope of the alternative data it acquires (i.e., suppose $\hat{\rho} < 1$). Then, it is optimal for the borrower to limit the extent to which they manipulate 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. This force thus drives the lender towards achieving the highest possible data coverage. In fact, in equilibrium, either the lender uses all available data ($\rho^* = 1$), or the low-type borrower fully manipulates their digital profile ($m^* = 1$).

We can now show that the lender earns a higher profit in the transparent regime, as compared to the opaque regime. As we show in the proof of Corollary 1, if the manipulation cost is sufficiently low, the lender's preference for the transparent regime is strict.

Corollary 1 (Lender prefers transparent regime)**.** *The lender's data coverage is (weakly) lower, while the expected profit is (weakly) higher in the transparent regime, compared to the opaque regime.*

3.6 Borrower Surplus and Total Surplus

We now turn to the surplus generated in equilibrium. To simplify notation, we let ρ and m respectively denote the equilibrium values of data coverage and manipulation intensity of the low-type borrower.

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

$$u_H(\rho) = q_H\Big\{\rho \int_{r_h(m)}^{R} (v - r_h(m))dF(v) + (1-\rho)\int_{r_0}^{R}(v - r_0)dF(v)\Big\}, \tag{10}$$

$$u_L(\rho) = q_L\Big\{\rho m \int_{r_h(m)}^{R} (v - r_h(m))dF(v) + \rho(1-m)\int_{r_\ell}^{R}(v - r_\ell)dF(v) + (1-\rho)\int_{r_0}^{R}(v - r_0)dF(v)\Big\} - C(m). \tag{11}$$

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

The borrower's ex ante expected payoff is

$$\mathcal{U} = \alpha\, u_H + (1-\alpha)\, u_L. \tag{12}$$

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

$$\mathcal{S} = \Pi + \mathcal{U}, \tag{13}$$

where the lender profit Π and the borrower surplus $\mathcal{U}$ are given by equations (7) and (12), 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 sometimes has their type fully revealed, and obtains a low payoff. Second, the increase in ρ 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).

In terms of the ex ante borrower surplus $\mathcal{U}$, the trade-off between these two effects depends on how much the equilibrium manipulation by the low type (m) and the interest rates offered by the lender (r_h and r_ℓ) change as ρ increases. The sizes of these effects, in turn, depend on the distribution of project profitability, v. To obtain a concrete result in the next proposition, we assume project profitability follows a generalized uniform distribution.

Proposition 4 (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, $\frac{du_H}{d\rho}\mid_{\rho=0} > 0$ and $\frac{du_L}{d\rho}\mid_{\rho=0} < 0$.*

(ii) *Suppose that (a) $q_L(1+R) > 1$ and (b) the project profitability v has a generalized uniform distribution, that is, $F(v) = \left(\frac{v}{R}\right)^{\beta}$, with $\beta > 0$. Then, there exist thresholds $\beta_1 < 1 < \beta_2 \leq \beta_3$ such that if $\beta \in (\beta_1, \beta_2)$, ex ante the borrower is better off with strictly positive data coverage (i.e., $\frac{\partial \mathcal{U}}{\partial \rho}\mid_{\rho=0} > 0$) whereas if $\beta > \beta_3$, ex ante the borrower is strictly worse off (i.e., $\frac{\partial \mathcal{U}}{\partial \rho}\mid_{\rho=0} < 0$).*

The condition $q_L(1 + R) > 1$ in part (ii) of the proposition ensures that the optimal interest rate given any signal d is given by equation (2) in Lemma 1 part (i).

As demonstrated in part (ii) of the Proposition, ex ante borrower surplus may either increase or decrease when ρ increases from 0. When β is relatively small, the positive effect on the high-type borrower outweighs the negative effect on the low-type borrower. Note that the range over which borrower surplus is increasing at $\rho = 0$ includes the special case of the uniform distribution (i.e., $\beta = 1$). When β becomes large and exceeds the upper threshold β_3, the negative effect dominates, and thus ex ante the borrower is worse off when the lender starts to acquire data.

The intuition behind this result is as follows. As β increases, the distribution of project profitability v shifts toward the right. For high values of β, because most borrowers have high profitability, the interest rates charged to the borrower are relatively high even when the lender believes the borrower has the high type. That is, the high type has little to gain from the lender's data collection efforts. Conversely, for low values of β, the interest rate offered to the high type can fall more steeply in ρ, resulting to a larger gain for this type of borrower. Therefore, in this latter case, the borrower too is ex ante better off when the lender has access to some digital data.

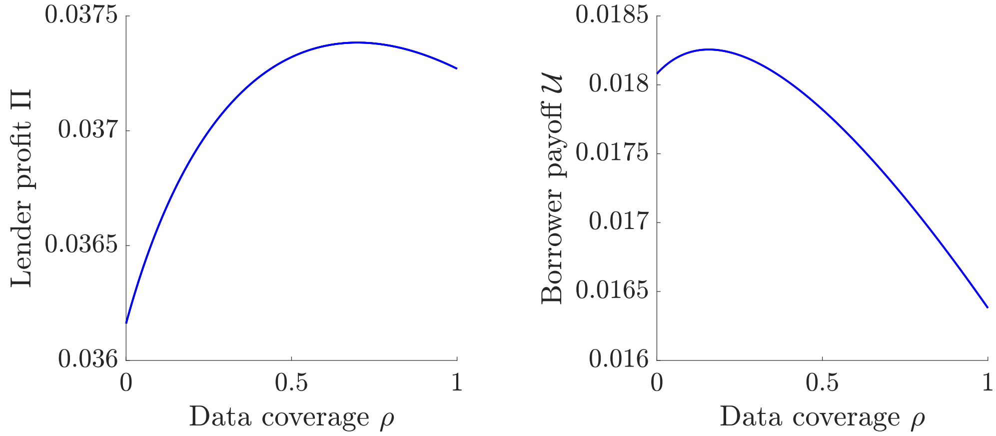
In terms of social surplus, it is immediate that when β is relatively small (i.e., $\beta \in (\beta_1, \beta_2)$, social surplus increases when the lender starts to acquire data. In this parameter region, both ex ante borrower surplus and the lender's profit increase when ρ increases by a small amount starting at $\rho = 0$. Numerically, we find that even for large values of β (i.e., $\beta > \beta_3$), social surplus increases in ρ at $\rho = 0$. That is, the gain to the lender outweighs the ex ante loss to the borrower.

We also find numerically that the thresholds β_2 and β_3 mentioned in Proposition 4 are equal. That is, there is a threshold $\bar{\beta} > 1$ such that for $\beta \in (\beta_1, \bar{\beta})$ ex ante borrower surplus is increasing in ρ at $\rho = 0$, and for $\beta > \bar{\beta}$, ex ante borrower surplus is decreasing in ρ at $\rho = 0$.

3.7 Example 1

We present a numerical example to show that, even when the condition $C'(1) \leq \Delta_B(1)$ in Proposition 2 is violated, the lender may nevertheless stop short of maximal data coverage in the transparent regime. Set $q_H = 0.95, q_L = 0.8, \alpha = 0.5, R = 0.4$ and $v \sim U[0, R]$. The manipulation cost is set to km^2.

When $v \sim U[0, R]$, the optimal interest rate given an average project quality q, shown in Equation (2) can be solved in closed form as $r^*(q) = \frac{1}{2}\left(\frac{1}{q} + R - 1\right)$. Thus, $r_0 = 0.2714$, and



This figure plots the effect of data coverage ρ on the equilibrium values of lender profit and ex ante borrower surplus. The manipulation cost function is $C(m) = 0.01 \cdot m^2$. In addition, we set $\alpha = 0.5, q_H = 0.95, q_L = 0.8, R = 0.4$, and $v \sim U[0, R]$.

Figure 3: The effect of data coverage

$r_\ell = 0.325$. Now, $\Delta_B(1)$ can be computed to be 0.0109. As $C'(1) = 2k$, it follows that when $k \geq 0.00545$, we have $C'(1) > \Delta_B(1)$.

Figure 3 shows the firm profit and ex ante borrower surplus when $k = 0.01$. The lender's profit is maximized at $\rho \approx 0.698$, and the borrower's ex ante surplus at $\rho \approx 0.157$.

In this example, if $k \geq 0.014$ (approximately), the lender chooses maximal data coverage, $\rho = 1$. Thus, the broader point from Proposition 2 continues to hold — if the marginal cost of manipulation is below some threshold, the lender endogenously limits its data coverage, whereas when this marginal cost is high, the lender opts for maximal data coverage.

4 Model with Privacy: Borrowers Own Their Data

A common theme of current regulations in different parts of the world is to grant consumers control rights over their own data. For example, under open banking, consumers can choose whom to share their banking data with. To analyze the effects of such regulations, we extend our base model to allow borrowers to determine whether to provide access to their data with the lender.

One downside of a consumer choosing to share their data with a lender is a potential loss of privacy. Suppose that in addition to different project success probabilities q_θ, borrowers have varying degrees of value for privacy. In particular, a borrower can be "privacy-conscious" and value their privacy at $y > 0$ or be "unconcerned" about privacy, and value their privacy at zero. We assume that y is sufficiently high that a privacy-conscious borrower will not provide the lender with access to their data. Conversely, unconcerned borrowers who do not value privacy provide access to their data if it will benefit them financially. A fraction $\delta > 0$ of borrowers are privacy-conscious, and each borrower knows their own privacy type. For simplicity, we assume that the borrower's value for privacy is independent of both the success probability q_θ and the project profitability v.

In this section, we focus on the transparent regime, in which borrowers observe ρ, the extent of data coverage by the lender. Let γ_i be the probability that an unconcerned borrower with success probability q_i provides their data to the lender. A borrower who provides such access may manipulate their information, as in the base model. A borrower who shares their data receives an interest rate offer r_d based on the digital signal obtained by the lender, $d \in \{d_h, d_\ell, d_0\}$. A borrower who does not provide access to their data receives an interest rate offer r_n. The timeline of events is shown in Figure 4.

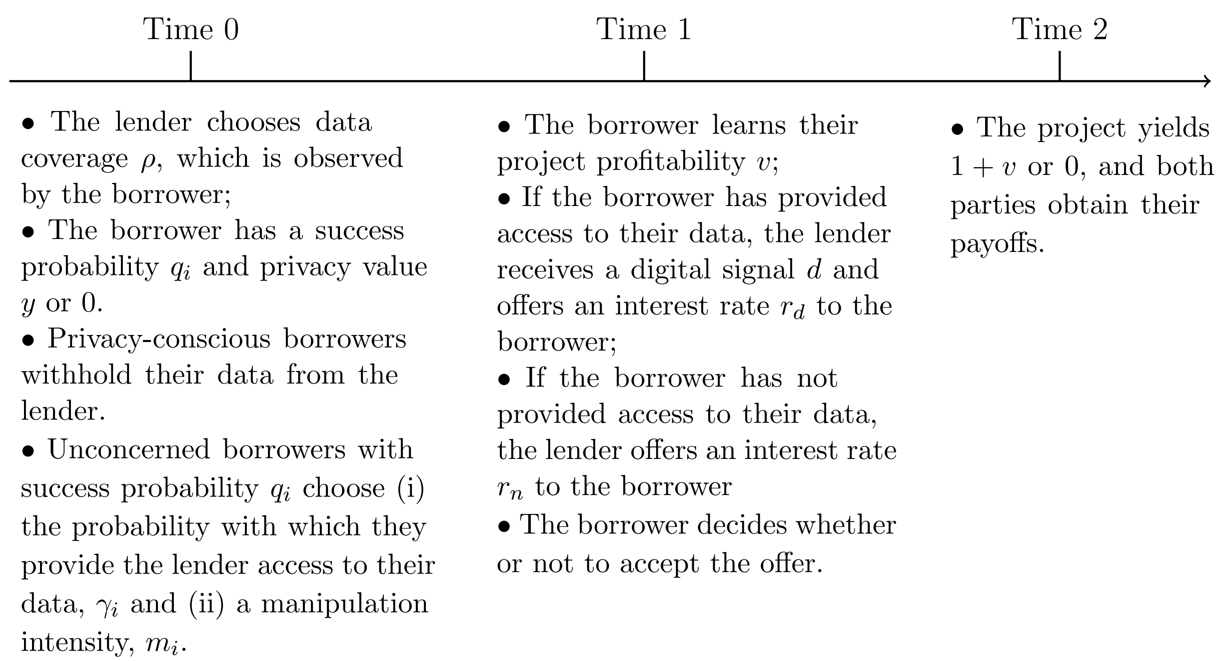


Figure 4: Timeline of model in which borrowers choose whether to provide access to data

Consider the optimal decisions of a borrower who has a low success probability q_L and is unconcerned about privacy. All privacy-conscious consumers withhold their data from the lender. Importantly, because the value for privacy is uncorrelated with the success probability of the project, the privacy-conscious pool includes high and low types in the same proportion as their prior. Now, to mask their type, the unconcerned low-type borrower therefore has two choices: withhold their data (in which case they pool with privacy-conscious borrowers) or share their data and manipulate their digital profile (in which if successful, they pool with unconcerned high-type borrowers who have chosen to share their data). In general, in equilibrium, unconcerned low-type borrowers adopt both masking strategies.

In this scenario, particularly for low values of ρ, there may exist an equilibrium in the continuation game in which no borrower shares their data with the lender (i.e., $\gamma_H = \gamma_L = 0$). Such an equilibrium may be supported with the off-equilibrium belief that any borrower sharing data has the low type. However, an equilibrium of this nature does not satisfy the refinement D1. Among equilibria that do satisfy this criterion, we find that unconcerned high-type borrowers both share their data with probability one and do not manipulate.

Proposition 5 (Low-type borrowers withhold data)**.** *Suppose that, in the transparent regime, the lender's data coverage is strictly positive, i.e., $\rho > 0$. In any equilibrium that survives the refinement D1 in the continuation game, among borrowers unconcerned about privacy:*

(i) The high-type borrower provides their data to the lender with probability 1 (that is, $\gamma_H^* = 1$), and does not manipulate.

(ii) The low-type borrower may withhold access to their data, and if they do provide access, may manipulate their digital profile with positive probability. That is, $\gamma_L^* \in [0, 1]$ and $m^* \in [0, 1]$.

(iii) The interest rates offered after different signals satisfy $r_\ell > r_n \geq r_0 \geq r_h$, with the second inequality being strict whenever $\gamma_L^* < 1$ and the third whenever $m^* < 1$.

Essentially, the lender faces four groups of borrowers: those who did not share their data (which includes all privacy-conscious borrowers and some fraction of unconcerned low-type borrowers), and, from the set that did share their data those who generated each of the high, low, and uninformative signals (respectively, d_h, d_ℓ, and d_0). Among borrowers unconcerned with privacy, only some low-type borrowers withhold their data. Thus, compared to the prior pool, the pool of borrowers who do not provide their data is skewed toward the low type. Conversely, the pool of those who do share data is skewed toward the high type. Therefore, we generally expect that $r_n > r_0$. As before, only low-type borrowers generate signal d_ℓ, so $r_\ell > r_n$. Finally, as long as low-type borrowers who share their data do not manipulate with probability 1, we will see $r_0 > r_h$.

Notice that in the special case that $\delta = 0$, the extended model reduces to the base model. Because all high-type borrowers share their data, when $\delta = 0$ any borrower who fails to share data is revealed to be the low type. Therefore, in equilibrium $\gamma_L^* = 1$.

Next, consider the lender's expected profit as ρ varies. As only the low-type unconcerned borrower may refuse to share their data, let γ denote the probability with which they do provide data access, and set $\gamma_H^* = 1$ as specified by Proposition 5. The lender's expected profit given signal $d \in \{d_h, d_\ell, d_0, d_n\}$ is $\pi_d(r_d) = (1 - F(r_d)) \cdot [\bar{q}_d \cdot r_d - (1 - \bar{q}_d)]$. Taking into account all types of available information, the lender's expected profit at the beginning of the game can be expressed as:

$$\Pi(\rho) = \{\delta + (1-\alpha)(1-\delta)(1-\gamma)\}\, \pi_n(r_n) + (1-\rho)(1-\delta)\{\alpha + (1-\alpha)\gamma\}\, \pi_0(r_0) \quad (14)$$
$$+\rho(1-\delta)[\{\alpha + (1-\alpha)\gamma m\}\, \pi_h(r_h) + (1-\alpha)\gamma(1-m)\, \pi_\ell(r_\ell)]. \quad (15)$$

Here, both γ and m (and in turn the interest rates r_n, r_0, and r_h) vary as data coverage ρ varies.

To explore the properties of equilibria in this section, we turn to a numerical example.

4.1 Example 2

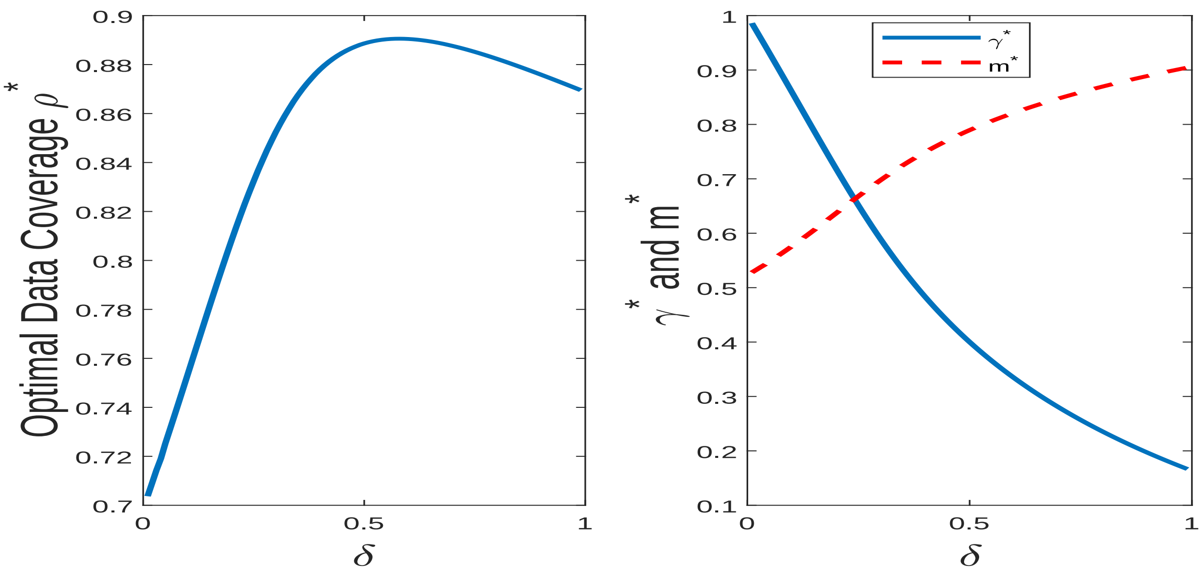
Set $\alpha = 0.5$, $q_H = 0.95$, $q_L = 0.8$, $R = 0.4$, $C(m) = 0.01m^2$, and $v \sim U[0, 0.4]$. We vary δ, the proportion of privacy-conscious borrowers, between 0.01 and 0.99.

We exhibit three features of the equilibrium as δ varies. First, given our parameters, the lender chooses an interior value of ρ for every δ. As shown in the left panel of Figure 5, ρ^* ranges between 0.7 and 0.89, and is strictly below 1 for all values of δ. Second, for the borrower who is unconcerned about privacy and has the low type, refusing to provide access to their data and manipulating their digital profile are complementary activities. That is, as shown in the right panel of Figure 5, as δ increases, the proportion of these borrowers who share their data (γ^*) falls, and the equilibrium manipulation (m^*) increases. Notice also that both γ^* and m^* are strictly between 0 and 1 in this example.

Third, we find that the equilibrium utility of both the high and low type of unconcerned borrower increases with δ, and in particular is greater when $\delta > 0$ than in the limiting case when δ goes to 0. To develop some intuition for this result, in the left panel of Figure 6, we exhibit the equilibrium interest rates faced by borrowers who withhold their data (r_n), those who share their data and generate the uninformative signal (r_0), and those who share their data and generate the high signal (r_h). As a point of comparison, the rate offered to borrowers who share their data (r_ℓ) is 0.325.

Notice that all three interest rates, r_n, r_0, and r_h are decreasing in δ. Essentially, as the proportion of privacy-conscious borrowers increases, it is easier for the unconcerned low-type borrower to to hide themselves by pooling with the privacy-conscious borrowers and refusing to share their data. In turn, this raises the quality of the pool of borrowers who do provide access to their data (recall that the unconcerned high-type borrower shares their data with probability 1), leading to a reduction in r_0 and r_h.

The fall in interest rates for all groups of borrowers as δ increases helps to explain the

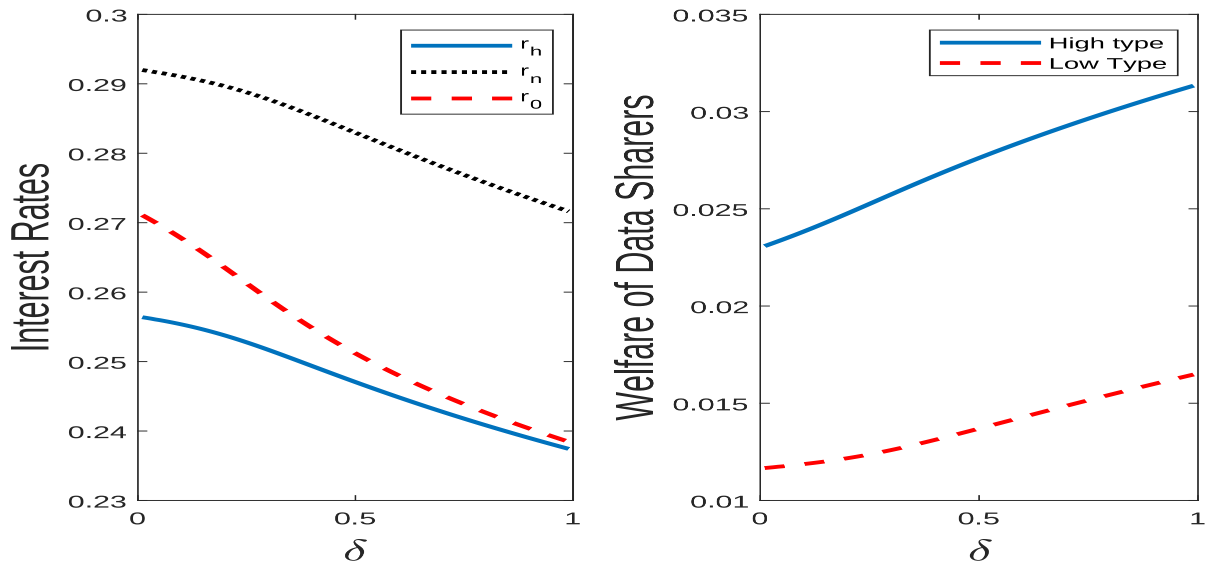


The left panel shows the lender's optimal data coverage as the proportion of privacy-conscious borrowers, δ changes. The right panel shows the equilibrium values of γ^* and m^*, respectively the probability the unconcerned low-type borrower shares their data and their manipulation intensity when they do share their data. The parameters are $\alpha = 0.5$, $q_H = 0.95$, $q_L = 0.8$, $R = 0.4$, $C(m) = 0.01m^2$, and $v \sim U[0, 0.4]$.

Figure 5: Effect of data coverage on data provision and manipulation when borrowers own their data

effect on the equilibrium utilities of unconcerned high and low type borrowers. As shown in the right panel of Figure 6, the welfare of both these borrowers increases in δ. In particular, they are both better off at positive values of δ than in the base model, where $\delta = 0$. Clearly, privacy-conscious borrowers are better off when they can withhold their data than in the base model, where there is no option to withhold data. Thus, in this example, we find that *all* borrowers are better off when they have the option of withholding or sharing their data, compared to when such an option is not available.

As the data that may be shared include banking data, our results contrast with those of (Parlour et al., 2022) and (He et al., 2023), who point out possible negative effects of open banking on borrowers. We find that this last property in particular, that both types of unconcerned borrower are better off when $\delta > 0$ compared to when the borrower does not have a choice about sharing their data, is robust, in the sense that it holds for different parameter values and also for some different distributions of project profitability v. Therefore, one benefit of privacy regulations is that even borrowers who choose to provide access to their data may be better off when the laws allow them to withhold their data.



The left panel in the figure plots the effect of changing the proportion of privacy-conscious borrowers (δ) on r_n, the interest rate offered to borrowers who do not share data (dotted line), r_0, the interest rate offered to borrowers who share data and generate the uninformative signal (dashed line), and r_h, the interest rate offered to borrowers who share data and generate the high signal (solid line). Given our parameters, r_ℓ, the interest rate offered to borrowers who share data and generate the low signal, is equal to 0.325. The right panel shows the equilibrium utilities of high and low type borrowers who are unconcerned about privacy. The parameters are $\alpha = 0.5$, $q_H = 0.95$, $q_L = 0.8$, $R = 0.4$, $C(m) = 0.01 \cdot m^2$, and $v \sim U[0, 0.4]$.

Figure 6: Effect of the proportion of privacy-conscious borrowers on interest rates and welfare of

5 Extensions to Base Model

We now consider two extensions of our base model: (i) the lender's data coverage directly affects the manipulation cost for the borrower, and (ii) acquiring the digital signal is costly for the lender. The main insights from our base model remain: in the transparent regime, under some conditions the lender chooses less than complete data coverage, and the lender's data coverage is lower in the transparent regime than the opaque regime.

5.1 Data Coverage Affecting Manipulation Cost

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 importance of each variable, 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 $C(0,\rho) = C'(0,\rho) = 0$, $\frac{\partial C(m,\rho)}{\partial m} > 0$, $\frac{\partial C(m,\rho)}{\partial \rho} > 0$, $\frac{\partial^2 C(m,\rho)}{\partial m^2} > 0$, and $\frac{\partial^2 C(m,\rho)}{\partial m \partial \rho} > 0$. That is, not only does more intensive manipulation incur a higher cost, similar to the baseline model, but also a higher level of data coverage in the lender's underwriting model induces an additional manipulation cost.

We find that in the transparent regime, if the borrower's manipulation cost is sufficiently low (specifically, $\frac{\partial C(m,\rho)}{\partial m} |_{m=1,\rho=1} \leq \Delta_B(1)$), the lender again avoids full data coverage.

In the opaque regime, where data coverage is unobservable to the borrower, it continues to be the case that maximal data coverage can be sustained in equilibrium. This finding aligns with Proposition 3. Furthermore, in the extended economy, the lender gains from the transparency enforced by regulations, as in Corollary 1.

Proposition 6 in Appendix B provides our formal results for this case.

5.2 Lender Incurs a Cost for Data Coverage

In the base model, the lender can acquire additional data on the borrower at no cost. In this section, we consider the effect of costly data acquisition. Assume that collecting data to an extent ρ incurs a cost for the lender denoted as $K(\rho)$. As is standard, let $K(0) = 0$, $K'(\rho) > 0$ (so the cost increases with the extent of data coverage) and $K''(\rho) > 0$ (so the cost is strictly convex in data coverage).

We find that in the transparent regime, under the sufficient condition characterized in Proposition 2, the lender again chooses less than complete data coverage. As is intuitive, with a cost of data collection, the optimal extent of data coverage is strictly lower than in the base model. The lender's profit decreases, and the intensity of borrower manipulation also decreases. In numerical examples we find that borrower surplus can be either higher or lower than in the base model.

In the opaque regime, once a data collection cost is introduced, the lender will choose a coverage level strictly less than the level at which the low success probability borrower manipulates with probability 1, even if the borrower's manipulation cost is low. This contrasts with our finding in the baseline model, as shown in Proposition 3. The rationale is that if the low-type borrower fully manipulates their information, the lender's signal becomes entirely useless, thereby undermining the initial investment in data technology by the lender. As in Proposition 3, when the borrower's manipulation cost is high and the cost of data collection for the lender is relatively low, the lender chooses full data coverage.

Finally, similar to the baseline model, the regulatory authority's request for transparency can assist the lender in committing to limit its data usage in credit underwriting, thereby enhancing profitability.

Our formal result for this model extension is exhibited in Proposition 7 in Appendix B.

6 Regulatory Implications

We now consider the implications of our framework for regulations and policies on the credit market.

6.1 Regulating the Use of Alternative Data in Underwriting Credit

Regulations on the use of alternative data in credit markets are quite different across different countries in the world. 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."[9] In contrast, the European Union 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 directive on consumer credit in June 2021. This proposal aligns with the GDPR and aims to address issues related to personal data processing in the consumer credit market, including the use of alternative data and the transparency of assessments conducted using machine-learning techniques.[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 three possible aspects of regulations that our model can shed light on: transparency on the use of alternative data, limits on its use, and consumers' control over their data.

6.1.1 Regulations on transparency

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

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

[10] 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.

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 opaque regime to the transparent regime. Proposition 3 shows that in the opaque regime, the lender tends to adopt the maximal data coverage in its underwriting model. However, when we transition to the transparent regime, Proposition 2 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. As shown in the proof of Corollary 1, when the manipulation cost is low, the lender's profit is strictly higher in the transparent regime, and the extent of its data coverage is lower. In other words, the observability of data coverage imposed by the regulation effectively grants the lender commitment power to restrict data usage.

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

6.1.2 Limits on the use of alternative data

Another form of regulation could be 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, say $\bar{\rho}$.

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 found on social media platforms or health data, including cancer data, should not be used when conducting a creditworthiness assessment." Further, the European Data Protection Supervisor (EDPS) explicitly recommends extending the prohibition to search query data or online browsing activities.

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 opaque 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. For example, as can be seen in Figure 3, completely prohibiting the use of alternative data hurts both the borrower and the lender.

6.1.3 Consumers' control over their own data

Some regulations are designed to let consumers control how their data are used. For example, Payment Services Directive 2 (PSD2) in the EU mandates that if consumers so request, their banks must make account information available to non-bank financial institutions. Similarly, in the US, the 2020 California Consumer Privacy Act (CCPA) gives consumers the right to know who their data are being sold to, and to prohibit such sales.

The extended model in Section 4 analyzes this scenario. We observe that our main findings remain robust in this extension. Particularly, in the transparent regime, the lender refrains from fully leveraging its data to mitigate borrowers' manipulation and maintain higher data quality. Similar to the base model, borrowers might also exhibit a preference for the lender to have access to certain digital data.

It is worth highlighting the intriguing interaction between borrowers' decisions regarding data sharing and manipulation. Choosing not to share data with the lender and manipulating digital data can both be seen as strategies to safeguard borrower privacy. The former is a passive approach, where the borrower simply opts not to grant permission to the lender, while the latter is an active approach, where the borrower actively manages their digital profile and, consequently, the information accessed by the lender.

Finally, as noted in the numerical example in Section 4, comparing the base model (i.e., the case of $\delta = 0$) to the model in which consumers can choose whether to share their data, we find that all borrowers are better off in the latter case. Privacy-conscious borrowers of course also directly benefit from keeping their data private. Thus, laws on consumer control over data are unambiguously beneficial to borrowers in our setting.

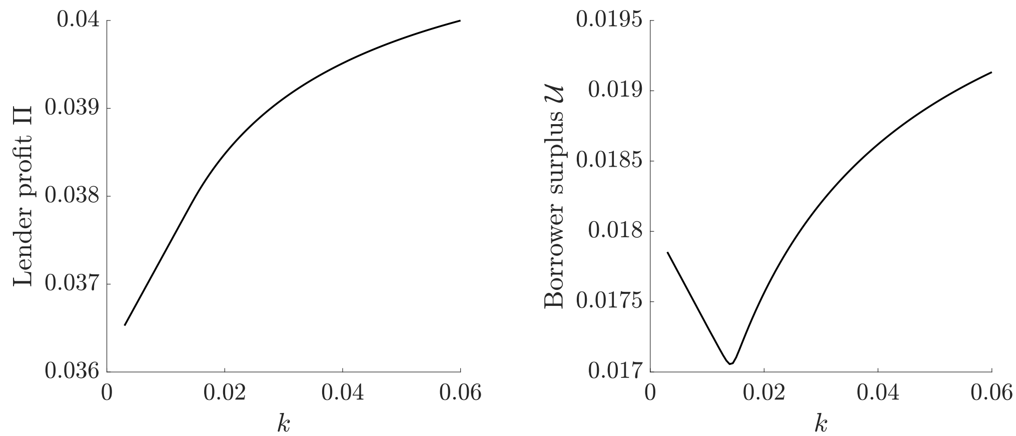
6.2 Policies that May Affect Manipulation Costs

The borrower's manipulation cost is a crucial input in our model. 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. Conversely, lenders may adopt more sophisticated algorithms and techniques to detect and prevent borrower manipulation. In our framework, this would correspond to an increase in the manipulation cost for the borrower.

In the opaque regime, as shown in Proposition 3, the lender continues to adopt maximal data coverage. To understand the effects of changes in the manipulation cost in the transparent regime, we consider a numerical example. We fix the parameters to be $q_H = 0.95$, $q_L = 0.8$, $\alpha = 0.5$, $R = 0.4$, and $v \sim U[0, R]$, the same as those for Figure 3. The manipulation cost is set to km^2. For each value of k, we first determine ρ^*, the optimal data coverage for the lenders in the transparent regime, and then the equilibrium values of the other variables. The resulting lender profit and ex ante borrower surplus are shown in Figure 7.

When the manipulation cost increases, the lender increases its data coverage, knowing that the borrower's actions are now less likely to compromise the quality of data it receives. As a result of the increase in k, the low-type borrower does indeed (weakly) reduce its manipulation. Interestingly, for low values of manipulation cost, the low-type's manipulation intensity remains constant. This is because despite the increasing cost for a given level of manipulation, the higher data coverage adopted by the lender implies higher marginal value for the low-type borrower to engage in manipulation. Consequently, this justifies and sustains the intensity of manipulation.

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 (a) of Figure 7. Panel (b) of the figure illustrates that when the manipulation cost k is low, the borrower surplus decreases as the manipulation cost increases. However, when the manipulation cost is high enough to deter the low-type's manipulation, the borrower surplus increases in manipulation costs. The total surplus monotonically increases with an increase in the manipulation cost.



(a) Lender profit (b) Ex ante borrower surplus

This figure plots the effect of manipulation cost on the lender's profit and borrower's ex ante surplus. The manipulation cost function is $C(m) = km^2$. As in Figure 3, we set $q_H = 0.95$, $q_L = 0.8$, $\alpha = 0.5$, $R = 0.4$, and $v \sim U[0, R]$. For each value of k, we first find the optimal ρ for the lender, and then compute the equilibrium values of the other variables.

Figure 7: Effect of changes in borrower's 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. First, an increase in financial literacy can potentially have negative implications for consumers, as a resultant decrease in the manipulation cost may lead to a rise in manipulation and a lower borrower surplus.

On the other hand, anti-fraud measures implemented by lenders may 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 may increase.

It is worth noting that we find 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, to allow for a better separation of borrowers on the dimension of success probability. 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, privacy costs may increase as the lender acquires more data, reducing borrower surplus. Hence, an intermediate manipulation cost may be optimal for the regulator.

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: a transparent regime in which the lender's use of alternative data is observable to the borrower and an opaque regime in which the usage is unobservable. In the opaque regime, the lender chooses maximal 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. Interestingly, we also find that in the aggregate borrowers may be 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 obtaining better credit terms. Even though the low-type borrower has a reduced payoff, aggregate borrower surplus can initially improve when the lender acquires some alternative data.

Finally, we examine the effects of various regulations on the use of alternative data by lenders. Regulations that aim to ensure transparency on what data a lender collects and how the data are used benefit the lender as well. They allow the lender to credibly commit to restricting the data they use, which in turn reduces borrower manipulation. Without such regulations, we are in the opaque regime, which leads to maximal data collection by lenders, greater manipulation by borrowers, and lower lender profit.

Regulations that establish a borrower as the owner of their data, and give the borrower the right to share (or not share, as the case may be) their data with a lender are beneficial for privacy-conscious borrowers. Importantly, in our framework, we show that they also benefit borrowers who do not value privacy. Among such borrowers, low types now have an extra way to hide that has no direct cost — they can just pool with privacy-conscious borrowers. Their payoff therefore improves. High-type borrowers who do not value privacy now find that their credit terms improve, as the pool of data sharers skews toward the high type. Thus, all borrowers can benefit from such regulations.

Overall, our model provides a framework to study the effects of digital data collection by lenders and borrower manipulation of such information. As the use of alternative data increases on the part of lenders, we expect that borrowers too will become more sophisticated and will manipulate their data. Regulatory and non-regulatory policies may both play an important role in shaping the future environment of credit markets.

Appendix

A Proofs of Results in the Main Text

Proof of Lemma 1

Suppose the lender obtains signal $d \in \{d_h, d_\ell, d_0\}$. Recall that $\mu_d = \text{Prob}(\theta = H \mid s)$, and $\bar{q}_d = \mu_d q_H + (1 - \mu_d) q_L$.

(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 θ, 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 d and interest rate offer r is therefore

$$\begin{aligned} \pi_d(r) &= (1 - F(r))[\mu_d\{q_H(1 + r) - 1\} + (1 - \mu_d)\{q_L(1 + r) - 1\}] \\ &= (1 - F(r))[\bar{q}_d(1 + r) - 1]. \end{aligned} \tag{16}$$

The first-order condition is:

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

which can be simplified to

$$r - \frac{1 - F(r)}{f(r)} = \frac{1}{\bar{q}_d} - 1, \tag{17}$$

which is equation (2) 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 $\bar{q}_d(1 + R) > 1$.

The second-order condition is

$$-2\bar{q}_d f(r) - f'(r_d)[\bar{q}_d r - (1 - \bar{q}_d)] < 0. \tag{18}$$

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 (2) is strictly increasing in r. Thus, the first-order condition provides a unique maximum to the lender's problem.

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

Proof of Proposition 1

Suppose that $\rho > 0$. Let $\hat{\rho}$ denote the borrower's belief about ρ (in equilibrium, of course, $\hat{\rho} = \rho$). We first show that if the lender's posterior beliefs are consistent with the borrower's strategy, the lender charges a strictly lower interest rate when it observes the signal $d = d_h$ rather than when it observes the signal $d = d_\ell$. Let r_j denote the optimal interest rate offer after signal d_j.

Claim: $r_h < r_\ell$.

Proof of Claim We prove the claim by contradiction. Suppose instead that $r_h > r_\ell$, that is, borrowers who generate signal d_h are charged higher interest rates than those who generate signal d_ℓ.

As shown in equation (3), the expected utility of a type θ borrower who chooses manipulation intensity m is

$$u(\theta, m; \hat{m}_\theta, \hat{\rho}) = q_\theta \Big\{ \hat{\rho} \Big(m \int_{r_{\tilde{\theta}}}^{R} (v - r_{\tilde{\theta}}) dF(v) + (1 - m) \int_{r_\theta}^{R} (v - r_\theta) dF(v) \Big) + (1 - \hat{\rho}) \int_{r_0}^{R} (v - r_0) dF(v) \Big\} - C(m_\theta). \quad (19)$$

Observe that the interest rates r_θ 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 $\frac{\partial u(\theta, m; \hat{m}_\theta, \hat{\rho})}{\partial m} |_{m=0} > 0$. As $C'(0) = 0$, this condition reduces to

$$\hat{\rho}\, q_\theta \Big\{ \int_{r_{\tilde{\theta}}}^{R} (v - r_{\tilde{\theta}})) dF(v) - \int_{r_\theta}^{R} (v - r_\theta)) dF(v) \Big\} > 0. \quad (20)$$

That is, for $m_\theta > 0$, 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 $m_\theta > 0$ in equilibrium, it must be that $\hat{\rho} > 0$ and $r_{\tilde{\theta}} < r_\theta$.

Now, suppose that $r_h \geq r_\ell$. Then, it must be that the low-type borrowers do not manipulate, i.e., $m_L = 0$. Therefore, on receiving signal d_h, the lender knows the borrower must have the high type. On receiving signal d_ℓ, at best the borrower is the high type with probability α (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 d_ℓ is received). Therefore, it must be that $r_h < r_\ell$, which is a contradiction. ■

(i) Given that $r_h < r_\ell$, 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 $r_h < r_\ell$, which is true. For simplicity, given that $m_H = 0$, we denote the low-type borrower's manipulation intensity m_L as m, and the lender's belief about this intensity as $\hat{m}$.

Given a belief $\hat{\rho}$ about the lender's data coverage, the manipulation intensity of the low-type borrower satisfies the first-order condition

$$\hat{\rho} q_L \left(\int_{r_h(\hat{m})}^{R} (v - r_h(\hat{m})) dF(v) - \int_{r_\ell}^{R} (v - r_\ell) dF(v) \right) = C'(m). \tag{21}$$

Since $C(\cdot)$ is convex, the second-order condition is immediately satisfied. Fixing $\hat{\rho}$ and $\hat{m}$, the left-hand side is a constant. Denote this constant by A. Then, the optimal manipulation intensity of the low-type borrower is $m = 1$ if $C'(1) \le A$, and $m = C'^{-1}(A)$ otherwise.

In equilibrium, it must be that $\hat{m} = m$; i.e., the lender's beliefs must match the actual equilibrium intensity of the low-type borrower. We impose $\hat{m} = m$ in the first-order condition (21), which yields the equilibrium condition for an interior manipulation intensity:

$$\hat{\rho} q_L \left(\int_{r_h(m)}^{R} (v - r_h(m)) dF(v) - \int_{r_\ell}^{R} (v - r_\ell) dF(v) \right) = C'(m). \tag{22}$$

The left-hand side is strictly positive for all $m \in [0, 1]$, and is strictly decreasing in m. The right hand side is zero at $m = 0$ and is strictly increasing in m.

If $C'(1) \le \hat{\rho} q_L \left(\int_{r_h(1)}^{R} (v - r_h(1)) dF(v) - \int_{r_\ell}^{R} (v - r_\ell) dF(v) \right) = \Delta_B(\hat{\rho})$, equation (22) cannot be satisfied for any $m \in (0, 1)$, so $m = 1$. Conversely, if $C'(1) > \Delta_B(\hat{\rho})$, there is a unique value of m that satisfies equation (22).

(iii) We have shown above that $r_h < r_\ell$. It remains to show that $r_0 \in (r_h, r_\ell)$. The consistency requirement on the borrower's best response requires that the lender's posterior beliefs be determined from 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 digital signal $d \in \{d_h, d_\ell, d_0\}$ satisfy $\mu_h = \frac{\alpha}{\alpha + (1-\alpha)m}$, $\mu_\ell = 0$, and $\mu_0 = \alpha$. That is, we have $\mu_L < \mu_0 < \mu_H$. It follows immediately that $r_h < r_0 < r_\ell$. ■

Proof of Lemma 2

In what follows, for notational convenience we write $m = m^*$. When $m < 1$, it satisfies the first-order condition for optimal manipulation, equation (22).

Denote $I_h = \int_{r_h(m)}^{R} (v - r_h(m)) dF(v)$, and $I_\ell = \int_{r_\ell}^{R} (v - r_\ell) dF(v)$. Then, this first-order condition may be written as $\hat{\rho} q_L (I_h - I_\ell) = C'(m)$.

Applying the implicit function theorem, we have

$$\frac{dm}{d\hat{\rho}} = -\frac{q_L(I_h(m) - I_\ell)}{-C''(m) + \hat{\rho} q_L \frac{\partial I_h(m)}{\partial m}} = \frac{q_L(I_h(m) - I_\ell)}{C''(m) - \hat{\rho} q_L \frac{\partial I_h(m)}{\partial m}}. \tag{23}$$

In the last expression, $I_h(m) > I_\ell$ because $r_h(m) < r_\ell$, 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 μ_H, the posterior probability of the high type after signal d_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 (23) is strictly positive. Hence, $\frac{dm}{d\hat{\rho}} > 0$. ■

Proof of Lemma 3

Suppose the borrower cannot manipulate their signal. Then, for any positive value of ρ, the lender's beliefs after each signal d 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 $r_h < r_0 < r_\ell$.

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

$$\Pi = \rho \left\{ \alpha \pi_h(r_h) + (1 - \alpha)\pi_\ell(r_\ell) \right\} + (1 - \rho)\pi_0(r_0). \tag{24}$$

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_0 do not depend on ρ. Thus, taking the derivative of the expected profit in (24) with respect to ρ yields

$$\frac{d\Pi}{d\rho} = \alpha \pi_h(r_h) + (1 - \alpha)\pi_\ell(r_\ell) - \pi_0(r_0).$$

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

$$\begin{aligned} \frac{d\Pi}{d\rho} > 0 &\iff \alpha \pi_h(r_h) + (1 - \alpha)\pi_\ell(r_\ell) > \pi_0(r_0) \\ &\iff \alpha \max_r \pi_h(r) + (1 - \alpha) \max_r \pi_\ell(r) > \max_r \pi_0(r) \\ &\iff \alpha \max_r \pi_h(r) + (1 - \alpha) \max_r \pi_\ell(r) > \max_r \left[\alpha \pi_h(r) + (1 - \alpha)\pi_\ell(r) \right]. \end{aligned} \tag{25}$$

As $r_h \neq r_\ell$, it is straightforward that the last inequality must hold. Therefore, the lender's expected profit is monotonically increasing in ρ and it thus chooses the maximum ρ in equilibrium. ■

Proof of Proposition 2

In the transparent regime, the borrower directly observes the extent of data coverage, ρ.

(i) Recall from equation (7) that the lender's profit is

$$\Pi(\rho) = \rho\Big(\{\alpha + (1-\alpha)m\}\pi_h(r_h) + (1-\alpha)(1-m)\pi_\ell(r_\ell)\Big) + (1-\rho)\pi_0(r_0), \qquad (26)$$

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

Thus,

$$\frac{d\Pi}{d\rho} = \frac{\partial \Pi}{\partial \rho} + \frac{\partial \Pi}{\partial m}\frac{dm}{d\rho} = \{\alpha + (1-\alpha)m\}\pi_h + (1-\alpha)(1-m)\pi_\ell - \pi_0$$
$$+\rho\{(1-\alpha)(\pi_h - \pi_\ell) + \{\alpha + (1-\alpha)m\}\pi_h'(r_h)r_h'(m)\}\frac{dm}{d\rho}. \qquad (27)$$

Now, r_h is chosen to maximize π_h, so $\pi_h'(r_h) = 0$. Therefore,

$$\frac{d\Pi}{d\rho} = \{\alpha + (1-\alpha)m\}\pi_h + (1-\alpha)(1-m)\pi_\ell - \pi_0 + \rho(1-\alpha)(\pi_h - \pi_\ell)\frac{dm}{d\rho}. \qquad (28)$$

Now, consider $\rho \to 0$ from above. We obtain

$$\pi_+'(0) = \{\alpha + (1-\alpha)m\}\pi_h + (1-\alpha)(1-m)\pi_\ell - \pi_0, \qquad (29)$$

where $\pi_+'(0)$ denotes the right derivative of Π evaluated at $\rho = 0$. Observe that when $\rho = 0$, we also have $m = 0$. Thus,

$$\pi_+'(0) = \alpha\pi_h + (1-\alpha)\pi_\ell - \pi_0. \qquad (30)$$

In the proof of Lemma 3, we have shown that $\alpha\pi_h + (1-\alpha)\pi_\ell - \pi_0 > 0$; see equation (25). Hence, $\pi_+'(0) > 0$, so that $\rho^* > 0$.

(ii) Suppose $C'(1) \leq \Delta_B(1)$. Then, if the lender chooses $\rho = 1$, from Proposition 1 part (ii), the low-type borrower manipulates with probability 1, that is, $m^* = 1$. Lemma 2 shows that this equilibrium manipulation intensity is strictly increasing in ρ when $m^* \in (0,1)$. By continuity, there exists some $\underline{\rho} = \min\{\tilde{\rho} \mid m^*(\tilde{\rho}) = 1\}$.

Observe that when $m = 1$, we have $\mu_H = \alpha = \mu_0$, so that $r_h = r_0$. Thus, when $m = 1$,

$$\Pi(\rho)\,|_{m=1} = \rho\pi_0 + (1-\rho)\pi_0 = \pi_0, \qquad (31)$$

independent of the level of data coverage ρ.

We show that at $\rho = \underline{\rho}$, the left derivative of the profit function is strictly less than zero. Denote this left derivative as $\Pi_-'(\underline{\rho})$. Recalling that $m = 1$ at $\rho = \underline{\rho}$ and that $\pi_h(r_h) = \pi_0(r_0)$ when $m = 1$, we have

$$\Pi_-'(\underline{\rho}) = \pi_0 - \pi_0 + \underline{\rho}(1-\alpha)(\pi_0 - \pi_\ell)m_-'(\underline{\rho}) = \underline{\rho}(1-\alpha)(\pi_0 - \pi_\ell)m_-'(\underline{\rho}). \qquad (32)$$

Now, as $\mu_0 > 0 = \mu_L$, it is immediate that $\pi_0 > \pi_\ell$. Further, in Lemma 2, we have shown that $m_-'(\underline{\rho}) < 0$ when $m^* < 1$. Therefore,

$$\Pi_-'(\underline{\rho}) < 0. \qquad (33)$$

Therefore, the lender earns a slightly higher profit at some ρ close to but strictly less than $\underline{\rho}$ than at $\rho = \underline{\rho}$. As $\Pi(1) = \Pi(\underline{\rho})$, it follows that the lender earns a strictly higher profit at some ρ strictly less than $\underline{\rho}$ than at $\rho = 1$. ■

Proof of Proposition 3

Let $\hat{\rho}$ denotes the borrower's belief about the extent of data coverage and ρ 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 d_h depends on $\hat{\rho}$ rather than ρ.

The lender's payoff function may be written as:

$$\begin{aligned}\Pi(\rho \mid \hat{\rho}) &= \rho\Big(\{\alpha + (1-\alpha)m(\hat{\rho})\}\pi_h(r_h(m(\hat{\rho}))) + (1-\alpha)(1-m(\hat{\rho}))\pi_\ell\Big) \\ &\quad +(1-\rho)\pi_0(r_0). \end{aligned} \tag{34}$$

The derivative with respect to ρ is

$$\frac{\partial \Pi}{\partial \rho} = \{\alpha + (1-\alpha)m(\hat{\rho})\}\pi_h(r_h) + (1-\alpha)(1-m(\hat{\rho}))\pi_\ell(r_\ell) - \pi_0(r_0).$$

Noting that $\pi_h(r_h) > \pi_\ell(r_\ell)$ and $0 \leq m(\hat{\rho}) < 1$ we have

$$\begin{aligned}\{\alpha + (1-\alpha)m(\hat{\rho})\}\pi_h(r_h) + (1-\alpha)(1-m(\hat{\rho}))\pi_\ell(r_\ell) &\geq \alpha\pi_h(r_h) + (1-\alpha)\pi_\ell(r_\ell) \\ &> \pi_0(r_0),\end{aligned}$$

where the last inequality was proved toward the end of the proof of Lemma 3.

Therefore, whenever $m(\hat{\rho}) < 1$, we have $\frac{\partial \Pi}{\partial \rho} > 0$, and the lender has an incentive to increase ρ. If $m(\hat{\rho}) = 1$, then the posterior beliefs after signal d_h and signal d_0 are the same and equal to the prior α. 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 ρ, it follows that $m(y) = 1$ for any $y \geq \hat{\rho}$). In particular, $\rho = 1$ is a best response.

Finally, note that following the arguments in the proof of Proposition 2, when $C'(1) \geq q_L\left(\int_{r_0}^{R}(v-r_0)dF(v) - \int_{r_\ell}^{R}(v-r_\ell)dF(v)\right)$, we have $m(\hat{\rho}) < 1$ for any $\hat{\rho} < 1$.

Both parts of the Proposition now follow. ■

Proof of Corollary 1

The proof follows Propositions 2 and 3. Specifically, when the manipulation cost is low, i.e., $C'(1) \leq \Delta_B(1)$, where $\Delta_B(1)$ is given by equation (9), there exists some $\underline{\rho}$ such that the left derivative of the lender's profit function is strictly less than zero. That is, the lender earns a strictly higher profit at some ρ strictly less than $\underline{\rho}$ than at $\rho = 1$. In contrast, when the data coverage is unobservable, the lender is indifferent between $\rho \in [\underline{\rho}, 1]$. 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 $C'(1) > \Delta_B(1)$, even at $\rho = 1$ the low-type borrower manipulates with probability less than 1. Here, the lender might choose full data coverage 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 4

(i) Denote $I_j = \int_{r_j}^{R}(v - r_j)dF(v)$, for digital signal $d_j \in \{d_h, d_\ell, d_0\}$. Specifically, $I_h(m) = \int_{r_h(m)}^{R}(v - r_h(m))dF(v)$, $I_\ell = \int_{r_\ell}^{R}(v - r_\ell)dF(v)$ 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,

$$\frac{du_H}{d\rho} = \frac{\partial u_H}{\partial \rho} + \frac{\partial u_H}{\partial m}\frac{dm}{d\rho} = q_H(I_h(m) - I_0) + \rho q_H \frac{\partial I_h}{\partial m}\frac{dm}{d\rho}. \tag{35}$$

Here, $\frac{\partial I_h}{\partial m} = -(1 - F(r_h(m)))\, r'_h(m)$, and $\frac{dm}{d\rho}$ is as in equation (23).

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

$$\frac{du_H}{d\rho}\,|_{\rho=0} \;=\; q_H(I_h(m) - I_0). \tag{36}$$

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

$$u_L(\rho, m(\rho)) = -C(m) + \rho m q_L I_h + \rho(1 - m)q_L I_\ell + (1 - \rho)q_L I_0.$$

Therefore,

$$\frac{du_L}{d\rho} = \frac{\partial u_L}{\partial \rho} + \frac{\partial u_L}{\partial m}\frac{dm}{d\rho}. \tag{37}$$

Here, $\frac{\partial u_L}{\partial \rho} = q_L\{mI_h + (1 - m)I_\ell - I_0\}$. Further, $\frac{\partial u_L}{\partial m} = -C'(m) + \rho q_L(I_h - I_\ell) + \rho m q_L \frac{\partial I_h}{\partial m}$. Observe that the low-type's first-order condition for optimal manipulation (see Proposition 1) specifies that $C'(m) = \rho q_L(I_h - I_\ell)$. Therefore, we have $\frac{\partial u_L}{\partial m} = \rho m q_L \frac{\partial I_h}{\partial m}$.

Substituting these expressions into equation (37), we obtain

$$\frac{du_L}{d\rho} = q_L\{mI_h + (1 - m)I_\ell - I_0\} + \rho m q_L \frac{\partial I_h}{\partial m}\frac{dm}{d\rho}. \tag{38}$$

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

$$\frac{du_L}{d\rho}\,|_{\rho=0} = q_L\{I_\ell - I_0\} < 0, \tag{39}$$

as $I_\ell < I_0$.

(ii) The ex ante borrower payoff is

$$\mathcal{U} \;=\; \alpha u_H + (1-\alpha)u_L. \tag{40}$$

Using the expressions for $\frac{du_H}{d\rho}\mid_{\rho=0}$ and $\frac{du_L}{d\rho}\mid_{\rho=0}$ in equations (36) and (39) respectively, we obtain

$$\frac{d\mathcal{U}}{d\rho}\mid_{\rho=0} \;=\; \alpha q_H(I_h(0)-I_0) + (1-\alpha)q_L(I_\ell - I_0). \tag{41}$$

Now, observe that when $q_L(1+R) \geq 1$, for each signal $d \in \{d_h, d_\ell, d_0\}$, the optimal interest rate offered by the lender will be satisfy (2) in Lemma 1. Denote a function $G(q) \equiv q\int_{r(q)}^{R}(v-r(q))dF(v)$, where $r(q)$ satisfies equation (2).

Then, we can write equation (41) as

$$\frac{d\mathcal{U}}{d\rho}\mid_{\rho=0} \;=\; \alpha G(q_H) + (1-\alpha)G(q_L) - G(\alpha q_H + (1-\alpha)q_L). \tag{42}$$

Hence, a sufficient condition for $\frac{d\mathcal{U}}{d\rho}\mid_{\rho=0} > 0$ is that G is strictly convex, that is, $G''(q) > 0$ for all q. Similarly, a sufficient condition for $\frac{d\mathcal{U}}{d\rho}\mid_{\rho=0} < 0$ is that G is strictly concave, that is, $G''(q) < 0$ for all q.

Now,

$$G'(q) \;=\; \int_{r(q)}^{R}(v-r(q))dF(v) - q\int_{r(q)}^{R} r'(q)dF(v), \tag{43}$$

$$G''(q) \;=\; -(1-F(r))\{2r'(q) + qr''(q)\} + q\,f(r(q))\,(r'(q))^2. \tag{44}$$

Define the inverse hazard rate as $H(r) = \frac{1-F(r)}{f(r)}$. Then, from Lemma 1, the optimal interest rate when $q(1+R) > 1$ may be written as:

$$r \;=\; \frac{1}{q} - 1 + H(r). \tag{45}$$

Thus,

$$r'(q) \;=\; -\frac{1}{q^2} + H'(r)r'(q), \tag{46}$$

$$r''(q) \;=\; \frac{2}{q^3} + H'(r)r''(q) + H''(r)\{r'(q)\}^2. \tag{47}$$

We can now compute

$$r'(q) \;=\; -\frac{1}{q^2(1-H'(r))}, \tag{48}$$

$$r''(q) \;=\; \frac{1}{1-H'(r)}\Big(\frac{2}{q^3} + H''(r)\{r'(q)^2\}\Big) = r'(q)\Big(-\frac{2}{q} + \frac{H''(r)r'(q)}{1-H'(r)}\Big). \tag{49}$$

Substituting into the right-hand side of equation (44), we have

$$\begin{aligned} G''(q) \;&=\; -(1-F(r))\{2r'(q) - 2r'(q) + \frac{qH''(r)(r'(q))^2}{1-H'(r)}\} + q\,f(r(q))\,(r'(q))^2 \\ &=\; \Big(-\frac{H(r)H''(r)}{1-H'(r)} + 1\Big)\,q\,f(r(q)\,(r'(q))^2. \end{aligned} \tag{50}$$

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

$$H(r)\,H''(r) \;\;<\;\; 1 - H'(r). \tag{51}$$

The right-hand side (LHS) is strictly positive, as $H'(r)$ is strictly decreasing (recall that we have assumed $F(\cdot)$ has an increasing hazard rate).

Consider the generalized uniform distribution: $F(r) = \left(\frac{r}{R}\right)^{\beta}$ such that $f(r) = \beta\frac{r^{\beta-1}}{R^{\beta}}$. Thus, the inverse hazard rate and its derivatives are

$$H(r) = \frac{1}{\beta}\Big(\frac{R^{\beta}}{r^{\beta-1}} - r\Big), \qquad H'(r) = \Big(\frac{1-\beta}{\beta}\Big)\frac{R^{\beta}}{r^{\beta}} - \frac{1}{\beta}, \qquad H''(r) = -(1-\beta)\frac{R^{\beta}}{r^{\beta+1}}.$$

Now, suppose $\beta = 1$, i.e., the distribution of $F(\cdot)$ is uniform. Then, for any r, $H(r) = R - r \geq 0$, $H'(r) = -1$, and $H''(r) = 0$. It is immediate that equation (51) is satisfied, so that $G''(q) > 0$ for all q. Therefore, when $\beta = 1$, we have $\frac{d\mathcal{U}}{d\rho}\mid_{\rho=0} > 0$. That is, ex ante consumer surplus is increasing in data coverage ρ at $\rho = 0$.

As $H(\cdot)$, $H'(\cdot)$ and $H''(\cdot)$ are all continuous in β, it follows now that there exist thresholds $\beta_1 < 1$ and $\beta_2 > 1$ such that $\frac{d\mathcal{U}}{d\rho}\mid_{\rho=0} > 0$ for all $\beta \in (\beta_1, \beta_2)$.

Now, consider the case of β becoming large. Observe that, for the generalized uniform distribution, condition (51) is equivalent to:

$$-\frac{1-\beta}{\beta}\Big(\frac{R^{2\beta}}{r^{2\beta}} - \frac{R^{\beta}}{r^{\beta}}\Big) < 1 + \frac{1}{\beta} - \frac{1-\beta}{\beta}\frac{R^{\beta}}{r^{\beta}}. \tag{52}$$

When $\beta > 1$, we can write this last inequality as

$$\Leftrightarrow \qquad \left(\frac{R}{r}\right)^{\beta}\left(\left(\frac{R}{r}\right)^{\beta} - 2\right) < \frac{1+\frac{1}{\beta}}{1-\frac{1}{\beta}}. \tag{53}$$

As mentioned earlier, the optimal interest rate for a given project success probability q satisfies equation (2) in Lemma 1. That is, $r - \frac{1-\left(\frac{r}{R}\right)^{\beta}}{\beta\frac{r^{\beta-1}}{R^{\beta}}} = \frac{1}{q} - 1$, which can be rewritten as following:

$$\left(\frac{R}{r}\right)^{\beta} = 1 + \beta - \frac{\beta}{r}\left(\frac{1}{q} - 1\right). \tag{54}$$

Now, consider condition (53), and substitute in the right-hand-side of equation (54) for $\left(\frac{R}{r}\right)^{\beta}$ and simplify. We obtain that condition (51) is equivalent to:

$$\beta^2\left(1 - \frac{1}{r}\left(\frac{1}{q} - 1\right)\right)^2 - 1 < \frac{1+\frac{1}{\beta}}{1-\frac{1}{\beta}}. \tag{55}$$

When $\beta \to \infty$, the right-hand side goes to 1. As long as $r \not\to \frac{1}{q} - 1$, the left-hand side goes to $+\infty$, so the condition is violated. We show that $r \not\to \frac{1}{q} - 1$ as $\beta \to \infty$ by contradiction. Suppose that $r \to \frac{1}{q} - 1$ as $\beta \to \infty$. Then, the right-hand side of equation (54) goes to 1 as $\beta \to \infty$. Therefore, for the equation to hold, it must be that $r \to R$, which is a contradiction, because we have assumed that $q_L(1+R) > 1$, so that for any $q \geq q_L$, $R > \frac{1}{q} - 1$.

Therefore, when $\beta \to \infty$, in the limit condition (55) is violated. By continuity, it now follows that there exists some β_3 such that for all $\beta > \beta_3$, the borrower's ex ante utility $\mathcal{U}$ is decreasing in ρ at $\rho = 0$. ■

Proof of Proposition 5

Suppose $\rho > 0$. The signal obtained by the lender on a borrower is $d \in \{d_h, d_\ell, d_0, d_n\}$, where the subscript n denotes borrowers who chose to not share their data with the lender. Let μ_d denote the posterior probability the borrower has the high success probability q_H given signal d, and let $\bar{q}_d = \mu_d q_H + (1 - \mu_d) q_L$ be the average success probability. The optimal interest rate offered after signal d then satisfies equation (2) in Lemma 1, and is inversely related to μ_d.

Suppose for now that at least one of γ_H or γ_L is non-zero. Then, the prior probability of the high-type borrower among those who choose to share their data is

$$\mu_0 \;=\; \frac{\alpha\gamma_H}{\alpha\gamma_H + (1-\alpha)\gamma_L} > 0. \tag{56}$$

With this modification, Proposition 1 goes through, and so $r_h > r_0 > r_\ell$ in any continuation equilibrium in which the lender chooses $\rho > 0$, i.e. positive data coverage.

In comparison, among borrowers who choose to not share their data, the posterior probability of the high type is

$$\mu_n \;=\; \frac{\alpha\{\delta + (1-\delta)(1-\gamma_H)\}}{\alpha\{\delta + (1-\delta)(1-\gamma_H)\} + (1-\alpha)\{\delta + (1-\delta)(1-\gamma_L)\}}. \tag{57}$$

Therefore, $\mu_n \geq \mu_0$ if and only if $\gamma_H \leq \gamma_L$.

There may exist an equilibrium in the continuation game in which $\gamma_H^* = \gamma_L^* = 0$, with the off-equilibrium belief that any borrower who shares their data is the low type. In such a case, a lender who obtains the signal d_0 charges $r_0 = r_\ell$. A low-type borrower is better off not sharing their data and obtaining $r_n < r_\ell$ for sure, where r_n is determined by $\mu_n = \alpha$. A high-type borrower who shares their data obtains r_h with probability ρ and $r_0 = r_\ell$ with probability $1 - \rho$. If ρ is sufficiently small, they too may prefer to not share their data. However, such an equilibrium does not survive the refinement criterion D1; as noted, the high type has a greater incentive to deviate and share their data than the low type does.

Therefore, consider an equilibrium in which at least one of γ_H and γ_L is strictly positive. In such an equilibrium, it must be that $\gamma_H > 0$ (if $\gamma_H = 0$, then it is optimal for the low type to set $\gamma_L = 0$, as any borrower that shares data is revealed to be the low type).

Suppose that $\gamma_H \in (0, 1)$. For a borrower with success probability q_θ, let

$$\psi_\theta(r) \;=\; q_\theta \int_r^R (v - r)\,dF(v) \tag{58}$$

denote the expected payoff from an interest rate offer r. If $\gamma_H \in (0,1)$, the type H borrower must earn the same expected payoff whether they share their data or not. That is, it must be that

$$\psi_H(r_n) = \rho\psi_H(r_h) + (1-\rho)\psi_H(r_0), \tag{59}$$

which implies that $\int_{r_n}^{R}(v-r_n)dF(v) = \hat{\rho}\int_{r_h}^{R}(v-r_h)dF(v) + (1-\hat{\rho})\int_{r_0}^{R}(v-r_0)dF(v)$. Multiplying throughout by q_L, we have

$$\psi_L(r_n) = \rho\psi_L(r_h) + (1-\rho)\psi_L(r_0). \tag{60}$$

Let m be the probability with which a low-type data sharer manipulates their data. The payoff to such a borrower is

$$\rho\{m\psi_L(r_h) + (1-m)\psi_L(r_\ell)\} + (1-\hat{\rho})\psi_L(r_0) - C(m). \tag{61}$$

Now, if $r_\ell > r_h$, for any $m \in [0,1]$ we have

$$\psi_L(r_n) = \rho\psi_L(r_h) + (1-\rho)\psi_L(r_0) \tag{62}$$

$$> \rho\{m\psi_L(r_h) + (1-m)\psi_L(r_\ell)\} + (1-\hat{\rho})\psi_L(r_0) - C(m). \tag{63}$$

That is, it must be that $\gamma_L = 0$. But if $\gamma_L = 0$, we have $\mu_0 = 1$, and so $r_0 < r_n$. But in that case, the high type has a strict incentive to reveal their data — by revealing, they obtain either r_0 or r_h, where $r_h \leq r_0 < r_n$. Therefore, it cannot be that $\gamma_H \in (0,1)$, and so in equilibrium we have $\gamma_H^* = 1$.

Now, when $\gamma_H^* = 1$, it follows that $\mu_n \leq \mu_0$, with equality only in the case that we also have $\gamma_L^* = 1$. Hence, $r_n \geq r_0$, with strict inequality whenever $\gamma_L^* < 1$. ■

B Model Extensions

When Data Coverage Affects Manipulation Cost

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

(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 $\frac{\partial C(m,\rho)}{\partial m}\big|_{m=1,\rho=1} \leq \Delta_B(1)$ (i.e., manipulation cost is sufficiently low), where $\Delta_B(1)$ is given by equation (9), the lender chooses less than full data coverage (i.e., $\rho^* < 1$).*

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

- *If $\frac{\partial C(m,\rho)}{\partial m}\big|_{m=1,\rho=1} < \Delta_B(1)$, 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 $\frac{\partial C(m,\rho)}{\partial m}\ |_{m=1,\rho=1} \geq \Delta_B(1)$, 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 1, 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.*

Proof: In the transparent regime, the derivation follows similar procedures in the baseline model. As in Proposition 1, we can show that $r_h < r_0 < r_\ell$. In addition, for a given $\hat{\rho} > 0$, if $\frac{\partial C(m,\rho)}{\partial m}\ |_{m=1} > \Delta_B(\hat{\rho})$, there is a unique value of m that satisfies the following equation:

$$\rho q_L \left(\int_{r_h(m)}^{R} (v - r_h(m)) dF(v) - \int_{r_\ell}^{R} (v - r_\ell) dF(v) \right) = \frac{\partial C(m,\rho)}{\partial m}. \tag{64}$$

Otherwise, if $\frac{\partial C(m,\rho)}{\partial m}\ |_{m=1} \leq \Delta_B(\hat{\rho})$, we have $m = 1$, i.e., the low-type borrower manipulates with probability 1.

As in equation (23) in the proof of Lemma 2, we have

$$\frac{dm}{d\hat{\rho}} = -\frac{q_L(I_h(m) - I_\ell)}{-C''(m) + \hat{\rho} q_L \frac{\partial I_h(m)}{\partial m}} = \frac{q_L(I_h(m) - I_\ell) - \frac{\partial^2 C(m,\rho)}{\partial m \partial \rho}}{\frac{\partial^2 C(m,\rho)}{\partial m^2} - \hat{\rho} q_L \frac{\partial I_h(m)}{\partial m}}. \tag{65}$$

Unlike the base model, $\frac{dm}{d\hat{\rho}} > 0$ only when $q_L(I_h(m) - I_\ell) > \frac{\partial^2 C(m,\rho)}{\partial m \partial \rho}$. Thus, to ensure that the increase in data coverage does not diminish the borrower's manipulation incentive, we assume that $q_L(I_h(1) - I_\ell) > \frac{\partial^2 C(m,\rho)}{\partial m \partial \rho}\ |_{m=1}$ so that $\frac{dm}{d\hat{\rho}} > 0$ for all values of $\hat{\rho}$.

Furthermore, suppose $\frac{\partial C(m,\rho)}{\partial m}\ |_{m=1,\rho=1} \leq \Delta_B(1)$ so that if the lender chooses $\rho = 1$, the low-type borrower manipulates with probability 1. Following the proof of part (ii) of Proposition 2, by continuity there exists some $\underline{\rho} = \min\{\tilde{\rho} \mid m^*(\tilde{\rho}) = 1\}$. And we can show that under the sufficient condition $\frac{\partial C(m,\rho)}{\partial m}\ |_{m=1,\rho=1} \leq \Delta_B(1)$ the left derivative of the profit function $\Pi(\rho)$ is strictly less than zero. Thus, the lender chooses less than full data coverage. This completes the proof of part (i) of the proposition.

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

B.1 When Data Coverage is Costly for the Lender

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

(i) *Suppose that the data coverage is observable to the borrower. The lender chooses strictly positive data coverage, i.e., $\rho^* > 0$. Moreover, the same condition in Proposition 2 identifies the sufficient condition for $\rho^* < 1$. That is, $C'(1) \leq \Delta_B(1)$ (i.e., manipulation cost is sufficiently low), where $\Delta_B(1)$ is given by equation (9).*

(ii) *Suppose that the data coverage is unobservable to the borrower. Unlike Proposition 3, even if $C'(1) \leq \Delta_B(1)$, the lender will not choose the optimal data coverage such that the low-type manipulates with probability 1. If $C'(1) > \Delta_B(1)$ and the marginal data collection cost $K'(\rho)$ is not that steep, like Proposition 3, 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 1, 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.*

Proof: (i) Consider the scenario in which the data coverage is observable to the borrower. Given a data coverage ρ, the subsequent game will be characterized in the same way as in the base 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 2. The lender's profit function is

$$\Pi(\rho) = \rho\Big(\{\alpha + (1-\alpha)m\}\pi_h(r_h) + (1-\alpha)(1-m)\pi_\ell(r_\ell)\Big) + (1-\rho)\pi_0(r_0) - K(\rho). \quad (66)$$

Compared with equation (26), there is an extra cost term $-K(\rho)$ here. Taking the partial derivative with respect to ρ yields

$$\begin{aligned} \frac{d\Pi}{d\rho} &= \{\alpha + (1-\alpha)m\}\pi_h + (1-\alpha)(1-m)\pi_\ell - \pi_0 \\ &\quad + \rho\{(1-\alpha)(\pi_h - \pi_\ell) + \{\alpha + (1-\alpha)m\}\pi_h'(r_h)r_h'(m)\}\frac{dm}{d\rho} - K'(\rho) \\ &= \{\alpha + (1-\alpha)m\}\pi_h + (1-\alpha)(1-m)\pi_\ell - \pi_0 + \rho(1-\alpha)(\pi_h - \pi_\ell)\frac{dm}{d\rho} - K'(\rho), \end{aligned}$$

where the second equality follows because by definition $\pi_h'(r_h) = 0$.

Similar to equation (30), as $\rho \to 0$, we obtain $\pi_+'(0) = \alpha\pi_h + (1-\alpha)\pi_\ell - \pi_0 > 0$ so that $\rho^* > 0$. Furthermore, to characterize the sufficient conditions for $\rho^* < 1$, we follow the same procedure as in the proof of Proposition 2 and denote $\underline{\rho} = \min\{\tilde{\rho} \,|\, m^*(\tilde{\rho}) = 1\}$. Like equation (32), we have

$$\Pi_-'(\underline{\rho}) = \underline{\rho}(1-\alpha)(\pi_0 - \pi_\ell)\frac{dm}{d\rho} - K'(\underline{\rho}) < 0. \quad (67)$$

Thus, the same condition is sufficient for $\rho^* < 1$.

(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 3. The lender's expected profit function (34) can be augmented as the following:

$$\begin{aligned}\Pi(\rho \,|\, \hat{\rho}) \;&=\; \rho\Big(\{\alpha + (1-\alpha)m(\hat{\rho})\}\pi_h(r_h(m(\hat{\rho}))) + (1-\alpha)(1-m(\hat{\rho}))\pi_\ell\Big\} \\ &\quad +(1-\rho)\pi_0(r_0) - K(\rho).\end{aligned}$$

The derivative with respect to ρ is

$$\frac{\partial \Pi}{\partial \rho} \;=\; \{\alpha + (1-\alpha)m(\hat{\rho})\}\pi_h(r_h) + (1-\alpha)(1-m(\hat{\rho}))\pi_\ell(r_\ell) - \pi_0(r_0) - K'(\rho). \quad (68)$$

Denote $\Delta(\hat{\rho}) = \{\alpha + (1-\alpha)m(\hat{\rho})\}\pi_h(r_h) + (1-\alpha)(1-m(\hat{\rho}))\pi_\ell(r_\ell) - \pi_0(r_0)$. Then

$$\frac{\partial \Pi}{\partial \rho} \;=\; \Delta(\hat{\rho}) - K'(\rho). \quad (69)$$

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 (68) and setting it to zero yields the optimal data coverage ρ, 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 ρ, 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 1 remains valid in this extension. ■

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