Data Regulation in Credit Markets*

Uday Rajan† Yan Xiong‡

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Abstract

We theoretically study a credit market in which lending depends on a digital profile that can be manipulated by a borrower. The manipulation intensity increases when the lender collects more data. As a result, the lender endogenously limits its own data coverage. Disclosure regulations allow the lender to credibly commit to limiting its data coverage. If borrowers can choose whether to share their data with the lender, withholding data and manipulation are often complementary strategies to hide the borrower's type. Privacy regulations can benefit all borrowers, including those who choose to share their data with the lender.

Keywords: FinTech lending, Digital data, Manipulation, Regulation

JEL: G21, G23

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†Stephen M. Ross School of Business, University of Michigan; E-mail: urajan@umich.edu.

‡University of Hong Kong; E-mail: yanxiong@hku.hk.

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Abstract

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1 Introduction

The online activities of people generate substantial amounts of valuable data. These big data are increasingly utilized by lending companies to assess 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 around 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, Goodhart's Law (Goodhart, 1975) implies that borrowers will 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. Moreover, many of the same technologies that lenders employ, such as generative artificial intelligence, can also be used by borrowers to manipulate elements of their digital profile. For example, in the U.S. the credit bureaus Equifax and TransUnion have both recently highlighted the phenomenon of synthetic identity fraud in the credit market.[3] Similarly, borrowers may use large language models to enhance their writing, thereby improving the perceived quality of loan applications (Cong et al., 2024), and may inject invisible text into PDF documents to fool an LLM.[4]

[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] Equifax: "Breaking the Code: How Criminals Use AI to Simplify Fraud and How to Fight It," March 12, 2026, available at https://www.equifax.com/business/blog/-/insight/article/breaking-the-code-how-criminals-use-ai-to-simplify-fraud-and-how-to-fight-it/; TransUnion: "Money 20/20: What's Behind the Rise in Synthetic Identity Fraud," June 30, 2025, available at https://www.transunion.com/blog/money-2020-whats-behind-rise-synthetic-identity-fraud.

[4] See, for example, https://snyk.io/articles/prompt-injection-exploits-invisible-pdf-text-to-pass-credit-score-analysis/.

To examine the equilibrium effects of such behavior and its regulatory implications, 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 provide a borrower who would otherwise manipulate their information with a new way to hide themselves, by pooling with borrowers who refuse to 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 that their 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 to mislead the lender about their type.

To study the effect of disclosure regulations, we first compare 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. To establish our result as starkly as possible, in our model we assume that there is no direct cost to acquiring data. The better the data that the lender has, the more likely those who generate high signals are indeed high types.

As a result, borrowers who generate high signals obtain credit on better terms (i.e., 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 reduces the data quality 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.

As information becomes cheap in the digital age, in the spirit of Holmström informativeness (Holmström, 1979), it seems that a lender should acquire and use unlimited amounts of data about 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.

We find that in the aggregate, borrowers may also prefer that the lender acquire some digital information. 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. The aggregate borrower payoff increases when high types gain more than low types lose.

From this transparency perspective, our model offers several insights into the ongoing regulatory discussion about the use of big data in the credit market. For example, 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. 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.

Some 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 find that such regulations are ineffective at best (if they have no impact on the equilibrium). In some cases, they can even reduce the welfare of both the borrower and the lender.

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. This motivates us to extend our base model to allow borrowers to provide access to their data or withhold them 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 unconcerned about privacy who 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.

We find that high-type borrowers always reveal their data, whereas low-type borrowers only do so with some probability. In fact, when the manipulation cost is low, withholding data and manipulation are complementary strategies employed by the low-type borrower to try and mask their type.

In a numerical example (verified across a wide range of parameters), we show that the presence of privacy-conscious borrowers can increase the utility of both high- and low-type borrowers who are willing to share their data. Some of the low-type borrowers pool with the privacy-concerned borrowers, thereby improving the pool of borrowers who do share their data. The result is that the data-sharers on average obtain lower interest rates and are better off.

Overall, our findings highlight the intriguing dynamics between privacy protection, data sharing, and borrower manipulation behavior in credit markets. 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 which an agent can strategically engage in manipulation to mislead a principal. In contracting settings, the moral hazard model of Goldman and Slezak (2006) shows that manipulation is more likely when managers face high-powered incentives. 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. Lacker and Weinberg (1989) analyze a setting 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) demonstrate that in the presence of manipulation, the optimal contract is less steep than otherwise.

Beyond contracting settings, manipulation incentives also have important implications across a variety of economic environments, including the reduced predictability of interest rates for default risk (Rajan, Seru, and Vig, 2015), the credit-rating process (Cohn, Rajan, and Strobl, 2024), the optimal design of tests (Perez-Richet and Skreta, 2022), the financing of green investments (Barbalau and Zeni, 2023), corporate announcements in the presence of media coverage (Goldman, Martel, and Schneemeier, 2022), labor markets (Liang and Madsen, 2024), and more general settings (Frankel and Kartik, 2022; Ball, 2025), among others. In addition, a line of research in computer science and econometrics explicitly considers the effect of strategic manipulation behavior on generated data and model estimation (e.g., Dekel et al., 2010; Chen et al., 2018; Björkegren et al., 2020; Hennessy and Goodhart, 2023; Gamba and Hennessy, 2024).

We contribute to this literature by examining how agents' manipulation incentives shape outcomes in credit markets, and we use this perspective to assess data-regulation policies in these markets. Accordingly, we focus on the normative implications of our framework and analyze how data regulations affect both borrower and lender welfare. Two closely related studies, Sun (2025) and Ozanne (2025), also investigate credit lending in the presence of borrower manipulation. Both have different focuses, and we view our work as complementary. Sun (2025) studies optimal disclosure policies when the lender's model is unobservable to the borrower, whereas Ozanne (2025) considers differences in the borrower's willingness to share data in transparent and opaque data regimes. The manipulation we focus on requires the borrower to have an understanding of how their data maps into creditworthiness, and for the bulk of the paper we focus on the case in which the lender's decision process is transparent and known to the borrower.

Our paper is also related to the growing literature on FinTech lending and the use of big data in credit markets; see Berg, Fuster, and Puri (2021) for a survey. A large body of empirical work documents that alternative data provide valuable information to lenders (e.g., Berg et al., 2020; Agarwal et al., 2020; Di Maggio and Yao, 2021; Di Maggio et al., 2022; Ghosh et al., 2025). For example, Berg, Burg, Gombović, and Puri (2020) and Agarwal, Alok, Ghosh, and Gupta (2020) show that digital-footprint variables are important predictors of default and meaningfully complement traditional credit-bureau information. Jansen, Nagel, Yannelis, and Zhang (2025) further analyze the welfare effects of increased data availability in credit markets. Recent theoretical studies also explore several new questions, including the impact of FinTech competition with traditional banks (Parlour, Rajan, and Zhu, 2022; Li and Pegoraro, 2026) and the effect of open banking on lending-market competition (He, Huang, and Zhou, 2023), among others.

We contribute to this literature by focusing on alternative data and borrowers' manipulation behavior and by studying how such behavior shapes lenders' decisions and overall credit-market outcomes. Although the specific types of alternative data we consider—those that are easily manipulable—are more relevant for smaller, unsecured loans, our framework applies to both collateralized and uncollateralized lending. For example, Buchak, Matvos, Piskorski, and Seru (2018) show that FinTech mortgage lenders in the U.S. rely on different sources of information than traditional (non-FinTech) lenders.

Privacy and the effects of privacy-related regulations have also attracted growing 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.

The remainder of the paper is organized as follows. Section 2 presents the base model. Sections 3 and 3.4 characterize the equilibrium in the base model. In Section 4, we introduce the extended model with borrower privacy concerns. Section 5 presents extensions to the base model, Section 6 discusses regulatory implications, and Section 7 concludes. Proofs of all results are in Appendix A.

2 Base Model

Consider a credit market with a lender and a continuum of borrowers. A borrower is penniless 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. 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 2. If the project succeeds, at time 2 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 2 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 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 that is potentially informative about their success probability. If this profile is uncovered by the lender, the latter obtains a digital signal $d_j \in \{d_h, d_\ell\}$ 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. For individuals, such alternative data includes information about educational and employment history and bank account cash flows. In our usage, it also includes the digital footprint 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 apps used by the borrower, their social media presence, and metrics of social connectivity (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 user engagement data.[5]

Manipulation: A key feature of our model is that the borrower can manipulate their digital profile to mask their type. A reasonable question is whether individual borrowers can be sophisticated enough to understand a lender's algorithm and then game it. Our perspective is that even when the borrower lacks the sophistication to do so, specialized

[5]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 prior 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.

third-party firms will emerge that coach them on how to manipulate their information before presenting it to the lender. For example, as mentioned in the introduction, AI tools are now being used for purposes such as generating fake identities, refining the language in credit applications, and even injecting invisible material into documents.

Denote the borrower's manipulation decision as $m \in [0, 1]$. The manipulation is relevant only if the lender succeeds in uncovering the borrower's digital profile. In this case, with probability m the manipulation is successful, and the borrower with a type j generates a signal d_{-j}. With probability $1 - m$ the manipulation is unsuccessful, and borrower type j generates signal d_j. 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 $C(\cdot)$. First, it includes the expenditure of time, effort, and money for 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. 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 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 $d_j \in \{d_h, d_\ell, d_0\}$. With probability $1 - \rho$, the lender does not learn anything extra from the borrower's digital profile, and we say that 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 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. Thus, the only reason that the lender may not choose the most informative technology, $\rho = 1$, is due to the fact that the manipulation by the borrower may lead to a reduction in signal quality.[6]

Regulatory regime: Depending on the regulatory regime, 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.

[6] In Section 5.2, we consider an extension in which the lender incurs costs to acquire and process data. Our qualitative insights remain valid 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's 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_j 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.

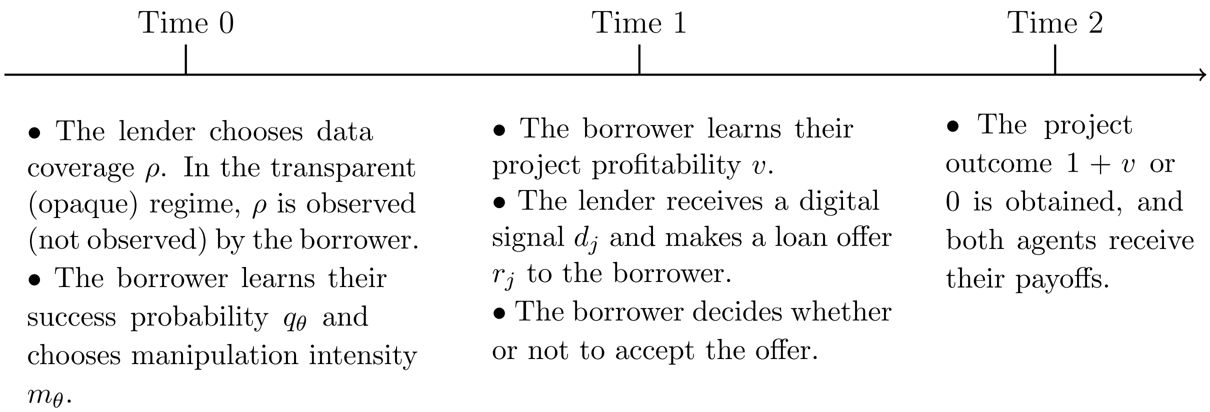
2.3 Sequence of Moves

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_j about the success probability of the borrower, and offers a loan contract at the interest rate r_j. The borrower either accepts or rejects the loan offer. If the borrower accepts, the project is undertaken and the outcome is realized at time 2.

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 $d_j \in \{d_h, d_\ell, d_0\}$, the borrower's manipulation intensity $m_\theta^* \in [0,1]$ for each $\theta \in \{H, L\}$ and loan acceptance decision, and the lender's posterior belief μ_j that the borrower has the high success probability given digital signal d_j, such that:*

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



This figure illustrates the sequence of events in the base model.

Figure 1: Timeline in the base model

(ii) *The lender's posterior belief* μ_j *given* d_j *satisfies Bayes' rule wherever possible.*

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

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

(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 Base Model

We now characterize the equilibrium in the base model. We first examine the borrower's loan acceptance decision and the lender's interest rate offer at time 1. We then turn to the borrower's manipulation decision and the lender's optimal data coverage at time 0.

3.1 Borrower's Loan Acceptance Decision at Time 1

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.[7]

3.2 Lender's Interest Rate Offers at Time 1

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

If the lender makes a loan offer at interest rate r, the borrower accepts with probability

[7]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 which 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.

$1 - F(r)$. 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

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

The offered interest rate r_j maximizes this expected payoff.

Lemma 1 (Lender's optimal interest rate offer)**.** *Suppose the lender obtains signal $d_j \in \{d_h, d_\ell, d_0\}$.*

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

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

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

Given signal d_j, if some projects have a weakly positive NPV (i.e., $\bar{q}_j(1 + R) \geq 1$), the lender sets an interest rate according to equation (2). This equation represents the first-order condition in the lender's maximization problem. As in auction theory, the left-hand side can be interpreted as the virtual interest rate. Rewriting the equation as $r_j = \frac{1}{\bar{q}_j} - 1 + \frac{1-F(r_j)}{f(r_j)}$, the lender charges a markup over the zero-profit interest rate $\frac{1}{\bar{q}_j} - 1$. Of course, if given signal d_j, all projects have negative NPV (i.e., $\bar{q}_j(1 + R) < 1$), the lender simply rejects the loan application by setting $r_j = R$.

Denote the optimal interest rate when the borrower is known to be of type θ by r^θ. It is immediate that $r^H < r^L$.

3.3 Borrower's Manipulation Decision at Time 0

Next, consider the manipulation decision of the borrower. 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. They hold a belief $\hat{\rho}$ about the lender's data coverage. 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). With probability $1 - \hat{\rho}$, the digital signal is d_0.

For the borrower's payoff, there are three cases to consider. First, with probability $\hat{\rho}\, m_\theta$ the borrower will successfully manipulate and generate digital signal $d_{\tilde{\theta}}$, where $\tilde{\theta} \neq \theta$. In this case, they are 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, her expected payoff in this scenario is $q_\theta \int_{r_{\tilde{\theta}}}^{R} (v - r_{\tilde{\theta}}) dF(v)$.

Second, with probability $\hat{\rho}(1 - m_\theta)$, manipulation is unsuccessful and the borrower generates digital signal d_θ. The offered interest rate is r_θ. Again, the loan offer r_θ is accepted if and only if $v \geq r_\theta$. Thus, the expected payoff in this case is $q_\theta \int_{r_\theta}^{R} (v - r_\theta) dF(v)$. Finally, with probability $1 - \hat{\rho}$, the lender's digital signal is uninformative (d_0), and the borrower will be offered the interest rate r_0. The resulting expected payoff for the borrower is $q_\theta \int_{r_0}^{R} (v - r_0) dF(v)$.

Putting all this together, the expected payoff of the borrower of type θ is

$$
\begin{aligned}
u_\theta(m_\theta; \hat{m}_\theta, \hat{\rho}) = -C(m_\theta) + \hat{\rho}\, m_\theta \cdot \quad & \underbrace{q_\theta \int_{r_{\tilde{\theta}}}^{R} (v - r_{\tilde{\theta}}) dF(v)}_{\text{payoff when manipulation is successful}} \\
+ \hat{\rho}\,(1 - m_\theta) \cdot \quad \underbrace{q_\theta \int_{r_\theta}^{R} (v - r_\theta) dF(v)}_{\text{payoff when manipulation is unsuccessful}} \quad & + (1 - \hat{\rho}) \cdot \quad \underbrace{q_\theta \int_{r_0}^{R} (v - r_0) dF(v).}_{\text{payoff when digital signal is uninformative}}
\end{aligned}
\tag{3}
$$

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.

We show in Proposition 1 below 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, as shown in part (iii) of the proposition, is that the low digital signal d_ℓ reveals the borrower to have low success probability, so that the offered interest rate increases to $r^L > r_0$, 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 $r_h < r_0$.

Recall that when the manipulation decision is chosen, the borrower knows their own success probability q_θ but not the project probability v. Denote the expected payoff to the low-type borrower from a loan with interest rate r by $W(r) \equiv q_L \int_r^R (v - r) dF(v)$.

Proposition 1 (Borrower's manipulation decision)**.** *Suppose that, in either the transparent or opaque regimes, the lender chooses data coverage $\hat{\rho} > 0$. Then, in any consistent best response of the borrower,*

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

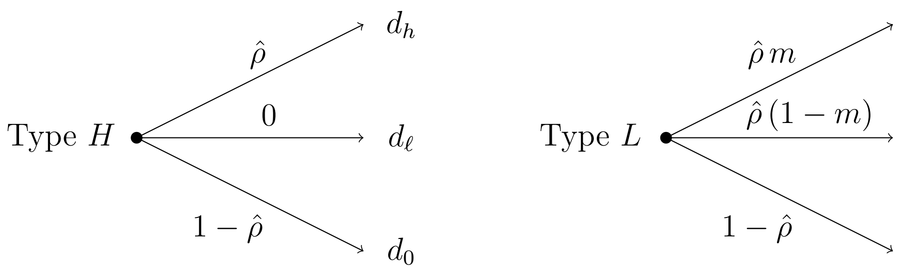
(ii) The low-type borrower manipulates with strictly positive probability. Specifically:

(a) If $C'(1) > \hat{\rho}\{W(r_0) - W(r^L)\}$, then $m_L^* \in (0, 1)$, and in this region m_L^* is strictly increasing in $\hat{\rho}$.

(b) If $C'(1) \leq \hat{\rho}\{W(r_0) - W(r^L)\}$, then $m_L^* = 1$.

(iii) The interest rates offered by the lender satisfy $r_h \leq r_0 < r^L$, with strict inequality whenever $C'(1) > \hat{\rho}\{W(r_0) - W(r^L)\}$.

The signal structure implied by Proposition 1 is shown in Figure 2.



This figure illustrates the structure of the digital signal when the high-type borrower does not manipulate, while the low-type borrower manipulates with intensity m. The left and right panels display the possible signal realizations and their corresponding probabilities for high-type and low-type borrowers, respectively.

Figure 2: Structure of digital signals

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 lender's belief about the low type's manipulation intensity is denoted by $\hat{m}$. As shown in the proof of the proposition, when $C'(1) > W(r_0) - W(r^L)$, the low-type borrower's equilibrium manipulation intensity m^* is in the interior and satisfies

$$C'(m) \;=\; \hat{\rho}\left\{W(r_h(m)) - W(r^L)\right\}. \tag{4}$$

We further 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 (Manipulation intensity increases with data coverage)**.** *Suppose $C'(1) > W(r_0) - W(r^L)$, so that $m^*(\hat{\rho}) < 1$. 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, $dm^*/d\hat{\rho} > 0$.*

When $\hat{\rho}$ is higher, the borrower believes that their digital profile is more likely to be revealed. Thus, the 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 at Time 0

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. 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. Observe that the optimal interest rate r_h depends on m. 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 $\pi_\ell(r^L)$. 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:

$$\Pi(\rho) = \rho\Big(\{\alpha + (1-\alpha)m\}\pi_h(r_h) + (1-\alpha)(1-m)\pi_\ell(r^L)\Big) + (1-\rho)\pi_0(r_0). \tag{5}$$

Note that in equation (5), 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.

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 $\theta \in \{H, L\}$.[8] Recall that $d_\theta = d_h$ (d_ℓ) and $d_{\tilde{\theta}} = d_\ell$ (d_h)

[8] 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 $m > 0$.

when $\theta = H$ (L). In the no-manipulation case, the digital signal fully reveals the borrower's success probability. That is,

$$d = \begin{cases} d_\theta & \text{with probability } \rho, \text{ for each } \theta \in \{H, L\} \\ d_0 & \text{with probability } 1 - \rho. \end{cases} \tag{6}$$

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

We are particularly interested in understanding the circumstances in which 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.

Denote $\bar{\rho} \equiv \frac{C'(1)}{W(r_0) - W(r^L)}$. We show that if the manipulation cost is low, the indirect effect outweighs the direct effect, and overall lender profit is greater at some $\rho < 1$ than at $\rho = 1$.

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) *If* $C'(1) \leq W(r_0) - W(r^L)$*, (i.e., the manipulation cost is sufficiently low), the lender chooses less than maximal data coverage (specifically,* $\rho^* < \bar{\rho} \leq 1$*).*

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 intuition is that if the data coverage hits $\bar{\rho}$ the low-type borrower manipulates with probability 1, making the digital signal completely uninformative to the lender. The lender thus benefits from reducing its data coverage, and thereby inducing less manipulation from the low-type borrower.

The condition $C'(1) \leq W(r_0) - W(r^L)$ 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. 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.[9]

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

[9]We illustrate this point numerically in Example 1.

when the data coverage is ρ. Here,

$$
\begin{aligned}
u_H(\rho) &= q_H\Big\{\rho\int_{r_h(m)}^{R}(v-r_h(m))dF(v)+(1-\rho)\int_{r_0}^{R}(v-r_0)dF(v)\Big\}, &(7)\\
u_L(\rho) &= q_L\Big\{\rho m\int_{r_h(m)}^{R}(v-r_h(m))dF(v)+\rho(1-m)\int_{r^L}^{R}(v-r^L)dF(v)\\
&\qquad +(1-\rho)\int_{r_0}^{R}(v-r_0)dF(v)\Big\}-C(m) &(8)\\
&= \rho\Big\{mW(r_h(m))+(1-m)W(r^L)\Big\}+(1-\rho)W(r_0)-C(m). &(9)
\end{aligned}
$$

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

The borrower's ex ante expected payoff is $\mathcal{U}=\alpha\, u_H+(1-\alpha)\, u_L$. The social planner cares about the total surplus, which is defined as the sum of the lender profit and the borrower surplus: $\mathcal{S}=\Pi+\mathcal{U}$, where the lender profit Π is given by equations (5).

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 (specifically, r_h) 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 part (b) of the next proposition, we assume project profitability follows a generalized uniform distribution.

Proposition 3 (Borrower surplus and total surplus)**.** *In the transparent regime, comparing small but strictly positive data coverage (i.e., $\rho > 0$) 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, $\frac{du_H}{d\rho}|_{\rho=0} > 0$ and $\frac{du_L}{d\rho}|_{\rho=0} < 0$.*

(ii) *Suppose that (a) $q_L(1+R) \geq 1$ 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., $\frac{\partial \mathcal{U}}{\partial \rho}|_{\rho=0} > 0$) whereas if $\beta > \beta_3$, ex ante the borrower is strictly worse off (i.e., $\frac{\partial \mathcal{U}}{\partial \rho}|_{\rho=0} < 0$).*

The condition $q_L(1+R) > 1$ in part (ii) of the proposition ensures that the optimal interest rate given any signal d_j 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 in a greater 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.

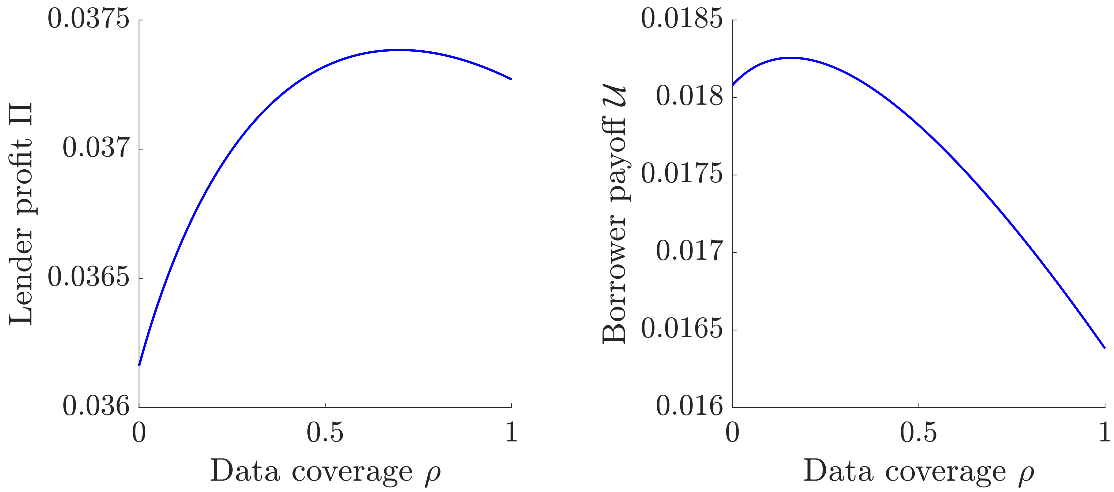
In terms of social surplus, it is immediate that when β is relatively small (i.e., $\beta \in (\beta_1, \beta_2)$, social surplus increases when the lender starts to acquire data. In this parameter region, both ex ante borrower surplus and the lender's profit increase when ρ increases by a small amount 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.

Example 1: Transparent Regime in the Base Model We present a numerical example to show that, even when the condition $C'(1) \leq W(r_0) - W(r^L)$ 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 $r^L = 0.325$. Now, $W(r_0) - W(r^L)$ can be computed to be 0.0109. As $C'(1) = 2k$, it follows that when $k \geq 0.00545$, we have $C'(1) > W(r_0) - W(r^L)$. We find that only if $k \geq 0.014$ (approximately) does the lender choose 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.

Figure 3 shows the lender 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 $\rho \approx 0.157$. It is immediate that the socially optimal level of data coverage lies between the lender's and the borrower's preferred values; in this example total surplus is maximized at $\rho \approx 0.342$.

More generally, when v is uniform, we find that in the transparent case the lender prefers



This figure plots the effect of data coverage ρ on the equilibrium values of lender profit Π and ex ante borrower surplus $\mathcal{U}$. The manipulation cost function is $C(m) = 0.01m^2$. 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: Effects of data coverage

a higher level of ρ than the borrower, and hence the lender over-invests in data collection relative to the social optimum.

3.4.3 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 digital profile, so digital signal is not fully informative about borrower type.

Proposition 4 (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* $C'(1) \geq W(r_0) - W(r^L)$ *(i.e., the manipulation cost is sufficiently high).*

Essentially, in the opaque regime the lender cannot credibly commit to acquiring limited information about the borrower. Suppose 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 fact, in equilibrium, either the lender uses all available data ($\rho^* = 1$), or the low-type borrower fully manipulates their digital profile ($m^* = 1$).

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.*

4 Privacy Concerns, with Borrowers Owning 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 with whom to share their banking data. To analyze the effects of such regulations, we extend our base model to allow borrowers to determine whether to provide access to their data to 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 it 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 will 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_j based on the digital signal obtained by the lender, $d_j \in \{d_h, d_\ell, d_0\}$. 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.

Time 0

- The lender chooses data coverage ρ, which is observed by the borrower.
- The borrower has a success probability q_i and privacy value y or 0.
- Privacy-conscious borrowers withhold their data from the lender.
- Unconcerned borrowers with success probability q_i choose (i) the probability with which they provide the lender access to their data, γ_i and (ii) a manipulation intensity, m_i.

Time 1

- The borrower learns their project profitability v.
- If the borrower has provided access to their data, the lender receives a digital signal d_j and offers an interest rate r_j to the borrower.
- If the borrower has not provided access to their data, the lender offers an interest rate r_n to the borrower.
- The borrower decides whether or not to accept the offer.

Time 2

- The project yields $1 + v$ or 0, and both parties obtain their payoffs.

This figure illustrates the sequence of events in the extended model in which borrowers choose whether to provide access to data.

Figure 4: Timeline in the extended model with privacy concerns

Recall the borrower's payoff in the base model, as shown in equation (3). For borrower type H, denote $d_\theta = d_h$ and $d_{\tilde{\theta}} = d_\ell$, with the corresponding expressions for borrower type L being $d_\theta = d_\ell$ and $d_{\tilde{\theta}} = d_h$. Then, the payoff of an unconcerned borrower with type $\theta = \{H, L\}$ may be written as:

$$
\begin{aligned}
u_\theta(\gamma_\theta, m_\theta; \hat{\rho}) \quad = \quad & \gamma_\theta \Big\{ -C(m_\theta) + \hat{\rho}\, m_\theta q_\theta \int_{r_{\tilde{\theta}}}^{R} (v - r_{\tilde{\theta}}) dF(v) + \hat{\rho}\,(1 - m_\theta) q_\theta \int_{r_\theta}^{R} (v - r_\theta) dF(v) \\
& + (1 - \hat{\rho}) q_\theta \int_{r_0}^{R} (v - r_0) dF(v) \Big\} + (1 - \gamma_\theta) q_\theta \int_{r_n}^{R} (v - r_n) dF(v). \qquad (10)
\end{aligned}
$$

Observe that the interest rates r_n, r_0 and r_h now depend on the sharing decisions of the unconcerned borrowers. As before, r_h also depends on the manipulation strategy of the low-type borrower.

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 the next proposition, we examine the equilibrium properties of the two masking strategies for unconcerned borrowers. Unconcerned high-type borrowers always share their data, and do not manipulate. In contrast, in equilibrium unconcerned low-type borrowers may use both non-sharing and manipulation together as devices to hide their type.

Let $\bar{r}_n$ be the interest rate offered to non-sharers if the lender believes that among unconcerned borrowers (i) all high-types share their data, i.e., $\gamma_H = 1$, and (ii) all low-types withhold their data, i.e., $\gamma_L = 0$. Under these conditions, the posterior probability of the high-type borrower among non-sharers is $\frac{\alpha\delta}{\alpha\delta + (1-\alpha)}$. With any other sharing strategies, the non-sharer pool has a higher proportion of high types, so $\bar{r}_n$ denotes the maximum rate that can be offered to non-sharers.

Proposition 5 (Withholding data and manipulation: two masking strategies for privacy-unconcerned borrowers)**.** *Suppose that the lender chooses a data coverage $\rho > 0$. In any equilibrium in the continuation game that survives the refinement D1, 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) *Further, if $W(\bar{r}_n) < \max\left\{W(r^H) - C(1),\, \rho W(r^L) + (1-\rho)W(r^H)\right\}$, then:*

  (a) *The low-type borrower shares data with strictly positive probability, i.e., $\gamma_L^* > 0$.*

  (b) *A low-type borrower who shares their data manipulates with strictly positive probability, i.e., $m^* > 0$.*

  (c) *Suppose that $m^* \in (0,1)$ and $\gamma_L^* \in (0,1)$. Then, m^* is strictly increasing in ρ. Further, there exists a $\bar{m} > 0$ such that if $m^* \leq \bar{m}$, γ_L^* is strictly decreasing in ρ.*

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

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 share their data with probability one and do not manipulate, as summarized in part (i) of Proposition 5.

For unconcerned low-type borrowers, we find that they generally adopt both masking strategies, as shown in parts (ii)(a) and (ii)(b) of Proposition 5. In the same spirit as in the base model, an unconcerned low-type borrower who shares her data tends to manipulate when the manipulation cost is low.

Suppose the lender has a belief $\hat{\gamma}_L$ about the probability the borrower will share their data. Given this belief, the posterior probability of high-type borrowers in the sharing pool is $\frac{\alpha}{\alpha+(1-\alpha)\hat{\gamma}_L}$. Thus, the interest rates r_n, r_0 and r_h depend on $\hat{\gamma}_L$. As before, r_h depends also on the low-type's manipulation strategy, which we denote by m. Let $\hat{m}$ denote the lender's belief over this manipulation strategy.

Then, the low-type borrower's payoff may be written as:

$$\gamma_L \Big\{ \rho \Big(mW(r_h(\hat{\gamma}_L, \hat{m})) + (1-m)W(r^L) \Big) + (1-\rho)W(r_0(\hat{\gamma}_L)) - C(m) \Big\} \\ + (1-\gamma_L)W(r_n(\hat{\gamma}_L)). \tag{11}$$

The borrower chooses their sharing and manipulation probabilities, γ_L and m, to maximize this payoff.

Consider the condition $W(\bar{r}_n) < \max \{W(r^H) - C(1),\, \rho W(r^L) + (1-\rho)W(r^H)\}$ in part (ii) of the proposition. Suppose the low-type borrower fully withholds their data. Then, they obtain the payoff on the left-hand side, $W(\bar{r}_n)$. The right-hand side is the payoff if they deviate and share their data, and manipulate either with probability one or with probability zero. Parts (ii) (a) and (b) of the proposition show that, when this condition holds, they share with positive probability, but also manipulate when they share.

In part (ii)(c) of Proposition 5, we examine the relationship between sharing and manipulation for the low-type borrower. First, as in the base model (Lemma 2), an increase in data coverage strengthens the unconcerned low-type borrower's incentive to manipulate (i.e., m^* is strictly increasing in ρ). Second, when the equilibrium manipulation intensity is low (i.e., the manipulation cost is high), the borrower also withholds data more often as ρ rises. In other words, the two masking strategies (withholding data and manipulating their type) act as complements.

The intuition follows from the trade-off faced by the unconcerned low-type borrower. All else equal, as ρ increases, a low-type borrower who shares their data is more likely to receive the interest rates r_h or r^L rather than the rate r_0. When the marginal cost of additional manipulation is low (i.e., m is low), an increase in ρ is somewhat countered by an increase in manipulation, increasing the likelihood of receiving interest rate r_h (while simultaneously raising r_h in equilibrium). In contrast, when the marginal cost of manipulation is high (i.e., m is high), increased sharing (i.e., increasing γ_L) allows the borrower to effectively bring the interest rates r_0 and r_h closer to each other.[10]

Finally, part (iii) of Proposition 5 examines the equilibrium interest rates in the extended model. 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 $r_\ell = r^L > r_n$. Finally, as long as low-type borrowers who share their data do not manipulate with probability 1, we will see $r_0 > r_h$.

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 $d_j \in \{d_h, d_\ell, d_0, d_n\}$ is $\pi_j(r_j) = (1 - F(r_j)) \cdot [\bar{q}_j \cdot r_j - (1 - \bar{q}_j)]$. Taking into account all types of available information, the lender's expected profit at the beginning of the game can be expressed as:

$$\begin{aligned}\Pi(\rho) \;&=\; \{\delta + (1-\alpha)(1-\delta)(1-\gamma)\}\,\pi_n(r_n) + (1-\rho)(1-\delta)\{\alpha + (1-\alpha)\gamma\}\,\pi_0(r_0) \\ &\quad + \rho(1-\delta)[\{\alpha + (1-\alpha)\gamma m\}\,\pi_h(r_h) + (1-\alpha)\gamma(1-m)\,\pi_\ell(r_\ell)]. \qquad (12)\end{aligned}$$

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

[10] Numerically, we find that for some parameter values, the threshold $\bar{m}$ in Proposition 5 part (ii) (c) is indeed strictly less than 1, and for high values of m^*, γ_L^* can increase in ρ.

As in Proposition 2, we show in Proposition 6 that, in the model with privacy concerns, the lender continues to choose a positive level of data coverage in the transparent regime.

Proposition 6 (Lender's optimal data coverage)**.** *The lender chooses a positive data coverage, i.e.,* $\rho^* > 0$*.*

Compared with the base model (Proposition 2), it is hard to cleanly identify an upper bound for ρ in the model with privacy concerns. Recall that, in the base model, the key force pushing the lender to limit data coverage is that once the unconcerned low-type borrower fully manipulates, the data signal d_h becomes uninformative—the posterior collapses to the prior, and the lender's profit reduces to its no-data benchmark. The lender therefore strictly prefers a coverage at which $m^* < 1$.

In the model with privacy concerns, this collapse is incomplete. Even when the unconcerned low-type borrowers fully manipulate so that d_h becomes uninformative, the borrower's sharing decision itself remains an informative signal: privacy-concerned borrowers always withhold while unconcerned high-type borrowers always share, so the withholding signal d_n continues to sort borrowers. The lender's profit at $m^* = 1$ may strictly exceed its no-data benchmark, and the clean comparison underlying Proposition 2 no longer goes through. Compounding this, the unconcerned low-type's equilibrium sharing probability γ_L^* also responds to ρ (Proposition 5 part (ii)(c)), so the lender's profit need not be monotone in ρ over the range where $m^* = 1$.

We therefore turn to a numerical example to explore the properties of equilibria in this section.

4.1 Example 2: Model with Privacy Concerns

Set $\alpha = 0.5$, $q_H = 0.95$, $q_L = 0.8$, $R = 0.4$, $C(m) = 0.01m^2$, and $v \sim U[0, 0.4]$ as in the base model. We vary δ, the proportion of privacy-conscious borrowers, between 0.01 and 0.99. Note that in the special case that $\delta = 0$, the extended model reduces to the base model.

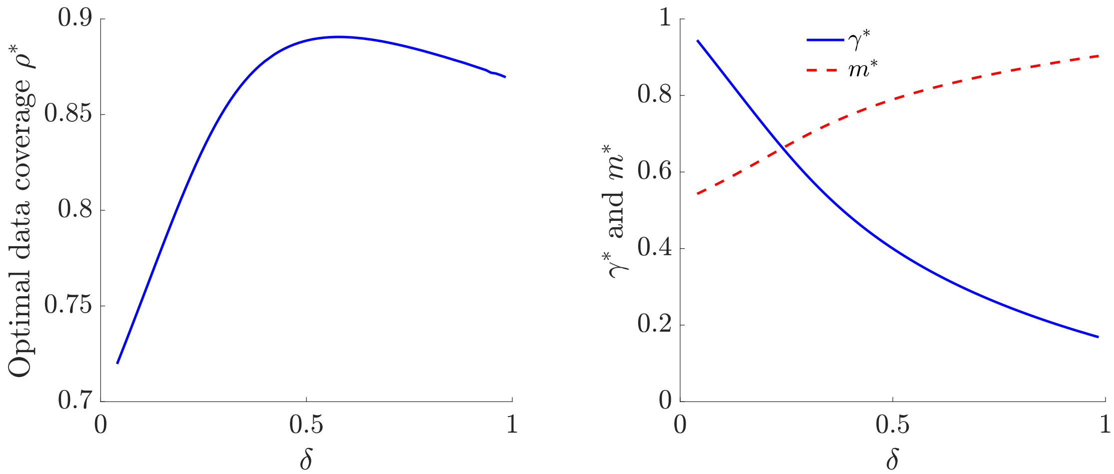
Because all high-type borrowers share their data, when $\delta = 0$ any borrower who fails to share data is revealed to be the low type. Therefore, in this case, in equilibrium $\gamma_L^* = 1$.

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. That is, as in the base model, the lender chooses to limit data coverage when borrowers can withhold their data.

Second, in this example, refusing to grant data access and manipulating the digital profile are complementary for low-type borrowers who are unconcerned about privacy. 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; both remain strictly between 0 and 1 in this example. Intuitively, greater privacy concerns raise the average quality of the pool of borrowers who withhold data, making withholding more attractive and further reducing γ_L^*. At the same time, the remaining unconcerned low-type borrowers who share data engage in more manipulation, leading to a higher m^*. Numerically, we find that this complementarity between the two masking strategies holds across a broad range of parameter values.

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 $\delta = 0$. 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. As δ rises, the pool of borrowers who withhold data becomes increasingly composed of privacy-concerned borrowers, which improves its average quality and lowers r_n. At the same time, as the proportion of privacy-conscious borrowers increases, it is easier for the unconcerned low-type



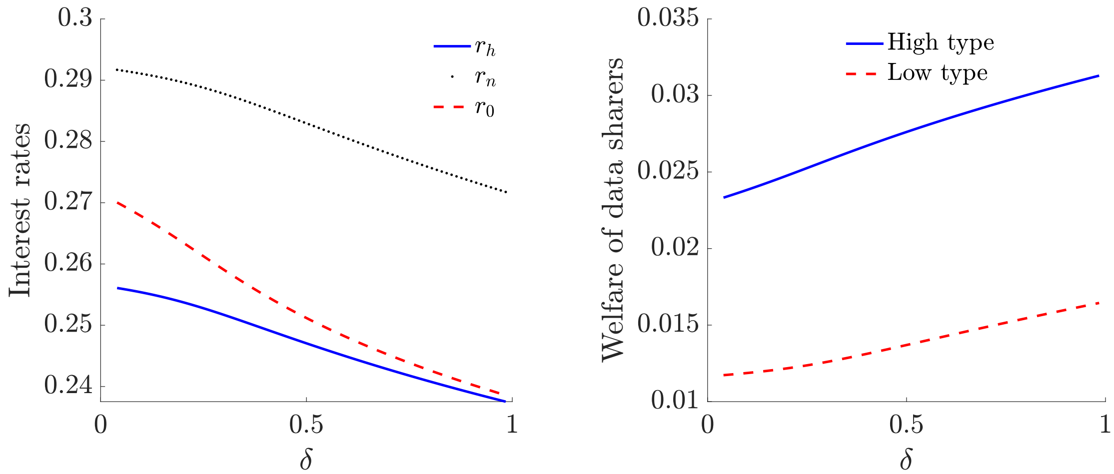
The left panel shows the lender's optimal data coverage as the proportion of privacy-conscious borrowers, δ changes. The right panel shows the equilibrium values of γ^* and m^*, respectively the probability the unconcerned low-type borrower shares their data and their manipulation intensity when they 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: Effects of the proportion of privacy-conscious borrowers on optimal data coverage, data provision, and manipulation when borrowers provide their data

borrower 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 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.

We find that the property that both types of unconcerned borrowers are better off when $\delta > 0$ (compared to when the borrower does not have a choice about sharing their data) is



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 $\alpha = 0.5$, $q_H = 0.95$, $q_L = 0.8$, $R = 0.4$, $C(m) = 0.01m^2$, and $v \sim U[0, 0.4]$.

Figure 6: Effects of the proportion of privacy-conscious borrowers on interest rates and welfare of data sharers

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.

As noted earlier, we include banking data in the set of alternative data that may be shared. Thus, our results here contrast with those of Parlour et al. (2022) and He et al. (2023), who point out possible negative effects of open banking on borrowers.[11] Parlour et al. (2022) feature a monopolist lender, and He et al. (2023) comment (page 462) that their result may obtain because there is less competition for the high-type borrower if the FinTech lender in their model has greatly superior screening ability to the bank. In other

[11]Note that the equilibrium we exhibit has the features of the semi-separating equilibrium described by He et al. (2023): among unconcerned borrowers, the high-type borrower shares data with probability 1, and the low-type borrower randomizes between sharing and not sharing.

words, in both these papers, under some conditions the high-type borrower may prefer to not be unmasked. In contrast, in our model, the high-type always gains from separating out from the low type. Potentially, the privately-known project profitability v (which also sets the reservation rate for a borrower), acts as a reduced-form device to capture a sense of competition in the credit market.

Two additional points are worth noting here. First, in our model, the information the lender generates pertains only to the success probability q_θ. In an alternative scenario, the lender may try to infer the project profitability v, as borrowers with a higher v have a higher willingness-to-pay. In such a scenario, we expect borrowers with a high profitability to try and manipulate their information, in order to convince the lender that their willingness-to-pay is low. In that case, some of the high-success-probability borrowers may also manipulate.

Second, we have considered just two privacy types. Our privacy-conscious borrowers are completely unwilling to trade off privacy for a better interest rate, and our unconcerned borrowers do not value privacy. In a more general setting, one can imagine a continuum of borrowers who trade off privacy and financial benefits at different rates. In such a scenario, we may expect some borrowers who wish to withhold their information from the lender to manipulate their information so that the lender cannot infer their type.

5 Model Extensions

We consider two additional 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 to 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 in 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 difficult 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, as in the base model, but a higher level of data coverage in the lender's underwriting model also induces an additional manipulation cost.

We find that in the transparent regime, if the borrower's manipulation cost is sufficiently low (specifically, $\frac{\partial C(m,\rho)}{\partial m} |_{m=1,\rho=1} \leq \Delta_1$), the lender again avoids full data coverage. In the opaque regime, where the 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 4. Furthermore, in the extended economy, the lender gains from the transparency enforced by regulations, as in Corollary 1.

Proposition 7 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 $K(0) = 0, K'(0) = 0$, $K'(\rho) > 0$ for $\rho > 0$ (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 base model, as shown in Proposition 4. 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 4, 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 base 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 8 in Appendix B.

6 Regulatory Implications

We now consider the implications of our framework for data 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 differ substantially across countries. Consider the U.S., for example. On July 25, 2019, in a U.S. House hearing entitled

"Examining the Use of Alternative Data in Underwriting and Credit Scoring to Expand Access to Credit," Stephen Lynch, Chairman of the Task Force on Financial Technology, commented that "oversight of the use of alternative data is either highly fragmented or completely nonexistent, leading to uncertainty for lenders and potential harm for consumers."[12] 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.[13]

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 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

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

[13] 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.

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 4 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 $\rho_{\max}$.

The specific level of $\rho_{\max}$ 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 $\rho_{\max}$.

In the EU, Recital 47 of the Proposal for the Consumer Credit Directive offers clear indications of the types of information that 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 $\rho_{\max}$ 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 $\rho_{\max}$ may decrease. In both the transparent and opaque regimes of the base model, if the regulation moderately restricts the use of alternative data based on privacy or fairness concerns, the equilibrium level of data coverage remains unaffected. However, if regulators impose highly restrictive regulations (i.e., setting a very low $\rho_{\max}$), 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 borrowers and lenders.

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 U.S., 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 full model in Section 4 analyzes this scenario. We observe that our main findings remain robust in this setting. Particularly, in the transparent regime, the lender may refrain from fully leveraging its data in order 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.

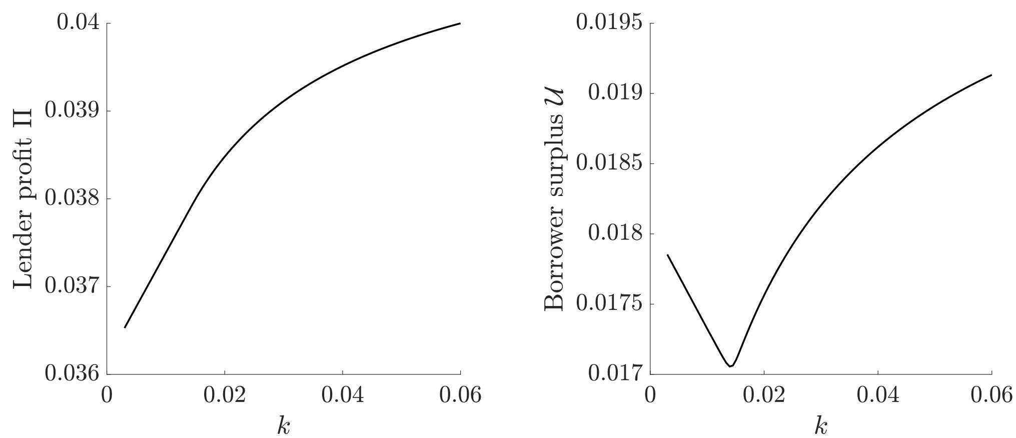
It is worth highlighting the intriguing interaction between borrowers' decisions regarding data sharing and manipulation. Choosing not to share data with the lender and manipulating digital data can both be seen as strategies to safeguard borrower privacy. The former is a passive approach, where the 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 full 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 granting 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 of the base model, as shown in Proposition 4, 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 lender 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.



(a) Lender profit

(b) Ex ante borrower surplus

This figure plots the effect of the manipulation cost on the lender's profit Π and borrower's ex ante surplus $\mathcal{U}$. 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 data coverage ρ for the lender, and then compute the equilibrium values of the other variables.

Figure 7: Effects of changes in the borrower's manipulation cost

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.

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.

To study the effect of disclosure regulations, 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.

As such, regulations that aim to ensure transparency about 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.

In addition, regulations that establish a borrower as the owners 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.

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Appendix

A Proofs

Proof of Lemma 1

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

(i) Suppose the lender offers the interest rate r. Borrowers of 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_j and interest rate offer r is therefore

$$\begin{aligned} \pi_j(r) &= (1-F(r))[\mu_j\{q_H(1+r)-1\} + (1-\mu_j)\{q_L(1+r)-1\}] \\ &= (1-F(r)[\bar{q}_j(1+r)-1]. \end{aligned} \tag{A1}$$

The first-order condition is:

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

which can be simplified to

$$r - \frac{1-F(r)}{f(r)} = \frac{1}{\bar{q}_j} - 1, \tag{A2}$$

which is equation (2) in the statement of the Lemma.

The second-order condition is

$$-2\bar{q}_j f(r) - f'(r)[\bar{q}_j r - (1-\bar{q}_j)] < 0. \tag{A3}$$

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.

Finally, note that 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 this is that $\bar{q}_j(1 + R) > 1$.

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

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 $r_h \geq r_\ell$, that is, borrowers who generate signal d_h are charged a weakly higher interest rate 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

$$\begin{aligned} u(\theta, m; \hat{m}_\theta, \hat{\rho}) \quad = \quad & q_\theta \Big\{ \hat{\rho} \Big(m \int_{r_{\tilde{\theta}}}^{R} (v - r_{\tilde{\theta}}) dF(v) + (1 - m) \int_{r_\theta}^{R} (v - r_\theta) dF(v) \Big) \\ & + (1 - \hat{\rho}) \int_{r_0}^{R} (v - r_0) dF(v) \Big\} - C(m_\theta). \end{aligned} \tag{A4}$$

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

$$\hat{\rho}\, q_\theta \Big\{ \int_{r_{\tilde{\theta}}}^{R} (v - r_{\tilde{\theta}}) dF(v) - \int_{r_\theta}^{R} (v - r_\theta) dF(v) \Big\} > 0. \tag{A5}$$

That is, for $m_\theta > 0$, it must be that (i) $\hat{\rho} > 0$ and (ii) $\int_{r_{\tilde{\theta}}}^{R}(v - r_{\tilde{\theta}}))dF(v) > \int_{r_\theta}^{R}(v - r_\theta))dF(v)$. Because $\int_{r}^{R}(v - r))dF(v)$ is decreasing in r, condition (ii) implies that $r_{\tilde{\theta}} < r_\theta$. 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 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, we must have $r_h < r_\ell$, contradicting the assumption $r_h \geq r_\ell$.

We return to the proof of the Proposition.

(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. 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 $\hat{m}$. Further, observe that $m_H = 0$ implies that $r_\ell = r^L$; i.e., on receiving signal d_ℓ, the lender knows that with probability one the borrower's type is θ_L.

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

$$\hat{\rho}\{W(r_h(\hat{m})) - W(r^L)\} = C'(m), \tag{A6}$$

where $W(r) \equiv q_L \int_{r}^{R}(v - r)dF(v)$. 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 $C'(1) \leq A$, 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 (A6), which yields the equilibrium condition for an interior manipulation intensity:

$$\hat{\rho}\left\{W(r_h(m)) - W(r^L)\right\} \quad = \quad C'(m). \tag{A7}$$

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.

Observe that when $m = 1$, we have $r_h = r_0$. Therefore, if $C'(1) \leq \hat{\rho}\{W(r_0) - W(r^L)\}$, equation (A7) cannot be satisfied for any $m \in (0, 1)$, so $m^* = 1$. Conversely, if $C'(1) > \hat{\rho}\{W(r_0) - W(r^L)\}$, there is a unique value of m^* that satisfies equation (A7).

Observe that the left-hand side of equation (A7) is strictly increasing in $\hat{\rho}$. Both parts (a) and (b) now follow.

(iii) It is immediate that $r_h < r^L$. It remains to show that $r_0 \in (r_h, r^L)$. 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 $d_j \in \{d_h, d_\ell, d_0\}$ satisfy $\mu_h = \frac{\alpha}{\alpha + (1-\alpha)m}$, $\mu_\ell = 0$, and $\mu_0 = \alpha$. That is, we have $\mu_\ell < \mu_0 < \mu_h$. It follows immediately that $r_h < r_0 < r^L$. ■

Proof of Lemma 2

In what follows, for notational convenience we write $m = m^*(\hat{\rho})$. When $m < 1$, it satisfies the first-order condition for optimal manipulation, equation (A7). Applying the implicit function theorem, we have

$$\frac{dm}{d\hat{\rho}} \quad = \quad -\frac{W(r_h(m)) - W(r^L)}{-C''(m) + \hat{\rho}\frac{\partial W(r_h(m))}{\partial m}} \quad = \quad \frac{W(r_h(m)) - W(r^L)}{C''(m) - \hat{\rho}\frac{\partial W(r_h(m))}{\partial m}}. \tag{A8}$$

In the last expression, $W(r_h(m)) > W(r^L)$ because $r_h(m) < r^L$, so the numerator is strictly positive. Further, $\frac{\partial W(r_h(m))}{\partial m} = -q_L(1 - F(r_h(m)))r_h'(m)$. Now, an increase in m implies a reduction in μ_h, the posterior probability of the high type after signal d_h. From Lemma 1 part (i), the rate r_h increases. That is, $r_h'(m) > 0$. Therefore $\frac{\partial W(r_h(m))}{\partial m} < 0$, and the denominator in the last expression in equation (A8) 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_j are $\mu_h = 1$, $\mu_\ell = 0$, and $\mu_0 = \alpha$. The corresponding optimal interest rates are as in Lemma 1, and it follows that $r_h < r_0 < r^L$.

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

$$\Pi = \rho \left\{ \alpha \pi_h(r_h) + (1 - \alpha)\pi_\ell(r^L) \right\} + (1 - \rho)\pi_0(r_0). \tag{A9}$$

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 (A9) with respect to ρ yields

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

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

$$\begin{aligned}
\frac{d\Pi}{d\rho} > 0 \iff\ & \alpha \pi_h(r_h) + (1 - \alpha)\pi_\ell(r^L) > \pi_0(r_0) \\
\iff\ & \alpha \max_r \pi_h(r) + (1 - \alpha) \max_r \pi_\ell(r) > \max_r \pi_0(r) \\
\iff\ & \alpha \max_r \pi_h(r) + (1 - \alpha) \max_r \pi_\ell(r) > \max_r \left[\alpha \pi_h(r) + (1 - \alpha)\pi_\ell(r) \right].
\end{aligned} \tag{A10}$$

As $r_h \neq r^L$, it is straightforward that the last inequality must hold. Therefore, the lender's expected profit is monotonically increasing in 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. It follows from the definition of $\bar{\rho}$ that $m^*(\bar{\rho}) = 1$. Recall from equation (5) that the lender's profit is

$$\Pi(\rho) \;=\; \rho\Big(\{\alpha + (1-\alpha)m\}\pi_h(r_h) + (1-\alpha)(1-m)\pi_\ell(r^L)\Big) + (1-\rho)\pi_0(r_0). \quad \text{(A11)}$$

Observe that when $\rho = 0$ or $m = 1$, the lender's profit reduces to $\pi_0(r_0) \equiv \Pi_u$ (where the subscript u denotes "uninformed"). For $\rho = 0$ it follows immediately from the expression for Π. When $m = 1$, after signal d_h, we have $\mu_h = \alpha$ and so $q_h = q_0$. Therefore, the optimal interest rate is equal to r_0, and so $\pi_h(r_h)$ reduces to $\pi_0(r_0)$.

Now, consider $\rho > 0$ and $m \in (0, 1)$. The argument is essentially the same as used in Lemma 3. Observe that

$$\{\alpha + (1-\alpha)m\}\pi_h(r_0) + (1-\alpha)(1-m)\pi_\ell(r_0) \;=\; \pi(q_0, r_0). \quad \text{(A12)}$$

That is, by charging the interest rate r_0 after signals d_h and d_ℓ, the lender recovers exactly Π_u. Now, r_h and r^L are by definition the optimal interest rates after signals d_h and d_ℓ respectively. Therefore, $\pi_h(r_h) > \pi_h(r_0)$ and $\pi_\ell(r^L) > \pi_\ell(r_0)$. Hence, we have

$$\{\alpha + (1-\alpha)m\}\pi_h(r_h) + (1-\alpha)(1-m)\pi_\ell(r^L) >$$
$$\{\alpha + (1-\alpha)m\}\pi_h(r_0) + (1-\alpha)(1-m)\pi_\ell(r_0) = \pi(q_0, r_0). \quad \text{(A13)}$$

Therefore,

$$\Pi(\rho \mid r_h, r^L, r_0) \;>\; \Pi(\rho \mid r_0, r_0, r_0) \equiv \Pi_u. \quad \text{(A14)}$$

That is, for all $\rho > 0$ such that $m^*(\rho) < 1$, the lender earns a higher profit than at $\rho = 0$ or when $m^*(\rho) = 1$ (i.e., when $\rho = \bar{\rho}$). It follows that $\rho^* > 0$ and $\rho^* < \bar{\rho}$, thus proving both parts of the Proposition. ■

Proof of Proposition 3

(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, $I_h(m) = \int_{r_h(m)}^{R}(v - r_h(m))dF(v)$, $I_\ell = \int_{r^L}^{R}(v - r^L)dF(v)$ and $I_0 = \int_{r_0}^{R}(v - r_0)dF(v)$.

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

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

Hence,

$$\frac{du_H}{d\rho} = \frac{\partial u_H}{\partial \rho} + \frac{\partial u_H}{\partial m}\frac{dm}{d\rho} = q_H(I_h(m) - I_0) + \rho q_H \frac{\partial I_h}{\partial m}\frac{dm}{d\rho}. \tag{A15}$$

Here, $\frac{\partial I_h}{\partial m} = -(1 - F(r_h(m)))\, r_h'(m)$, and $\frac{dm}{d\rho}$ is as in equation (A8).

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

$$\frac{du_H}{d\rho}\mid_{\rho=0} = q_H(I_h(m) - I_0). \tag{A16}$$

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

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,

$$\frac{du_L}{d\rho} = \frac{\partial u_L}{\partial \rho} + \frac{\partial u_L}{\partial m}\frac{dm}{d\rho}. \tag{A17}$$

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 (A17), we obtain

$$\frac{du_L}{d\rho} = q_L\{mI_h + (1-m)I_\ell - I_0\} + \rho m q_L \frac{\partial I_h}{\partial m}\frac{dm}{d\rho}. \tag{A18}$$

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

$$\frac{du_L}{d\rho}\mid_{\rho=0} = q_L\{I_\ell - I_0\} < 0, \tag{A19}$$

as $I_\ell < I_0$.

(ii) The ex ante borrower payoff is

$$\mathcal{U} = \alpha u_H + (1-\alpha)u_L. \tag{A20}$$

Using the expressions for $\frac{du_H}{d\rho}\mid_{\rho=0}$ and $\frac{du_L}{d\rho}\mid_{\rho=0}$ in equations (A16) and (A19) respectively, we obtain

$$\frac{d\mathcal{U}}{d\rho}\mid_{\rho=0} = \alpha q_H(I_h(0)-I_0)+(1-\alpha)q_L(I_\ell-I_0). \tag{A21}$$

Now, observe that when $q_L(1+R)\geq 1$, for each signal $d_j \in \{d_h, d_\ell, d_0\}$, 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 (A21) as

$$\frac{d\mathcal{U}}{d\rho}\mid_{\rho=0} = \alpha G(q_H)+(1-\alpha)G(q_L)-G(\alpha q_H+(1-\alpha)q_L). \tag{A22}$$

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,

$$G'(q) = \int_{r(q)}^{R}(v-r(q))dF(v) - q\int_{r(q)}^{R} r'(q)dF(v), \tag{A23}$$

$$G''(q) = -(1-F(r))\{2r'(q)+qr''(q)\}+q\,f(r(q))\,(r'(q))^2. \tag{A24}$$

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:

$$r = \frac{1}{q}-1+H(r). \tag{A25}$$

Thus,

$$r'(q) = -\frac{1}{q^2}+H'(r)r'(q), \tag{A26}$$

$$r''(q) = \frac{2}{q^3}+H'(r)r''(q)+H''(r)\{r'(q)\}^2. \tag{A27}$$

We can now compute

$$r'(q) = -\frac{1}{q^2(1-H'(r))}, \tag{A28}$$

$$r''(q) = \frac{1}{1-H'(r)}\Big(\frac{2}{q^3}+H''(r)\{r'(q)^2\}\Big) = r'(q)\Big(-\frac{2}{q}+\frac{H''(r)r'(q)}{1-H'(r)}\Big). \tag{A29}$$

Substituting into the right-hand side of equation (A24), we have

$$\begin{aligned} G''(q) &= -(1-F(r))\{2r'(q)-2r'(q)+\frac{qH''(r)(r'(q))^2}{1-H'(r)}\}+q\,f(r(q))\,(r'(q))^2 \\ &= \Big(-\frac{H(r)H''(r)}{1-H'(r)}+1\Big)\,q\,f(r(q))\,(r'(q))^2. \end{aligned} \tag{A30}$$

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

$$H(r)\,H''(r) \;<\; 1-H'(r). \tag{A31}$$

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

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 (A31) 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 (A31) is equivalent to:

$$-\frac{1-\beta}{\beta}\Big(\frac{R^{2\beta}}{r^{2\beta}}-\frac{R^\beta}{r^\beta}\Big) < 1+\frac{1}{\beta}-\frac{1-\beta}{\beta}\frac{R^\beta}{r^\beta}. \tag{A32}$$

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

$$\Leftrightarrow \qquad \Big(\frac{R}{r}\Big)^\beta\Big(\Big(\frac{R}{r}\Big)^\beta-2\Big) < \frac{1+\frac{1}{\beta}}{1-\frac{1}{\beta}}. \tag{A33}$$

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 follows:

$$\left(\frac{R}{r}\right)^{\beta} = 1 + \beta - \frac{\beta}{r}\left(\frac{1}{q} - 1\right). \tag{A34}$$

Now, consider condition (A33), and substitute in the right-hand-side of equation (A34) for $\left(\frac{R}{r}\right)^{\beta}$ and simplify. We obtain that condition (A31) is equivalent to:

$$\beta^2\left(1 - \frac{1}{r}\left(\frac{1}{q} - 1\right)\right)^2 - 1 < \frac{1 + \frac{1}{\beta}}{1 - \frac{1}{\beta}}. \tag{A35}$$

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 (A34) 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 (A35) 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 4

Let $\hat{\rho}$ denote 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:

$$\begin{aligned} \Pi(\rho \mid \hat{\rho}) &= \rho\Big(\{\alpha + (1-\alpha)m(\hat{\rho})\}\pi_h(r_h(m(\hat{\rho}))) + (1-\alpha)(1-m(\hat{\rho}))\pi_\ell\Big) \\ &\quad + (1-\rho)\pi_0(r_0). \end{aligned} \tag{A36}$$

The partial derivative with respect to ρ is

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

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

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

where the last inequality is shown in 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 $C'(1) \geq q_L \left(\int_{r_0}^{R}(v-r_0)dF(v) - \int_{r^L}^{R}(v-r^L)dF(v)\right)$, we have $m(\hat{\rho}) < 1$ for any $\hat{\rho} < 1$.

Both parts of the Proposition now follow. ■

Proof of Corollary 1

The proof follows from Propositions 2 and 4. Specifically, when the manipulation cost is low, i.e., $C'(1) \leq W(r_0) - W(r^L)$, there exists some $\underline{\rho}$ such that the left derivative of the lender's profit function at $\underline{\rho}$ 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 $C'(1) > W(r_0) - W(r^L)$, 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 5

(i) Suppose $\rho > 0$. There are two possibilities in the subsequent equilibrium: $r_n^* > r_0^*$ or $r_n^* \leq r_0^*$. We consider each case in turn. Define $w(r) \equiv \int_r^R (v-r)dF(v)$ and $W(r) \equiv q_L \int_r^R (v-r)dF(v)$.

Case 1: Suppose $r_n^* > r_0^*$. Consider a borrower who is not privacy-conscious and has type H. Following the proof of Proposition 1, the high-type borrower never manipulates their data ($m_H = 0$): any manipulation strictly hurts them by lowering μ_h and thus raising r_h, while also incurring the manipulation cost. Thus, if they share their data, they obtain an interest rate $r_h^* \leq r_0^*$ with probability ρ and an interest rate r_0^* with probability $1-\rho$. Their expected payoff is $q_H\{\rho \cdot w(r_h^*) + (1-\rho) \cdot w(r_0^*)\} > q_H w(r_n^*)$. The right-hand side is the expected payoff from not sharing their data. Therefore, it is optimal to set $\gamma_H = 1$.

Case 2: Suppose $r_n^* \leq r_0^*$ and $\gamma_H^* > 0$. Denote the low-type borrower's manipulation intensity by m. For each type $\theta \in \{H, L\}$, let Δ_θ denote the payoff gap between sharing and not sharing data. We have:

$$\Delta_H \equiv q_H \left[\rho \cdot w(r_h^*) + (1-\rho) \cdot w(r_0^*)\right] - q_H w(r_n^*),$$

$$\Delta_L \equiv q_L \left[\rho m \cdot w(r_h^*) + \rho(1-m) \cdot w(r^L) + (1-\rho) \cdot w(r_0^*)\right] - C(m) - q_L w(r_n^*).$$

Taking the normalized difference, we obtain:

$$\frac{\Delta_H}{q_H} - \frac{\Delta_L}{q_L} = \rho(1-m)\left[w(r_h^*) - w(r_L)\right] + \frac{C(m)}{q_L} > 0. \tag{A37}$$

Consequently, no equilibrium can feature $\gamma_H^* \in (0,1)$ and $\gamma_L^* \in (0,1)$ simultaneously, as that would require $\Delta_H = \Delta_L = 0$, contradicting (A37). Thus, it must be that $\gamma_L^* = 0$. But in this case, the pool of borrowers who share their data consists solely of high types, implying $r_0^* = r^H$ (as the borrower type is now known to have the high type). Since the non-sharing pool contains a strictly positive mass of low types, we have $r_n^* > r^H = r_0^*$, contradicting the premise $r_n^* \leq r_0^*$.

Next, suppose $r_n^* \leq r_0^*$ and $\gamma_H^* = 0$. If $\gamma_L^* > 0$, then the pool of data-sharers consists solely of (non-privacy-conscious) low types, so $r^L = r_0^* > r_n^*$. Hence $\gamma_L^* = 0$, contradicting $\gamma_L^* > 0$. Therefore, it must be that $\gamma_L^* = 0$. Potentially, such an equilibrium can be sustained with off-equilibrium beliefs that any borrower who shares their data has a high probability of being the low-type. However, these beliefs fail to satisfy the refinement criterion D1, because type H has a higher potential benefit from deviating and sharing their data than type L does.

Therefore, putting Case 1 and Case 2 together, if $\rho > 0$, the only feasible equilibria have $r_n^* > r_0^*$ and $\gamma_H^* = 1$.

(ii) (a) Consider the sharing strategy of the low-type borrower who is unconcerned about privacy. Suppose there is an equilibrium in which they do not share their data, i.e., $\gamma_L^* = 0$. Then, the interest rate offered to non-sharers is $\bar{r}_n$ and is based on an average success probability $\frac{\alpha\delta}{\alpha\delta+(1-\alpha)}$. Thus, the payoff to the unconcerned low-type borrower is $W(\bar{r}_n)$.

Now suppose the unconcerned low-type borrower deviates, and shares their data with positive probability. In equilibrium, the lender believes that all sharers have the high type, so $r_h = r_0 = r^H$. Therefore, if the deviator manipulates with probability m, their payoff is

$$\rho\{mW(r^H) + (1-m)W(r^L)\} + (1-\rho)W(r^H) - C(m). \tag{A38}$$

Consider two manipulation strategies for the deviator:

1. Manipulate with probability zero, i.e., set $m = 0$. This strategy yields a deviation payoff $\rho W(r^L) + (1-\rho)W(r^H)$.

2. Manipulate with probability 1, i.e., set $m = 1$. This strategy yields a deviation payoff $W(r^H) - C(1)$.

If the deviator chooses an optimal manipulation probability, their payoff must weakly exceed each of these two expressions. Therefore, if

$$\max\{W(r^H) - C(1),\ \rho W(r^L) + (1-\rho)W(r^H)\} > W(\bar{r}_n), \tag{A39}$$

there cannot be an equilibrium in which $\gamma_L^* = 0$. Hence, in equilibrium, it must be that $\gamma_L^* > 0$.

(ii) (b) When $\gamma_H^* = 1$ and $\gamma_L^* > 0$, the pool of borrowers who share data contains both high- and low-type borrowers. It now follows from the same arguments as in Proposition 1 that $m^* > 0$.

(ii) (c) The unconcerned low-type borrower is maximizing

$$U_L = \gamma_L\{\rho(mW(r_h) + (1-m)W(r^L)) + (1-\rho)W(r_0) - C(m)\} + (1-\gamma_L)W(r_n).$$

Suppose that $m^* \in (0,1)$ and $\gamma_L^* \in (0,1)$. Then, the first-order conditions with respect to m and γ_L are:

$$F(\rho,\gamma_L,m) \equiv C'(m) - \rho\{W(r_h(\gamma_L,m)) - W(r^L)\} = 0 \tag{A40}$$

$$\begin{aligned} G(\rho,\gamma_L,m) \equiv\ & \rho\{mW(r_h(\gamma_L,m)) + (1-m)W(r^L)\} \\ & +(1-\rho)W(r_0(\gamma_L)) - C(m) - W(r_n(\gamma_L)) = 0. \end{aligned} \tag{A41}$$

Denoting $F_x = \frac{\partial F}{\partial x}$ and $G_x = \frac{\partial G}{\partial x}$, we obtain:

$$\frac{d\gamma_L}{d\rho} = \frac{-G_\rho F_m + G_m F_\rho}{G_\gamma F_m - G_m F_\gamma}, \tag{A42}$$

$$\frac{dm}{d\rho} = \frac{-G_\gamma F_\rho + G_\rho F_\gamma}{G_\gamma F_m - G_m F_\gamma}, \tag{A43}$$

where

$$G_\rho = mW(r_h) + (1-m)W(r_L) - W(r_0), \tag{A44}$$

$$G_m = \rho m\frac{\partial W(r_h)}{\partial m} < 0, \tag{A45}$$

$$G_\gamma = \rho m\frac{\partial W(r_h)}{\partial \gamma_L} + (1-\rho)\frac{\partial W(r_0)}{\partial \gamma_L} - \frac{\partial W(r_n)}{\partial \gamma_L} < 0, \tag{A46}$$

$$F_\rho = -[W(r_h) - W(r_L)] < 0, \tag{A47}$$

$$F_m = C''(m) - \rho\frac{\partial W(r_h)}{\partial m} > 0, \tag{A48}$$

$$F_\gamma = -\rho\frac{\partial W(r_h)}{\partial \gamma_L} > 0. \tag{A49}$$

Observe that the posterior belief that the borrower has the high-type after no data is shared, $\mu_n \equiv \frac{\alpha\delta}{\alpha\delta+(1-\alpha)\{\delta+(1-\delta)(1-\gamma_L\}}$ is strictly increasing in γ_L. Similarly, the posterior belief over the high type for those who share data is $\mu_0 = \frac{\alpha}{\alpha+(1-\alpha)\gamma_L}$, and is decreasing in γ_L. Finally, the posterior belief among data sharers who generate the high signal is $\mu_h = \frac{\alpha}{\alpha+(1-\alpha)\gamma_L m}$, and is decreasing in both γ_L and in m. Therefore, r_n is increasing in γ_L, r_0 is decreasing in γ_L, and r_h is increasing in both γ_L and m. As $W(r) = \int_r^R (v-r)dF(r)$ is strictly decreasing in r, it follows that $W(r_n)$ is increasing in γ_L, $W(r_0)$ is decreasing in γ_L, and $W(r_h)$ is decreasing in γ_L and m. This observation leads to the signs of the expressions in equations (A45), (A46), (A48), and (A49) above.

Consider the common denominator of $\frac{d\gamma_L}{d\rho}$ and $\frac{dm}{d\rho}$. We have

$$G_\gamma F_m - G_m F_\gamma \quad = \quad C''(m)G_\gamma - \rho\frac{\partial W(r_h)}{\partial m}\Big((1-\rho)\frac{\partial W(r_0)}{\partial \gamma_L} - \frac{\partial W(r_n)}{\partial \gamma_L}\Big) \ < \ 0. \quad \text{(A50)}$$

Next, consider the numerator of $\frac{d\gamma_L}{d\rho}$. We have

$$\begin{aligned} J \equiv -G_\rho F_m + G_m F_\rho \quad &= \quad -\{W(r^L) - W(r_0) + m(W(r_h) - W(r^L))\}\{C''(m) - \rho\frac{\partial W(r_h)}{\partial m}\} \\ &\quad -\{W(r_h) - W(r^L)\}\rho m \frac{\partial W(r_h)}{\partial m} \qquad \text{(A51)} \\ &= \quad C''(m)\{W(r_0) - W(r^L) - m(W(r_h) - W(r^L))\} \\ &\quad -\rho\frac{\partial W(r_h)}{\partial \gamma_L}(W(r_0) - W(r^L)). \qquad \text{(A52)} \end{aligned}$$

The second term in equation (A52), $-\rho\frac{\partial W(r_h)}{\partial \gamma_L}(W(r_0) - W(r^L))$, is strictly positive when $\rho > 0$. Further, the first term, $C''(m)\{W(r_0) - W(r^L) - m(W(r_h) - W(r^L))\}$, is weakly positive whenever $m \leq \frac{W(r_0)-W(r^L)}{W(r_h)-W(r^L)}$.

Therefore, a sufficient condition to ensure that $J \geq 0$ is $m \leq \frac{W(r_0)-W(r^L)}{W(r_h)-W(r^L)}$. Observe that when $m = 0$, we have $r_h = r^H$, and so the right-hand side of the condition is strictly positive. Therefore, the condition holds at $m = 0$. By continuity, there exists some $\bar{m}$ (possibly equal to 1) such that $m \leq \frac{W(r_0)-W(r^L)}{W(r_h)-W(r^L)}$ for all $m \leq \bar{m}$.

Finally, observe that $J \geq 0$ is sufficient to ensure that $\frac{d\gamma_L}{d\rho} < 0$. Thus, whenever $m^* \leq \bar{m}$, we have $\frac{d\gamma_L}{d\rho} < 0$.

Next, consider the numerator of $\frac{dm}{d\rho}$. We have

$$\begin{aligned} -G_\gamma F_\rho + G_\rho F_\gamma &= [\rho m \frac{\partial W(r_h)}{\partial \gamma_L} + (1-\rho)\frac{\partial W(r_0)}{\partial \gamma_L} - \frac{\partial W(r_n)}{\partial \gamma_L}]\{W(r_h) - W(r_L)\} \\ &\quad -\rho \frac{\partial W(r_h)}{\partial \gamma_L}\{W(r^L) - W(r^0) + m(W(r_h) - W(r^L))\} \quad \text{(A53)} \\ &= \Big\{(1-\rho)\frac{\partial W(r_0)}{\partial \gamma_L} - \frac{\partial W(r_n)}{\partial \gamma_L}\Big\}\{W(r_h) - W(r^L)\} \\ &\quad +\rho \frac{\partial W(r_h)}{\partial \gamma_L}\{W(r_0) - W(r^L)\} < 0. \quad \text{(A54)} \end{aligned}$$

Hence, it follows that $\frac{dm}{d\rho} > 0$.

(iii) This part follows from $\gamma_L^* > 0$ and $m^* > 0$. ■

Proof of Proposition 6

Let $\mu_0 \equiv \frac{\alpha\gamma_H^*}{\alpha\gamma_H^* + (1-\alpha)\gamma_L^*}$ be the posterior probability that a consumer who shares their data has the high type. Similarly, let $\mu_n \equiv \frac{\alpha\{\delta+(1-\delta)(1-\gamma_H^*)\}}{\alpha\{\delta+(1-\delta)(1-\gamma_H^*)\}+(1-\alpha)\{\delta+(1-\delta)(1-\gamma_L^*)\}}$ be the posterior probability that a consumer who does not share their data has the high type.

Suppose $\rho = 0$. Then, in equilibrium, it must be that $\gamma_H^* = \gamma_L^*$. Suppose not; in particular, suppose that $\gamma_H^* > \gamma_L^*$. Then, $\mu_0 > \alpha > \mu_n$. Hence, $r_0^* < r_n^*$. But then, all consumers unconcerned about privacy should choose to share their data, so that $\gamma_H^* = \gamma_L^* = 1$, contradicting the assumption that $\gamma_H^* > \gamma_L^*$. Next, suppose that $\gamma_L^* > \gamma_H^*$. Then, we have $\mu_0 < \alpha < \mu_n$. Hence, $r_0^* > r_n^*$. But then no consumer unconcerned about privacy should share their data, so we must have $\gamma_H^* = \gamma_L^* = 0$, again contradicting that $\gamma_L^* > \gamma_H^*$. Therefore, $\gamma_H^* = \gamma_L^*$ in equilibrium.

It then follows that $r_0^* = r_n^*$, and the posterior belief regardless of whether the consumer shares their data is equal to the prior, i.e., that the consumer has the high type with probability α. Denote this value of r_0^* by r_1.

Now, suppose the lender increases ρ slightly to $\tilde{\rho} > 0$. As discussed in Proposition 5, it now obtains one of four signals, with $d_j \in \{d_h, d_\ell, d_0, d_n\}$. If it charges r_1 regardless of signal, it earns exactly the same profit as when $\rho = 0$. But it follows from Lemma 1 that the optimal interest rates are different from r_1. As shown in Propostion 5, we in fact have $r^L > r_n \geq r_0 > r_h$ (at $\rho = 0$, we have $m^* = 0$, so for a small increase in ρ it continues to be the case that $m^* < 1$). Because these interest rate offers earn a higher profit than offering r_1 regardless of signal, the profit of the lender must have strictly increased compared to setting $\rho = 0$. ■

B Extensions to Base Model

B.1 Data Coverage Affects Manipulation Cost

Proposition 7 (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 $\frac{\partial^2 C(m,\rho)}{\partial m \partial \rho} \in (0, q_L(I_h(1) - I_\ell))$.*

(i) *In the transparent regime, the lender chooses strictly positive data coverage in equilibrium, i.e., $\rho^* > 0$. Moreover, if $\frac{\partial C(m,\rho)}{\partial m} |_{m=1,\rho=1} \leq W(r_0) - W(r^L)$ (i.e., the manipulation cost is sufficiently low), the lender chooses less than full data coverage (i.e., $\rho^* < 1$).*

(ii) *In the opaque regime:*

  (a) *If $\frac{\partial C(m,\rho)}{\partial m} |_{m=1,\rho=1} < W(r_0) - W(r^L)$, 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., $m^* = 1$).*

  (b) *If $\frac{\partial C(m,\rho)}{\partial m} |_{m=1,\rho=1} \geq W(r_0) - W(r^L)$, 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) In the transparent regime, the derivation follows similar procedures in the baseline model. As in Proposition 1, we can show that $r_h < r_0 < r^L$. In addition, for a given $\hat{\rho} > 0$, if $\frac{\partial C(m,\rho)}{\partial m} \mid_{m=1} > \Delta(\hat{\rho})$, there is a unique value of m that satisfies the following equation:

$$\rho\left(W(r_h(m)) - W(r^L)\right) = \frac{\partial C(m,\rho)}{\partial m}. \tag{A55}$$

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

As in equation (A8) in the proof of Lemma 2, we have

$$\frac{dm}{d\hat{\rho}} = -\frac{W(r_h(m)) - W(r^L)}{-C''(m) + \hat{\rho}\frac{\partial W(r_h(m))}{\partial m}} = \frac{W(r_h(m)) - W(r^L) - \frac{\partial^2 C(m,\rho)}{\partial m \partial \rho}}{\frac{\partial^2 C(m,\rho)}{\partial m^2} - \hat{\rho}\frac{\partial W_h(m)}{\partial m}}. \tag{A56}$$

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

Now, suppose $\frac{\partial C(m,\rho)}{\partial m} \mid_{m=1,\rho=1} \leq W(r_0) - W(r^L)$ so that if the lender chooses $\rho = 1$, the low-type borrower manipulates with probability 1. Then, by continuity there exists some $\bar{\rho} = \min\{\rho \mid m^*(\rho) = 1\}$. The same arguments as in the Proof of Proposition 2 now go through, so that $\rho^* \in (0, \bar{\rho})$.

(ii) The proof of this part is similar to the proof of Proposition 4, replacing $C'(1)$ with $\frac{\partial C(m,\rho)}{\partial m}|_{m=1,\rho=1}$.

(iii) The proof of this part is similar to that of Corollary 1. ∎

B.2 Data Coverage is Costly for the Lender

Proposition 8 (Direct cost to data collection)**.** *Suppose that to acquire and process the data with data coverage ρ costs the lender $K(\rho)$, where $K(0) = 0, K'(0) = 0, K'(\rho) > 0$ for $\rho > 0$, and $K''(\rho) > 0$.*

(i) *In the transparent regime, the lender chooses strictly positive data coverage, i.e., $\rho^* > 0$. Moreover, the same condition as in Proposition 2, $c'(1) \leq W(r_0) - W(r^L)$ identifies* *the sufficient condition for $\rho^* < 1$.*

(ii) *In the opaque regime, in contrast to Proposition 4, even if $C'(1) \leq W(r_0) - W(r^L)$, the lender will not choose the optimal data coverage such that the low-type manipulates with probability 1. If $C'(1) > W(r_0) - W(r^L)$ and the marginal data collection cost $K'(\rho)$ is not that steep, like Proposition 4, there is a unique equilibrium in which the lender chooses maximal data coverage, i.e., $\rho^* = 1$, and the low-type borrower manipulates with strictly positive probability (i.e., $m^* > 0$).*

(iii) *As in Corollary 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 transparent regime. 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

$$\Pi(\rho) = \rho\Big(\{\alpha + (1-\alpha)m\}\pi_h(r_h) + (1-\alpha)(1-m)\pi_\ell(r^L)\Big) + (1-\rho)\pi_0(r_0) - K(\rho). \quad \text{(A57)}$$

Compared with equation (5), there is an extra cost term $-K(\rho)$ here.

Because $K'(0) = 0$, using the same arguments as in the proof of Proposition 2, it follows that the lender's profit is strictly greater when $\rho > 0$ but sufficiently close to 0, rather than at $\rho = 0$. Further, recalling that $\bar{\rho} = \min\{\rho \mid m^*(\rho) = 1\}$, because $K'(\bar{\rho}) > 0$, it follows that the lender's profit is strictly greater when $\rho < \bar{\rho}$ but sufficiently close to $\bar{\rho}$ than at $\rho = \bar{\rho}$. Thus, the lender's optimal data coverage ρ^* is strictly between 0 and $\bar{\rho}$.

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

We then move back to the beginning of the game to determine the lender's optimal data coverage, following similar procedures as in Proposition 4. The lender's expected profit function (A36) can be augmented as the following:

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

The derivative with respect to ρ is

$$\frac{\partial\Pi}{\partial\rho} = \{\alpha + (1-\alpha)m(\hat{\rho})\}\pi_h(r_h) + (1-\alpha)(1-m(\hat{\rho}))\pi_\ell(r^L) - \pi_0(r_0) - K'(\rho). \quad \text{(A58)}$$

Denote $\Gamma(\hat{\rho}) = \{\alpha + (1-\alpha)m(\hat{\rho})\}\pi_h(r_h) + (1-\alpha)(1-m(\hat{\rho}))\pi_\ell(r^L) - \pi_0(r_0)$. Then

$$\frac{\partial\Pi}{\partial\rho} = \Gamma(\hat{\rho}) - K'(\rho). \quad \text{(A59)}$$

When $m(\hat{\rho}) = 1$ so that $\Gamma(\hat{\rho}) = 0$, 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 have shown $\Gamma(\hat{\rho}) > 0$ in the baseline model. Inserting $\hat{\rho} = \rho$ in equation (A58) and setting it to zero yields the optimal data coverage ρ, which is the solution implicitly determined by: $\Gamma(\rho) = K'(\rho)$. 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. ■