Payments and the Provision of Privacy by Digital Platforms*

Pedro Gomis-Porqueras[†] — *Queensland University of Technology*

Zijian Wang[‡] — *Wilfrid Laurier University*

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Abstract

Digital platforms, such as social media and video streaming sites, often collect large amounts of personal data from their users. In recent years, most platforms also started offering payment services, such as Apple Pay, Amazon Pay, and WeChat Pay. In this paper, we characterize conditions under which digital platforms find it profitable to monetize users' data. We show that platforms' monetization policies are in general socially inefficient. When platforms do not offer payment services, they tend to under-utilize consumers' data, i.e., platforms may not monetize users' data even when it is welfare-improving. However, when platforms offer payment services, they may over-utilize users' data. Competition among platforms may lead to specialization in data monetization and in the provision of privacy. Under certain conditions, platforms specializing solely in payment services may emerge.

JEL Codes: D8, E42, L1.

Keywords: Privacy, Platform, Payment system

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[†]School of Economics and Finance, Queensland University of Technology, 2 George St Block Z, Brisbane, QLD 4000. Email: peregomis@gmail.com

[‡]Department of Economics, Lazaridis School of Business and Economics, Wilfrid Laurier University, Canada, N2L 3C5. Email: zijianwang@wlu.ca

1 Introduction

Digital platforms, such as social media and e-commerce sites, are ubiquitous in modern society. On most platforms, sharing personal information is by design an integral part of the consumer experience.[1] How digital platforms utilize users' data is an important issue that users and policymakers face. A sense of urgency around data usage has grown especially after the 2018 Facebook–Cambridge Analytica scandal, where millions of users' data was sold to third parties without users' consent.[2] In addition to data collection, in recent years, many digital platforms also started to offer payment services. In some countries, platform payment services have revolutionized how people conduct transactions (Ouyang, 2021). The goal of this paper is to study digital platforms' data monetization and payment services in an environment where users have limited control over the data they share. We ask (1) whether digital platforms may have the incentive to offer privacy by not monetizing users' data, and (2) how platform payment services may affect data monetization and platforms' incentive to offer privacy.

To answer these questions, we build a general equilibrium framework based on Rocheteau and Wright (2005). A key feature of the framework is that user data can be used by a digital platform to reduce frictions in the goods market at the cost of users' privacy. Specifically, we assume that there exists a monopolistic digital platform (this assumption is relaxed later) that offers digital services, such as social networking and video streaming, to consumers. The platform can also create, at a cost, an online goods market that competes with an *offline* (i.e., brick and mortar) goods market. Thanks to data analytic technologies, data generated by digital activities on the platform can reveal consumers' preferences and help match consumers with sellers of goods more efficiently in online markets. However, monetizing consumers' data in such a way creates a risk of the data being leaked or misused, which delivers a negative payoff to consumers. We assume that the platform generates profits by charging a fee to buyers for accessing its digital services and the online market, as well as a fee to sellers for setting up an online store in the online market. In both online and offline markets, goods trade requires a medium of exchange, for which a government-issued fiat money is available.

We find that the privacy cost of data monetization lowers the amount of surplus the digital

[1] For instance, to connect with friends and family through Facebook, a user will disclose their social network as well as their posts and messages to the platform.

[2] In the 2010s, political consulting firm Cambridge Analytica obtained over 87 million users' profiles through Facebook. The data was later used without users' authorization by various political campaigns in the U.S. and the U.K. for political advertising. For more details, see Cadwalladr and Graham-Harrison (2018). After the scandal, the European Parliament passed the Digital Services Act, which allows regulators to better understand digital platforms' algorithms (The European Union, 2022).

platform can extract from consumers. As a result, when the privacy cost is large, the platform opts to offer privacy to consumers by *not* monetizing their data. Furthermore, the profitability of data monetization depends on the surpluses in both online and offline markets. An increase in inflation, which raises the cost of holding cash, lowers the surpluses in both types of markets and decreases the profits from monetization. We also find that the platform may not monetize buyers' data even when it is welfare improving. This is because in online markets, consumers carry more money and consume more due to the higher matching efficiency. Consequently, they incur a higher inflation cost, which is fully internalized by the monopolistic platform.

Next, we allow the platform to provide payment services. Specifically, the digital platform can issue nominal *tokens* that can be used as payment in both online and offline markets. These tokens are nominal and can be exchanged one-for-one for fiat money. The platform may also offer a nominal interest rate on its tokens. This interest rate can differ depending on where the tokens are used (i.e., online or offline markets). We find that in this environment, the platform may monetize consumers' data even when data monetization lowers aggregate welfare. This is because the payment service allows the platform to manipulate consumers' surpluses in both online and offline markets through the interest on tokens. By offering a higher rate on tokens that are used in the online market, the platform effectively lowers the value of consumers' outside option (i.e., the offline markets). This strategy enables the platform to extract more surplus from online markets, which can lead to over-utilization of consumers' data. Furthermore, when the platform also collects and monetizes payment data, it does not always fully internalize the privacy cost. As a result, payment data monetization can lower aggregate welfare.

In practice, many digital platforms compete to offer similar services. To capture this fact, we extend the benchmark model to consider two competing platforms. In this richer environment, we find that when the profit from data monetization is neither too large nor too small compared to the privacy cost, one platform chooses to monetize consumers' data, while the other does not. Such specialization in data monetization generates higher profits for both platforms. Under certain conditions, one platform may also specialize in providing solely payment services. This scenario happens when platforms' data analytic technology exhibits increasing return to scale, and consumers' data is more effective at improving matching efficiency in online markets when data is concentrated in one platform. The increase in matching efficiency leads to higher consumption in online markets and a higher demand for platform payment services. As a result, the platform that specializes in payment services also benefits from the data monopoly.

This paper contributes to two strands of literature. One that studies privacy and the emerging literature that explores the provision of private payment services by platforms. Papers that study privacy and data monetization in non-monetary settings include Acemoglu et al. (2019), Bergemann et al. (2020), and Ichihashi (2020, 2021).[3] These authors assume that it is the buyers who decide whether to disclose their personal information in exchange for better production recommendations or customization. The downside of disclosing personal information is the risk of price discrimination. We complement this literature by emphasizing the role of digital platforms in the provision of privacy. We find that it is possible for platforms to offer privacy even when consumers have limited control over the data they share.

When payments are explicitly considered, the seminal paper on privacy by Kahn et al. (2005) argues that cash payments can deliver privacy by protecting buyers' personal information. Along the same lines, Garratt and Van Oordt (2021), Lee and Garratt (2021), Kang (2021), and Guennewig (2021) assume that transaction data can be used to predict buyers' preferences through data analytics. This information may lead to price discrimination and data monopoly. In such cases, consumers may choose to use privacy-preserving payment instruments (such as cash) to protect their information. Other work focuses on the negative consequences of privacy (tax evasion and money laundering) includes Wang (2020, 2023) and Xiao (2021). In contrast to these papers, we focus on data monetization by digital platforms, where consumers often do not have a choice over what information they share, unless they do not use the platforms' services. This gives platforms the power to determine how they use consumers' data.

Within the emerging literature that explores the provision of private payment services by platforms, Chiu and Wong (2021) study a platform's business model choice between accepting cash and issuing tokens. The authors find that the platform issues tokens if the interest rate is high, the platform scope is large, and the cyber risk is small. This outcome is not necessarily socially optimal because the platform does not internalize its impacts on off-platform activities. We complement this work by exploring effect of platform payment services on data monetization and the provision of privacy.

The paper closest to ours is Chiu and Koeppl (2020), who study digital platforms' monetization of consumer data and how platform payment services affect monetization strategies. The authors show that there is a trade-off between the value of such data and users' privacy concerns. This is the case as platforms need to compensate users for their privacy loss by subsidizing activities. The authors find that when data can help the provision of better payments (data-driven payments), platforms have little incentive to adopt payment systems. In contrast, when

[3]See also Easley et al. (2018), Choi et al. (2019), and Bergemann et al. (2020). Acquisti et al. (2016) for a broad review of the literature regarding privacy.

payments generate additional data (payments-driven data), platforms may adopt payments inefficiently. We complement their work, by deriving the necessary and sufficient conditions for platforms to offer privacy. We show how such conditions are affected by platform payment services, payment data monetization, as well as platform competition.

The rest of the paper is organized as follows. Section 2 describes the environment. Section 3 solves the benchmark equilibrium with cash as the only payment instrument. Section 4 introduces platform payment services, while Section 5 studies the effects of platform competition. Section 6 discusses the empirical relevance of our results and its policy implications. Finally, Section 7 concludes the paper.

2 Environment

Our framework builds on Lagos and Wright (2005) and Rocheteau and Wright (2005). Time is discrete, denoted by t, and each period is divided into two sub-periods. The first sub-period is characterized by a decentralized market (DM), and the second sub-period by a centralized and frictionless market (CM). There is a unit measure of infinitely-lived buyers and a large measure of infinitely-lived sellers. Both types of agents discount time periods at a rate $\beta \in (0, 1)$. In the DM, buyers consume a DM good that can only be produced by sellers. Buyers and sellers in DM are anonymous to each other, thus credit is not feasible, and medium of exchange is necessary for trade to take place. We assume there exists a fiat money (cash) supplied by a government. In the CM, both sellers and buyers can produce and consume a homogeneous CM good. In the CM, there is also a monopolistic digital platform that offers digital services valued by buyers.[4] We assume that at the end of each CM, the platform distributes its profits to buyers and sellers.

A buyer's instantaneous utility is given by

$$\mathcal{U}_b \equiv u(q_t) + x_t - h_t + \mathcal{P}_t, \tag{2.1}$$

where q_t, x_t, and h_t are the consumption of DM goods, consumption of CM goods, and labor supplied in CM, respectively. The payoff derived from platform services, $\mathcal{P}_t$, is given by

$$\mathcal{P}_t = a\tau_t - v(\tau_t) - c\,\mathbb{1}(\mathcal{M} = 1),$$

where τ_t is time spent on the digital platform and $a > 0$ is a constant. The function $v(\tau_t)$

[4] These services can be interpreted as social networking or video streaming. In Section 5, we relax the assumption of a monopolistic digital platform by introducing platform competition. In Appendix B, we further extend the model by assuming free entry of digital platforms.

represents the opportunity cost of consuming platform services, which is the time that could have been spent on other activities. We assume $u'(\cdot) > 0$, $u''(\cdot) < 0$, $u'(0) = \infty$ and $u'(\infty) = 0$, while $v'(\cdot) > 0$, $v''(\cdot) > 0$, and $v(0) = v'(0) = 0$. The constant c denotes the buyer's privacy cost when the platform decides to use her data and $\mathbb{1}$ is an indicator function that takes the value of one when buyers' data is monetized, zero otherwise. The privacy cost captures the risk of buyers' data being leaked or misused as a result of the platform's data monetization.[5] A seller's instantaneous utility is given by

$$\mathcal{U}_s \equiv -l_t + X_t - H_t, \tag{2.2}$$

where l_t is labor supplied in DM, X_t is the consumption of CM goods, and H_t is labor supplied when producing CM goods. Only sellers can produce the DM goods by transforming one unit of their labor into one unit of DM goods.

In the DM, there exists an *offline* market for agents to trade the DM good. In this market, buyers and sellers are randomly and bilaterally matched. The matching function is given by

$$M^O(B_t^O, S_t^O) = \alpha \min\{B_t^O, S_t^O\}, \tag{2.3}$$

where B_t^O and S_t^O are the measures of buyers and sellers in the offline market, respectively, and $\alpha \in (0, 1)$ denotes the matching efficiency. This *offline* market is costless for buyers to enter, but sellers must pay a cost k^O, in terms of the CM good, in the preceding CM. This cost can be interpreted as resources needed to up and operate brick-and-mortar stores. The terms of trade in the *offline* market are determined via an ex-post proportional bargaining protocol, where buyers' bargaining power is equal to $\theta \in (0, 1)$.

In the CM, the digital platform provides services to buyers for a fixed fee s_t.[6] For simplicity, the cost of producing platform services is assumed to be zero. The platform may also monetize the data collected from buyers' platform activities by paying a fixed cost $\mathcal{C}$ and setting up an *online* market for the DM. Similar to the offline market, the matching in the online market is random and bilateral, and the terms of trade are determined by proportional bargaining. In contrast to the offline market, buyers' data can be used to improve matching efficiency in the online market. Specifically, the matching process is governed by the following function

$$M^P(B_t^P, S_t^P, \mathbb{T}_{t-1}) = g(\mathbb{T}_{t-1}) \min\{B_t^P, S_t^P\}, \tag{2.4}$$

where B_t^P and S_t^P are the measures of buyers and sellers in the online market, respectively, and

[5] We refer to Kahn et al. (2005) for more on privacy concerns.

[6] We show later that a fixed fee is optimal, because it does not distort buyers' choice of τ_t.

$\mathbb{T}_{t-1}$ is the total consumption of platform services by buyers in the preceding CM

$$\mathbb{T}_{t-1} \equiv \int_{\iota} \tau_{t-1}^{\iota} \, \mathrm{d}\iota, \tag{2.5}$$

where τ_{t-1}^{ι} is buyer ι's consumption. We assume that $g'(\cdot) > 0$ and $g(\infty) = 1$, and that $g(0) = \alpha$, so the matching in the online market is at least as efficient as the matching in the offline market. The interpretation of function g is as follows. We assume that buyers have heterogeneous preferences regarding the characteristics of the DM good, which are determined by an idiosyncratic shock at the beginning of each CM. Data collected from buyers' activities on the platform can be used to infer buyers' preferences, and the inference is more accurate if buyers consume more platform services.[7] The knowledge of buyers' preferences can then be shared with sellers to improve the matching efficiency in the online market. We assume that the platform announces its data monetization policy at the beginning of the CM.

Recall that buyers incur a utility cost c if the platform monetizes their data. We interpret it as the risk of buyers' information being leaked or misused in the monetization process. Furthermore, we assume that buyers will incur the utility cost c unless the platform does not set up the online market. This is to capture the fact that in practice, all digital platforms employ proprietary algorithms and confidential operational arrangements, which prevents consumers from verifying if their privacy is indeed protected. Hence, as long as a platform has the incentive to monetize buyers' data (i.e., when it has paid $\mathcal{C}$ to set up the online market), it cannot credibly commit to not monetizing buyers' data. Finally,

To enter the online market, buyers and sellers must pay fees b_t and k_t^P to the platform, respectively. However, we assume that not all buyers can trade in the online market. Specifically, at the beginning of each CM, buyers receive another idiosyncratic shock in addition to the preference shock. With probability ρ, a buyer is a P-type, and her desired DM good is available in both online and offline markets (e.g., clothes, electronics, and certain groceries). With probability $1 - \rho$, a buyer is an N-type, and her desired DM good is only available in the offline market (e.g., massages, some groceries, and most medical procedures). This assumption guarantees that there are always buyers who shop in the offline market, which in turn means there are always sellers in the offline market. As we will show later, this ensures that the offline market serves as an outside option for buyers.

Figure 1 summarizes the timing as well as the main features of our environment.

[7] The digital platform in this paper is more akin to Facebook or YouTube than Amazon or eBay in the sense that the main services provided are not online shopping, and that buyers' data generated by platform services helps the platform connect buyers with sellers.

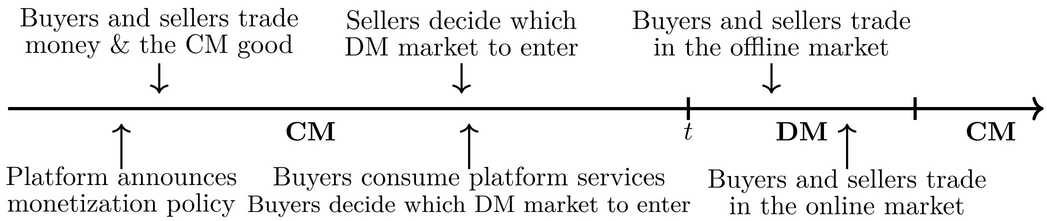


Figure 1: Sequence of Events

3 Equilibrium

Throughout the rest of the paper, we focus on stationary equilibria where all real variables remain constant over time. Let μ denote the long-run inflation rate associated with fiat money. We assume that $\frac{1+\mu}{\beta} > 1$.

In what follows, we first take the buyers' fee to use platform services, s, and the buyers' and sellers' fees to enter the online market, b and k^P, as given. Then, we solve for the optimal fees that maximize the platform's profit, while taking into account buyers' and sellers' behavior.

3.1 Agents' Problems in DM

We first solve agents' DM problems taking as given the total consumption of platform services by buyers in the previous period, $\mathbb{T}$. Suppose the platform sets up the online market and monetizes buyers' data. Consider a buyer who is matched with a seller in the online market. Let q and z denote the quantity of DM goods produced and the corresponding payment (in real term), respectively. Let z^P denote the buyer's holdings of real balances. According to proportional bargaining, the optimal terms of trade solve the following problem.

$$\max_{q,z}\{u(q) - z\} \text{ s.t. } u(q) - z = \frac{\theta}{1-\theta}(z - q) \text{ and } z \leq z^P. \tag{3.1}$$

The solution is such that $q^P = \min\{\tilde{q}^P, q^*\}$, where $\theta\tilde{q}^P + (1-\theta)u(\tilde{q}^P) = z^P$ and q^* is the first DM consumption, which satisfies $u'(q^*) = 1$.

Before analyzing sellers' entry decisions, we consider the optimal holding of real balances of a buyer who chooses to go to the online market in the next DM. Due to inflation, to accumulate z^P units of real balances for the next period, a buyer needs to supply $(1+\mu)z^P$ units of labor in CM. The optimal holding of real balances solves the following problem.

$$V^P(\mathbb{T}) \equiv \max_{z^P}\left\{-(1+\mu)z^P + \beta g(\mathbb{T})\min\{1, \nu^P\}\theta[u(q^P) - q^P] + \beta z^P\right\}, \tag{3.2}$$

where B_t^P and S_t^P are the measures of buyers and sellers in the online market, respectively. The seller-to-buyer ratio is given by $\nu^P \equiv \frac{S^P}{B^P}$, and $\theta[u(q^P) - q^P]$ is the payoff for the buyer if she meets a seller in the online market, which happens with the following probability

$$\frac{g(\mathbb{T})\min\{B^P, S^P\}}{B^P} = g(\mathbb{T})\min\{1, \nu^P\}.$$

If she does not meet a seller, she carries the z^P units of real balances to the next CM. Having described the buyer's optimal portfolio, we can establish the following result.

Lemma 1 *If $\nu^P < 1$, z^P and q^P are strictly increasing in ν^P. If $\nu^P \geq 1$, then z^P and q^P are independent of ν^P. In either case, $V^P(\mathbb{T})$ is strictly increasing in $\mathbb{T}$.*
Proof: see Appendix A.

Now, let us now consider sellers' entry problem. The probability of a seller being matched with a buyer in the online market is given by

$$g(\mathbb{T})\min\{1, 1/\nu^P\},$$

and the seller's payoff is $(1-\theta)[u(q^P) - q^P]$. If $\nu^P < 1$, then as more sellers join the online market, buyers will increase their cash holdings. This implies that the expected surplus of a seller is strictly *increasing* in ν^P. In other words, if $\nu^P < 1$, a larger seller-to-buyer ratio attracts *more* sellers to the online market. This means that $\nu^P \geq 1$ is necessary for the following free entry condition to be satisfied.

$$\beta g(\mathbb{T})\min\{1, 1/\nu^P\}(1-\theta)[u(q^P) - q^P] = k^P. \tag{3.3}$$

Note that the seller's expected surplus is discounted by β because the entry fee , k^P, is paid to the platform in the previous CM. We can now conclude that, in the online market, buyers are matched with probability $g(\mathbb{T})$, while sellers are matched with probability $g(\mathbb{T})/\nu^P$.

So far, we have assumed implicitly that the measure of buyers, B^P, in the online markets is strictly positive. However, it is possible that all buyers choose the offline market, which implies $B^P = 0$. Now, suppose $B^P = 0$, and consider a buyer who deviates by visiting the online market. Since $B^P = 0$, the seller-to-buyer ratio in the offline market, ν^P, is not well-defined. In such case, we follow Chang (2018) and assume that the buyer expects the seller-to-buyer ratio to be the lowest that would still attract sellers to enter the online market. In other words, the buyer-to-seller ratio in the offline market is such that the free entry condition (3.3) is satisfied. Intuitively, this assumption implies that the buyer expects sellers to queue up in the online market until it is not profitable to do so. It is then straightforward to show that under this assumption, the payoff for the deviating buyer is given by $V^P(0)$, which solves (3.2) given $\mathbb{T} = 0$.

Next, we consider the offline market. Let q^O represent the quantity traded DM in the offline market and z^O denote a buyer's holding of real balances. The optimal terms of trade are given by $q^O = \min\{\tilde{q}^O, q^*\}$, where $\theta\tilde{q}^O + (1-\theta)u(\tilde{q}^O) = z^O$. To decide the optimal choice of z^O, buyers solve the following problem.

$$V^O \equiv \max_{z^O} \left\{ -(1+\mu)z^O + \beta\alpha \min\{1, \nu^O\}\theta[u(q^O) - q^O] + \beta z^O \right\}, \tag{3.4}$$

where B_t^O and S_t^O are the measures of buyers and sellers in the offline market, respectively. The free entry condition for the offline market is given by

$$\beta\alpha \min\{1, 1/\nu^O\}(1-\theta)[u(q^O) - q^O] = k^O. \tag{3.5}$$

Similar to the online market, we have $\nu^O \equiv \frac{S^O}{B^O} \geq 1$. Hence, in the offline market, buyers are matched with probability α, while sellers are matched with probability α/ν^O, where ν^O solves (3.5). It should be noted that, unlike the online market, the measure of buyers in the offline market is always strictly positive. This is because a fraction $1-\rho$ of buyers only consume goods sold in the offline market.

Finally, recall that P-type buyers who joined the platform in the previous CM have the option to choose between the online and the offline markets. It is clear that $V^P(\mathbb{T}) \geq V^O$, with strict inequality if $\mathbb{T} > 0$. We assume that a buyer prefers the online market if $V^P(\mathbb{T}) = V^O$.

3.2 The Platform's Digital Services

We now turn to buyers' choices of whether to pay the fee, s, to access the platform's digital services and how much time to spend on them. Let U denote the value of platform services experienced by buyers (excluding potential privacy cost).

$$U \equiv \max_{\tau}\{a\tau - v(\tau)\}. \tag{3.6}$$

It is straightforward to verify that there is a unique solution, τ^*, which is implicitly defined by $v'(\tau^*) = a$. Note that τ^* does not depend on buyers' surplus in the following DM regardless of whether the platform monetizes buyers' data or not. This is because the matching efficiency in the online market only depends on the aggregate time spent by all buyers in the platform, $\mathbb{T}$.

Now, suppose that the platform does not monetize buyers' data. Buyers will pay the fee, s, to use platform services if and only if $U \geq s$. From now on, we assume that buyers pay the fee if they are indifferent. Next, assume that the platform monetizes buyers' data. P-type buyers will pay the fee s to use platform services if and only if $U - c \geq s$. Furthermore, P-type buyers will also pay the fee, b, to enter the online market if

$$V^P(\mathbb{T}) - V^O \geq b. \tag{3.7}$$

Since there is measure one of buyers, we can conclude that $\mathbb{T}$ is given by

$$\mathbb{T} = \begin{cases} \tau^*, \text{ if } U - c \geq s; \\ 0, \text{ if } U - c < s. \end{cases} \tag{3.8}$$

3.3 The Platform's Problem

The digital platform maximizes its profit by choosing the various fees (s, b, and k^P) and by deciding whether to monetize buyers data or not. In what follows, we first solve for the optimal fees (s, b, and k^P) taking as given the platform's monetization choice. Then we solve for the optimal monetization policy.

Assume first that the platform chooses to monetize buyers' data. Let $\gamma^T(s) \in [0, 1]$ denote the share of buyers who pay the fee s to access the platform's digital services. Let $\gamma^P(b) \in [0, \rho]$ represent the share of buyers who pay the fee b to enter the online market. Then, the total fee income from buyers is given by $\gamma^T(s)s + \gamma^P(b)b$, and the fee income from sellers is given by

$$k^P S^P = \beta g(\mathbb{T}) B^P (1-\theta)[u(q^P(\mathbb{T})) - q^P(\mathbb{T})] = \beta \gamma^P(s) g(\mathbb{T})(1-\theta)[u(q^P(\mathbb{T})) - q^P(\mathbb{T})], \tag{3.9}$$

where the first equality uses the free entry condition (3.3). The results in Sections 3.1 and 3.2 imply that $\mathbb{T} = \gamma^T(s)\tau^*$ and $\theta q^P(\mathbb{T}) + (1-\theta)u(q^P(\mathbb{T})) = z^P(\mathbb{T})$, where $z^P(\mathbb{T})$ solves problem (3.2). The platform's profit can then be written as

$$\Pi^M(s, b) \equiv \gamma^T(s)s + \gamma^P(b)\{b + \beta g(\gamma^T(s)\tau^*)(1-\theta)[u(q^P(\gamma^T(s)\tau^*)) - q^P(\gamma^T(s)\tau^*)]\} - \mathcal{C}.$$

Notice that the platform's profit does not depend on the sellers' fee, k^P, to access the online market. This is because an increase in k^P always leads to a decrease in S^P, while leaving $k^P S^P$ unchanged. It is straightforward to show then that the profit-maximizing fees are given by $s = U - c$ and $b = V^P(\tau^*) - V^O$. Now, let Π^{M*} denote the profits when s and b are chosen optimally, and the platform opts to monetize buyer's data. We have

$$\Pi^{M*} = U - c + \rho\{V^P(\tau^*) - V^O + \beta g(\tau^*)(1-\theta)[u(q^P(\tau^*)) - q^P(\tau^*)]\} - \mathcal{C} \tag{3.10}$$

When the platform does not monetize buyers' data, it is straightforward to see that the profit is maximized if $s = U$. The platform's profit is therefore given by $\Pi^{N*} = U$.

Now, we derive the optimal monetization policy. We assume that the platform monetizes buyers' data if it is indifferent. Then, data monetization is optimal if and only if $\Pi^{M*} - \Pi^{N*} \geq 0$.

Definition 1 *An equilibrium consists of buyer's fees and DM consumption, $\{s, b, q^P, q^O\}$, share of buyers using platform services and share of buyers buying in the online market, $\{\gamma^T(s), \gamma^P(b)\}$, as well as the digital platform's data monetization policy that satisfy:* (i) *q^P and q^O solve buyers' problems in DM; and* (ii) *s, b, and the data monetization policy maximize the platform's profit.*

Proposition 1 *There exists a unique stationary equilibrium. Furthermore, $\Pi^{M*} - \Pi^{N*}$, is strictly increasing in the share of P-types (ρ) and the data analytic technology ($g(\cdot)$) and strictly decreasing in the long-run inflation rate (μ).*
Proof: see Appendix A.

It is easy to see that by substituting the definitions of $V^P(\tau^*)$ and V^O (see problems (3.2) and (3.4)) into the optimal platform profits, we can write $\Pi^{M*} - \Pi^{N*}$ as follows

$$\begin{aligned}\Pi^{M*} - \Pi^{N*} = \rho\{\beta &\left[g(\tau^*)[u(q^P) - q^P] - \alpha\theta[u(q^O) - q^O]\right] \\ &- (1 + \mu - \beta)[(1 - \theta)u(q^P) + \theta q^P - (1 - \theta)u(q^O) - \theta q^O]\} - c. \qquad (3.11)\end{aligned}$$

Proposition 1 shows that, in addition to the privacy cost, c, and monetization cost, $\mathcal{C}$, the optimality of data monetization depends on the following three factors.

(1) The size of the online market (ρ). The platform profits from both buyers and sellers in the online market. The existence of N-type buyers (whose DM goods are only available in the offline market) limits the profitability of the platform's data monetization. In the next section, we show how the platform may nevertheless profit from the trade in the offline market by attracting N-type buyers to use a platform-issued payment instrument.

(2) Inflation (μ). The cost of holding money affects the intensive margin of the platform's online market. Recall that the consumption in the online market, q^P, is given by

$$u'(q^P) = \frac{\beta\theta g(\tau^*) + \theta(1 + \mu - \beta)}{\beta\theta g(\tau^*) - (1 - \theta)(1 + \mu - \beta)}. \qquad (3.12)$$

It is easy to check that given ρ, higher inflation (μ) decreases q^P. This in turn lowers the total surplus in the online market and the fees that can be charged to buyers and sellers. In the next section, we show how the platform manipulate the intensive margin in both online and offline markets by paying interest on the platform-issued payment instrument.

(3) The platform's data mining technology ($g(\tau^*)$). The data technology available to the platform determines the matching efficiency in the online market. Note that for any given ρ and

μ, a higher $g(\tau^*)$ (which may be achieved through better data analytic technology) increases q^P. This enables the platform to charge higher fees. In the next section, we show how data collected by the platform via its payment instrument may aid data analytics and further improve matching efficiency.

Before ending this section, we explore if the platform's data monetization policy is socially efficient. Aggregate welfare is defined to be the equal-weighted sum of buyers' and sellers' utility. Let $\mathcal{W}^M$ denote the aggregate welfare when the platform monetizes buyers' data.

$$\mathcal{W}^M = -c - \mathcal{C} - S^O k^O + U + \beta\rho g^M[u(q^P) - q^P] + \beta(1-\rho)\alpha[u(q^O) - q^O]. \tag{3.13}$$

Notice that the online market's entry cost does not appear in (3.13). This is because, by assumption, the platform distributes its profit to buyers and sellers at the end of CM. The production and consumption of CM goods do not appear in (3.13) either, because they cancel each other out due to buyers' and sellers' linear CM preferences. Finally, the surplus in DM is discounted because the costs (c, $\mathcal{C}$, and k^O) are incurred in the preceding CM.

Next, suppose the platform does not monetize buyers' data. Aggregate welfare in such scenario, $\mathcal{W}^N$, is given by

$$\mathcal{W}^N = U + \beta\alpha\theta[u(q^O) - q^O]. \tag{3.14}$$

We can now establish the following result.

Proposition 2 *The platform's data monetization policy is socially inefficient. Specifically,* $\Pi^{M*} - \Pi^{N*} \geq 0$ *implies* $\mathcal{W}^M \geq \mathcal{W}^N$*, but* $\mathcal{W}^M \geq \mathcal{W}^N$ *does not imply* $\Pi^{M*} - \Pi^{N*} \geq 0$.
Proof: see Appendix A.

Proposition 2 highlights that the platform may choose not to monetize buyers' data even when data monetization increases aggregate welfare. To see why, note that by monetizing buyers' data, the platform improves matching efficiency in the online market. This in turn provides incentives for buyers to bring more real balances to trade in DM. However, holding more money is costly due to inflation. As a monopoly, the platform fully internalizes this cost when considering buyers' fees. Hence, when the data mining technology cost, $\mathcal{C}$, is neither too large nor too small, data monetization does not happen even when it is socially efficient.

This result seemingly runs counter to the popular belief that digital platforms, such as Facebook, over-monetize buyers' data. It is important to note that our result hinges on the assumption that consumers are fully aware of the privacy cost from data monetization. As a result, they demand compensation when the platform monetizes their data. In other words, buyers' fee, s, is comparatively lower to compensate for the privacy cost, c. If consumers are unaware of the risk of their personal information being leaked or misused, then the platform will not need to compensate buyers. In such a scenario, the platform may monetize buyers' data even when it is not the socially optimal policy.

4 Platform Payment Service

In this section, we allow the digital platform to introduce a payment service. Specifically, the platform may issue *platform tokens*, which can be directly transferred among agents in both online and offline markets. The platform tokens are nominal, and they can be exchanged one-for-one for fiat money in CM. The platform also promises to pay a nominal interest rate, R, on its tokens when held for one period. We allow the possibility that when the platform sets up the online market and monetizes buyers' data, the interest on tokens may differ depending on whether the tokens are used in the online market ($R = R^P$) or in the offline market ($R = R^O$). To be able to issue tokens, the platform is required by the government to hold cash reserves equal to a fraction $\delta \in [0, 1]$ of the nominal value of the outstanding tokens. We focus on two cases: $\delta = 1$ and $\delta = 0$. When $\delta = 1$, platform tokens are similar to account balances in Apple Cash, PayPal, and Venmo, which are backed entirely by commercial deposits. When $\delta = 0$, platform tokens are similar to unbacked private digital currencies such as Bitcoin or Ether.

In what follows, we first discuss the optimal choices of R^P and R^O and how the issuance of platform tokens affects the platform's monetization policy. In Section 4.2, we allow the platform to collect data from buyers via platform tokens. Throughout this section, we assume that buyers use platform tokens instead of fiat money if they are indifferent.

4.1 Tokens and Data Monetization Policies

Since platform tokens are nominal, if the interest on tokens is lower than 0, no buyers in the online market will use tokens. If the interest on tokens is larger than $\frac{1+\mu-\beta}{\beta}$, then the demand for them will be infinite. Thus, the lower and upper bounds of the nominal interest rates on platform tokens (R^P and R^O) are 0 and $\frac{1+\mu-\beta}{\beta}$, respectively.

Suppose that the platform sets up the online market and monetizes buyers' data. Let m^P_{t+1} (m^O_{t+1}) denote a buyers' holding of tokens in the online (offline) markets at the beginning of period $t + 1$. Let $\pi^P_t(R^P)$ denote the real profit from selling m^P_{t+1} units of tokens in CM in period t. This profit is given by

$$\pi_t^P(R^P) \equiv \frac{m_{t+1}^P(1-\delta)}{p_t} - \beta\left(\frac{(1+R^P)m_{t+1}^P - m_{t+1}^P\delta}{p_{t+1}}\right), \tag{4.1}$$

where p_t denotes the price of CM goods in period t. Note that m_{t+1}^P is the platform's nominal cash income from selling tokens in CM of period t. A fraction δ of this income must be kept as reserves. However, these can be used later to satisfy the next period's nominal liabilities, which are given by $(1+R^P)m_{t+1}^P$. Now, define the real value of tokens in terms of CM goods (interest included) in period $t+1$ as $z_{t+1}^P \equiv (1+R^P)m_{t+1}^P/p_{t+1}$.We can now rewrite (4.1) as follows

$$\pi_t^P(R^P) = z_{t+1}^P[(1-\delta)(1+\mu-\beta) - \beta R^P]/(1+R^P). \tag{4.2}$$

Similarly, let z_{t+1}^O denote the real value of tokens held by a buyer in the offline market in period $t+1$. The real profit from selling z_{t+1}^O worth of tokens to offline buyers is then given by

$$\pi_t^O(R^O) \equiv z_{t+1}^O[(1-\delta)(1+\mu-\beta) - \beta R^O]/(1+R^O). \tag{4.3}$$

In what follows, we omit the time subscript so long as there is no confusion. Using the results from Section 3.3, it is straightforward to derive the platform's total profit.

$$\begin{aligned}\Pi^M =& U - c + \rho\{V^P(R^P) - V^O(R^O) + \beta g(\tau^*)(1-\theta)[u(q^P) - q^P]\} \\ &+ \underbrace{\rho\pi^P(R^P) + (1-\rho)\pi^O(R^O)}_{\text{Profit from token issuance}} - \mathcal{C},\end{aligned} \tag{4.4}$$

where $V^P(R^P)$ and $V^O(R^O)$ are buyers' value functions that are given by

$$V^P(R^P) = \max_{z^P}\left\{-[(1+\mu)/(1+R^P) - \beta]z^P + \beta g(\tau^*)\theta[u(q^P) - q^P]\right\}, \tag{4.5}$$

$$V^O(R^O) = \max_{z^O}\left\{-[(1+\mu)/(1+R^O) - \beta]z^O + \beta\alpha\theta[u(q^O) - q^O]\right\}. \tag{4.6}$$

If the platform does not monetize buyers' data, then tokens are only used in the offline market. The platform's profit is therefore given by $\Pi^N = U + \pi^O(R^O)$.

It is important to highlight that the platform faces several trade-offs when choosing its interest rate policy on tokens. First, a higher interest incentivizes buyers to consume more in DM. As a result, there is an increased demand for tokens. However, a high interest rate also decreases the real profit per token issued. In particular, it is easy to show that equations (4.2) and (4.3) imply that if the interest on tokens is larger than $(1-\delta)(1+\mu-\beta)/\beta$, then the profit becomes negative. Second, if the platform monetizes buyers' data, then in addition to income from token issuance, the platform also profits from buyers' and sellers' fees, which are increasing in R^P because the fees depend on buyers' and seller's surpluses, $V^P(R^P)$, and $\beta g(\tau^*)(1-\theta)[u(q^P)-q^P]$, respectively. In contrast, a higher R^O decreases the platform's fee income, because buyers' surplus in the offline market, $V^O(R^O)$, is increasing in R^O.

Let us now denote the optimal nominal interest choices when the platform monetizes buyers' data as R^{P*} and R_M^{O*}. Similarly, let R_N^{O*} represent the optimal nominal interest choice when the platform does not monetize buyers' data. Finally, let Π^{M*} and Π^{N*} denote the optimal profits when data is monetized and when it is not, respectively.

Proposition 3 *The optimal interest rate policies are given by the following:*
(i) *When $\delta = 0$, nominal interest rates are such that $0 \leq R_M^{O*} < R^{P*} = \frac{1+\mu-\beta}{\beta}$. In addition, $R_M^{O*} \leq R_N^{O*}$ with strict inequality when $R_N^{O*} > 0$.*
(ii) *When $\delta = 1$, nominal interest rates are such that $0 = R_M^{O*} = R_N^{O*} < R^{P*}$.*
In both cases, $\Pi^{M*} - \Pi^{N*}$ increases after the platform issues tokens.
Proof: see Appendix A.

As we can see, the nominal interest on tokens associated with payments in the online market (R^P) is higher than the nominal interest on tokens used in the offline market (R^O). This is because the platform benefits from a high R^P through the fees collected from buyers and sellers. When $\delta = 0$, tokens allow the platform to also profit from the trade in the offline market. However, the profitability of the offline market is limited because the platform cannot collect additional fees from buyers and sellers. As a result, the platform has less incentive to offer a high nominal interest rate. When the platform monetizes buyers' data, R^O is even lower. This is because the platform has the incentive to decrease the surplus in the offline market, which serves as the outside option for buyers. This allows the platform to promote trade in the online market and discourage trade in the offline market.[8]

Next, we analyze whether the platform's data monetization decision is socially optimal. Recall that aggregate welfare is defined by (3.13) and (3.14).

Proposition 4 *If the platform issues tokens, then depending on parameter values, the platform may under- or over-utilize buyers' data. However, there exists an inflation rate μ' such that if $\mu \leq \mu'$ and $\delta = 0$, then*
(i) *The platform's data monetization decision is socially optimal.*
(ii) *Aggregate welfare is higher when the platform issues tokens and monetizes buyers' data.*
Proof: see Appendix A.

[8]There are many examples of similar pricing strategies in practice. See Section 6 for more details.

Recall that when the platform does not issue tokens, it tends to under-utilize buyers' data, i.e., the platform may opt not to monetize buyers' data even when monetization is socially optimal (see Proposition 2). It is because buyers' cost of carrying money (due to inflation) is fully internalized by the monopolistic platform. Such a cost is higher in the online market because buyers consume more (due to the superior matching efficiency) and carry more money. This in turn lowers the value of data monetization to the platform.

When the platform issues tokens, it may over-utilize buyers' data, because tokens used in the online market offer a higher interest rate than tokens used in the offline market. This differential treatment of online and offline markets increases the platform's profits from data monetization (see Proposition 3). Nevertheless, we can show that when inflation is low and $\delta = 0$, the (aforementioned) forces that cause the platform to under and over utilize buyers' data cancel each other out. As a result, the platform's monetization decision is socially optimal. Aggregate welfare is also higher due to the interest on tokens, which promotes trade in DM.

4.2 Payment Data and Monetization

We now consider the possibility that the platform has the option to collect and monetize payment data through the tokens. We assume that in each period, payment data from the *offline* market can be used to complement the data collected through buyers' use of platform services (hereafter "service data") and improve the matching efficiency in the online market. Specifically, we assume that the offline market opens before the online market in the DM, and that payment data from the offline market contains information regarding the characteristics of the DM goods purchased by offline buyers (e.g., the types of meat and dairy products purchased at local grocery stores). Such information can be used to infer other buyers' preferences for online goods (e.g., the types of cookware and kitchen electronics) and aid the matching processing in the online market. We assume that the matching function in the online market is given by

$$M^P(B^P, S^P, \mathbb{T}, \mathcal{P}) = g(\mathbb{T}, \mathcal{P}) \min\{B^P, S^P\}, \tag{4.7}$$

where B^P and S^P are the measures of buyers and sellers in the online market, respectively. $\mathbb{T}$ is the total consumption of platform services by buyers in the preceding CM, and $\mathcal{P}$ is the measure of buyers who choose to use platform tokens in the offline market. We assume that $g_{\mathbb{T}}(\cdot) > 0$, $g_{\mathcal{P}}(\cdot) > 0$, $g(\infty, 1) = 1$, and $g(0, 0) = \alpha$, so the matching in the online market is at least as efficient as the matching in the offline market. Compared to the matching function (2.4) in the benchmark, the only difference is that the matching probability also depends on offline buyers' usage of platform tokens. The matching function in the offline market remains unchanged.

Recall that when the platform monetizes service data, buyers incur utility costs c from data generated when consuming the platform's digital services. Given that there is now additional data being collected, buyers in the offline market incur additional utility costs d. This occurs whenever the platform uses their payment data to improve the matching efficiency in the online market (i.e., when the platform monetizes their payment data). Intuitively, different or more accurate personal information can be extracted from payment data. This generates additional privacy concerns for buyers. In what follows, we allow the platform to also offer a fixed reward equal to λ. This reward is given to buyers who use platform tokens in the offline market. As in the benchmark, the platform announces whether it will monetize payment data at the beginning of the CM. If the platform decides not to monetize payment data, platform tokens will function as described in Section 4.1, and buyers in the offline market do not incur the privacy cost d.

Suppose that the platform sets up the online market and monetizes service and payment data. In the online market, a buyer's expected surplus when she uses platform tokens is

$$V^P(\mathbb{T}, \mathcal{P}) = \max_{z^P} \left\{ -\left(\frac{1+\mu}{1+R^P} - \beta \right) z^P + \beta g(\mathbb{T}, \mathcal{P}) \theta [u(q^P) - q^P] \right\}, \tag{4.8}$$

where we use the result from Section 3.1 that buyer-to-seller ratios in DM markets cannot exceed one. A buyer's expected surplus when she uses platform tokens in the offline market is given by

$$V^O(R^O, \lambda) \equiv \max_{z^P} \left\{ -\left(\frac{1+\mu}{1+R^O} - \beta \right) z^O + \beta \alpha \theta [u(q^O) - q^O] - \beta d + \beta \lambda \right\}. \tag{4.9}$$

Note that a buyer will use platform tokens in the offline market if $V^O(R^O, \lambda)$ is larger than the expected surplus when fiat money is used, which is given by (3.4).

Proposition 5 *Suppose the platform issues tokens and sets up the online market. Then,*
(i) *There exists $\bar{d}_1$ such that if $d \leq \bar{d}_1$, the platform monetizes both service and payment data.*
(ii) *When $\delta = 0$ and when $\delta = 1$, the optimal R^O and λ satisfy $R^O > 0$ and $\lambda < d$.*
(iii) *Under certain parameter values, payment data monetization hurts aggregate welfare.*
Proof: see Appendix A.

As long as the privacy cost d is not too large, the platform finds it profitable to attract buyers in the offline market to use platform tokens. In such a case, tokens in offline markets offer a higher return than cash. This means the platform does not need to compensate buyers in the offline market for the entirety of the privacy cost through the fixed reward (i.e., $\lambda < b$). Now, recall from Proposition 3 that when $\delta = 0$, the platform has the incentive to offer a positive interest rate in the offline market even when it does not monetize payment data. This implies that when the platform does monetize payment data, the interest on tokens, which the platform offers with or without payment data monetization, can partially offset buyers' privacy costs. Consequently, the platform does not fully internalize buyers' privacy costs, and payment data monetization may hurt aggregate welfare.

4.3 Unsecured Credit

In this section, we assume that the platform offers unsecured credit to buyers. Specifically, buyers can borrow from the platform to pay for goods in both online and offline markets. In CM, buyers repay their loans, and the platform transfers the payment to sellers. We assume that the platform can always enforce the loans to buyers, and that it can commit to paying sellers. The platform can charge buyers both a fixed fee, $\mathcal{A}$, and a proportional fee, $\mathcal{R}$ (proportional to the amount of credit used). Both fees are in real term. We allow the fees to differ depending on whether credit is used in the online market ($\mathcal{A}^P$ and $\mathcal{R}^P$) or the offline market ($\mathcal{A}^O$ and $\mathcal{R}^O$).

Proposition 6 *The optimal credit fees satisfy $\mathcal{R}^O = 0$ when the platform does not monetize buyers' data, and $\mathcal{R}^P = \mathcal{R}^O = 0$ when it monetizes buyers' data. Furthermore, the platform's monetization decision is socially efficient.*
Proof: see Appendix A.

A proportional fee distorts the demand for credit and therefore lowers the total surplus in DM. Hence, it is optimal for the platform to charge zero proportional fees and use the fixed fee to extract surplus from buyers. Recall that we obtain a similar result when the platform can issue tokens without holding reserves (i.e., when $\delta = 0$). As shown in Proposition 3, in this case, the platform sets the interest on tokens in the online market to $\frac{1+\mu-\beta}{\beta}$, which eliminates the cost of holding tokens. The platform can then extract buyers' surplus through the buyers' fee to access the online market. Finally, recall that the cost of carrying a payment instrument (i.e., cash or tokens) is fully internalized by the platform. Because platform credit eliminates such a cost, the platform's monetization decision is socially efficient.

5 Platform Competition and Privacy

In practice, many digital platforms compete to offer similar services. In this section we extend the benchmark model to study platform competition. We assume that there are two infinitely-lived digital platforms, which we refer to as platforms A and B.[9] At the beginning of each CM, platforms simultaneously choose: (i) whether or not to set up the online market for DM and monetize buyers' data; (ii) buyers' fee to use platform services, s, and buyers' fee to access the online market, b; and (iii) sellers' fee to access the online market, k^P. For simplicity, we assume that the two platforms have access to the same technologies. Hence, buyers derive the same utility from their platform services, which is given by

$$a\tau_i - v(\tau_i), \tag{5.1}$$

where τ_i is a buyer's time spent on the services from platform $i \in \{A, B\}$. The matching in the platforms' online markets is also governed by the same matching function

$$M^P(B_i^P, S_i^P, \mathbb{T}_i) = g(\mathbb{T}_i)\min\{B_i^P, S_i^P\}, \tag{5.2}$$

where B_i^P and S_i^P are the measures of buyers and sellers in platform i's online market, respectively, and $\mathbb{T}_i$ is the total amount of time spent on platform services in the preceding CM. We maintain the rest of the assumptions in the benchmark model. In particular, we assume that a fraction $1-\rho$ of buyers can only purchase DM goods from the offline market (i.e., N-type buyers), while the rest can choose between the online and offline markets (i.e., P-type buyers).

5.1 Equilibrium With Bertrand Competition

Before solving for the equilibrium with infinitely lived digital platforms, we consider a simpler environment where the two platforms only exist for one period. More precisely, both platforms simultaneously enter the economy at the beginning of CM, choose their monetization policies and prices for their services, and exit the economy before the end of the following DM. We refer the equilibrium of this simplified environment as the "one-shot" equilibrium.

To solve for the equilibrium, first let $\mathbb{U}_i^S$ denote a buyer's expected surplus from paying the fee s_i and accessing platform i's platform services, where $i \in \{A, B\}$. Recall that buyers incur a utility cost c if the platform monetizes their data. We have

$$\mathbb{U}_i^S = \begin{cases} U_i - s_i, \text{ if platform } i \text{ does not monetize buyers' data,} \\ U_i - s_i - c, \text{ if platform } i \text{ monetizes buyers' data,} \end{cases} \tag{5.3}$$

where $U_i = \max\{a\tau_i - v(\tau_i)\}$. We assume that buyers randomly pick one of the two platforms

[9]In Appendix B, we assume free entry of digital platforms. In equilibrium, more than two platforms may enter the economy. However, the main results in this section are unchanged.

if $\mathbb{U}_A^S = \mathbb{U}_B^S$, so each platform attracts half of the buyers.

Next, suppose platform i also sets up the online market and monetizes buyers' data. Let $\mathbb{U}_i^M$ denote a P-type buyer's expected surplus from paying the fee b_i and accessing the online market. Then, $\mathbb{U}_i^M$ is given by

$$\mathbb{U}_i^M = V^P(\mathbb{T}_i) - V^O - b_i, \tag{5.4}$$

where $V^P(\mathbb{T}_i)$ and V^O are buyers' expected surpluses in the online and offline markets:

$$V^P(\mathbb{T}_i) = \max_{z^P} \left\{ -(1+\mu-\beta)z^P + \beta g(\mathbb{T}_i)\theta[u(q^P(\mathbb{T}_i)) - q^P(\mathbb{T}_i)] \right\}, \tag{5.5}$$

$$V^O = \max_{z^O} \left\{ -(1+\mu-\beta)z^O + \beta\alpha\theta[u(q^O) - q^O] \right\}. \tag{5.6}$$

The aggregate time spent by buyers on platform i, $\mathbb{T}_i$, is given by

$$\mathbb{T}_i = \begin{cases} 0, \text{ if } \mathbb{U}_i^S < \mathbb{U}_j^S, \\ \tau^*, \text{ if } \mathbb{U}_i^S > \mathbb{U}_j^S, \\ \frac{\tau^*}{2}, \text{ if } \mathbb{U}_i^S = \mathbb{U}_j^S, \end{cases} \tag{5.7}$$

where $\tau^* = \arg\max\{a\tau - v(\tau)\}$, $j \in \{A, B\}$ and $j \neq i$. If only one platform sets up the online market and monetizes buyers' data, it will attract all P-type buyers as long as $\mathbb{U}_i^M > 0$. We assume that P-type buyers opt the online market if they are indifferent (i.e., when $\mathbb{U}_i^M > 0$). If both platforms monetize buyers' data and $\mathbb{U}_A^M = \mathbb{U}_B^M$, we assume that P-type buyers randomly pick one of the two platforms, so each platform will attract half of P-type buyers.

Let γ_i^S denote the measure of buyers who pay s_i and access platform i's platform services. If platform i does not monetize buyers' data, its profit is given by

$$\Pi_i = \gamma_i^S s_i. \tag{5.8}$$

If platform i monetizes buyers' data, its profit is given by

$$\Pi_i = \gamma_i^S s_i + b_i B_i^P + k_i^P S_i^P - \mathcal{C}. \tag{5.9}$$

The revenue from the online market, $b_i B_i^P + k_i^P S_i^P$, can be rewritten as follows

$$b_i B_i^P + k_i^P S_i^P = b_i B_i^P + \beta g(\mathbb{T}_i) B_i^P (1-\theta)[u(q^P(\mathbb{T}_i)) - q^P(\mathbb{T}_i)], \tag{5.10}$$

where the equality uses the free entry condition (3.3). Now, we are ready to formally define the equilibrium. For simplicity, in the rest of this section, we focus only on pure strategy equilibria.

Definition 2 *An equilibrium consists of vectors $\{s_i, b_i\}$, $i \in \{A, B\}$, and data monetization policies such that $\{s_i, b_i\}$ and platform i's data monetization policy maximize its profit conditional on $\{s_j, b_j\}$ and platform j's data monetization policy, where $j \neq i$.*

The following lemma summarizes the one-shot equilibrium with Bertrand competition.

Lemma 2 *Define Γ_1 and Γ_2 to be such that*

$$\Gamma_1 = \beta(1-\theta)\rho g(\tau^*)u(q^P(\tau^*)) - q^P(\tau^*)] + \rho[V^P(\tau^*) - V^O] - \mathcal{C}, \tag{5.11}$$

$$\Gamma_2 = \beta(1-\theta)\rho g(\tau^*/2)[u(q^P(\tau^*/2)) - q^P(\tau^*/2)] + \rho[V^P(\tau^*/2) - V^O] - \mathcal{C}. \tag{5.12}$$

Then, we have the following properties:
(i) *If $c \geq \Gamma_1$ and $c > 2\Gamma_2$, there exists a unique equilibrium where $s_A = s_B = 0$, $\Pi_A = \Pi_B = 0$, and neither platform monetizes buyers' data;*
(ii) *If $c \geq \Gamma_1$ and $c = 2\Gamma_2$, there exists a unique equilibrium where only one platform (assumed to be platform A) monetizes buyers' data. In equilibrium, $s_A = -c$, $s_B = 0$, $b_A = V^P(\tau^*/2) - V^O$, and $\Pi_A = \Pi_B = 0$;*
(iii) *In all other scenarios, there does not exist an equilibrium.*
Proof: see Appendix A.

To understand the lemma, first note that if neither platform monetizes buyers' data, Bertrand competition implies that $s_A = s_B = 0$. However, for this to be an equilibrium, the platforms must not have an incentive to deviate and monetize buyers' data. Note that for the deviating platform to attract buyers, it must offer $s \leq -c$. If $s < -c$, the deviating platform can attract all buyers. However, $c \geq \Gamma_1$ ensures that the cost of attracting buyers (i.e., c) is larger than the net benefit of data monetization (i.e., Γ_1). If $s_i = -c$, the deviating platform attracts half of the buyers, but $\frac{c}{2} > \Gamma_2$ ensures that the cost of deviation is again larger than the net benefit.

When $c = 2\Gamma_2$, there exists an equilibrium where only one platform monetizes buyers' data. In equilibrium, $s_A = -c$ and $s_B = 0$, so buyers are indifferent between the platforms' services, and each platform attracts half of the buyers. Because $c = 2\Gamma_2$, the net benefit of data monetization is zero. Since $c \geq \Gamma_1$, platform A does not have the incentive to further lower s_A to attract all buyers. Note that if $c < 2\Gamma_2$, platform A will earn a strictly positive profit. Then, platform B has the incentive to choose a slightly lower s_B while also monetizing buyers' data, which would allow platform B to attract all buyers and earn a strictly positive profit.

Finally, when $c < \Gamma_1$ or $c < 2\Gamma_2$, the aforementioned equilibria no longer exist, because the platforms will always have the incentive to deviate. Note that there does not exist an equilibrium where both platforms monetize buyers' data. To see why, first note that for this scenario to be part of an equilibrium, both platforms must be able to attract buyers so that they can pay for the monetization cost $\mathcal{C}$. Furthermore, in equilibrium, the platforms must not earn strictly positive profits. Otherwise, one platform can always increase its profits by lowering the fee s slightly and attract all buyers. However, we show in the proof that even if s_A and s_B are such that $\Pi_A = \Pi_B = 0$ (which implies that $s_A = s_B < 0$), platform i will still have an incentive to further lower s_i and attract more buyers. This is because the cost from subsidizing the access fee can be offset by the increase in the revenue from the online market. As a result, for s to be sufficiently low so that such deviation is no longer profitable, the platforms would be earning negative profits. This cannot be part of an equilibrium, since the platforms can always obtain zero profit by choosing $s = 0$ and opting for no data monetization.

5.2 Infinitely-lived Platforms

In this section, we relax the assumption that platforms only live for one period and consider two infinitely lived digital platforms that enter the model economy in CM of period $t = 0$. Note that because there is no fixed cost to remain in the market, the platforms do not face an exit decision. At the beginning of each CM, platforms simultaneously choose their data monetization policies and their fees $(s_{i,t}, b_{i,t})$. The interactions between the platforms, therefore, constitute a *repeated game* as in Fudenberg and Tirole (1991).

To formally define the repeated game, we must specify the platforms' strategies and payoffs. First, let $a_{i,t}$ denote platform i's choices of monetization policy and fees $(s_{i,t}, b_{i,t})$ in period t. Next, define $a_t \equiv (a_{A,t}, a_{B,t})$, and let $h_t \equiv (a_0, a_1, ..., a_{t-1})$ denote the history of realized actions before period t. We assume that h_t is common knowledge for all t. Platform i's strategy of the repeated game can be written as $\hat{a}_i \equiv \{a_{i,t}(h_t)\}_{t=0}^{\infty}$, which, for all t, maps the history h_t to an action $a_{i,t}$. Platform i's profits/payoffs can be written as follows

$$\hat{\Pi}_i(\hat{a}_A, \hat{a}_B) = \sum_{t=0}^{\infty} \beta^t \Pi_{i,t}(a_{A,t}(h_t), a_{B,t}(h_t)), \tag{5.13}$$

where $\Pi_{i,t}$ is given by either (5.8) or (5.9) depending on the platform's monetization policy. We can now formally define the equilibrium.

Definition 3 *An equilibrium is a set of strategies* $(\hat{a}_A, \hat{a}_B)$ *such that for* $i, j \in \{A, B\}$, $\hat{a}_i$ *maximizes* $\hat{\Pi}_i(\hat{a}_A, \hat{a}_B)$ *given* $\hat{a}_j$.

To solve for the equilibrium, we first define $\underline{\hat{\Pi}}_i$ to be the *minmax value* of platform i.

$$\underline{\hat{\Pi}}_i = \min_{\hat{a}_j} \left[\max_{\hat{a}_i} \hat{\Pi}_i(\hat{a}_A, \hat{a}_B) \right] \tag{5.14}$$

which describes the lowest possible platform i's profit provided that platform i correctly foresees platform j's strategies and reacts optimally. Define $\underline{\hat{a}}_j \equiv \arg\min_{\hat{a}_j} \left[\max_{\hat{a}_i} \hat{\Pi}_i(\hat{a}_A, \hat{a}_B) \right]$. Following game theory literature, we refer to $\underline{\hat{a}}_j$ as the *minmax strategy* against platform i. We can now establish this result.

Lemma 3 $\underline{\hat{\Pi}}_i = 0$ *for* $i \in \{A, B\}$.
Proof: see Appendix A.

It is worth mentioning that platform j earns zero profit while playing $\underline{\hat{a}}_j$. In the proof of the lemma, we also derive explicitly the minmax strategy $\underline{\hat{a}}_j$. Now, we can apply the Folk theorem and obtain the following results.

Lemma 4 *For every feasible payoff vector* $(\hat{\Pi}_A, \hat{\Pi}_B)$ *with* $\hat{\Pi}_i > \underline{\hat{\Pi}}_i$ *for all* i*, there exists* $\underline{\beta} < 1$ *such that for all* $\beta \in (\underline{\beta}, 1)$*, there is an equilibrium with payoffs* $(\hat{\Pi}_A, \hat{\Pi}_B)$.
Proof: see the proof of Theorem 5.1 in Fudenberg and Tirole (1991).

Intuitively, an equilibrium always exists for $(\hat{\Pi}_A, \hat{\Pi}_B)$ that satisfies $\hat{\Pi}_i > \underline{\hat{\Pi}}_i$ for all i. This is because if one platform deviates from the strategies $(\hat{a}_A, \hat{a}_B)$ that generate $(\hat{\Pi}_A, \hat{\Pi}_B)$, the other platform can punish it by playing the minmax strategy forever. This is feasible in our environment because the minmax strategy does not imply a negative profit for the punisher platform. Then, as long as β is sufficiently large, the loss from being punished will be larger than any gain from deviation.

Proposition 4 also suggests that there is a continuum of equilibria. For our analysis to be useful, equilibrium selection is necessary. A frequently used selection criterion requires the equilibrium to be symmetric (i.e., both platforms play the same strategy) and to be Pareto optimal from the two platforms' points of view (Tirole, 1988). In what follows, we require the equilibrium to be symmetric and Pareto optimal if both platforms choose the same data monetization policy. However, we also allow platforms to specialize (i.e., only one platform monetizes buyers' data) as long as it is Pareto *superior*. Next, we describe various possibilities.
Scenario I: Neither platforms monetizes buyers' data. The symmetric and Pareto optimal strategies are given by the following: both platforms choose $s_{i,t} = U$ $\forall t$ unless one platform deviates, then the other platform plays the minmax strategy forever. This strategy implies that

each platform attracts half of the buyers. The platforms' per-period profits are then given by

$$\Pi_{A,t} = \Pi_{B,t} = \frac{U}{2}. \tag{5.15}$$

Scenario II: Both platforms monetize buyers' data. The symmetric and Pareto optimal strategies are as follows: both platforms choose $s_{i,t} = U - c$ and $b_{i,t} = V^P(\tau^*/2) - V^O$ for all t unless one platform deviates, in which case the other platform plays the minmax strategy forever. This strategy profile implies that each platform attracts half of the buyers to its platform services as well as to their online markets. The platforms' per-period profits are then given by

$$\Pi_{A,t} = \Pi_{B,t} = \frac{U-c}{2} + \frac{\rho}{2}\left[\beta(1-\theta)g(\tau^*/2)[u(q^P(\tau^*/2)) - q^P(\tau^*/2)] + V^P(\tau^*/2) - V^O\right] - \mathcal{C}. \tag{5.16}$$

Scenario III: One platform (assume it is platform A) opts to monetize buyers' data, but the other platform does not. Recall that by assumption, for this scenario to potentially be part of an equilibrium, it needs to be Pareto superior to the other scenarios. This implies that both platforms must earn positive profits. Hence, equilibrium strategies must be the following: $s_{A,t} = U - c$, $s_{B,t} = U$, and $b_{A,t} = V^P(\tau^*/2) - V^O$ $\forall t$ unless one platform deviates, then the other platform plays the minmax strategy forever. This implies that each platform attracts half of the buyers to its platform services, while platform A attracts all P-type buyers to its online market. The platforms' per-period profits are given by

$$\Pi_{A,t} = \frac{U-c}{2} + \rho\left[\beta(1-\theta)g(\tau^*/2)[u(q^P(\tau^*/2)) - q^P(\tau^*/2)] + V^P(\tau^*/2) - V^O\right] - \mathcal{C}, \tag{5.17}$$

and $\Pi_{B,t} = \frac{U}{2}$. Now, define $\mathbb{D} \equiv g(\tau^*/2)$, which is the matching probability in the online market. Note that $\mathbb{D}$ determines the profitability of data monetization. The following proposition summarizes the equilibrium with infinitely lived platforms.

Proposition 7 *For any $c > 0$, there exist $\hat{\mathbb{D}}_1(c)$ and $\hat{\mathbb{D}}_2(c)$ such that the unique Pareto optimal equilibrium is given by:*
(i) Scenario II *if* $\mathbb{D} \geq \hat{\mathbb{D}}_2(c)$. (ii) Scenario III *if* $\hat{\mathbb{D}}_1(c) \leq \mathbb{D} < \hat{\mathbb{D}}_2(c)$. (iii) Scenario I *if* $\mathbb{D} < \hat{\mathbb{D}}_1(c)$.
Furthermore, platforms tend to under-utilize buyers' data.
Proof: see Appendix A.

Figure 2 is a visualization the proposition.[10] Platform specialization happens when the profitability of data monetization is neither too high nor too low compared to the privacy cost of data monetization. When $\mathbb{D}$ is sufficiently large or when c is sufficiently small. In such cases,

[10]In this example, we assume that $u(q) = \frac{q^{1-\sigma}}{1-\sigma}$, $\sigma = 0.5$, $\beta = 0.98$, $\mu = 0.02$, $\theta = 0.5$, $\alpha = 0.1$, $\mathcal{C} = 0.01$, $\rho = 0.7$. In addition, c ranges from 0.1 to 1, and $\mathbb{D}$ ranges from 0.5 to 1.

platform B strictly prefers to monetize buyers' data, and no platform provides privacy to buyers.

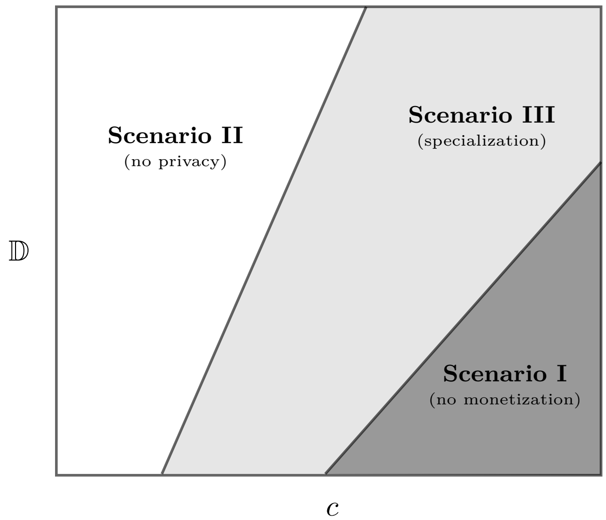
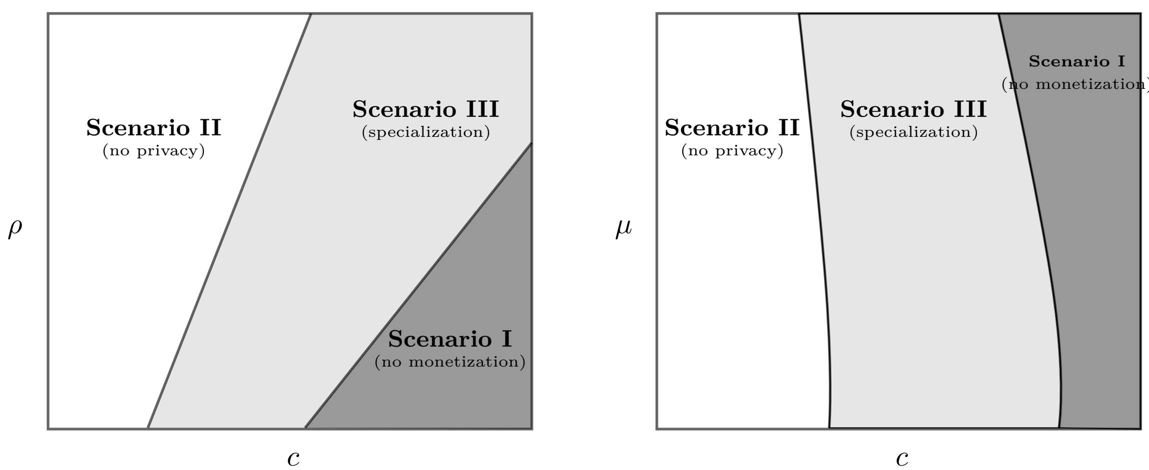


Figure 2: Pareto Optimal Equilibrium Conditional on c and $\mathbb{D}$

In addition to $\mathbb{D}$, the profit from monetization also depends on the following fundamentals: (i) ρ, the measure of P-type buyers, which determines the size of the online market; and (ii) μ, long-run inflation, which determines the total surplus of DM trade. It is straightforward to derive that there are similar cutoff values for ρ and μ that divide the equilibrium into the three scenarios, which are depicted in Figure 3.



(a) Equilibrium Conditional on c and ρ (b) Equilibrium Conditional on c and μ

Figure 3: Pareto Optimal Equilibrium Conditional on ρ and μ

As we can see, similar to $\mathbb{D}$, platform specialization happens only when ρ is neither too large nor too small compared to the privacy cost. The platforms are also less likely to monetize buyers' data when both inflation and privacy costs are high.

5.3 Platforms Payment Services and Data Monetization

We now study how payment services affect platform competition and the provision of privacy once platforms face competition. We modify the model in Section 5.2 by allowing both platforms to issue tokens that can be exchanged one-for-one for cash in CM. The platforms may pay nominal interest rates (R_i, $i \in \{A, B\}$) on tokens. These rates are allowed to differ depending on whether the tokens are used in the platform's online market ($R_i = R_i^P$) or not ($R_i = R_i^O$). As in the benchmark model, the two platforms are required to hold cash reserves when issuing tokens, and we consider two scenarios, $\delta = 1$ and $\delta = 0$, where δ is reserve ratio.

Compared to the repeated game in Section 5.2, the main difference is that, in addition to choosing their data monetization policies and fees $(s_{i,t}, b_{i,t})$ at the beginning of each CM, the platforms will also choose whether to issue platform tokens and decide the nominal interest rates $(R_{i,t}^P, R_{i,t}^O)$. We follow Section 5.2 and require the equilibrium to be symmetric (where both platforms choose identical strategies) and Pareto optimal from the perspective of the platforms unless an asymmetric equilibrium is Pareto superior. We can now establish the following result.

Lemma 5 *If both platforms choose the same monetization policy, then there does not exist an asymmetric equilibrium that is Pareto superior to the Pareto optimal symmetric equilibrium.*
Proof: see Appendix A.

The lemma simplifies the analysis by eliminating the possibility that both platforms benefit from choosing the same monetization policy but different strategies in other dimensions (i.e., $(s_{i,t}, b_{i,t})$ and $(R_{i,t}^P, R_{i,t}^O)$). For an asymmetric equilibrium to be (potentially) Pareto superior, the platforms must specialize and choose different monetization policies. In what follows, we first assume that $\delta = 1$ and define $\mathbb{D} \equiv g(\tau^*/2)$, which is the matching probability in the online market. The following proposition summarizes the resulting equilibrium.

Proposition 8 *Suppose $\delta = 1$. For any $c > 0$, there exist $\tilde{\mathbb{D}}_1(c)$ and $\tilde{\mathbb{D}}_2(c)$ such that:*

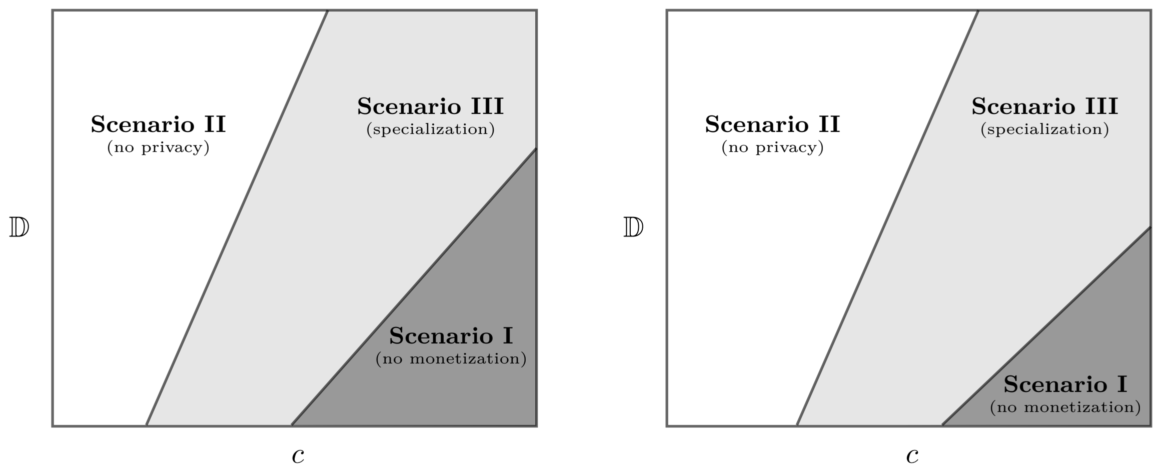
(i) *If $\mathbb{D} \geq \tilde{\mathbb{D}}_2(c)$, both platforms monetize buyers' data in equilibrium.*

(ii) *If $\tilde{\mathbb{D}}_1(c) \leq \mathbb{D} < \tilde{\mathbb{D}}_2(c)$, only one platform monetizes buyers' data in equilibrium.*

(iii) *if $\mathbb{D} < \tilde{\mathbb{D}}_1(c)$, no platform monetizes buyers' data in equilibrium.*

Furthermore, $\tilde{\mathbb{D}}_1(c) < \hat{\mathbb{D}}_1(c)$ and $\tilde{\mathbb{D}}_2(c) < \hat{\mathbb{D}}_2(c)$. In equilibrium, the platforms may under- or over-utilize buyers' data.
Proof: see Appendix A.

The results in Proposition 8 are an extension of the results in Proposition 7. The only difference is that cutoff values, $\tilde{\mathbb{D}}_1(c)$ and $\tilde{\mathbb{D}}_2(c)$, are smaller than the corresponding cutoff values when the two platforms do not issue tokens, $\hat{\mathbb{D}}_1(c)$ and $\hat{\mathbb{D}}_2(c)$ (see Proposition 7). This means that the set of parameters under which the platforms monetize buyers' data is larger when the two platforms issue tokens (see Figure 4 for an example). Intuitively, platform payment services increase the profit of data monetization by allowing the platform to promote trade in the online markets and discourage trade in the offline market. This result is reminiscent of Proposition 3, while the welfare result is reminiscent of Proposition 4.



(a) Equilibrium w/o Platform Payment Services (b) Equilibrium w/ Platform Payment Services

Figure 4: Effect of Platform Payment Services

Now, suppose $\delta = 0$. Recall that the per-period profit from token issuance is given by

$$\pi(R) = \frac{z[(1-\delta)(1+\mu-\beta) - \beta R]}{1+R}, \tag{5.18}$$

where z is the demand for real tokens. It is straightforward to see that when $\delta = 0$, the platforms can earn a profit directly from issuing tokens as long as $R < \frac{1+\mu}{\beta} - 1$.

Proposition 9 *Suppose $\delta = 0$. There exists a set of parameter values such that in the Pareto optimal equilibrium, one platform offers only payment services while the other platform offers platform services and monetizes buyers' data.*
Proof: see Appendix A.

We show in the proof that under certain conditions, the asymmetric equilibrium described in the proposition is Pareto superior, not only to all symmetric equilibria but also to all asymmetric equilibria where both platforms provide platform services. One of the necessary conditions is that $g(\tau^*)$ is sufficiently large while $g(\tau^*/2)$ is sufficiently small. Recall that τ^* is the total consumption of platform services if a platform can attract all buyers. When the condition holds, the profit from data monetization is low if the two platforms compete in offering platform services. This is the case as each platform only attracts half of the buyers. The platforms, therefore, have the incentive to specialize not only in monetization policy but also in platform services. Specifically, one platform (assume it is platform B) offers payment services but not platform services. This allows platform A to attract all buyers, which ensures high matching efficiency in the online market. More importantly, platform B also benefits from the increase in matching efficiency, since the demand for its tokens increases with the expected surplus in the online market. As a result, such specialization results in higher profits for both platforms.

6 Empirical Relevance and Policy Implications

One of the key assumptions of this paper is that digital platforms, rather than their users, have the most control over users' privacy. This is the case as platforms often have proprietary algorithms and confidential operational arrangements. These features were highlighted during the investigations of the 2018 Facebook–Cambridge Analytica data scandal. In particular, Facebook whistleblower, Frances Haugen, stated in a testimony to U.S. Congress that "*[o]nly Facebook knows how it personalizes your feed for you. It hides behind walls that keep the eyes of researchers and regulators from understanding the true dynamics of the system*" (Haugen, 2021). In the aftermath of the scandal, the European Parliament passed the Digital Services Act, which allows regulators to better understand digital platforms' algorithms (The European Union, 2022). Tech giants, such as Google, Facebook, and Amazon, lobbied strongly against the law (The Financial Times, 2020), with Google claiming that the law could hamper Europe's economic recovery from the COVID-19 pandemic (Google, 2020).

A key result of this paper is that when digital platforms offer payment services, the terms of such services can differ depending on where the services are used (see Proposition 3). This pricing strategy allows the platforms to promote trade in their online markets and discourage trade in the offline market, which serves as an outside option for consumers. One example of such a strategy is that of the Apple Card (a credit card issued by Apple). This payment method pays 2% cash back if the Apple Card purchases are made digitally through Apple's mobile phones and computers. However, if purchases are made using the accompanying physical card in offline stores, users only obtain a 1% cash back.[11] In this paper we find that such a strategy

[11]For details on Apple Card, see `https://www.apple.com/apple-card/` A similar example is Amazon's credit card, which offers 3% cash back on online purchases at Amazon.com, but only 1% cash back on other purchases.

can increase digital platforms' profits, but it also distorts platforms' monetization policies. This in turn can potentially reduce aggregate welfare (see Propositions 4 and 8). Furthermore, when digital platforms monetize payment data, they may fail to fully internalize users' privacy costs and hurt aggregate welfare as well (see Proposition 5).

There is ample empirical evidence of digital platforms specializing in the services they provide. Propositions 7 and 8 show that under certain conditions, some platforms opt to monetize users' data, while others choose to offer users privacy. One example of such specialization is Apple's mobile operating system iOS and its Google counterpart, Android. Kollnig et al. (2021) show that iOS has more restrictions on how third-party applications collect user data and track users across different applications. Apple also promises to not sell or share users' personal data.[12] These differences are consistent with the fact that in 2020, more than 80% of Google's revenue comes from advertising, while most of Apple's revenue comes from the sale of iOS devices. Finally, Proposition 9 shows some digital platforms may also specialize in providing payment services. Examples of such specialization include PayPal, Venmo, and Square.

7 Conclusion

In this paper, we characterize conditions under which a monopolistic digital platform finds it profitable to monetize consumers' data. We show that platforms' monetization policies are generally socially inefficient. When the platform does not offer payment services, it tends to under-utilize consumers' data, i.e., platforms may not monetize buyers' data even when it is welfare improving. This is because the cost of holding cash is higher in online markets, since buyers carry more money balances and consume more due to the higher efficiency in bilateral matches. The cost is fully internalized by the monopolistic platform, which leads to under-utilization of consumers' data.

However, when the platform offers payment services, they may begin to over-utilize consumers' data. This is because the payment service allows the platform to manipulate consumers' surpluses in online and offline markets through the nominal interest rates on tokens. By offering a higher rate on tokens used in the online market, the platform effectively lowers the value of consumers' outside options (i.e., the offline markets). This strategy enables the platform to extract more surplus from online markets, which may lead to over-utilization of consumers' data. When the platform offers unsecured credit, the platform charges zero proportional fees and uses the

For more details, see https://www.amazon.com/Prime-Visa/dp/BT00LN946S.

[12] For details, see https://www.apple.com/ca/legal/privacy/en-ww/.

fixed fee to extract surplus from buyers. The platform can then extract buyers' surplus through the buyers' fee to access the online market. Because the platform's credit eliminates the cost of carrying a payment instrument, the platform's monetization decision is socially efficient.

Finally, we consider competition among platforms. We show that this may lead to platforms specializing in data monetization and in the provision of privacy. When nominal tokens can be offered by the digital platforms, we find that, under certain conditions, there exists an equilibrium where one platform is data a monopoly in platform digital services, while the other platform solely provides nominal tokens. This is a direct consequence of an increase in matching efficiency, since the demand for its tokens increases with the expected surplus in the online market. As a result, such specialization results in higher profits for both platforms.

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Appendix A Proofs

Proof of Lemma 1: The maximization problem can be rewritten as

$$V^P(\mathbb{T}) \equiv \max_q \Big\{-(1+\mu-\beta)[\theta q + (1-\theta)u(q)] + \beta g(\mathbb{T}) \min\{1, \nu^P\}\theta[u(q) - q]\Big\}, \tag{A.1}$$

where we use the condition that $z = \theta q + (1-\theta)u(q)$. Then, the first order condition is

$$u'(q) - 1 = \frac{1+\mu-\beta}{\beta g(\mathbb{T}) \min\{1, \nu^P\}\theta - (1+\mu-\beta)(1-\theta)}. \tag{A.2}$$

Then, it is clear that if $\nu^P < 1$, z^P and q^P are strictly increasing in ν^P. If $\nu^P \geq 1$, then z^P and q^P are independent of ν^P. Finally, using Envelop Theorem, we have that $V^P(\mathbb{T})$ is strictly increasing in $\mathbb{T}$. □

Proof of Proposition 1: First, note that $\Pi^{M*} - \Pi^{N*}$ can be rewritten as

$$\rho\{V^P(\tau^*) - V^O + \beta g(\tau^*)(1-\theta)[u(q^P(\tau^*)) - q^P(\tau^*)]\} - c. \tag{A.3}$$

As shown in Section 3.1, $V^P(\tau^*)$ and $g(\tau^*)(1-\theta)[u(q^P(\tau^*)) - q^P(\tau^*)]$ are strictly increasing in $g(\tau^*)$, which means $\Pi^{M*} - \Pi^{N*}$ is strictly increasing in ρ given $g(.)$ and strictly increasing in $g(\tau^*)$ given ρ. Next, use the Envelop Theorem to get:

$$\frac{\partial V^P(\tau^*)}{\partial \mu} = -[(1-\theta)u(q^P) + \theta q^P], \tag{A.4}$$

$$\frac{\partial V^O}{\partial \mu} = -[(1-\theta)u(q^O) + \theta q^O]. \tag{A.5}$$

From Section 3.1 we know that $q^P > q^O$. Hence, $\frac{\partial V^P(\tau^*)}{\partial \mu} - \frac{\partial V^O}{\partial \mu} < 0$. Since $u(q^P(\tau^*)) - q^P(\tau^*)$ is also strictly decreasing in μ, we can conclude that $\Pi^{M*} - \Pi^{N*}$ is strictly decreasing in μ. □

Proof of Proposition 2: The platform monetizes buyers' data if and only if

$$\begin{aligned}\rho\{\beta &\Big[g^M[u(q^P) - q^P] - \alpha\theta[u(q^O) - q^O]\Big] \\ &- (1+\mu-\beta)[(1-\theta)u(q^P) + \theta q^P - (1-\theta)u(q^O) - \theta q^O]\} - c \geq \mathcal{C}.\end{aligned} \tag{A.6}$$

Using the free entry condition (3.5), we can rewrite $\mathcal{W}^M$ as

$$\mathcal{W}^M = -c - \mathcal{C} + U + \beta\rho g^M[u(q^P) - q^P] + \beta(1-\rho)\alpha\theta[u(q^O) - q^O]. \tag{A.7}$$

Hence, $\mathcal{W}^M \geq \mathcal{W}^N$ when

$$\beta\rho\Big[g^M[u(q^P) - q^P] - \alpha\theta[u(q^O) - q^O]\Big] - c \geq \mathcal{C}. \tag{A.8}$$

It is straightforward to see that (A.6) implies (A.8), but the reverse is not true. □

Proof of Proposition 3: Note that the optimal R^P (R^O) only affects q^P (q^O) but not q^O (q^P). This means that R^P and R^O can be solved separately. The optimal R^P solves

$$\max_{R^P}\{V^P(R^P) + \beta g(\tau^*)(1-\theta)[u(q^P) - q^P] + \pi^P(R^P)\}. \tag{A.9}$$

Using the definition for V^P, the objective function can be rewritten as

$$-\frac{\delta(1+\mu-\beta)z^P}{1+R^P} + \beta g(\tau^*)[u(q^P) - q^P]. \tag{A.10}$$

Take the derivative with respect to R^P to get

$$\frac{\delta(1+\mu-\beta)z^P}{(1+R^P)^2} + \beta g(\tau^*)[u'(q^P) - 1]\frac{\mathrm{d}q^P}{\mathrm{d}R^P} - \frac{\delta(1+\mu-\beta)}{1+R^P}[(1-\theta)u'(q^P) + \theta]\frac{\mathrm{d}q^P}{\mathrm{d}R^P}. \tag{A.11}$$

It is straightforward to derive that

$$u'(q^P) = \frac{\theta(1 + [g(\tau^*) - 1](1 + R^P)\beta + \mu)}{(1 + R^P)\beta(1 + \theta[g(\tau^*) - 1]) - (1 - \theta)(1 + \mu)}, \tag{A.12}$$

$$\frac{\mathrm{d}q^P}{\mathrm{d}R^P} = -\frac{g(\tau^*)\beta\theta(1 + \mu)}{u''(q^P)[(1 + R^P)\beta(\theta[g(\tau^*) - 1] + 1) - (1 - \theta)(1 + \mu)]^2} > 0. \tag{A.13}$$

Substitute the results into the derivative to get

$$\frac{\delta(1 + \mu - \beta)z^P}{(1 + R^P)^2} + \frac{g(\tau^*)\beta[-\beta R^P + (1 - \delta\theta)(1 + \mu - \beta)]}{(1 + R^P)\beta(1 + \theta[g(\tau^*) - 1]) - (1 - \theta)(1 + \mu)} \frac{\mathrm{d}q^P}{\mathrm{d}R^P}. \tag{A.14}$$

Suppose $\delta = 0$, then it is clear that $-\beta R^P + 1 + \mu - \beta \geq 0$ since $R^P \leq \frac{1+\mu}{\beta} - 1$. Hence, $R^{P*} = \frac{1+\mu}{\beta} - 1$ is the optimal choice. Suppose $\delta = 1$, then the derivative is strictly positive if $R^P = 0$. Hence, the optimal R^{P*} must be positive.

Now, consider the optimal choices of R^O. First, suppose the platform does not monetize buyers' data. Take the derivative of $\pi^O(R^O)$ with respect to R^O to get

$$\frac{\partial \pi^O(R^O)}{\partial R^O} = -\frac{[\beta + (1 - \delta)(1 + \mu - \beta)]z^O}{(1 + R^O)^2} + \frac{(1 - \delta)(1 + \mu - \beta) - \beta R^O}{1 + R^O} \frac{\mathrm{d}z^O}{\mathrm{d}R^O} \tag{A.15}$$

If $\delta = 0$, then the derivative may be positive if $R^O = 0$. Hence, the optimal $R_N^{O*} \geq 0$. Note that $\frac{\partial \pi^O(R^O)}{\partial R^O}\big|_{R^O = \frac{1+\mu-\beta}{\beta}} < 0$. Hence, $R_N^{O*} < \frac{1+\mu-\beta}{\beta}$. If $\delta = 1$, $\frac{\partial \pi^O(R^O)}{\partial R^O}$ is negative for all $R^O \geq 0$, so the optimal R_N^{O*} is zero. Next, suppose the platform monetizes buyers' data. Then, R^O solves

$$\max_{R^O} \{-\rho V^O(R^O) + (1 - \rho)\pi^O(R^O)\}. \tag{A.16}$$

Since $\frac{\partial V^O(R^O)}{\partial R^O} < 0$, then if $\delta = 0$, the optimal R_M^{O*} must be smaller than R_N^{O*} (weakly smaller if $R_N^{O*} = 0$). If $\delta = 1$, the optimal R_M^{O*} is zero.

Finally, we show that the benefit of data monetization increases with token issuance. First, let $R^P = R_M^O = R_N^{O*}$. If $R_N^{O*} = 0$, then Π^M and Π^N remain unchanged compared to when the platform does not issue tokens. However, $R^P = R_M^O = R_N^{O*}$ is feasible but not optimal if the platform plans to monetize buyers' data. Hence, if R^P and R_M^O are chosen optimally, Π^M is strictly larger compared to when the platform does not issue tokens. Next, if $R_N^{O*} > 0$, then $\rho\pi^P(R^P) + (1 - \rho)\pi^O(R^O) = \pi_N^{O*}$, but $V^P(R^P) - V^O(R^O) + \beta g(\tau^*)(1 - \theta)[u(q^P) - q^P]$ is strictly larger compared to when the platform does not issue tokens. This is because $u(q^P) - q^P$ is strictly increasing in R^P, and

$$\frac{\partial(V^P(R) - V^O(R))}{\partial R} = \frac{(1 + \mu)(z^P - z^O)}{(1 + R)^2} > 0 \tag{A.17}$$

when $R^P = R_M^O = R = R_N^{O*}$. In other words, $\Pi^M - \Pi^N$ increases after the platform issues tokens. Similar to the first scenario, $R^P = R_M^O = R_N^{O*}$ is feasible but not optimal. Hence, if R^P and R_M^O are chosen optimally, $\Pi^M - \Pi^N$ must also be strictly larger compared to when the platform does not issue tokens. □

Proof of Proposition 4: Note that $\mathcal{W}^M \geq \mathcal{W}^N$ when

$$\beta\rho g(\tau^*)[u(q^P) - q^P] + \beta(1 - \rho)\alpha\theta[u(q_M^O) - q_M^O] - \beta\alpha\theta[u(q_N^O) - q_N^O] - c - \mathcal{C} \geq 0. \tag{A.18}$$

The platform monetizes buyers' data if and only if

$$\rho\left\{\left(\frac{1 + \mu}{1 + R_M^{O*}} - \beta\right)[(1 - \theta)u(q_M^O) + \theta q_M^O] - \left(\frac{1 + \mu}{1 + R^{P*}} - \beta\right)[(1 - \theta)u(q^P) + \theta q^P]\right\} - c$$

$$+\beta\rho g(\tau^*)[u(q^P)-q^P]-\beta\rho\alpha\theta[u(q_M^O)-q_M^O]+\rho\pi^P(R^{P*})+(1-\rho)\pi^O(R_M^{O*})-\pi^O(R_N^{O*})\geq\mathcal{C}, \quad \text{(A.19)}$$

First, suppose $\delta=0$. Recall that in this case, $\frac{1+\mu}{1+R^{P*}}=\beta$ but $\frac{1+\mu}{1+R_M^{O*}}\geq\frac{1+\mu}{1+R_N^{O*}}>\beta$. Hence, $\rho\pi^P(R^{P*})=0$ but $0<\pi^O(R_M^{O*})\leq\pi^O(R_N^{O*})$. Substitute in the definition of $\pi^O(R_M^{O*})$ to get

$$\Pi^M-\Pi^N=\beta\rho g(\tau^*)[u(q^P)-q^P]-\beta\rho\alpha\theta[u(q_M^O)-q_M^O]-c+\pi^O(R_M^{O*})-\pi^O(R_N^{O*}). \quad \text{(A.20)}$$

Then,

$$\begin{aligned}\Pi^M-\Pi^N-(\mathcal{W}^M-\mathcal{W}^N)=&\beta\alpha\theta[u(q_N^O)-q_N^O]-\beta\alpha\theta[u(q_M^O)-q_M^O]+\pi^O(R_M^{O*})-\pi^O(R_N^{O*})\\=&V^O(R_N^{O*})-V^O(R_M^{O*}).\end{aligned} \quad \text{(A.21)}$$

It is straightforward to see that when $R_M^O=R_N^{O*}$, we have $\Pi^M-\Pi^N=\mathcal{W}^M-\mathcal{W}^N$. Since $R_M^{O*}\leq R_N^{O*}$, we have $\Pi^M-\Pi^N\geq\mathcal{W}^M-\mathcal{W}^N$ with strict inequality when $R_M^{O*}<R_N^{O*}$. In other words, the platform over-utilizes buyers' data as long as $R_N^{O*}>0$, which implies that $R_M^{O*}<R_N^{O*}$ (see Proposition 3).

Next, suppose $\delta=1$. In this case, $R^{P*}>0$ but $R_M^{O*}=R_N^{O*}=0$. Substitute in the definition of $\pi^P(R^{P*})$ to get

$$\begin{aligned}\Pi^M-\Pi^N=&\rho\left\{(1+\mu-\beta)\left[(1-\theta)u(q_M^O)+\theta q_M^O\right]-\left(\frac{1+\mu-\beta}{1+R^{P*}}\right)\left[(1-\theta)u(q^P)+\theta q^P\right]\right\}\\&+\beta\rho g(\tau^*)[u(q^P)-q^P]-\beta\rho\alpha\theta[u(q_M^O)-q_M^O]-c.\end{aligned} \quad \text{(A.22)}$$

Note that the term in the curly bracket may be positive or negative. Hence, in general $\Pi^M-\Pi^N\geq0$ and $\mathcal{W}^M\geq\mathcal{W}^N$ do not imply one another.

Now we prove the second result. Define $r=\frac{1+R^O}{1+\mu}$. Then, $\pi^O(R^O)$ can be rewritten as

$$\pi^O(R^O)\equiv\frac{z^O[(1-\delta)(1+\mu-\beta)-\beta R^O]}{1+R^O}=\frac{z^O(1-\delta+\mathcal{A}\delta-\beta r)}{r}=\pi^O(r), \quad \text{(A.23)}$$

where $\mathcal{A}=\frac{\beta}{1+\mu}$. We have

$$\frac{\mathrm{d}\pi^O(r)}{\mathrm{d}r}=-\frac{z^O(1-\delta+\mathcal{A}\delta)}{r^2}+\frac{(1-\delta+\mathcal{A}\delta-\beta r)}{r}\frac{\mathrm{d}z^O}{\mathrm{d}r}. \quad \text{(A.24)}$$

From the previous analysis, we know that $\frac{\mathrm{d}z^O}{\mathrm{d}r}>0$. Furthermore, when $\delta=0$ and $r=\frac{1}{\beta}$, $\frac{\mathrm{d}\pi^O(r)}{\mathrm{d}r}<0$. Since $\frac{\mathrm{d}\pi^O(r)}{\mathrm{d}r}$ is continuous, there exists r' such that for all $r\in[r',1/\beta]$, $\frac{\mathrm{d}\pi^O(r)}{\mathrm{d}r}<0$. Now, define $\mu'=\frac{1}{r'}-1$. If $\mu\in[\beta-1,\mu']$, then $\frac{\mathrm{d}\pi^O(R^O)}{\mathrm{d}R^O}<0$ for all $R^O\in[0,(1+\mu-\beta)/\beta]$. So, the optimal choices are $0=R_M^{O*}=R_N^{O*}<R^{P*}=\frac{1+\mu-\beta}{\beta}$. It also means that q^O will be the same after the platform issue tokens. Now, suppose $\delta=0$ and $\mu\leq\mu'$. Then, (A.20) becomes

$$\Pi^M-\Pi^N=\beta\rho g(\tau^*)[u(q^P)-q^P]-\beta\rho\alpha\theta[u(q_M^O)-q_M^O]-c-\mathcal{C}=\mathcal{W}^M-\mathcal{W}^N. \quad \text{(A.25)}$$

Hence, the platform's monetization decision is efficient. Finally, consider aggregate welfare. It is straightforward to see that $\mathcal{W}^M$ is strictly higher after the platform issues tokens, while $\mathcal{W}^N$ remains the same. Since the platform's monetization decision is efficient, aggregate welfare must increase if the platform opts to monetizes buyers' data after issuing tokens. □

Proof of Proposition 5: It is straightforward to see that R^P and (R^O,λ) can be solved independently. First, consider R^P. Define $\tilde{V}^P(R^P)$ to be the following

$$\tilde{V}^P(R^P)=\max_{z^P}\left\{-\left(\frac{1+\mu}{1+R^P}-\beta\right)z^P+\beta g(\mathbb{T},\mathcal{P})\theta[u(q^P)-q^P]\right\}. \quad \text{(A.26)}$$

Then, R^P solves the following problem

$$\tilde{\Pi} \equiv \max_{R^P} \{\tilde{V}^P(R^P) + \beta g(\tau^*, \mathcal{P})(1-\theta)[u(q^P) - q^P] + \pi^P(R^P)\}. \tag{A.27}$$

Using the Envelop Theorem, it is straightforward to show that $\tilde{\Pi}$ is increasing in $g(\tau^*, \mathcal{P})$. In other words, payment data increases the platform's profit from the online market.

Next, denote buyers' surplus when using cash in the offline market as V_c^O. Define $\tilde{V}^O(R^O)$ to be the following

$$\tilde{V}^O(R^O) \equiv \max_{z^P} \left\{ -\left(\frac{1+\mu}{1+R^O} - \beta \right) z^O + \beta\alpha\theta[u(q^O) - q^O] \right\}. \tag{A.28}$$

In this case, $\beta\lambda = \max\{0, V_c^O - \tilde{V}^O(R^O) + \beta d\}$. Hence, R^O solves

$$\max_{R^O} \{-\rho\tilde{V}^O(R^O) + (1-\rho)\pi^O(R^O) - \beta \max\{0, V_c^O - \tilde{V}^O(R^O) + \beta d\}\}. \tag{A.29}$$

Assume $V_c^O - \tilde{V}^O(R^O) + \beta d > 0$. Let us take the derivative with respect to R^O.

$$\frac{\delta(1+\mu-\beta)z^O}{(1+R^O)^2} + \beta\alpha\theta[u'(q^O) - 1]\frac{\mathrm{d}q^O}{\mathrm{d}R^O} - \frac{\delta(1+\mu-\beta)}{1+R^O}[(1-\theta)u'(q^O) + \theta]\frac{\mathrm{d}q^O}{\mathrm{d}R^O}. \tag{A.30}$$

Substitute in $u'(q^O)$ to get

$$\frac{\delta(1+\mu-\beta)z^O}{(1+R^O)^2} + \frac{\alpha\beta\theta[-\beta R^O + (1-\delta)(1+\mu-\beta)]}{(1+R^O)\beta(1+\theta[\alpha-1]) - (1-\theta)(1+\mu)}\frac{\mathrm{d}q^O}{\mathrm{d}R^O}, \tag{A.31}$$

which is strictly positive when $R^O = 0$, because $\frac{\mathrm{d}q^O}{\mathrm{d}R^O} > 0$. Hence, the optimal $R^O > 0$ regardless of the value of δ, which implies that $\lambda < d$.

Finally, suppose $\delta = 0$. The interest rate on tokens issued to them when the platform does not monetize payment data, R_M^{O*}, may be positive (see Proposition 3). If it is positive and d is not too large, then it is straightforward to see that $\lambda = 0$, since the platform already compensates buyers in the offline market via the interest on tokens. In such a case, there exists $\mathcal{B}(d)$ (which is decreasing in d) such that if $0 < g(\tau^*, 1-\rho) - g(\tau^*, 0) < \mathcal{B}(d)$, the platform will monetize buyers' data, but it hurts aggregate welfare. To see this, first note that data monetization increases the surplus in the online market. If $0 < g(\tau^*, 1-\rho) - g(\tau^*, 0) < \mathcal{B}(d)$, then the increase in surplus is small but positive, which means the platform will monetize payment data even though the benefit does not offset the cost, d. □

Proof of Proposition 6: First, note that an online buyer will use platform credit if $V^P(\mathcal{R}^P) - V_c^P \geq \mathcal{A}^P$, where V_c^P is the surplus when using cash, and $V^P(\mathcal{R}^P)$ is given by

$$V^P(\mathcal{R}^P) = \max_{z^P} \beta \left\{ -\mathcal{R}^P z^P + g(\tau^*)\theta[u(q^P) - q^P] \right\}. \tag{A.32}$$

It is clear that the optimal $\mathcal{A}^P$ satisfies $\mathcal{A}^P = V^P(\mathcal{R}^P) - V_c^P$. We can derive similar conclusions for the offline market. The platform's total profit is given by

$$\Pi^M = U - c + \rho\{V^P(\mathcal{R}^P) - V_c^O + \beta g(\tau^*)(1-\theta)[u(q^P) - q^P]\} \tag{A.33}$$

$$+ \beta\rho\mathcal{R}^P z^P + (1-\rho)[V^O(\mathcal{R}^O) - V_c^O + \beta\mathcal{R}^O z^O] - \mathcal{C}. \tag{A.34}$$

It is straightforward to see that the optimal fees are $\mathcal{R}^P = \mathcal{R}^O = 0$. This implies that $q^P = q^O = q^*$. We can derive similar results when the platform does not monetize buyers' data. Now, consider aggregate welfare. Note that $\mathcal{W}^M \geq \mathcal{W}^N$ when

$$\beta\rho g(\tau^*)[u(q^*) - q^*] + \beta(1-\rho)\alpha\theta[u(q^*) - q^*] - \beta\alpha\theta[u(q^*) - q^*] - c - \mathcal{C} \geq 0. \tag{A.35}$$

The platform monetizes buyers' data when

$$\Pi^M - \Pi^N = \beta\rho g(\tau^*)[u(q^*) - q^*] + \beta(1-\rho)\alpha\theta[u(q^*) - q^*] - \beta\alpha\theta[u(q^*) - q^*] - c - \mathcal{C} \geq 0. \quad (A.36)$$

Hence, the platform's monetization decision is socially optimal. □

Proof of Lemma 2: There are three scenarios depending on the platforms' monetization policies. **Scenario I.** Assume that neither platform monetizes buyers' data. It must be that $s_A = s_B = 0$, because $s_A > 0$ means platform B has the incentive to set $s_B = s_A - \epsilon$ for an infinitesimal but positive ϵ and capture the entire market. Hence, in equilibrium, $s_A = s_B = 0$, and both platforms earn zero profit. This is an equilibrium of the one-shot game if and only if no platform has the incentive to deviate and monetize buyers' data. This requires that

$$c > \beta(1-\theta)\rho g(\tau^*)u(q^P(\tau^*)) - q^P(\tau^*)] + \rho[V^P(\tau^*) - V^O] - \mathcal{C}, \quad (A.37)$$

and

$$\frac{c}{2} > \beta(1-\theta)\rho g(\tau^*/2)[u(q^P(\tau^*/2)) - q^P(\tau^*/2)] + \rho[V^P(\tau^*/2) - V^O] - \mathcal{C}. \quad (A.38)$$

(A.37) says no platform has the incentive to charge $s_i = -c - \epsilon$, which will allow it capture all buyers for platform services and earn $\beta(1-\theta)\rho g(\tau^*)u(q^P(\tau^*)) - q^P(\tau^*)] + \rho[V^P(\tau^*) - V^O]$ from the online market. (A.38) says no platform has the incentive to charge $s_i = -c$, which will allow it capture half of the buyers for platform services and earn $\beta(1-\theta)\rho g(\tau^*/2)[u(q^P(\tau^*/2)) + \rho[V^P(\tau^*/2) - V^O]$ from the online market.

Scenario II. Assume that both platforms choose to monetize buyers' data. Note that in this case, the platforms have three sources of income: the fee for buyers to access platform services (s_i), the fee for buyers to access the online market (b_i), and the fee for sellers to access the online market (k_i^P). The platforms do not have the incentive to choose $b_i < 0$ or $k_i^P < 0$. Now, consider $(\mathbb{T}_A, \mathbb{T}_B)$. We have

$$\begin{cases} \mathbb{T}_A, \mathbb{T}_B) = (\tau^*, 0), \text{ if } \mathbb{U}_A^S > \mathbb{U}_B^S; \\ (\mathbb{T}_A, \mathbb{T}_j B) = (0, \tau^*), \text{ if } \mathbb{U}_A^S > \mathbb{U}_B^S; \\ (\mathbb{T}_A, \mathbb{T}_B) = (\tau^*/2, \tau^*/2), \text{ if } \mathbb{U}_A^S = \mathbb{U}_B^S. \end{cases} \quad (A.39)$$

We can also derive platform i 's income from the online market

$$b_i B_i^P + k_i^P S_i^P = b_i B_i^P + \beta g(\mathbb{T}_i) B_i^P (1-\theta)[u(q^P(\mathbb{T}_i)) - q^P(\mathbb{T}_i)], \quad (A.40)$$

where B_i^P and S_i^P are the measures of buyers and sellers in the market, and the first equality uses the free entry condition (3.3).

Now, suppose that $(\mathbb{T}_A, \mathbb{T}_B) = (\tau^*, 0)$. This implies that platform B will have negative profit after factoring the cost of monetization $\mathcal{C}$. Hence, $(\mathbb{T}_A, \mathbb{T}_B) = (\tau^*, 0)$ or $(0, \tau^*)$ cannot be part of an equilibrium. Next, suppose that $(\mathbb{T}_A, \mathbb{T}_B) = (\tau^*/2, \tau^*/2)$. In equilibrium, it must be that $b_A = b_B = 0$. In other words, the platform can only profit from the online market via sellers. Next, consider s_A and s_B. Suppose $s_A \geq 0$. Then, platform B has the incentive to charge $s_B = s_A - \epsilon$, which allows it to capture the entire market. Hence, in equilibrium, it must be that $s_A < 0$ and $s_B < 0$. Let $\underline{s}$ to be such that

$$\frac{\underline{s}}{2} = \underbrace{\beta(1-\theta)\{g(\tau^*)\rho[u(q^P(\tau^*)) - q^P(\tau^*)] - g(\tau^*/2)\rho/2[u(q^P(\tau^*/2)) - q^P(\tau^*/2)]\}}_{\text{Increase in revenue from seller fee}} + \underbrace{\rho(\underline{b} - \epsilon)}_{\text{Increase in revenue from buyer fee}}. \quad (A.41)$$

Then, it must be that $s_A = s_B = -\underline{s}$. To see why this price is necessary to prevent deviations, note that if platform B deviates and charges $s_B = s_A - \epsilon$, its cost will increase by $\frac{\underline{s}+\epsilon}{2}$. In return, it will capture all P-type buyers. Since $b_A = 0$, it can charge $b_B = V^P(\tau^*) - V^O - \epsilon$. However, (A.41) says that the increases in revenue do not offset the increase in cost. Hence, platforms do not have the incentive to deviate. But, for $s_A = s_B = -\underline{s}$ and $b_A = b_B = 0$ to be part of an equilibrium, we need platform's profit to be non-negative. However, we have

$$\begin{aligned}\Pi_i =& \beta(1-\theta)g(\tau^*/2)\rho/2[u(q^P(\tau^*/2)) - q^P(\tau^*/2)] - \frac{\underline{s}}{2} \\ =& \beta(1-\theta)\rho\{g(\tau^*/2)[u(q^P(\tau^*/2)) - q^P(\tau^*/2)] - g(\tau^*)[u(q^P(\tau^*)) - q^P(\tau^*)]\} \\ &- \rho(V^P(\tau^*) - V^O) - \mathcal{C} < 0. \end{aligned} \tag{A.42}$$

Hence, s_i can never be low enough to prevent deviation before the platforms' profits become negative. In other words, there does not exist an equilibrium in this scenario.

Scenario III. Assume that platform A monetizes buyers' data, but platform B does not. Suppose $\mathbb{T}_A = 0$. This implies that platform A only source of income is from the online market. However, since $g(0) = \alpha$, this part of income is zero as well. Since platform A has to pay $\mathcal{C}$ to monetize buyers' data, $\mathbb{T}_A = 0$ cannot be part of the equilibrium.

Next, suppose $\mathbb{T}_A = \tau^*/2$, so buyers are indifferent between the two platforms. Note that $s_B > 0$ cannot be part of an equilibrium, since platform B will then have the incentive to lower s_B by ϵ and attract all buyers. For $s_B = 0$ to be part of an equilibrium, we need

$$\beta(1-\theta)\rho g(\tau^*/2)[u(q^P(\tau^*/2)) - q^P(\tau^*/2)] + \rho[V^P(\tau^*/2) - V^O] - \mathcal{C} \geq \frac{c}{2}, \tag{A.43}$$

so that platform A has the incentive to set $s_A = -c$. But at same we also need

$$\begin{aligned}&\beta(1-\theta)\rho\{g(\tau^*)[u(q^P(\tau^*)) - q^P(\tau^*)] - g(\tau^*/2)[u(q^P(\tau^*/2)) - q^P(\tau^*/2)]\} \\ &+ \rho[V^P(\rho\tau^*) - V^P(\tau^*/2)] < \frac{c}{2}, \end{aligned} \tag{A.44}$$

so that platform A has no incentive to further lower s_A and attract all buyers. Furthermore, for this to be an equilibrium, we also need we need platform A's profit to be non-positive, because otherwise platform B will have the incentive to deviate and monetize buyers' data. Hence, (A.43) must hold at equality.

Finally, suppose $\mathbb{T}_A = \tau^*$. Suppose also that

$$-c + \beta(1-\theta)\rho g(\tau^*)[u(q^P(\tau^*)) - q^P(\tau^*)] + \rho[V^P(\tau^*) - V^O] - \mathcal{C} > 0. \tag{A.45}$$

For $\mathbb{T}_A = \tau^*$ to be part of an equilibrium, we need platform B to set $s_B = 0$ and platform A to set $s_A = -c - \epsilon$ and $b_A = V^P(\tau^*) - V^O$. This implies all buyers use platform A's platform services, and all P-type buyers pay b_A and access the online market. If s_B is larger than 0, platform A will have the incentive to increase s_A, which means platform B can then lower s_B and capture all buyers. However, for $s_B = 0$, $s_A = -c - \epsilon$, and $b_A = V^P(\tau^*) - V^O$ to be an equilibrium, we need platform A's profit to be non-positive, because otherwise platform B will have the incentive to deviate and monetize buyers' data. This contradicts with (A.45).

Equilibrium of the one-shot game. To conclude, if

$$c \geq \beta(1-\theta)\rho g(\tau^*)u(q^P(\tau^*)) - q^P(\tau^*)] + \rho[V^P(\tau^*) - V^O] - \mathcal{C} \tag{A.46}$$

and

$$\frac{c}{2} > \beta(1-\theta)\rho g(\tau^*/2)[u(q^P(\tau^*/2)) - q^P(\tau^*/2)] + \rho[V^P(\tau^*/2) - V^O] - \mathcal{C}, \tag{A.47}$$

the unique equilibrium features $s_A = s_B = 0$ and no monetization. If

$$\beta(1-\theta)\rho g(\tau^*/2)[u(q^P(\tau^*/2)) - q^P(\tau^*/2)] + \rho[V^P(\tau^*/2) - V^O] - \mathcal{C} \geq \frac{c}{2} \tag{A.48}$$

and

$$\beta(1-\theta)\rho\{g(\tau^*)[u(q^P(\tau^*))-q^P(\tau^*)]-g(\tau^*/2)[u(q^P(\tau^*/2))-q^P(\tau^*/2)]\}$$
$$+\rho[V^P(\rho\tau^*)-V^P(\tau^*/2)]<\frac{c}{2}, \tag{A.49}$$

then there also exists another equilibrium where platform A monetizes buyers' data, but platform B does not. Furthermore, in equilibrium, $s_B=0$, $s_A=-c$, and $b_A=V^P(\tau^*)-V^O$. In all the other scenarios, there does not exist an equilibrium. □

Proof of Lemma 3: First note that the minmax profit is non-negative, since the platforms can always opt not to monetize buyers' data, charge $s_i=0$ for platform services, and get zero profit. Now, assume that $c\geq\Gamma_1$ and $c\geq 2\Gamma_2$, where Γ_1 and Γ_2 are defined in Lemma 2. According to Lemma 2, in this case, if one platform opts not to monetize buyers' data and charges $s=0$, the best response of the other platform is either to do the same (which results in zero profit) or to monetize buyers' data and also obtain zero profit. Hence, the minmax profit is zero.

Now, suppose $c<\Gamma_1$ or $c<2\Gamma_2$. As shown by the proof of Lemma 3 shows that charging $s=0$ without monetization is no longer a minmax strategy, since the other platform always has the incentive to monetize buyers' data and receive a strictly positive profit. In this case, consider the following strategy: platform j opts to monetize buyers' data and sets $b_j=V^P(\tau^*)-V^O$ and s_j to be such that

$$U-s_j-c+\beta(1-\theta)\rho g(\tau^*)u(q^P(\tau^*))-q^P(\tau^*)]+\rho[V^P(\tau^*)-V^O]-\mathcal{C}=0. \tag{A.50}$$

Then, platform i's optimal strategy is to not monetize buyers' data and charge $s_i=0$. If platform i monetizes buyers' data, it will have to at least offer $s_i=s_j-\epsilon$ to attract all buyers or $s_i=s_j$ to attract half of the buyers. Both options will result in negative profits. Hence, the minmax profit is zero. □

Proof of Proposition 7: Define $\mathbb{D}\equiv g(\tau^*/2)$. First, scenario II is Pareto superior to scenario I if

$$\frac{\rho}{2}\left[\beta(1-\theta)g(\tau^*/2)[u(q^P(\tau^*/2))-q^P(\tau^*/2)]+V^P(\tau^*/2)-V^O\right]-\mathcal{C}>\frac{c}{2}. \tag{A.51}$$

Scenario III is Pareto superior to scenario II if

$$\frac{\rho}{2}\left[\beta(1-\theta)g(\tau^*/2)[u(q^P(\tau^*/2))-q^P(\tau^*/2)]+V^P(\tau^*/2)-V^O\right]-\mathcal{C}<\frac{c}{2} \tag{A.52}$$

but

$$\rho\left[\beta(1-\theta)g(\tau^*/2)[u(q^P(\tau^*/2))-q^P(\tau^*/2)]+V^P(\tau^*/2)-V^O\right]-\mathcal{C}>\frac{c}{2}. \tag{A.53}$$

Now, for any c define $\hat{\mathbb{D}}_1(c)$ and $\hat{\mathbb{D}}_2(c)$ to be such that

$$\rho\left[\beta(1-\theta)g(\tau^*/2)[u(q^P(\tau^*/2))-q^P(\tau^*/2)]+V^P(\tau^*/2)-V^O\right]-\mathcal{C}=\frac{c}{2} \tag{A.54}$$

$$\frac{\rho}{2}\left[\beta(1-\theta)g(\tau^*/2)[u(q^P(\tau^*/2))-q^P(\tau^*/2)]+V^P(\tau^*/2)-V^O\right]-\mathcal{C}=\frac{c}{2}. \tag{A.55}$$

Then, the symmetric and Pareto optimal equilibrium is scenario II if $\mathbb{D}\geq\hat{\mathbb{D}}_2(c)$ and is scenario I if $\mathbb{D}<\hat{\mathbb{D}}_1(c)$. If $\hat{\mathbb{D}}_1(c)\leq\mathbb{D}<\hat{\mathbb{D}}_2(c)$, then scenario III is Pareto superior to both scenario I and II.

Finally, to check if platforms' monetization policies are socially efficient, note that at least one of the platform monetizes buyers' data if

$$\rho\left[\beta(1-\theta)g(\tau^*/2)[u(q^P(\tau^*/2))-q^P(\tau^*/2)]+V^P(\tau^*/2)-V^O\right]-\mathcal{C}\geq\frac{c}{2}. \tag{A.56}$$

But such data monetization increases aggregate welfare (define in (3.13)) if

$$\rho\beta\left[g(\tau^*/2)[u(q^P(\tau^*/2))-q^P(\tau^*/2)]-\alpha[u(q^O)-q^O]\right]-\mathcal{C}\geq\frac{c}{2}. \tag{A.57}$$

Using the proof of Proposition 4, it is straightforward to show that (A.56) implies the (A.57), but the reverse is not true. □

Proof of Lemma 5: We prove the lemma in several steps.

Step 1. We solve for $R^{P*}_{1/2}$, R^{P*}_1, R^{O*}_M, and R^{O*}_N. First, let $\tilde{\Pi}^M(\tau^*/2)$ be given by

$$\tilde{\Pi}^M(\tau^*/2) = U - c + \rho\{V^P(R^P) - V^O(R^O) + \beta g(\tau^*/2)(1-\theta)[u(q^P) - q^P]\} \tag{A.58}$$

$$+ \rho\pi^P(R^P) + (1-\rho)\pi^O(R^O) - \mathcal{C}, \tag{A.59}$$

where

$$\pi^P(R^P) = \frac{z^P[(1-\delta)(1+\mu-\beta) - \beta R^P]}{1+R^P}, \tag{A.60}$$

$$\pi^O(R^O) = \frac{z^O[(1-\delta)(1+\mu-\beta) - \beta R^O]}{1+R^O}. \tag{A.61}$$

Then, $\tilde{\Pi}^M(\tau^*/2)$ is the total profit of the two platforms when they each attract half of the buyers to their platform services, and at least one of them opts to monetize buyers' data. Let $R^{P*}_{1/2}$ solve

$$\max_{R^P}\{V^P(R^P) + \beta g(\tau^*/2)(1-\theta)[u(q^P) - q^P] + \pi^P(R^P)\}. \tag{A.62}$$

Using the proof of Proposition 3, we obtain the following first derivative with respect to R^P:

$$\frac{\delta(1+\mu-\beta)z^P}{(1+R^P)^2} + \frac{g(\tau^*/2)\beta[-\beta R^P + (1-\delta\theta)(1+\mu-\beta)]}{(1+R^P)\beta(1+\theta[g(\tau^*/2)-1]) - (1-\theta)(1+\mu)}\frac{\mathrm{d}q^P}{\mathrm{d}R^P}. \tag{A.63}$$

We know from the proof of Proposition 3 that $R^{P*}_{1/2} = \frac{1+\mu}{\beta} - 1$ if $\delta = 0$, and $R^{P*}_{1/2} > 0$ if $\delta = 1$. Similarly, let $R^{P*}_1 = \arg\max_{R^P} \tilde{\Pi}^M(\tau^*)$. We also have $R^{P*}_1 = \frac{1+\mu}{\beta} - 1$ if $\delta = 0$, and $R^{P*}_1 > 0$ if $\delta = 1$.

Next, we solve for R^{O*}_M and R^{O*}_N. Define $\tilde{\Pi}^N$ to be the total profit when neither platform monetizes buyers' data:

$$\tilde{\Pi}^N = U + \pi^O(R^O). \tag{A.64}$$

Take the derivative of $\pi^O(R^O)$ with respect to R^O to get

$$\frac{\partial\pi^O(R^O)}{\partial R^O} = -\frac{[\beta + (1-\delta)(1+\mu-\beta)]z^O}{(1+R^O)^2} + \frac{(1-\delta)(1+\mu-\beta) - \beta R^O}{1+R^O}\frac{\mathrm{d}z^O}{\mathrm{d}R^O} \tag{A.65}$$

We know from the proof of Proposition 3 that $R^{O*}_N \geq 0$ and that $R^{O*}_N < \frac{1+\mu-\beta}{\beta}$ if $\delta = 0$, and $R^{O*}_N = 0$ if $\delta = 1$. Next, consider $\max_{R^O} \tilde{\Pi}^M$. Then, R^{O*}_M solves

$$\max_{R^O}\{-\rho V^O(R^O) + (1-\rho)\pi^O(R^O)\}. \tag{A.66}$$

We know from the proof of Proposition 3 that R^{O*}_M is smaller than R^{O*}_N (weakly smaller if $R^{O*}_N = 0$) if $\delta = 0$, and $R^{O*}_M = 0$ if $\delta = 1$.

Step 2. We solve for the minmax strategy. First, suppose $\delta = 0$. Let $R^* = \frac{1+\mu}{\beta} - 1$. Define Γ_1 and Γ_2 to be such that

$$\Gamma_1 = \beta(1-\theta)\rho g(\tau^*)u(q^P(\tau^*, R^*)) - q^P(\tau^*, R^*)] + \rho[V^P(\tau^*, R^*) - V^O(R^*)] - \mathcal{C}, \tag{A.67}$$

$$\Gamma_2 = \beta(1-\theta)\rho g(\tau^*/2)[u(q^P(\tau^*/2, R^*)) - q^P(\tau^*/2, R^*)] + \rho[V^P(\tau^*/2, R^*) - V^O(R^*)] - \mathcal{C}. \tag{A.68}$$

Suppose $c \geq \Gamma_1$ and $c \geq 2\Gamma_2$. The minmax strategy $\underline{\hat{a}}_j$ is given by the following: platform j issues tokens but does not monetize buyers' data, and it chooses $s_j = 0$ and $R^O = R^*$. The best response of platform i is either to do the same and obtain zero profit, or to monetize buyers' data, issue tokens, offer $R^P = R^*$, and obtain zero profit. Next, suppose $c < \Gamma_1$ or $c < 2\Gamma_2$. The minmax strategy strategy is given by the following: platform j opts to monetize buyers' data, sets $R^P = R^O = R^*$, $b_j = V^P(\tau^*, R^*) - V^O$, and sets s_j to be such that

$$U - s_j - c + \beta(1-\theta)\rho g(\tau^*)u(q^P(\tau^*, R^*)) - q^P(\tau^*, R^*)] + \rho[V^P(\tau^*, R^*) - V^O(R^*)] - \mathcal{C} = 0. \quad \text{(A.69)}$$

Then, platform i's optimal strategy is to not monetize buyers' data, charge $s_i = 0$, and earn zero profit. Suppose platform i monetizes buyers' data, it will have to at least offer $s_i = s_j - \epsilon$ to attract all buyers or $s_i = s_j$ to attract half of the buyers. Both options will result in negative profits.

Second, suppose that $\delta = 1$. Define $R^{P*}_{1/2} = \arg\max_{R^P} \tilde{\Pi}^M(\tau^*/2)$ and $R^{P*}_1 = \arg\max_{R^P} \tilde{\Pi}^M(\tau^*)$, respectively. Define Γ_1 and Γ_2 to be such that

$$\Gamma_1 = \beta(1-\theta)\rho g(\tau^*)u(q^P(\tau^*, R^{P*}_1)) - q^P(\tau^*, R^{P*}_1)] + \rho[V^P(\tau^*, R^{P*}_1) - V^O] - \mathcal{C}, \quad \text{(A.70)}$$

$$\Gamma_2 = \beta(1-\theta)\rho g(\tau^*/2)[u(q^P(\tau^*/2, R^{P*}_{1/2})) - q^P(\tau^*/2, R^{P*}_{1/2})] + \rho[V^P(\tau^*/2, R^{P*}_{1/2}) - V^O] - \mathcal{C}. \quad \text{(A.71)}$$

Suppose $c \geq \Gamma_1$ and $c \geq 2\Gamma_2$. The minmax strategy $\underline{\hat{a}}_j$ is given by the following: platform j issues tokens but does not monetize buyers' data, and it chooses $s_j = 0$ and $R^O = 0$. The best response of the other platform is either to do the same and obtain zero profit, or to monetize buyers' data, issue tokens, offer $R^P = R^{P*}_1$ or $R^{P*}_{1/2}$, and obtain zero profit. Next, suppose $c < \Gamma_1$ or $c < 2\Gamma_2$. Consider the following strategy: platform j opts to monetize buyers' data, sets $R^P = R^{P*}_1$, $R^O = 0$, $b_j = V^P(\tau^*, R^{P*}_1) - V^O$, and sets s_j to be such that

$$U - s_j - c + \beta(1-\theta)\rho g(\tau^*)u(q^P(\tau^*, R^{P*}_1)) - q^P(\tau^*, R^{P*}_1)] + \rho[V^P(\tau^*, R^{P*}_1) - V^O] + \rho\pi^P(R^{P*}_1) - \mathcal{C} = 0. \quad \text{(A.72)}$$

Then, platform i's optimal strategy is to not monetize buyers' data, charge $s_i = 0$, and earn zero profit. Suppose platform i monetizes buyers' data, it will have to at least offer $s_i = s_j - \epsilon$ to attract all buyers or $s_i = s_j$ to attract half of the buyers. Both options will result in negative profits.

Step 3. We prove the statement in the lemma. First, suppose no platform monetizes buyers' data. Then, the symmetric and Pareto optimal strategies are the following: for all t, both platform issue tokens and choose $s_A = s_B = U$ and $R^O_A = R^O_B = R^{O*}_N$. This means that each platform attracts half of the buyers to both their platform services and their payment services. The platforms' per-period profits are given by

$$\Pi_A = \Pi_B = \frac{U}{2} + \frac{\pi^O(R^{O*}_N)}{2}. \quad \text{(A.73)}$$

If any symmetric strategies are Pareto improving, then $R^{O*}_N \neq \arg\max_{R^O} \tilde{\Pi}^N$, a contradiction. Hence, the above strategies are the only Pareto optimal symmetric strategies.

Second, suppose both platforms opt to monetize buyers' data. The symmetric and Pareto optimal strategies are: for all t, both platform issue tokens and choose $s_A = s_B = U - c$, $b_A = b_B = V^P(\tau^*/2, R^{P*}) - V^O(R^{O*}_M)$, $R^P_A = R^P_B = R^{P*}$, and $R^O_A = R^O_B = R^{O*}_M$. Note that since $R^{P*} > R^{O*}_M$, no buyer uses the other platform's payment service in the online market. Furthermore, each platform attracts half of the buyers to their platform services and payment services in the offline market. The platforms' per-period profits are given by

$$\begin{aligned}\Pi_A = \Pi_B =& \frac{\rho}{2}\left[\beta(1-\theta)g(\tau^*/2)[u(q^P(\tau^*/2, R^{P*}_{1/2})) - q^P(\tau^*/2, R^{P*}_{1/2})] + V^P(\tau^*/2, R^{P*}_{1/2}) - V^O(R^{O*}_M)\right] \\ &+ \frac{U-c}{2} + \frac{\rho\pi^P(R^{P*}_{1/2})}{2} + \frac{(1-\rho)\pi^O(R^{O*}_M)}{2} - \mathcal{C}. \end{aligned} \quad \text{(A.74)}$$

If any symmetric strategies are Pareto improving, then $(R^{P*}_{1/2}, R^{O*}_M)$ does not maximize $\tilde{\Pi}^M(\tau^*/2)$, a contradiction. Hence, the above strategies are the only Pareto optimal symmetric strategies.

Note that there may exist asymmetric equilibria that are Pareto superior. In any of such equilibria, it must be that one platform monetizes buyers' data, while the other does not. To see why, first note that if neither platform monetizes buyers' data, then the total platform profit in any asymmetric equilibrium can be replicated with symmetric strategies. Hence, such an asymmetric equilibrium cannot be Pareto superior to the symmetric equilibrium described above. Second, suppose that both platform monetize buyers' data, and the equilibrium is asymmetric. Then, it must be that each platform attracts half of all buyers to their platform services and half of P-type buyers to their online markets. This is because if one platform fails to attract buyers to its platform services or its online market, a Pareto improvement would be for the platform to not monetize buyers' data. It is then clear that the symmetric strategies maximize their profit. Hence, an asymmetric equilibrium cannot be Pareto superior. In conclusion, for an asymmetric equilibrium to be Pareto superior, only one platform monetizes buyers' data. □

Proof of Proposition 8: Without loss of generality, assume that platform A monetizes buyers' data, but platform B does not. Note that because $\delta = 1$, if platform B issues tokens, it will not have the incentive to pay any interest. Similarly, from the proof of Lemma 5, we know that $R^{P*}_{1/2} > 0$ but $R^{O*}_{M} = 0$. Hence, the platform's profit can be written as

$$\Pi_A = \frac{U-c}{2} + \rho\left[\beta(1-\theta)g(\tau^*/2)[u(q^P(\tau^*/2)) - q^P(\tau^*/2)] + V^P(\tau^*/2) - V^O\right] + \rho\pi^P(R^{P*}_{1/2}) - \mathcal{C}, \tag{A.75}$$

$$\Pi_B = \frac{U}{2}. \tag{A.76}$$

Then, scenario II is Pareto superior to scenario I if

$$\frac{\rho}{2}\left[\beta(1-\theta)g(\tau^*/2)[u(q^P(\tau^*/2)) - q^P(\tau^*/2)] + V^P(\tau^*/2) - V^O\right] + \frac{\rho\pi^P(R^{P*}_{1/2})}{2} - \mathcal{C} > \frac{c}{2}. \tag{A.77}$$

Scenario III is Pareto superior to scenario II if

$$\frac{\rho}{2}\left[\beta(1-\theta)g(\tau^*/2)[u(q^P(\tau^*/2)) - q^P(\tau^*/2)] + V^P(\tau^*/2) - V^O\right] + \frac{\rho\pi^P(R^{P*}_{1/2})}{2} - \mathcal{C} < \frac{c}{2} \tag{A.78}$$

but

$$\rho\left[\beta(1-\theta)g(\tau^*/2)[u(q^P(\tau^*/2)) - q^P(\tau^*/2)] + V^P(\tau^*/2) - V^O\right] + \rho\pi^P(R^{P*}_{1/2}) - \mathcal{C} > \frac{c}{2}. \tag{A.79}$$

Now, for any c define $\tilde{\mathbb{D}}_1(c)$ and $\tilde{\mathbb{D}}_2(c)$ to be such that

$$\rho\left[\beta(1-\theta)g(\tau^*/2)[u(q^P(\tau^*/2)) - q^P(\tau^*/2)] + V^P(\tau^*/2) - V^O\right] + \rho\pi^P(R^{P*}_{1/2}) - \mathcal{C} = \frac{c}{2}, \tag{A.80}$$

$$\frac{\rho}{2}\left[\beta(1-\theta)g(\tau^*/2)[u(q^P(\tau^*/2)) - q^P(\tau^*/2)] + V^P(\tau^*/2) - V^O\right] + \frac{\rho\pi^P(R^{P*}_{1/2})}{2} - \mathcal{C} = \frac{c}{2}. \tag{A.81}$$

Then, if $\mathbb{D} \geq \tilde{\mathbb{D}}_2(c)$, scenario II is the symmetric and Pareto optimal equilibrium. If $\mathbb{D} < \tilde{\mathbb{D}}_1(c)$, then scenario I is the symmetric and Pareto optimal equilibrium. If $\tilde{\mathbb{D}}_1(c) \leq \mathbb{D} < \tilde{\mathbb{D}}_2(c)$, then scenario III is Pareto superior to both scenario I and II. Finally, it is easy to see that $\tilde{\mathbb{D}}_1(c) = \hat{\mathbb{D}}_1(c)$ and $\tilde{\mathbb{D}}_2(c) = \hat{\mathbb{D}}_2(c)$ if $R^P = 0$. Since the platform has the incentive to offer $R^{P*}_{1/2} > 0$, doing so must increase their profits. Because the profit from monetization is increasing in $\mathbb{D}$, we have $\tilde{\mathbb{D}}_1(c) < \hat{\mathbb{D}}_1(c)$ and $\tilde{\mathbb{D}}_2(c) < \hat{\mathbb{D}}_2(c)$.

Finally, to check if platforms' monetization policies are socially efficient, note that at least one of the platform monetizes buyers' data if

$$\rho\left[\beta(1-\theta)g(\tau^*/2)[u(q^P(\tau^*/2)) - q^P(\tau^*/2)] + V^P(\tau^*/2) - V^O\right] + \rho\pi^P(R^{P*}_{1/2}) - 2\mathcal{C} \geq c. \tag{A.82}$$

But such data monetization increases aggregate welfare (define in (3.13)) if

$$\rho\left[\beta g(\tau^*/2)[u(q^P(\tau^*/2)) - q^P(\tau^*/2)] - \alpha[u(q^O) - q^O]\right] - 2\mathcal{C} \geq c. \tag{A.83}$$

As shown in the proof of of Proposition 4, (A.82) and (A.83) do not imply each other. Hence, the platforms may under- or-over utilize buyers' data. □

Proof of Proposition 9: We first solve the asymmetric equilibrium described in the proposition, and then we derive conditions under which the asymmetric equilibrium is Pareto optimal. Without loss of generality, we assume that platform A offers platform serves and monetizes buyers' data. Platform B only offers payment services. Recall that R^P and R^O are the interest rates on tokens issued to buyers in the online market and the offline market, respectively. Platform A's profit is given by

$$\Pi_A^a \equiv U - c + \rho \Big[\beta(1-\theta)g(\tau^*)[u(q^P(\tau^*, R^P)) - q^P(\tau^*, R^P)] + V^P(\tau^*, R^P) - V^O(R^O)\Big] - \mathcal{C}, \quad \text{(A.84)}$$

It is straightforward to show that Π_A is increasing in $g(\tau^*)$ and R^P and decreasing in R^O. Platform B's profit is given by

$$\Pi_B^a \equiv \rho\pi^P(R^P) + (1-\rho)\pi^O(R^O), \quad \text{(A.85)}$$

where

$$\pi^P(R^P) = z^P\left(\frac{1+\mu}{1+R^P} - \beta\right) \text{ and } \pi^O(R^O) = z^O\left(\frac{1+\mu}{1+R^O} - \beta\right). \quad \text{(A.86)}$$

Now, let $R^{P*} \equiv \arg\max_{R^P} \pi^P(R^P)$ and $R^{O*} \equiv \arg\max_{R^O} \pi^O(R^O)$. In what follows, we assume $R^P = 0$ and $R^O = R^{O*}$ and prove that under certain conditions, the asymmetric equilibrium described above is Pareto superior to all symmetric equilibria and all asymmetric equilibria where platform B also provides platform services. Note that since $R^{P*} \geq 0$, both platforms can only be better off if $R^P = R^{P*}$. Hence, the arguments below also prove the statement in the proposition that the Pareto optimal equilibrium involves platform B not offering any services besides payment services.

First, consider platform A. Suppose the equilibrium is symmetric and both platforms monetize buyers' data. Platform A's profit is given by (see the proof of Lemma 5 for more details)

$$\begin{aligned}\Pi_A^{SM} \equiv& \frac{\rho}{2}\Big[\beta(1-\theta)g(\tau^*/2)[u(q^P(\tau^*/2, R_{1/2}^{P*})) - q^P(\tau^*/2, R_{1/2}^{P*})] + V^P(\tau^*/2, R_{1/2}^{P*}) - V^O(R_M^{O*})\Big] \\ &+ \frac{U-c}{2} + \frac{\rho\pi^P(R_{1/2}^{P*})}{2} + \frac{(1-\rho)\pi^O(R_M^{O*})}{2} - \mathcal{C}. \quad \text{(A.87)}\end{aligned}$$

Note that Π_A is increasing in $g(\tau^*/2)$. As $g(\tau^*/2) \to 0$ (which implies that $\alpha \to 0$, since we assume that $g(0) = \alpha$), $\Pi_A \to \frac{U-c}{2} - \mathcal{C}$. Hence, if $g(\tau^*)$ and ρ are sufficiently large while $g(\tau^*/2)$ is sufficiently small, we have $\Pi_A^a > \Pi_A^{SM}$. Next, suppose the equilibrium is symmetric and neither platform monetizes buyers' data. Platform A's profit is given by

$$\Pi_A^{SN} \equiv \frac{U}{2} + \frac{\pi^O(R_M^{O*})}{2}.$$

Similarly, if $g(\tau^*)$ and ρ are sufficiently large while α, c, and $\mathcal{C}$ are sufficiently small, we have $\Pi_A^a > \Pi_A^{SN}$. Finally, suppose both platforms offer platform services but only platform A monetizes buyers' data. Platform A's profit is bounded above by

$$\begin{aligned}\Pi_A^{aM} \equiv& \rho\Big[\beta(1-\theta)g(\tau^*/2)[u(q^P(\tau^*/2)) - q^P(\tau^*/2)] + V^P(\tau^*/2) - V^O\Big] \quad \text{(A.88)} \\ &+ \frac{U-c}{2} + \rho\pi^P(R_{1/2}^{P*}) + (1-\rho)\pi^O(R_M^{O*}) - \mathcal{C}, \quad \text{(A.89)}\end{aligned}$$

because this is the profit when R^P and R^O chosen optimally for platform A, and the platform extracts all profits from token issuance. Again, if $g(\tau^*)$ and ρ are sufficiently large while $g(\tau^*/2)$ is sufficiently small, we have $\Pi_A^a > \Pi_A^{aM}$.

Next, consider platform B. Suppose the equilibrium is symmetric and both platforms monetize buyers' data. Platform B's profit is given by (see the proof of Lemma 5 for more details)

$$\Pi_B^{SM} \equiv \frac{\rho}{2}\left[\beta(1-\theta)g(\tau^*/2)[u(q^P(\tau^*/2,R_{1/2}^{P*}))-q^P(\tau^*/2,R_{1/2}^{P*})]+V^P(\tau^*/2,R_{1/2}^{P*})-V^O(R_M^{O*})\right]$$
$$+\frac{U-c}{2}+\frac{\rho\pi^P(R_{1/2}^{P*})}{2}+\frac{(1-\rho)\pi^O(R_M^{O*})}{2}-\mathcal{C}. \quad \text{(A.90)}$$

Note that z^P is increasing in $g(\tau^*)$, which means Π_B^a is increasing in $g(\tau^*)$. Hence, if $g(\tau^*)$ and ρ are sufficiently large while $g(\tau^*/2)$ and U are sufficiently small, we have $\Pi_B^a > \Pi_B^{SM}$. Next, suppose the equilibrium is symmetric and neither platform monetizes buyers' data. Platform B's profit is given by

$$\Pi_B^{SN} \equiv \frac{U}{2}+\frac{\pi^O(R_M^{O*})}{2}.$$

Similarly, if $g(\tau^*)$ and ρ are sufficiently large while α and U are sufficiently small, we have $\Pi_B^a > \Pi_B^{SN}$. Finally, suppose both platforms offer platform services but platform B does not monetize buyers' data. Platform B's profit is bounded above by

$$\Pi_B^{aN} \equiv \frac{U-c}{2}+\rho\pi^P(R_{1/2}^{P*})+(1-\rho)\pi^O(R_M^{O*}), \quad \text{(A.91)}$$

because this is the profit when platform B extracts all profits from token issuance. Again, if $g(\tau^*)$ and ρ are sufficiently large while α, $g(\tau^*/2)$ and U are sufficiently small, we have $\Pi_B^a > \Pi_B^{aM}$.

To conclude, if $g(\tau^*)$ and ρ are sufficiently large while $g(\tau^*/2)$, α, U, c, and $\mathcal{C}$ are sufficiently small, the asymmetric equilibrium with platform B only offering payment services and platform A offering platform services and monetizing buyers' data is Pareto superior to all symmetric equilibria as well as all asymmetric equilibria where platform B also provides platform services. □

Appendix B Extension: Free Entry of Platforms

In this section, we extend the model in Section 5.2 and assume that there exists many digital platforms that, at the beginning of each CM, can choose to enter the model economy upon paying an entry cost κ. After the entry decisions are made, all platforms simultaneously choose their data monetization policies and $(s_{i,t}, b_{i,t})$. To solve for the equilibrium, we first assume that there are $N \geq 2$ platforms in the model economy and solve the subgame. We follow Section 5.2 and require the equilibrium to be symmetric and Pareto optimal. However, we also allow asymmetric equilibria as long as they are Pareto superior.

First, we derive the minmax values and the minmax strategy. Define Γ_1 and Γ_N to be such that

$$\Gamma_1 = \beta(1-\theta)\rho g(\tau^*)u(q^P(\tau^*))-q^P(\tau^*)]+\rho[V^P(\tau^*)-V^O]-\mathcal{C}, \quad \text{(B.1)}$$
$$\Gamma_N = \beta(1-\theta)\rho g(\tau^*/N)[u(q^P(\tau^*/N))-q^P(\tau^*/N)]+\rho[V^P(\tau^*/N)-V^O]-\mathcal{C}. \quad \text{(B.2)}$$

Assume that $c \geq \Gamma_1$ and $c \geq N\Gamma_N$. According to Lemma 2, in this case, if all but one platform (denote it as i) opt not to monetize buyers' data and charges $s = 0$, the best response of platform i is either to do the same (which results in zero profit) or to monetize buyers' data and also obtain potentially negative profit. Hence, the minmax profit is zero. Next, suppose $c < \Gamma_1$ or $c < N\Gamma_N$. In this case, consider the following strategy: all but platform i monetize buyers' data and set $b_j = V^P(\tau^*/(N-1)) - V^O$ and s_j to be such that

$$\frac{U-s_j-c+\beta(1-\theta)\rho g\left(\frac{\tau^*}{N-1}\right)\left[u(q^P\left(\frac{\tau^*}{N-1}\right))-q^P\left(\frac{\tau^*}{N-1}\right)\right]+\rho\left[V^P\left(\frac{\tau^*}{N-1}\right)-V^O\right]}{N-1}-\mathcal{C}=0. \quad \text{(B.3)}$$

Then, platform i's optimal strategy is to not monetize buyers' data and charge $s_i = 0$. If platform i

monetizes buyers' data, it will have to at least offer $s_i = s_j - \epsilon$ to attract all buyers or $s_i = s_j$ to attract $1/N$ of the buyers. Both options will result in negative profits. Hence, the minmax profit is zero.

We solve for the equilibrium. Let $\mathbb{D} \equiv g(\tau^*/N)$. For any c, define $\hat{\mathbb{D}}_1(c)$ and $\hat{\mathbb{D}}_2(c)$ to be such that

$$\rho \left[\beta(1-\theta)g(\tau^*/N)[u(q^P(\tau^*/N)) - q^P(\tau^*/N)] + V^P(\tau^*/N) - V^O\right] - \mathcal{C} = \frac{c}{N} \tag{B.4}$$

$$\frac{\rho}{N} \left[\beta(1-\theta)g(\tau^*/N)[u(q^P(\tau^*/N)) - q^P(\tau^*/N)] + V^P(\tau^*/N) - V^O\right] - \mathcal{C} = \frac{c}{N}. \tag{B.5}$$

First, suppose $\mathbb{D} < \hat{\mathbb{D}}_1(c)$ The symmetric and Pareto optimal strategies consist of the following: all platforms choose $s_{i,t} = U$ for all t unless one platform deviates, then other platforms play the minmax strategy forever. The platforms' per-period profits are given by

$$\Pi_{i,t} = \frac{U}{N}. \tag{B.6}$$

Second, suppose $\mathbb{D} \geq \hat{\mathbb{D}}_2(c)$. The symmetric and Pareto optimal strategies are as follows: all platforms choose $s_{i,t} = U - c$ and $b_{i,t} = V^P(\tau^*/N) - V^O$ for all t unless one platform deviates, then other platforms play the minmax strategy forever. The platforms' per-period profits are given by

$$\Pi_{i,t} = \frac{U-c}{N} + \frac{\rho}{N} \left[\beta(1-\theta)g(\tau^*/N)[u(q^P(\tau^*/N)) - q^P(\tau^*/N)] + V^P(\tau^*/N) - V^O\right] - \mathcal{C}. \tag{B.7}$$

Finally, suppose $\hat{\mathbb{D}}_1(c) \leq \mathbb{D} < \hat{\mathbb{D}}_2(c)$. Denote N^M to be the number of platforms that monetizes buyers' data. Then $1 \leq N^M < N$. The per-period profits of platforms that monetize buyers' data are given by

$$\Pi_{i,t} = \frac{U - c + \rho\left[\beta(1-\theta)g(\tau^*/N)[u(q^P(\tau^*/N)) - q^P(\tau^*/N)] + V^P(\tau^*/N) - V^O\right]}{N^M} - \mathcal{C}, \tag{B.8}$$

The per-period profits of platforms that do not monetize buyers' data are given by

$$\Pi_{i,t} = \frac{U}{N}. \tag{B.9}$$

To conclude, platform specialization happens when the profitability of data monetization is neither too high nor too low compared to the privacy cost of data monetization. Finally, a platform will opt to enter the economy if and only if $\sum_{t=0}^{\infty} \beta^t \Pi_{i,t} \geq \kappa$.