Queen's Economics Department Working Paper No. 1490

PayTech and the D(ata) N(etwork) A(ctivities) of BigTech Platforms

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5-2022

PayTech and the D(ata) N(etwork) A(ctivities) of BigTech Platforms*

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May, 2022

Abstract

Why do BigTech platforms introduce payment services? Digital platforms often run business models where activities on the platform generate data that can be monetized off the platform. There is a trade-off between the value of such data and the privacy concerns of users, since platforms need to compensate users for their privacy loss by subsidizing activities. The nature of complementarities between data and payments determines the introduction of payments. When data help to provide better payments (data-driven payments), platforms have too little incentives to adopt. When payments generate additional data (payments-driven data), platforms may adopt payments inefficiently.

Keywords: BigTech, Payments, Privacy, Digital Platform, Data JEL Classification: D8, E42, L1

*The views expressed in this paper are not necessarily the views of the Bank of Canada.

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1 Introduction

Digital platforms like Alibaba, Amazon, Facebook or Google have introduced payment services. These services range from providing credit to incorporating existing payment methods within the platform to potentially issuing stand alone, virtual currencies. Why do digital platforms offer payment services? And is the introduction of payment services by BigTech platforms socially efficient?

BigTech platforms offer core services – for example a social media network, a market place or a search engine – that generate data from the activities of their users. Since the data provide information about users, the platform can sell this information for profit to enhance transactions off platform. Such monetization of data has developed into the leading business model for BigTech platforms.

Data generation is not free, however, as users have privacy concerns. These concerns arise from the fact that data monetization by the platform can sometimes make users worse off even when data can improve the efficiency of transactions. As a consequence, users will reduce their activities to the detriment of the platform's business model. Hence, in order to generate and monetize its data, the platform needs to optimally subsidize user activities, often offering services free of charge such as email, maps, social networking or web searching.

We capture this insight in a formal model where a monopoly platform faces a trade-off between the costs associated with privacy concerns and the revenue from data services. The data are socially valuable as they increase overall surplus when users transact off the platform with sellers. Privacy concerns, however, arise because users lose their share of surplus in these transactions whenever information has been sold to sellers.

As privacy concerns are not perfectly observable by the platforms, users can extract an information rent when being compensated through cheap platform activities. As long as this rent is not too large, the platform still chooses to monetize its data. We show that the business model of bundling data monetization with cheap platform activities tends to be welfare-improving. However, while the average user gains from data sales, some users can be worse off, implying a conflict of interest among users.

We then use the basic model to analyze the platform's introduction of payment services, which involves interesting feedback effects between data and payments. Figure (1) illustrates the business model of a data-driven platform, which generates and monetizes data (D) within a network (N) from user activities (A). PayTech – the ability to leverage technology for and from payments – gives rise to two feedback loops. First, data accumulated by the platform's core business can be used to alleviate payments frictions and offer better payment services. For example, a platform can leverage their user data to control credit risk in the payment process. Better payments facilitate transactions and, hence, leverage the value of the platform's data. We call this feedback loop *data-driven payments*. Second, payment services provide an additional source of data to enhance the platform's data services. For example, off-platform transaction data can be combined with data from a social media network to enrich the platform's ad-targeting capability. We call this feedback loop *payment-driven data*.

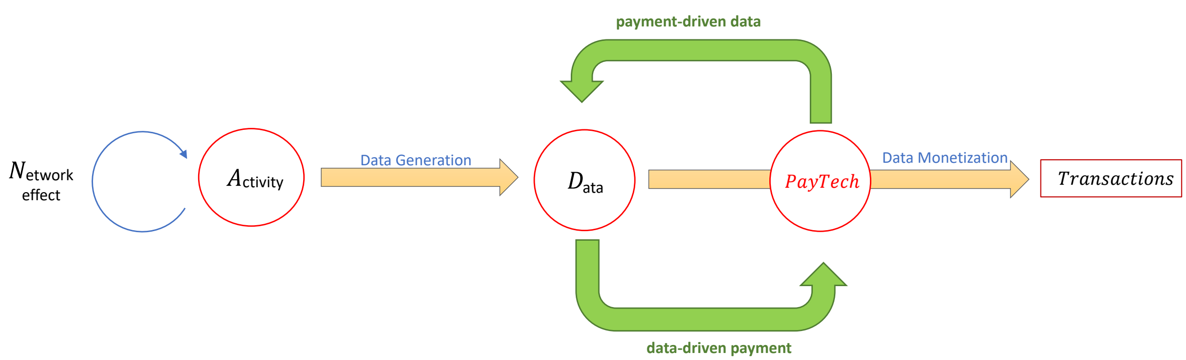

Figure 1: BigTech Business Model and Payment-Data Feedback Loops

To model the first feedback loop, we study the platform's choice to run a data-driven payment technology which can potentially dominate the existing payment option available to users. Interestingly, there is a fundamental complementarity between monetizing data and using data in payments. Data acquired help improve payment technology, facilitating data monetization, further increasing the return to acquire more data. If strong enough, this complementarity can even lead to increasing returns to scale in data monetization. In that case, once payments services are provided, the platform will generate as much data as possible.

We show that the platform has an incentive to provide payment services based on its data technology as long as payments frictions are sufficiently large. All users gain from the introduction of a better payment technology. The platform, however, tends to under-adopt payment services relative to the socially optimal level, due to the fact that the users' privacy concerns are not observable.

To capture the second feedback loop, payments-driven data, we allow the platform to "add-on" a new technology to its payments services that can generate additional data from payments. While increasing the platforms profits from data further, this technology creates a negative data externality as individual users do not take into account how their activities on the platform improve payment services and, thus, generate additional data which can be used to extract surplus from all users.

We show that the platform has a larger incentive to use payments-driven data when it can extract sufficient surplus by selling its data. The reason is that – due to the data externality – users are not directly compensated for the extra loss of their surplus from transactions. When payments frictions are sufficiently small, this can lead to socially inefficient adoption of payments by the platform, since it has an extra benefit from acquiring data through payments due to the externality.

Our results have stark policy implications that we discuss in more detail at the end of the paper. First, data monetization is not necessarily inefficient from a social point of view because data are socially valuable and users are compensated for their privacy concerns with cheaper platform services. Second, when assessing BigTechs' introduction of payment services, one needs to consider the bundling of data and payments and the implied complementarity. In economies with large payment frictions, data-driven payments tend to increase social surplus. In advanced economies, however, where payments are already fairly efficient, payments-driven data can lead to inefficient adoption by platforms that seek to generate data beyond what is socially efficient.

Evidence There is ample evidence that many Big Tech companies running a data-focused business model have ventured into payments, both in advanced and emerging markets economies. Figure 2 gives an overview of large BigTech platforms and their payment services. Many of these platforms generate a significant fraction of their revenues from monetizing their data. Google, for example, accounts for 88.14 percent of the US search engine market in 2020, with 83 percent of the company's total revenue in 2019 coming from digital advertising. Another example is Facebook which accounts for 55.9 percent of all US social media site visits with advertising accounting for almost all of its revenues in 2019. Both these platform offer their core services for free to their users in order to generate activities – and, thus, data – on their platforms.

	Main area	Main Business	Market Cap (Jun 2020)	Profits (2019)	Est. domestic market Share (%)	Payment products (introduction year)
Advanced Economies						
Amazon	Worldwide	E-commerce	1,366 B	$11.6 B	38%	Amazon Pay (2007)
Apple	Worldwide	Electronic Hardware	1,580 B	$55.2 B	49%	Apple Pay (2014)
Facebook	Worldwide	Social Media & Advertising	640 B	$18.5 B	51%	Facebook Pay (2019) Libra (announced)
Google	Worldwide	Search & Advertising	956 B	$34.3 B	89%	Google Wallet (2011)/ Google Pay (2018)
Uber	Worldwide	Rideshare	54 B	($8.5 B)	70%	Uber Cash (2018)
Emerging market economies						
Alibaba/Ant Financial	China	E-commerce	582 B	$13.1 B	56%	Alipay (2004)
Baidu	China	Search & Advertising	42 B	$296 M	67%	Baidu Wallet (2014)
Tencent	China	Gaming	613 B	$13.5 B	52%	Tenpay (2005)/ WeChat Pay (2013)
Grab	Southeast Asia	Rideshare	Private - Est. 14 B	not profitable	65%	GrabPay (2016)
Mercado Libre	Argentina, Brazil, Mexico	E-commerce	49 B	(172 M)	33%	Mercado Pago (2003)

Figure 2: Digital Platforms & Payments

For data-driven payments, the introduction of Alipay by Alibaba in China provides a vivid example of how payment frictions imply a complementarity between data and payment services. Alibaba Group's first e-commerce platform, Alibaba.com, was launched in 1998. In its early days, most transactions on the platform were "cash on delivery". As the inefficiency – and the impossibility for cross-border transactions – of this payment method became apparent, Alibaba decided to create its own payments product, Alipay, in 2004. Initially, Alipay was based on the idea of escrow accounts that withheld payment until delivery. In 2015, Alibaba Group's affiliate Ant Financial Services launched Sesame credit which used its user data base to assess the creditworthiness – or, equivalently, the ability to pay – to facilitate transactions.

Another example is Lenddo, a Singapore-based company, who assigns credit scores based on information of its users' social networking profiles that contain data on education, employment, followers and friends (Rusli (2013)). Frost et al. (2019) study a similar credit scoring algorithm used by Mercado Libre, an e-commerce firm that operates in Latin America. Using data from Mercado Credito, which provides credit lines to small business in Argentina on Mercado Libre, they find that credit scoring techniques based on big data and machine learning can outperformed credit bureau ratings in terms of loan loss prediction. Berg et al. (2020) show that soft information such as digital footprints can be a good predictor of default rates, suggesting that the analysis of simple, easily accessible variables from digital footprints is equal to or better than the information from credit bureau scores.

For payment-driven data, a recent FSB report documents BigTechs' entry into financial services. According to the report,

> "Provision of financial services allows BigTech firms to collect additional data on the spending habits and financial positions of their clients. Such information – which has traditionally been the preserve of banks – could now be combined with that gathered from customers' other activities, for example from users' online searches, social media accounts, or e-commerce activity ... These data can then be used to improve BigTech firms' core business lines – for example by allowing them to better target advertising on their social media platforms." (FSB (2019))

For example, Facebook and Google recommend products to customers through ad-targeting and ad experimentation. These platforms, however cannot see the outcomes whenever the purchases are made outside their platforms. The provision of payment services, however, enables the platforms to "close the loop" and learn whether transactions took place or not and, consequently, whether the ad-targeting/experiment was successful. The usefuleness of payment data is also supported by some empirical studies. For example, Martens et al. (2016) examine the use of massive, fine-grained data on consumer payments for targeted marketing and find that it can substantially improve predictive performance. In addition, past payment data also provide useful information for credit services (see for example Tobback and Martens (2019)).

Review of the Literature Our work is at the intersection of the economics of payments, the economics of data and privacy, and the economics of platforms. The literature on the economics of data and privacy is relatively new, but has recently gathered a lot of attention. Our work emphasizes that privacy concerns give rise to informational externalities like in the contributions of Acemoglu et al. (2019), Choi et al. (2019), Bergemann et al. (2020) and Ichihashi (2020). We differ from this literature in that we endogenously connect the social value of information and privacy concerns to study the incentives for platforms to provide payments.

Such privacy concerns in the provision of payments have also been studied by Garratt and Lee (2020) and Garratt and Van Oordt (2019b) who look at publicly provided payments instruments as a way to protect privacy. Parlour et al. (2020) and He et al. (2020)) are interested in competition among private payments providers and study the effects of entry by FinTech companies on banks who traditionally provide payment services. Relative to these papers, we study a different aspect of payments provision where BigTech platforms offer payments as a component of their data-driven business model.

The traditional payments literature has also explored the effects on information frictions on payments arrangements (see for example the seminal work by Kocherlakota (1998) and Kocherlakota and Wallace (1998) and Nosal and Rocheteau (2017) for an overview of this literature). In an important contribution to this literature, Kahn et al. (2005) have looked into the connection between payments services and privacy, studying the role of money relative to other payments services for protecting privacy. However, this literature has not looked into data generation, its monetization and how it is related to the provision of payments.

Finally, the literature on the economics of platforms focuses on two-sided markets and highlights the role of network externalities. A main lesson is that platforms maximize profits by getting both sides of the market on board – a feature that also drives some important results in our paper. These models have been successully applied to the study of traditional payment platforms such as the card payment industry. Early examples are Rochet and Tirole (2002) or Schmalensee (2002). More recently, there has been a new line of research studying the provision of digital tokens by non-payment platforms. Gans and Halaburda (2015) study the design of private digital currencies from a platform management perspective and show that a profit-maximizing platform may choose to limit the functionality of digital currencies. Other papers focus on how initial coin offerings help finance the development and operation of a platform (see for example Catalini and Gans (2018), Cong e al. (2018) or Garratt and van Oordt (2019a)). These contributions have not looked, however, at the importance of privacy concerns when a platform looks at the introduction of payments from a data perspective.

2 Data-driven Platforms

We first develop a model that formalizes the key trade off between the value of data generated by a platform and the privacy concerns that arise from the use of this data. There are two stages. In the first one – the *platform stage* – a digital platform generates data from activities that take place on the platform. The data generated on that platform can then be used in the second stage – *the trading stage* – to increase surplus in transactions between buyers and sellers. Buyers, however, cannot profit directly from this data and, indeed, will lose some surplus if the data are being used by the seller. This gives rise to fundamental privacy concerns.

2.1 Set-up

A platform allows a measure 1 of users to engage in activities a_i in exchange for a price p per unit of activity. Users derive marginal utility v from the activity, but incur a disutility or time cost which – for simplicity – is given by $a_i^2/2$.

The platform also has a technology – think of data analytics – that generates data. There is no direct cost of running this technology which is described by the probability of determining a user's preference for a good as a function of his activities on the platform

$$D(a_i) = \min\{\delta a_i, 1\}. \tag{1}$$

The parameter δ captures the efficiency of the technology and the probability of learning a user's preferences is increasing in the activity a_i.

After their activities on the platform, the users will be randomly matched with a measure 1 of sellers. We assume a *payment friction* so that only a fraction $\eta \in (0, 1]$ of buyers can pay the seller.[1] The size of a buyer's demand ε is drawn from a distribution $G(\varepsilon)$ with support $[\underline{\varepsilon}, \bar{\varepsilon}]$ and is known to the buyer upfront, but cannot be observed by the platform.[2] If there is trade, buyers obtain a surplus of $\mathcal{S}_b$ per unit demanded from trading, while the seller's surplus is normalized to 0.

Sellers can also purchase the data about a buyer's preferences from the platform before matching takes place. Since the data is useful in a transaction, the total surplus from trading increases by $\mathcal{S} > 0$ per unit of demand. Sellers have an incentive to acquire data since they can make an offer that extracts this surplus and the initial surplus $\mathcal{S}_b$ from buyers. Finally, we assume that the platform sells the information to sellers at a price that extracts the entire payoff from trading with information, $\mathcal{S}_s = \mathcal{S} + \mathcal{S}_b$.

This captures that the platform has market power when selling its information. This information is valuable as it increases surplus in the economy. But it also raises a privacy concern for the platform's users as they are worse off when information is sold to sellers by the platform. Before analyzing the platform's problem of selling data, we provide a concise microfoundation for this set-up where privacy concerns arise endogenously when data are sold that generate additional surplus.

2.2 Privacy Concerns – a Microfoundation

Buyers There are two types of goods, customized goods, $q(i)$, and a generic good, $\bar{q}$. A buyer j consumes only a specific type j customized good so that the marginal utility derived from $q(i)$ is $\bar{u}$ for $i = j$, and is zero for $i \neq j$. For a generic good, the marginal utility $\tilde{u} \in [0, \bar{u}]$ is randomly drawn from a distribution $H(u)$.

[1] There are different possible interpretations of $\eta < 1$. One is due to frictions in the payment system that make it hard to pay for certain transactions (e.g. cross-border transactions). Another interpretation is credit frictions where a buyers cannot commit to pay the seller.

[2] An alternative setup that delivers the same results is one where the buyer purchases one unit from ε different sellers.

The buyer's utility is thus given by

$$U_j(q(i), \bar{q}) = \bar{u} \cdot q(i)\mathbf{1}_{i=j} + \tilde{u} \cdot \bar{q} \tag{2}$$

where $\mathbf{1}_{i=j}$ is an indicator function capturing whether the customized good matches the buyer's type. Finally, we assume that the preference for a particular customized good is private information for the buyer.

Sellers A seller can produce either a customized good or a generic good, but not both. The marginal cost of producing a customized good is 1, while for a generic good it is $1 + \bar{c}$. Hence, the customization of a product not only increases the utility from consuming it, but also reduces the cost of producing it.

Trading In the trading stage, the seller makes a take-it-or-leave-it offer to the buyer for either producing the customized good or the generic good. The seller, however, cannot offer a customized good as the buyer's type is not known. Hence, the seller will offer a generic good at a price P that solves

$$\max_P P[1 - H(P)] - 1 - \bar{c}. \tag{3}$$

where $1 - H(P)$ is the probability of the buyer to accept the offer. The optimal price is given by the reciprocal of the hazard rate

$$P^* = \frac{1 - H(P^*)}{H'(P^*)} \tag{4}$$

We can normalize the sellers profits to zero at the optimal price P^* so that the expected surplus of the buyer from purchasing a generic good is given by

$$\mathcal{S}_b = \big(1 - H(P^*)\big)\big(\mathbb{E}[u|u \geq P^*] - P^*\big) \tag{5}$$

Information about Buyer's Preferences The seller can buy information from the platform to learn the preference of the buyer for the customized good. With this information, the seller can offer a customized good and charge the price $P = \bar{u}$. The payoffs from trading can be summarized in the following table.

	Unknown (trade generic)	**Known (trade special)**
Buyer's surplus	$\mathcal{S}_b$	0
Seller's surplus	0	$\mathcal{S}_s = \bar{u} - 1$
Total surplus	$\mathcal{S}_b$	$\mathcal{S}_s = \bar{u} - 1$

When the preference of the buyer is known, selling a customized good increases the total surplus by

$$\mathcal{S} = \mathcal{S}_s - \mathcal{S}_b. \tag{6}$$

which is the social value of the information provided by the platform. Sellers are willing to purchase the information from the platform and offer a customized good up to a price that is equal to the additional surplus $\mathcal{S}_s$. This surplus is not only the additional social value $\mathcal{S}$ generated from the information, but also the buyer's informational rent $\mathcal{S}_b$ good. It is this utility loss of the buyer that gives rise to *endogenous privacy concerns* from engaging on activities on the platform.

2.3 Platform Pricing and Data Sales

We first determine the demand for activities when the platform sells its data. The platform's users take into account that they will lose surplus in the trading stage when the platform sells its data. Hence, a user with realization ε for his demand in the trading stage solves the following problem

$$V(\varepsilon) = \max_{a(\varepsilon)} va(\varepsilon) - pa(\varepsilon) + \eta(1 - D(a(\varepsilon)))\mathcal{S}_b\varepsilon - \frac{a(\varepsilon)^2}{2} \tag{7}$$

A user faces three costs. First, he has to pay the price p per unit of activities on the platform. Second, he faces the private cost $a(\varepsilon)^2/2$ from engaging in the activities. And, finally, he takes into account that – with probability $D(a(\varepsilon))$ – he will lose his surplus from trading $\mathcal{S}_b\varepsilon$ whenever he can trade which occurs with probability η.

Assuming $D(a(\varepsilon)) < 1$,[3] the optimal choice for activities is given by

$$a(\varepsilon) = v - p - \delta\eta\mathcal{S}_b\varepsilon \tag{8}$$

so that the total activity on the platform is

$$\bar{a} = v - p - \delta\eta\mathcal{S}_b\mathbb{E}(\varepsilon). \tag{9}$$

The platform faces two markets, one for its activities and another one for the information it generates. It sets a price p per unit of platform activities[4] and sells the data obtained from user's activities to sellers at a price that is equal to the expected value of such information,

$$\eta \int \delta a(\varepsilon)\mathcal{S}_s\varepsilon dG(\varepsilon). \tag{10}$$

With probability η, a seller can trade with a user of the platform. In such a trade, the seller expects to be able to use the data with probability $\delta a(\varepsilon)$ where he obtains a surplus of $\mathcal{S}_s\varepsilon$. Using the demand functions, the platform's profits are then given by

$$\Pi = \max_p \int pa(\varepsilon) + \delta\eta a(\varepsilon)\mathcal{S}_s\varepsilon dG(\varepsilon) = \max_{\bar{a}} \bar{a}\left(v - \bar{a} + \delta\eta\mathcal{S}\mathbb{E}(\varepsilon)\right) - \delta^2\eta^2\mathcal{S}_s\mathcal{S}_b\mathbb{V}(\varepsilon). \tag{11}$$

The solution to this problem is given by

$$\bar{a} = \frac{v + \delta\eta\mathcal{S}\mathbb{E}(\varepsilon)}{2} \tag{12}$$

with individual users choosing their activity on the platform according to

$$a(\varepsilon) = \bar{a} + \delta\eta\mathcal{S}_b\left(\mathbb{E}(\varepsilon) - \varepsilon\right) \tag{13}$$

The optimal price the platform sets is thus given by

$$p = \frac{v - \delta\eta(\mathcal{S}_b + \mathcal{S}_s)\mathbb{E}(\varepsilon)}{2}. \tag{14}$$

The pricing formula for activities is interesting to interpret, especially when viewing the platform as a *producer of data as an intermediate good.* The marginal costs of producing

[3] This is the case if and only if $\mathcal{S}_b\underline{\varepsilon} \geq \frac{v}{2\delta} + \frac{1}{2}\mathbb{E}(\varepsilon)(\mathcal{S}_b + \mathcal{S}_s) - \frac{1}{\delta^2}$.

[4] An alternative interpretation of p is that the platform sets the quality, instead of the price, of platform activities. That is, it chooses to enhance the (marginal) value of activity by $-p$ subject to a linear cost. A negative price is then interpreted as a positive enhancement of the platforms quality.

data arises from the privacy concerns $\mathcal{S}_b\mathbb{E}(\varepsilon)$ that are offset by the marginal value of activities v for the platform's users. Since the platform also sells the data, it acts as a monopolist for supplying the data to sellers which is reflected by the last term, $\mathcal{S}_s\mathbb{E}(\varepsilon)$. Note that this implies that the price p can be negative when the platform subsidizes activities. The pricing structure is akin to a two-sided platform where the prices are targeted to each side of the platform. Sellers are captive, but the demand for activities is elastic and, hence, the platform has an incentive to subsidize activities.

The profit from the platform's operation is then given by

$$\Pi = \left(\frac{v + \delta\eta\mathcal{S}\mathbb{E}(\varepsilon)}{2}\right)^2 - \delta^2\eta^2\mathcal{S}_s\mathcal{S}_b\mathbb{V}(\varepsilon). \tag{15}$$

Hence, when deciding to sell data ($\delta > 0$) or not ($\delta = 0$), the platform faces a trade-off. Data sales lead to additional revenue which is equal to the expected additional social trading surplus $\mathcal{S}$ from the data since users get compensated on average for the privacy loss $\mathcal{S}_b$. But there is cost of generating them, since users demand an informational rent as their individual privacy concerns cannot be observed by the platform.[5] We have the following result.

Proposition 1. *The platform offers data sales whenever*

$$\frac{2v}{\delta\eta} \geq \Lambda \tag{16}$$

where

$$\Lambda = 4\frac{\mathcal{S}_s\mathcal{S}_b}{\mathcal{S}}\frac{\mathbb{V}(\varepsilon)}{\mathbb{E}(\varepsilon)} - \mathcal{S}\mathbb{E}(\varepsilon). \tag{17}$$

Payments and data sales are substitues; i.e., as payments frictions decrease, the platform has a smaller incentive to sell its data.

The (net) costs of privacy concerns are summarized by Λ and increase in the heterogeneity of the users as expressed by the variance-to-mean ratio $\mathbb{V}(\varepsilon)/\mathbb{E}(\varepsilon)$ and the cost $\mathcal{S}_b$ from losing

[5] If users' types were observable, the platform would offer a lower price to a user with a higher ε. When the types are not observable, the price is too high (low) for high (low) ε users who incur a high (low) privacy loss and yield a high (low) data sales revenue.

privacy. Note that Λ can be negative whenever the heterogeneity of privacy concerns are small relative to the average surplus $\mathcal{S}\mathbb{E}(\varepsilon)$ generated from data sales. The cost vanishes when there is no heterogeneity ($\mathbb{V}(\varepsilon) \to 0$). If heterogeneity is large, the costs are large enough so that the platform will not sell data.

The role of payments frictions is interesting. Conditional on selling data, profits are increasing in η whenever $\frac{v}{\delta\eta} \geq \Lambda$; i.e., when privacy concerns are not too large. The reason is that the platform can sell its data at a higher price to merchants. Surprisingly, however, smaller payments frictions decrease the incentives to monetize the data in the first place. The reason is that it is costly for the platform to compensate users for their expected loss of privacy. This cost increases as there are more transactions (less payments frictions). Hence, the platform has a lower incentive to generate and sell its data in the first place. For the remainder of the paper, we assume that $\frac{2v}{\delta} \geq \Lambda$, so that data sales are optimal for the platform independent of the payments friction.

2.4 Efficiency and Heterogeneity

We now take the pricing choice of the platform as given and evaluate whether data sales are optimal from a social perspective. The utility for the average user is given by

$$\begin{aligned} V &= \int (v-p)a(\varepsilon) - \frac{a(\varepsilon)^2}{2} + \eta_0(1-\delta a(\varepsilon))\mathcal{S}_b\mathbb{E}(\varepsilon)dG(\varepsilon) \\ &= \frac{1}{2}\bar{a}^2 + \eta\mathcal{S}_b\mathbb{E}(\varepsilon) + \frac{1}{2}\delta^2\eta^2\mathcal{S}_b^2\mathbb{V}(\varepsilon). \end{aligned} \tag{18}$$

The last term implies that the average user always benefits from data sales, since he is compensated for the loss of privacy and earns an information rent which is given by the third term in the expression above.

We define welfare by the sum of the platforms profit and the utility of the average user

$$\begin{aligned} W &= \int va(\varepsilon) - \left(\frac{a(\varepsilon)}{2}\right)^2 + \eta\delta a(\varepsilon)\mathcal{S}\varepsilon dG(\varepsilon) \\ &= \bar{a}\left(v - \frac{\bar{a}}{2} + \delta\eta\mathcal{S}\mathbb{E}(\varepsilon)\right) - \frac{1}{2}\delta^2\eta^2\mathcal{S}_b(\mathcal{S}_s+\mathcal{S})\mathbb{V}(\varepsilon) + \eta\mathcal{S}_b\mathbb{E}(\varepsilon) \end{aligned} \tag{19}$$

where $\bar{a}$ is the average choice of activities induced by the platform's pricing policy (see equations (12) and (14)). The welfare funtion considers the entire surplus from their activities and the social surplus from data sales given by $\mathcal{S}$. Hence, from a social perspective there is a larger incentive to sell data.

Proposition 2. *Data sales are optimal if and only if*

$$\frac{2v}{\delta\eta} \geq \Lambda - 2\mathcal{S}_b \frac{\mathbb{V}(\varepsilon)}{\mathbb{E}(\varepsilon)}. \tag{20}$$

While data sales can increase average welfare, individual users will be affected differently by data and payment services. For $\delta a(\varepsilon) < 1$, the value of the platform for an individual user, $V(\varepsilon)$, is strictly convex and increasing in ε. The effect of data sales on individual users, however, is ambiguous. The marginal value of an increase in data sales for a user with ε is given by

$$\begin{aligned}\frac{\partial V(\varepsilon)}{\partial \delta} &= (v - p - a(\varepsilon))\frac{\partial a(\varepsilon)}{\partial \delta} - \frac{\partial p}{\partial \delta}a(\varepsilon) - \tilde{\eta}\mathcal{S}_b\varepsilon\left(\delta\frac{\partial a(\varepsilon)}{\partial \delta} + a(\varepsilon)\right) \\ &= -\frac{\partial p}{\partial \delta}a(\varepsilon) - \tilde{\eta}\mathcal{S}_b\varepsilon a(\varepsilon) \end{aligned} \tag{21}$$

where we have used the envelope theorem in the second step.

Even though data services make all users suffer a higher privacy loss, users are compensated by cheaper platform activities. The first term represents this price effect ($\partial p/\partial\delta < 0$), which is positive and decreases in ε. Hence, users with low privacy concerns gain the most from the drop in the platform price because they are the most active. The second effect expresses the change in privacy costs for the user, is negative and convex in ε. Hence, intermediate users suffer the greatest privacy loss as users with large privacy concerns adjust their activities more aggressively.

Proposition 3. *The average user prefers data sales, but some users may suffer a welfare loss from data sales.*

Before introducing payment services, we breifly discuss the effects of privacy concerns on these results. Consider an increase in privacy concerns where the surplus of buyers increases to $\mathcal{S}_b + \Delta$, but the total surplus that can be generated by better data, $\mathcal{S}$, stays constant. From equations (12) and (13), it follows directly that there is a mean preserving spread in the distribution of activities across the platform. Individual users being concerned about their loss of privacy change their behaviour, while the aggregate amount of activities remain the same.

The reason is simple. As privacy concerns increase, the platform needs to be more aggressive to generate the same amount of data, dropping the price on the platform (see equation (14)). It has an incentive to do so, as it can sell data at a higher price to sellers since $\mathcal{S}_s$ has also increased by Δ. Hence, users with low (high) concerns increase (decrease) their activities. As a result, the platform's profits drop, because it becomes harder for the platform to compensate users for their privacy loss when there is imperfect information.

3 PayTech: Data-driven Payments

3.1 Technology

So far, the platform took the existing payments technology as given. We now allow the platform to use its data to provide an enhanced payments technology. We refer to this technology as *data-driven payments* since the use of data from activities can alleviate payments frictions like in the case of Alibaba. Specifically, we assume that the aggregate data $\bar{a}$ generated by the platform mitigates the payment friction according to the linear[6] technology

$$\eta(\bar{a}) = \min\{\rho\bar{a}, 1\}. \tag{22}$$

We denote the original payment technology by η_0. We assume that all transactions are conducted using the best available technology $\max\{\eta(\bar{a}), \eta_0\}$. We make the following assumption which ensures that the productivity of data-driven payments is not so large that the platform can set $\eta(\bar{a}) = 1$ with its choice of activities when the technology is absent.

[6]To capture network effects from generating data, one could assume that $\eta(0) = 0$, $\eta' > 0$ and $\eta'' \geq 0$. This feature would – by assumption – generate increasing returns-to-scale in data.

Assumption 4. $\frac{1}{\rho} \geq \frac{v+\delta\mathcal{S}\mathbb{E}(\varepsilon)}{2}$

Finally, we assume that the platform cannot extract any surplus generated from the payments technology directly.[7] However, the platform can still profit from the technology indirectly since it enhances its data sales which is the channel we investigate in this paper.

3.2 Complementarity between Data and Payments

For expositional purposes, we first assume that $\eta(\bar{a}) \geq \eta_0$ so that using data allows the platform to reduce payment frictions. Consumers take both, p and $\bar{a}$, as given when making their choices about activities. Hence, they forecast the payment friction $\eta(\bar{a})$ – and, hence, their cost of losing privacy – when choosing their individual $a(\varepsilon)$. Individual and aggregate demand are then again given by

$$a(\varepsilon) = v - p - \delta\eta(\bar{a})\mathcal{S}_b\varepsilon \tag{23}$$

$$\bar{a} = v - p - \delta\eta(\bar{a})\mathcal{S}_b\mathbb{E}(\varepsilon). \tag{24}$$

The platform maximizes its profits by choosing the aggregate level of data according to

$$\Pi(\bar{a}) = \max_{\bar{a}} \bar{a}\left(v - \bar{a} + \delta\eta(\bar{a})\mathcal{S}\mathbb{E}(\varepsilon)\right) - \delta^2\eta(\bar{a})^2\mathcal{S}_s\mathcal{S}_b\mathbb{V}(\varepsilon) \tag{25}$$

where the ability to make transactions is now also a function of aggregate activities $\bar{a}$. Adopting data-driven payments introduces a new trade-off for the platform. On the one hand, more data reduce the payment friction and thus increase the sale price of the data. On the other hand, data are costly because of the information rent linked to the unobservable privacy costs of its users.

With the linear payments technology, the objective function is quadratic in $\bar{a}$ and strictly increasing at $\bar{a} = 0$. Hence, the solution will depend on the curvature of the profit function which is related to

$$\Phi = -\Big(1 - \rho\delta\mathcal{S}\mathbb{E}(\varepsilon) + \rho^2\delta^2\mathcal{S}_s\mathcal{S}_b\mathbb{V}(\varepsilon)\Big) = \frac{1}{2}\frac{\partial^2\Pi}{\partial\bar{a}^2}. \tag{26}$$

[7] This is motivated by the fact that many data-driven platforms provide their payment services for free. Also, regulation could tax any direct returns associated with the provision of the better payment technology.

The expression Φ captures the *returns of scale* of the data technology for the platform. The input in the technology are the activities a on the platform. The output is given by data sales $\delta a(\varepsilon)$ and improvements in payments technology $\rho\bar{a}$.

In the absence of PayTech, we have that $\Phi = -1$ and the profit function is strictly concave. When data can also be used for PayTech, there are two extra terms

$$\delta\rho\mathcal{S}\mathbb{E}(\varepsilon) - \delta^2\rho^2\mathcal{S}_s\mathcal{S}_b\mathbb{V}(\varepsilon) \geq 0.$$

The first term captures that more activities generate data, which are useful in reducing payments frictions and making data sales more valuable. The second term, however, captures that the platform has to pay more to compensate users for their privacy loss as payments frictions decrease.

By Assumption 4 and the assumption that $\frac{2v}{\delta} \geq \Lambda$, the sum of these two terms is positive. Hence, these terms express a *complementarity* between data sales and using data for payments so that $\Phi \geq -1$. If the sum of these terms is larger than 1, the complementarity is strong enough to generate *increasing returns to scale* for the data-driven platform. In this case, the complementarity "overwhelms" the cost of generating data.

Lemma 5. *Suppose the platform uses data-driven payments.*

If $\frac{v\rho}{2} \geq -\Phi$, *the platform chooses* $\bar{a} = \frac{1}{\rho}$ *with profits given by*

$$\Pi = \frac{v}{\rho} + \frac{\Phi}{\rho^2}.$$

If $\Phi \in [-1, -\frac{v\rho}{2})$, *the platform chooses* $\bar{a} = -\frac{1}{2\Phi}v < \frac{1}{\rho}$ *with profits given by*

$$\Pi = -\frac{1}{4\Phi}v^2 > 0.$$

The lemma characterizes the optimal choice by the platform, when data is monetized in two ways. First, data is sold to sellers. Second, data is used to improve payment frictions which increases the number of transactions and, thus, the value of the data for sellers. If the complementarity is strong enough, the platform exploits as much data as possible to completely resolve payments frictions.

3.3 Payments Introduction

We will now look at the incentives to introduce payment services by the platform. The complementarity between payments and data generates an incentive for introducing payments whenever the payment frictions are large enough (η_0 sufficiently low). Despite this complementarity, however, if the existing payments technology is sufficiently good (η_0 close to 1), the platform has no incentives to introduce payments. In that case, the platform only sells its data, and transactions take place using the existing payments technology η_0.

Proposition 6. *The platform introduces payments if and only if payments frictions are large enough (i.e., $\eta_0 \leq \hat{\eta}(\Phi)$).*

The platform is more likely to introduce payments as the complementarity becomes stronger (i.e., $\partial\hat{\eta}/\partial\Phi > 0$).

For given η_0, the platform will introduce payments as soon as the data use for selling information and payments becomes complementary enough. The complementarity depends again on the privacy concerns of the platform's users. For $\mathcal{S}_b + \Delta$, holding $\mathcal{S}$ constant, we have that the complementarity decreases making it again less likely for the platform to introduce payments. The reason is that the platform has to compensate users more for their privacy loss making the introduction of payments less likely.

3.4 Efficiency and Payments

We again take the pricing decision of the platform as given when evaluating whether the introduction of payments is efficient or not. With data-driven payments, welfare now also takes into account that there is a direct benefit from better payments. Hence, we have

$$W(\bar{a}) = \bar{a}\left(v - \frac{\bar{a}}{2} + \delta\eta(\bar{a})\mathcal{S}\mathbb{E}(\varepsilon)\right) - \frac{1}{2}\delta^2\eta(\bar{a})^2\mathcal{S}_b(\mathcal{S}_s + \mathcal{S})\mathbb{V}(\varepsilon) + \eta(\bar{a})\mathcal{S}_b\mathbb{E}(\varepsilon) \tag{27}$$

where the extra term reflects that there are more transaction that generate a basic surplus of $\mathcal{S}_b$.

There are now two changes from the platform's problem. The curvature of the welfare function is given by

$$\Psi = -\left(\frac{1}{2} - \delta\rho\mathcal{S}\mathbb{E}(\varepsilon) + \frac{1}{2}\delta^2\rho^2\mathcal{S}_b(\mathcal{S}_s + \mathcal{S})\mathbb{V}(\varepsilon)\right) = \frac{1}{2}\frac{\partial^2 W}{\partial\bar{a}^2}. \tag{28}$$

Note that the complementarity of payments and data is stronger from a social point of view ($\Psi > \Phi$) or, equivalently, there is also an extra, social return from introducing payments. Hence, it is optimal to generate more data than the platform when using the data-driven payments technology and there are stronger, social incentives to introduce data-driven payments. Hence, we have the following result.

Corollary 7. *Data-driven payments always increase overall welfare whenever the platform introduces them.*

Consider next an individual user after the platform introduces payments ($\eta(\bar{a}) > \eta_0$). His payoff is given by

$$\begin{aligned} V(\varepsilon) &= \frac{1}{2}\left(a(\varepsilon)\right)^2 + \eta(\bar{a})\mathcal{S}_b\varepsilon \\ &= \frac{1}{2}\left(v - p - \delta\eta(\bar{a})\mathcal{S}_b\varepsilon\right) + \eta(\bar{a})\mathcal{S}_b\varepsilon. \end{aligned} \tag{29}$$

Hence, there are two effects associated with the introduction of payments. First, there is a direct effect expressed by the second term. Better payments benefits all users, since they can conduct more transactions. Second, there is an indirect effect as payments introduction changes the pricing on the platform as well as the likelihood of a user to lose privacy which is expressed in the first term. Differentiating, we have

$$\frac{\partial V(\varepsilon)}{\partial\eta} = -a(\varepsilon)\left(\frac{\partial p}{\partial\eta} + \delta\mathcal{S}_b\varepsilon\right) + \mathcal{S}_b\varepsilon = -a(\varepsilon)\frac{\partial p}{\partial\eta} + (1 - \delta a(\varepsilon))\mathcal{S}_b\varepsilon. \tag{30}$$

Since the price for platform activities falls after payments introduction, we have the following result.

Corollary 8. *All users benefit from the introduction of payments.*

This result is surprising. All users benefit directly from payments introduction. But the platform also compensates users for their lose of privacy to entice them to engage in activities on the platform. This is necessary to generate data. The direct benefit and the lower price are sufficient to compensate *all* users for the loss of their privacy.

Furthermore, the gains from payments introduction are increasing in ε. Users with larger trade sizes benefit more from payments introduction. Since users with intermediate transactions sizes are most negatively affected by data sales in the first place, introducing better payments by the platform may, hence, make all users prefer data sales.

4 PayTech: Payments-Driven Data

4.1 Technology

We consider now a second technology that allows the platform to extract extra information from payments. This technology is an "add-on" to the data-driven payments technology of the platform. We assume that this new technology generates additional data with probability γ from each completed transaction, where the platform had no information yet. To run this technology the platform needs to incur a cost $F \geq 0$ per transaction.[8] We call this a *payments-driven data* technology since it captures the data feedback from payments that enriches a platform's data from activities like in the case of Facebook or Google.[9]

The extra data can again be sold to sellers at a price equal to $\mathcal{S}_s\mathbb{E}(\varepsilon)$.[10] Since the technology only depends on aggregate data through the payments introduction, users will not be taking into acccount how their individual activities $a(\varepsilon)$ and the introduction of payments will impact their loss of privacy. In other words, the payments-driven data technology causes

[8] Alternatively, we could assume that the platform needs to make an investment at a fixed cost F. Our results would not change for $\Phi \geq -\frac{v\rho}{2}$.

[9] We provide a microfoundation for this set-up in the appendix.

[10] We assume that this information is available simultaneously with the transaction itself. It is straightforward to consider a dynamic model where data from payments in one period are available only in the next. The steady state outcome is similar to one of the static model we consider.

a negative externality on users as they will not be compensated directly for their loss of privacy, but only indirectly when the platform lowers its price to generate more data.

4.2 Feedback from Payments Data

The availability of the new technology changes the incentives to introduce data-driven payments. When $\gamma\mathcal{S}_s\mathbb{E}(\varepsilon) \geq F$ the platform can generate additional profit from redistributing surplus through this new technology. There is now an additional complementarity between data and payments.

Consider the platform's profit function with data-driven payments and payments-driven data which is given by

$$\Pi(a) = \max_{\bar{a}} \bar{a}\left(v - \bar{a} + \delta\eta(\bar{a})\mathcal{S}\mathbb{E}(\varepsilon)\right) - \delta^2\eta(\bar{a})^2\mathcal{S}_s\mathcal{S}_b\mathbb{V}(\varepsilon) + \eta(\bar{a})\left(\gamma\mathcal{S}_s\mathbb{E}(\varepsilon) - F\right). \tag{31}$$

The last term expresses the additional complementarity between payments and data. As payments-driven data are profitable, the platform can increase this profit by relying on data-driven payments $\eta(\bar{a}) \geq \eta_0$. Note that this feedback effect shifts profits upwards for all levels of data $\bar{a}$ without changing the overall returns-to-scale Φ of the data technology.[11] This yields the following result.

Lemma 9. *When the platform uses payments-driven data, the profit-maximizing amount of data $\bar{a}$ increases and the platform is more likely to introduce data-driven payments; i.e. the cut-off point $\hat{\eta}(\Phi)$ increases.*

This shows that there is a feedback effect where payments generate new data that lead to more data generation in the core business of the platform to support even better payments. From a social perspective, however, this feedback from payments-driven data may lead to suboptimal outcomes. The reason is that the social return on such data is given by $\mathcal{S}\mathbb{E}(\varepsilon) < \mathcal{S}_s\mathbb{E}(\varepsilon)$. The platform has a return not only from generating more surplus, but also from

[11] The reason is that the aggregate activities enter only indirectly through the payments technology into the return for data generation.

redistributing surplus from transactions. Hence, the platform can now have an incentive to *inefficiently* introduce its own payments technology to acquire payments-driven data.

4.3 Inefficient Payments Introduction

We first consider the introduction of payments-driven data. We have that the return from the technology differs for the platform and the planner since $\mathcal{S}_s > \mathcal{S}$. Whereas the platform looks at the total surplus it can redistribute when generating such data, the planner only takes into account the social surplus. Hence, conditional on introducing the new payments technology, payments-driven data are inefficient whenever

$$\gamma \mathcal{S}_s \mathbb{E}(\varepsilon) > F > \gamma \mathcal{S} \mathbb{E}(\varepsilon).$$

Suppose for the remainder of this section that $\Phi \geq -\frac{v\rho}{2}$, so that when using the data-driven payment technology the platform chooses to induce $\bar{a} = 1/\rho$ so that $\bar{\eta} = 1$. For $\gamma \mathcal{S}_s \mathbb{E}(\varepsilon) \geq F$, the platform will introduce the payments technology if

$$\Delta_\Pi = \frac{1}{\rho}\left(v - \frac{1}{\rho} + \delta \mathcal{S} \mathbb{E}(\varepsilon)\right) - \bar{a}_0^2 - (1-\eta_0^2)\delta^2 \mathcal{S}_s \mathcal{S}_b \mathbb{V}(\varepsilon) + \gamma \mathcal{S}_s \mathbb{E}(\varepsilon) - F \geq 0 \tag{32}$$

where $\bar{a}_0$ is activtiy level induced by the platform the optimal choice when using the existing payments technology η_0. Here, we have taken into account that the platform will always use data-driven payments and payments-driven data simultaneously.

The planner will prefer data-driven payments whenever

$$\Delta_W = \frac{1}{\rho}\left(v - \frac{1}{2\rho} + \delta \mathcal{S} \mathbb{E}(\varepsilon)\right) - \frac{3}{2}\bar{a}_0^2 - (1-\eta_0^2)\delta^2 \mathcal{S}_b (\mathcal{S}_s + \mathcal{S}) \mathbb{V}(\varepsilon) + (1-\eta_0)\mathcal{S}_b \mathbb{E}(\varepsilon) + \\ + \max\{\gamma \mathcal{S} \mathbb{E}(\varepsilon) - F, 0\} \geq 0. \tag{33}$$

For intuition, it is instructive to look at the case where $\gamma \mathcal{S} \mathbb{E}(\varepsilon) \geq F$. The platform's incentives to introduce payments are thus larger whenever

$$\gamma \mathcal{S}_b \mathbb{E}(\varepsilon) \geq \frac{1}{2}\left(\frac{1}{\rho^2} - \bar{a}^2\right) + \frac{1}{2}(1-\eta_0^2)\delta^2 \mathcal{S}_b^2 \mathbb{V}(\varepsilon) + (1-\eta_0)\mathcal{S}_b \mathbb{E}(\varepsilon). \tag{34}$$

The left-hand side of this expression gives the extra return for the platfrom from payments-driven data since it cares about redistributing total surplus rather than the increase in social surplus. The right-hand side recalls the three reasons why data-driven payments have a higher social return than the platform's private return. Hence, the incentives are larger when $\eta_0 \to 1$ provided the new technology is good enough or, equivalently, ρ is sufficiently large.

Proposition 10. *Suppose $\gamma \mathcal{S}\mathbb{E}(\varepsilon) - F < 0 < \gamma \mathcal{S}_s \mathbb{E}(\varepsilon) - F$. As $\eta_0 \to 1$, there is inefficient introduction of data-driven payments by the platform if ρ is large enough.*

Suppose $\gamma \mathcal{S}\mathbb{E}(\varepsilon) - F > 0$, but sufficiently small. As $\eta_0 \to 1$, there is an intermediate region for ρ such that the introduction of data-driven payments by the platform is inefficient.

This result is intuitive. Assumption 4 ensures that the platform has no incentives to introduce data-driven payments when η_0 is sufficiently close enough. With the add-on technology, however, the platform has an extra return that – if large enough – can compensate for the loss that is incurred by the platform when introducing payments. The loss is not too large, if the new technology can overcome payments frictions easily; i.e., if ρ is sufficiently large.

The choice by the platform becomes inefficient, if welfare does not increase with the introduction of data-driven payments. If the additional social gain from the add-on technology is small enough, the planner will not introduce the technology. For this, however, the technology to decrease payment frictions must be not too powerful; i.e., ρ is sufficiently small.

Figure 3 provides a numerical example demonstrating four possible outcomes of payment introduction over the space (ρ, η_0) for the case where$\gamma \mathcal{S}\mathbb{E}(\varepsilon) < F < \gamma \mathcal{S}_s \mathbb{E}(\varepsilon)$.[12] In the figure, condition (33) defines a downward sloping curve below which the planner prefers payment adoption. Condition (32) defines a upward sloping curve below which the platform introduces payment services. Hence there are four regions. When η_0 is low, introducing payment services is socially efficient, but the platform chooses not to do so when ρ is small as it cannot fully internalize the benefits, leading to under-adoption. When η_0 is high, introducing payment services is socially inefficient, but the platform chooses to do so when

[12] The parameter values for this example are $\delta = 0.9$, $\mathcal{S}_b = 0.57$, $\mathcal{S}_b = 0.6$, $\upsilon = 0.1$, $\gamma = 0.01$, $F = 0.06$ and the distribution for ε is given by $Prob(\varepsilon = 10) = Prob(\varepsilon = 10.1) = 0.5$.

ρ is large because payments produce data for extracting surplus from buyers, leading to over-adoption of payments.

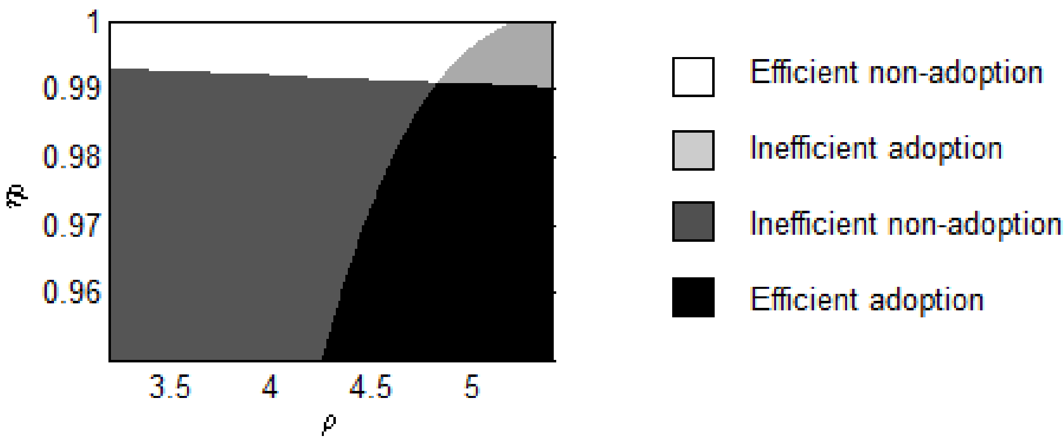

Figure 3: Example – Payments Adoption

Finally, we turn to how the users of the platform are affected by the introduction of payments-driven data. The average user will benefit from the add-on technology as long as

$$\Delta_V = \frac{1}{2}\left(\frac{1}{\rho^2} - \bar{a}_0^2\right) + (1-\eta_0)\mathcal{S}_b\mathbb{E}(\varepsilon) + \frac{1}{2}(1-\eta_0^2)\delta^2\mathcal{S}_b^2\mathbb{V}(\varepsilon) - \gamma\mathcal{S}_b\mathbb{E}(\varepsilon) \geq 0. \tag{35}$$

The first term is positive and expresses the indirect compensation for users due to lower prices and, hence, more activities on the platform. The two middle terms give the direct net benefit from the introduction of data-driven payments. Users can carry out more transactions and obtain a larger information rent. The last term is the additional loss of privacy from payments-driven data for which the consumer is not being directly compensated. Comparing this expression with equation (34) gives the following result.

Corollary 11. *Whenever the platform has larger incentives to introduce payments-driven data, the average user will lose from the introduction of the payments technology.*

This is an interesting result. Even if it is efficient to introduce payments-driven data – and, hence, the payments technology – it can lead to suboptimal outcomes for the users of the platform. The planner takes into account both, platform profits and user surplus, but does not value the redistribution of surplus given by $\gamma\mathcal{S}_b\mathbb{E}(\varepsilon)$ which does not affect overall welfare. Hence, from the perspective of an average user, payments-driven data – even though it is efficient to introduce them – can lead to worse outcomes.

For the individual users, consider the case where $\eta_0 \to 1$. We have that a user with transaction size ε benefits from payments-driven data as long as

$$\Delta_V(\varepsilon) = \frac{1}{2}\left(\frac{1}{\rho^2} - \left(\frac{v + \delta\mathcal{S}\mathbb{E}(\varepsilon)}{2}\right)^2\right) - \delta\mathcal{S}_b(\mathbb{E}(\varepsilon) - \varepsilon)\left(\frac{1}{\rho} - \frac{v + \delta\mathcal{S}\mathbb{E}(\varepsilon)}{2}\right) - \gamma\mathcal{S}_b\varepsilon. \tag{36}$$

The first two terms express the net benefits from a change in activities on the platform. The last term is the loss in surplus from payments-driven data. By Assumption 4, users with higher privacy concerns as expressed by ε gain more from the introduction of data-driven payments, but they also lose more when payments are used to generate additional data. The net effect is negative whenever

$$\frac{\gamma}{\delta} \geq \frac{1}{\rho} - \frac{v + \delta\mathcal{S}\mathbb{E}(\varepsilon)}{2}. \tag{37}$$

If the new payments technology is relatively efficient and the externality large, the net benefits tend to decline with users privacy concerns. This yields the following result.

Corollary 12. *As $\eta_0 \to 1$, users with sufficiently large privacy concerns lose from the introduction of payments-driven data, if ρ is sufficiently large.*

5 Policy Implications for Payments

Many digital platforms and BigTech companies have introduced payments into their business model. To evaluate the impact on platform users and efficiency overall, policy makers need to understand the data-driven business model that many digital platforms have adopted. Activities on the platform or core services provided by the platform generate data that can be monetized as the information contained in this data has social value.

When these activities or services are bundled together with payments, there are two key policy considerations. First, to what degree does the platform compensate users for their data and privacy concerns? And second, how do data and payments interact on the platform?

Data generated from activities and payment services cause a privacy loss for platform members. However, the business model of BigTech relies on indirectly compensating users for this loss. BigTech platforms subsidize their core platform activities – or, even offering them for free to their users. Hence, losing privacy or giving up data when using the platform's payment solutions does not necessarily imply that users suffer an overall loss.

As we have pointed out, PayTech can increase surplus in two ways. Platform data can be used to overcome fundamental payments frictions. And payments generate additional data that the platform can use to generate additional surplus. At the same time, however, data and payments can also be used by the platform to redistribute existing surplus. Hence, how to view payments introduction by BigTech companies depends on the relative importance of these two channels, implying once again that a platform's payment solutions are not necessarily inefficient.

Based on these insights, we have derived several important considerations for payments policy. First, in less financially developed markets there tend to be large payments frictions. Data-driven payments can have important benefits to achieve better payments solutions. Examples are mobile payments that increase financial inclusion or the introduction of P2P real-time payments. But as platform users can extract rents from their privacy concerns, to achieve full efficiency, subsidies may still be required for the platform to optimally implement data-driven payments.

Second, in advanced economies, payments systems are already quite efficient. Hence, data-driven payments offer little benefits and may be outweighed by costs when the platform uses payments data to redistribute surplus from users to itself. Examples are data mining and A/B testing that require native payments solutions on the platform. Hence, preventing BigTech from introducing payments or regulating the use of payments data can be welfare-improving.

Third, while privacy concerns matter, payments regulation cannot treat such concerns in isolation. If users lose their privacy, they are not necessarily worse off, as better information leads to better payments technology. Some users may be worse off as they are not being fully compensated for their privacy loss. But the social gains from data and better payments can outweigh these concerns. Hence, regulators need to look at the effects of data-driven payments and payments-driven data in a nuanced way that recognizes other aspects than just privacy concerns.

Fourth, public provision of payment services may not necessarily lead to efficiency. The reason is that one cannot replicate the data-driven business model of digital platforms. The feedback effects between data and payments generate additional surplus that a stand-alone payment technology cannot provide. This points to a second best solution where softer privacy regulation combined with restrictions on the usage of payments data leads to better outcomes.

Fifth, regulating or prohibiting the monetization of data can have negative consequence for improvement in payments. Digital platforms may lose the incentives to offer payments solutions that can improve welfare. Such restrictions would negate the complementarity between data and payments that give platforms a special technological advantage for payments solutions. Hence, from a social perspective, it may be necessary to accept that BigTech companies obtain some rents from payments introduction as this guarantees higher surplus even though some users of the platform may be worse off after the introduction of payments.

6 Extensions

6.1 Regular Network Effects

Bigtech platforms often exhibit network externality through their activities. This feature can readily be introduced into our model. Suppose users derives utility from the activity according to

$$(v + n\bar{a})a_i \tag{38}$$

where $\bar{a}$ is the total activity on the platform. The parameter $n \in [0, \frac{1}{2})$ captures the network effect on the platform as the activity of a buyer is increasing in the average activity on the platform. The aggregate activity on the platform is now given by

$$\bar{a} = \frac{v + \eta_0 \delta \mathcal{S} \mathbb{E}(\varepsilon)}{2(1-n)} \tag{39}$$

with the platform's profit given by

$$\Pi(\tilde{\eta}) = \left(\frac{1}{1-n}\right)\left(\frac{v + \eta_0 \delta \mathcal{S} \mathbb{E}(\varepsilon)}{2}\right)^2 - \eta_0^2 \delta^2 \mathcal{S}_s \mathcal{S}_b \mathbb{V}(\varepsilon) \tag{40}$$

6.2 Privacy Option on the Platform

Some platforms offer a pricing struture that lets users protect their privacy against an increased price for activities on the platform. Assume that a user can pay a fee ϕ_o to "opt out". Paying the fee ensures that the platform will not monetize the personal data.

The platform thus sets different prices depending on the user's opt-out choice. The user's problem is now given by

$$V(\varepsilon, \mathbf{1}_o) = \max_a va - p(\mathbf{1}_o)a + \eta_0 \left(1 - (1 - \mathbf{1}_o)\delta a_i\right) \mathcal{S}_b \varepsilon - \frac{a(\varepsilon)^2}{2} - \mathbf{1}_o \phi_o \tag{41}$$

where $\mathbf{1}_o$ is an indicator variable for opting out and $p(\mathbf{1}_o)$ is the price for platform activities depending on the choice by the user.

For users that opt out users, it is straightforward to show that $p(1) = v/2$, and $a = v - p(1) = v/2$ for all ε. Hence,

$$V(\varepsilon, 1) = \frac{v^2}{8} + \eta_0 \mathcal{S}_b \varepsilon - \phi_o \tag{42}$$

Denote by $\mathbb{E}_0(\varepsilon)$ and $\mathbb{V}_0(\varepsilon)$ the mean and the variance of the remaining users for which the platform can monetize the data. The optimal price is then given by

$$p(0) = \frac{v - \delta \eta_0 \mathbb{E}_0(\varepsilon)(\mathcal{S}_b + \mathcal{S}_s)}{2} \tag{43}$$

Since $a(\varepsilon) = \bar{a} + \delta\eta_0\mathcal{S}_b\left(\mathbb{E}_0(\varepsilon) - \varepsilon\right)$, the payoff for a user with ε is thus

$$V(\varepsilon, 0) = \frac{1}{2}\left(\bar{a} + \delta\eta_0\mathcal{S}_b\left(\mathbb{E}_0(\varepsilon) - \varepsilon\right)\right)^2 + \eta_0\mathcal{S}_b\varepsilon \tag{44}$$

which is convex in ε. Hence, given $p(0)$ and ϕ_o, the incentive to opt-out

$$V(\varepsilon, 1) - V(\varepsilon, 0) \tag{45}$$

is concave in ε so that users with intermediate ε have higher incentives to opt out.

To solve the intial stage of the model, let $g_1(\phi_o)$ be the fraction of users opting out. The platform then sets ϕ_o to maximize $g_1(\phi_o)\Pi_1(\phi_o) + (1 - g_1(\phi_o))\Pi_0(\phi_o)$ where

$$\Pi_1(\phi_o) = \frac{v^2}{4} + \phi_o, \tag{46}$$

$$\Pi_0(\phi_o) = \left(\frac{v + \delta\eta_0\mathcal{S}\mathbb{E}_0(\varepsilon)}{2}\right)^2 - \delta^2\eta_0^2\mathcal{S}_s\mathcal{S}_b\mathbb{V}_0(\varepsilon) \tag{47}$$

6.3 Ex-ante Fees for Payments

In the basic model, we have assumed that the platform cannot charge lump-sum fees when users are ex-ante identical. We believe this is a reasonable assumption for settings where users are intrinsically different. For completeness, we briefly discuss the case where it is feasible for the platform to also charge a lump-sum entry fee ϕ before ε is realized. Suppose the fees are determined such that the platform can extract a fraction θ of the user's expected surplus

$$\phi_0 = \theta\mathbb{E}[V_0(\varepsilon) - \eta_0\mathcal{S}_b\varepsilon] \tag{48}$$

$$\phi_1 = \theta\mathbb{E}[V_1(\varepsilon) - \eta_0\mathcal{S}_b\varepsilon] \tag{49}$$

where we denote the ex-ante value of the platform for the user with and without payments as V_1 and V_0 respectively. Note that we allow the fees ϕ_1 and ϕ_0 to differ depending on whether the platforms introduces a data-driven payment technology or not. The term $\eta_0\mathcal{S}_b\varepsilon$ captures the payoff for the user for not participating on the platform.

Denote Π_i as the platform profit *after* initial fees ϕ_i which corresponds to the platform's profits in the benchmark model. Recall that social welfare is simply the sum of profits for the platform after initial fees and the expected value of the platform for the user. Hence,

$$\begin{aligned} W_1 - W_0 &= \Pi_1 - \Pi_0 + \mathbb{E}V_1(\varepsilon) - \mathbb{E}V_0(\varepsilon) \\ &= (\Pi_1 + \phi_1/\theta) - (\Pi_0 + \phi_0/\theta) \\ &\geq (\Pi_1 + \phi_1) - (\Pi_0 + \phi_0) \end{aligned} \tag{50}$$

The last line expresses the platform's incentives to adopt data-driven payments. Hence, the platform's incentive coincides with welfare if and only if the platform can perfectly extract all surplus form its users by charging an ex-ante fees – or, equivalently, if and only if $\theta = 1$. Otherwise, the platform still tends to under-adopt data-driven payment services. With payment-driven data, however, the platform still tends to over-adopt payment services because users do not internalize the informational externality from their payments.

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Appendix: Derivation of Objective Functions

Average User Payoff

$$\begin{aligned} V &= \int (v-p)a(\varepsilon) - \frac{a(\varepsilon)^2}{2} + \eta(1-\delta a(\varepsilon))\mathcal{S}_b\mathbb{E}(\varepsilon)dG(\varepsilon) \\ &= \int \left(a(\varepsilon) + \delta\eta\mathcal{S}_b\varepsilon\right) a(\varepsilon) - \frac{a(\varepsilon)^2}{2} + \eta(1-\delta a(\varepsilon))\mathcal{S}_b\mathbb{E}(\varepsilon)dG(\varepsilon) \\ &= \int \frac{1}{2}a(\varepsilon)^2 + \eta\mathcal{S}_b\varepsilon dG(\varepsilon) \\ &= \frac{1}{2}\int \left(\bar{a} + \delta\eta\mathcal{S}_b(\mathbb{E}(\varepsilon)-\varepsilon)\right)^2 dG(\varepsilon) + \eta\mathcal{S}_b\mathbb{E}(\varepsilon) \\ &= \frac{1}{2}\bar{a}^2 + \frac{1}{2}\delta^2\eta^2\mathcal{S}_b^2\mathbb{V}(\varepsilon) + \eta\mathcal{S}_b\mathbb{E}(\varepsilon) \end{aligned}$$

Individual User Payoff

$$V(\varepsilon) = \frac{1}{2}a(\varepsilon)^2 + \eta\mathcal{S}_b\varepsilon$$

Profit Function

$$\begin{aligned} \Pi &= \int pa(\varepsilon) + \delta\eta a(\varepsilon)\mathcal{S}_s\varepsilon dG(\varepsilon) \\ &= \int (v - \bar{a} - \delta\eta\mathcal{S}_b\mathbb{E}(\varepsilon) + \delta\eta\mathcal{S}_s)a(\varepsilon)dG(\varepsilon) \\ &= \int \big(v - \bar{a} + \delta\eta\mathcal{S}\mathbb{E}(\varepsilon) - \delta\eta\mathcal{S}_s(\mathbb{E}(\varepsilon)-\varepsilon)\big)(\bar{a} + \delta\eta\mathcal{S}_b(\mathbb{E}(\varepsilon)-\varepsilon)dG(\varepsilon) \\ &= (v - \bar{a} + \delta\eta\mathcal{S}\mathbb{E}(\varepsilon))\bar{a} - \int \delta^2\eta^2\mathcal{S}_s\mathcal{S}_b(\mathbb{E}(\varepsilon)-\varepsilon)^2 dG(\varepsilon) \\ &= \bar{a}(v - \bar{a} + \delta\eta\mathcal{S}\mathbb{E}(\varepsilon)) - \delta^2\eta^2\mathcal{S}_s\mathcal{S}_b\mathbb{V}(\varepsilon) \end{aligned}$$

Welfare Function

$$
\begin{aligned}
W &= \Pi + V \\
&= \bar{a}\left(v - \frac{\bar{a}}{2} + \delta\eta\mathcal{S}\mathbb{E}(\varepsilon)\right) + \frac{1}{2}\delta^2\eta^2\mathcal{S}_b^2\mathbb{V}(\varepsilon) - \delta^2\eta^2\mathcal{S}_s\mathcal{S}_b\mathbb{V}(\varepsilon) + \eta\mathcal{S}_b\mathbb{E}(\varepsilon) \\
&= \bar{a}\left(v - \frac{\bar{a}}{2} + \delta\eta\mathcal{S}\mathbb{E}(\varepsilon)\right) - \frac{1}{2}\delta^2\eta^2\mathcal{S}_b\mathbb{V}(\varepsilon)\left(2\mathcal{S}_s - \mathcal{S}_b\right) + \eta\mathcal{S}_b\mathbb{E}(\varepsilon) \\
&= \bar{a}\left(v - \frac{\bar{a}}{2} + \delta\eta\mathcal{S}\mathbb{E}(\varepsilon)\right) - \frac{1}{2}\delta^2\eta^2\mathcal{S}_b(\mathcal{S}_s + \mathcal{S})\mathbb{V}(\varepsilon) + \eta\mathcal{S}_b\mathbb{E}(\varepsilon)
\end{aligned}
$$

Appendix: Proofs

Proof of Lemma 5

Proof. The slope of the firm's profit function is given by $v + 2\bar{a}\phi$. Hence, profits are increasing over the interval $[0, 1/\rho]$ as long as $v\rho/2 \geq -\Phi$. By Assumption 4, the profit function is decreasing for $\bar{a} > 1/\rho$ when there are no payments frcitions ($\eta(\bar{a}) = 1$). Since the profit function is strictly concave for $\Phi < 0$, this completes the proof. □

Proof of Proposition 6

Proof. Consider first the case where $v\rho/2 \geq -\Phi$. The platform introduces payments with $\eta(\bar{a}) = 1$ whenever

$$
v\rho + \Phi \geq \rho^2\left(\frac{v + \delta\eta_0\mathcal{S}\mathbb{E}(\varepsilon)}{2}\right)^2 - \delta^2\rho^2\eta_0^2\mathcal{S}_s\mathcal{S}_b\mathbb{V}(\varepsilon)
$$

The right-hand side is a quadratic function in η_0 that is concave (convex) for $\Lambda > 0$ ($\Lambda < 0$). Set $\eta_0 = 0$. Then, the platform prefers to introduce payments whenever

$$
v\rho + \Phi \geq \frac{1}{4}v^2\rho^2
$$

Since, $\Phi \geq -v\rho/2$, this inequality holds whenever

$$
1 \geq \frac{v\rho}{2}
$$

which holds by Assumption 4.

Next, set $\eta_0 = 1$. Then, the platform prefers to introduce payments whenever

$$\frac{1}{\rho}\left(v - \frac{1}{\rho} + \delta\mathcal{S}\mathbb{E}(\varepsilon)\right) \geq \left(\frac{v + \delta\mathcal{S}\mathbb{E}(\varepsilon)}{2}\right)^2$$

Note that the left-hand side reaches a maximum at $\frac{1}{\rho} = \frac{1}{2}(v + \delta\mathcal{S}\mathbb{E}(\varepsilon))$ where the inequality holds with equality and the platform is indifferent. Hence, for all values of $1/\rho$ that are larger, the platform is worse off. There exists, therefore, a cut-off point $\hat{\eta}$ such that the platform introduces payments if and only if $\eta_0 \leq \hat{\eta}$.

Consider now the case where $v\rho/2 \leq -\Phi$. The platform will introduce payments if and only if

$$-\frac{1}{4\Phi}v^2 \geq \left(\frac{v + \delta\eta_0\mathcal{S}\mathbb{E}(\varepsilon)}{2}\right)^2 - \delta^2\eta_0^2\mathcal{S}_s\mathcal{S}_b\mathbb{V}(\varepsilon)$$

or

$$\Lambda\eta_0^2 - \frac{2v}{\delta}\eta_0 - \left(\frac{1}{\Phi} + 1\right)\frac{v^2}{\delta^2\mathcal{S}\mathbb{E}(\varepsilon)} \geq 0$$

which again is a quadratic function in η_0. Note that the first two terms are always negative since $2v/\delta > \Lambda$.

This implies that the function has a maximum at $\eta_0 = 0$ and, since $\Phi \geq -1$, is positive at $\eta_0 = 0$. Since profits for introducing payments increase in Φ for any given η_0, we have that for $\eta_0 = 1$, the platform will not introduce payments as $\Phi \to -\frac{v\rho}{2}$.

Since the function is quadratic, there is a value $\eta_1(\Phi)$ such that for all $\eta_0 \leq \eta_1(\Phi)$, the platform has larger profits if payments are carried out at $\eta(\bar{a})$.

Finally, consider $\eta(\bar{a}) = -\frac{1}{\Phi}\frac{v\rho}{2}$ as a function of Φ on the interval $[-1, -v\rho/2]$. It is strictly increasing and strictly convex, with $\rho\bar{a} = 1$ and a slope greater than 1 at $-v\rho/2$. Hence, there exists $\eta_2 \in [0, 1)$ such that for all $\eta_0 \leq \eta_2(\Phi)$, we have $\eta_0 \leq \eta(\bar{a})$. Define now the cut-off point $\hat{\eta}(\Phi) = \min\{\eta_1(\Phi), \eta_2(\Phi)\}$, which completes the first part of the proof.

For the second part, observe that the profit function for introducing payments is increasing in Φ since $\Phi \geq -1$. □

Proof of Lemma 9

Proof. The slope of the profit function is now given by $v + 2\bar{a}\Phi + \gamma\rho\mathcal{S}_s\mathbb{E}(\varepsilon)$. Assumption (4) ensures again that we have $\bar{a} = 1/\rho$ if and only if

$$\frac{1}{2}\left(v\rho + \rho^2\gamma\mathcal{S}_s\mathbb{E}(\varepsilon)\right) \geq -\Phi$$

as the profit function is strictly increasing on the interval $[0, \frac{1}{\rho}]$.

If this condition does not hold, there is an interior optimum given by

$$\bar{a} = -\frac{1}{2\Phi}\left(v + \rho\gamma\mathcal{S}_s\mathbb{E}(\varepsilon)\right) > -\frac{1}{2\Phi}v$$

□

Proof of Proposition 10

Proof. Let $\eta_0 \to 1$. The platform introduces data-driven payments if and only if

$$\gamma\mathcal{S}_s\mathbb{E}(\varepsilon) - F \geq \left(\frac{v + \delta\mathcal{S}\mathbb{E}(\varepsilon)}{2}\right)^2 - \frac{1}{\rho}\left(v - \frac{1}{\rho} + \delta\mathcal{S}\mathbb{E}(\varepsilon)\right) \equiv A$$

while it is not efficient to introduce payments if and only if

$$\gamma\mathcal{S}\mathbb{E}(\varepsilon) - F \leq A + \frac{1}{2}\left(\left(\frac{v + \delta\mathcal{S}\mathbb{E}(\varepsilon)}{2}\right)^2 - \frac{1}{\rho^2}\right) \equiv B$$

The function

$$\frac{1}{\rho}\left(v - \frac{1}{\rho} + \delta\mathcal{S}\mathbb{E}(\varepsilon)\right)$$

is decreasing in $1/\rho$ for all

$$\frac{1}{\rho} \geq \frac{v + \delta S\mathbb{E}(\varepsilon)}{2}$$

and $A \to 0$ for $1/\rho \to (v + \delta S\mathbb{E}(\varepsilon)/2$. Hence, for ρ sufficiently large, the first inequality holds.

For the second inequality, $B \to 0$ for $1/\rho \to (v + \delta S\mathbb{E}(\varepsilon)/2$. Also, B has a maximum at

$$\frac{1}{\rho} = v + \delta\mathcal{S}\mathbb{E}(\varepsilon)$$

with

$$B = \left(\frac{v + \delta\mathcal{S}\mathbb{E}(\varepsilon)}{2}\right)^2$$

Hence, when $\gamma\mathcal{S}\mathbb{E}(\varepsilon) - F < 0$, there is inefficient introduction of data-driven payments if ρ is sufficiently large.

Finally, note that

$$\frac{\partial B}{\partial \frac{1}{\rho}} = \frac{\partial A}{\partial \frac{1}{\rho}} - \frac{1}{\rho}$$

Hence, the first inequality tightens faster than the second inequality is being relaxed as $1/\rho$ increases. Furthermore, for $1/\rho \geq 3/2(v + \delta\mathcal{S}\mathbb{E}(\varepsilon)$, $B \leq 0$.

Hence, when $\gamma\mathcal{S}\mathbb{E}(\varepsilon) - F > 0$ sufficiently small, there is an intermediate region for $1/\rho$ such that both inequalities are fulfilled which completes the proof. $\square$

Appendix: Microfoundation for Payment-Driven Data

The model assumes that the platform can acquire additional data from its payments technology that are complementary to the data it generates on the platform. There is also a cost F for generating the data and how much data can be generated is captured by the parameter γ. We briefly develop a microfoundation for how payments can be used to generate additional data that is based on experiments to learn the preferences of the platform's users.

In the basic model, when the platform cannot identify a buyer's type, it chooses to recommend sellers to offer a generic good. With the payment service, the platform could still make a recommendation to sellers to sell customized goods even though it has no information on a buyer's preference for a customized good. Upon observing the outcome of the trade, the platform has generated additional information that could be helpful for its data services. Think of Facebook and Google that run A/B tests to learn about their users and need feedback from payments for these tests.

The trade-off is that the platform will make some mistakes in predicting preferences. However, the platform can also get additional information when a trade for a customize good has been completed successfully. The provision of payment services is crucial for testing as it allows the platform to monitor whether or not a trade happens after a recommendation is made.

Suppose that the platform can perform τ tests. Recall that buyers belong to different types $j = 1, 2, ..., J$ with equal probability and that a type j buyer only likes type j customized goods. For buyers that have been identified from the data on the platform, the platform will recommend the correct customized goods. For buyers that have not been identified, the platform can run a test by recommending a random type to the seller.

With probability $1/J$, the recommendation is correct so that the information about buyers improves by an amount τ/J, which defines the parameter γ in the formal model. The cost of performing a test is that a seller that follows the platform's recommendation incurs an expected loss of $\tau(1 - \frac{1}{J}\mathcal{S}_s\mathbb{E}(\varepsilon))$ due to the recommendation error. The platform will have to compensate sellers for these errors and, hence, has to charge a lower price which corresponds to the parameter F in the formal model.

Interestingly, there is a second, social cost of such testing. Buyers also suffer an expected loss of $\tau\mathcal{S}_b\mathbb{E}(\varepsilon)$ whenver a recommendation error occurs. This cost is not taken into account by the platform, so that testing gives rise to a negative externality on buyers. Hence, the costs for running tests are different from a private and a social point of view which strengthens our result about inefficient adoption of payments in the presence of payments-driven data.

This microfoundation captures what practitioners in the payment industry have called a "closed loop" as reflected in the two quotes below.

> " 'There's a lot of excitement around buying Facebook ads, but the critical missing link is, if I put down $5, how do I know if it worked?' said Saumil Mehta, Square's customer engagement lead. 'The ability to track and close the loop from advertisement to sale — that's the holy grail.' " (New York Times, March 23, 2016).

> "Jeremy Epstein, who has worked with marketing technology for decades, likewise mentions Amazon upon hearing a description of Facebook's project [Libra]. 'It

makes sense in terms of a closed loop. It will bring payments back in house and show Facebook who's buying what,' Epstein says. 'Right now, Facebook doesn't know the last mile like Amazon does.' " (Fortune, June 18, 2019)