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WHY DO SOCIAL NETWORKS INTRODUCE VIRTUAL CURRENCIES?

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Why do social networks introduce virtual currencies?

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Abstract

This paper models how internet platforms decide whether to introduce virtual currencies. Since platforms operate two-sided markets, virtual currencies may attract users who buy goods/services as well as external firms who accept virtual currency as payment. We find that platform incentives to introduce virtual currencies depend on the distribution of wages across the population of users as well as the distribution of preferences for online activities ("digital" preferences). We use Luxembourg data from the EU Survey on Information and Communication Technologies to test model predictions on user time allocation. In particular, we identify various individual socio-economic characteristics linked to time spent on social networks. Then, we use the user net income distribution (conditional on digital preferences) to evaluate conditions determining the platform's choice of virtual currency design.

Keywords: private virtual currencies, social networks, retail payments.
JEL classification: E42, E5, G23, L5, L82, L86.

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Résumé Non Technique

En principe, les monnaies virtuelles, telles que Bitcoin, peuvent remplir certaines fonctions des monnaies émises par les États (moyen d'échange, réserve de valeur) et pourraient donc affecter la transmission de la politique monétaire. C'est pourquoi les banques centrales surveillent de près leur développement. Les plus souvent, les monnaies virtuelles sont introduites par des plateformes dédiées qui permettent d'effectuer des transactions bilatérales (peer-to-peer). Cependant, des plateformes destinées à d'autres fonctions (par exemple, les réseaux sociaux ou les plateformes de commerce en ligne) ont aussi introduit des monnaies virtuelles pour attirer de nouveaux utilisateurs (par exemple, Amazon coins, Facebook credits).

Pour réussir, une monnaie virtuelle doit bénéficier d'un réseau qui atteint une masse critique. De ce point de vue, les réseaux sociaux ont un avantage clé par rapport aux plateformes dédiées aux paiements. De plus, les réseaux sociaux et les plateformes de commerce en ligne sont bien placés pour attirer la clientèle jeune qui est plus susceptible d'abandonner les banques. Dans cet article, nous analysons la décision des plateformes Internet, et notamment les réseaux sociaux, d'introduire des monnaies virtuelles.

Nous développons un cadre théorique afin d'analyser comment certaines caractéristiques de la population des utilisateurs peuvent inciter la plateforme à introduire une monnaie virtuelle. Dans notre modèle théorique, la plateforme peut vendre la monnaie virtuelle directement aux utilisateurs, ou leur permettre de gagner la monnaie virtuelle par certaines activités en ligne, ce qui modifie leur utilisation du temps. La plateforme peut également profiter à travers les informations que les utilisateurs révèlent par leur comportement en ligne. Ses bénéfices dépendent de la distribution de salaires à travers la population des utilisateurs, ainsi que de la distribution de leurs préférences "digitales". Ces deux distributions sont susceptibles d'évoluer en fonction du processus de vieillissement démographique, ce qui pourra augmenter la rentabilité des monnaies virtuelles pour les plateformes internet.

Notre analyse empirique utilise une mesure des préférences digitales construit à partir des réponses à l'enquête européenne sur l'usage des technologies de l'information et de la communication par les individus. L'indicateur regroupe plusieurs dimensions liées aux préférences digitales dont les compétences numériques et les perceptions vis-à-vis la sécurité et l'utilité d'internet. Cet indicateur composite est négativement corrélé avec le niveau de revenu et positivement corrélé avec le temps passé sur les réseaux sociaux, ce qui est cohérent avec notre modèle théorique. De plus, les estimations économétriques confirment que les utilisateurs aux revenus plus élevés passent moins de temps sur les réseaux sociaux. Enfin, nous évaluons la symétrie de la distribution du revenu net mensuel pour différents niveaux des préférences digitales afin d'établir si l'introduction d'une monnaie virtuelle pourrait être rentable.

Contents

1 Introduction

This paper proposes a theoretical model to study how internet platforms, including social networks, decide whether to introduce virtual currency schemes (VCS) and what features they should have. The empirical part of this paper uses Luxembourg data to test the theoretical predictions and to evaluate different conditions governing platform decisions.

We provide several extensions to the theoretical model of Gans and Halaburda (2015). First, we allow more heterogeneity across platform users, in terms of income but also in terms of preferences for online activities. Second, we explicitly account for the two-sided nature of a social network platform, modelling firms that advertise through the platform, but also use it to sell goods and services. Third, we allow the platform to benefit if virtual currency use reveals valuable information about users. Finally, we analyse how platform incentives to introduce a virtual currency can depend on the distribution of characteristics through the population of users.

According to our results, platforms may introduce virtual currencies to encourage high-wage users to increase the time they spend online. Platforms may also encourage traffic from low-wage users by allowing them to earn virtual currency from certain online activities. Allowing users to earn virtual currency online has two opposing effects on platform revenue. Users will spend less time on other online activities that generate platform revenue from advertising. However, users spending virtual currency may reveal information that the platform can sell to firms. Finally, our results indicate that the shape of the wage distribution affects platform incentives to allow virtual currency to be earned online as well as bought with state currency. If most users with similar digital preferences have high wages, then a platform will benefit from allowing virtual currency to be earned online. However, if most users with similar digital preferences have low wages, then the platform will only benefit if virtual currency earned online reveals information that can be sold to firms.

Motivation

Depending on their design, virtual currencies can at least partially perform some of the roles of money (unit of account, medium of exchange and store of value) and therefore compete with state-issued currencies, potentially affecting the transmission of monetary policy. The first widely adopted virtual currency, Bitcoin, was created expressly to bypass the banking system. It is not surprising, therefore, that monetary authorities monitor virtual currencies closely.[1]

Fung and Halaburda (2014) suggest that virtual currencies developed along two distinct avenues. First, some payment platforms were dedicated to peer-to-peer transactions using specific virtual currencies based on distributed ledger technology (DLT) and the blockchain

[1]See Cœuré (2019a), Cœuré (2019b), Mersch (2019a), Mersch (2019b), Carstens (2018), Cœuré (2018), Mersch (2018), Claeys et al. (2018), BIS (2018), Davoodalhosseini et al. (2018), He (2018), Pichler et al. (2018), Aaron et al. (2017), Camera (2017), Stevens (2017), He et al. (2016) CPMI (2015) and ECB (2015).

(e.g. Bitcoin). Second, other platforms, including social networks but also online commerce sites, introduced private tokens to enhance their services and attract new users (e.g. Amazon Coins, Facebook Credits). Despite attracting significant media attention, the payments platforms in the first group failed to develop a viable alternative to state currencies because of technical problems linked to scalability and dramatic price instability due to speculative behaviour (Carstens 2018, Demertzis and Wolff 2018, Grym 2018, Mersch 2018). However, some social networks and online commerce platforms in the second group also adopted DLT and moderated volatility by using stablecoins backed by reserve assets.[2]

To succeed, any network needs to attain critical mass (Economides 1996). In this respect, online commerce and social network platforms have a key advantage over payment platforms. In the context of the current demographic shift, social networks are also better placed to attract younger clients for financial services. Following the Global Financial Crisis, the millions of digital natives entering adulthood are more likely to abandon banks in favour of new FinTech companies (McKinsey&Company 2016).

Gans and Halaburda (2015) argued that Facebook's reliance on advertising revenue would prevent it from introducing a virtual currency that could reduce time spent online. In fact, however, Facebook Credits did appear in 2009. Facebook phased out this virtual currency in 2013 following strong opposition from firms selling goods and services on the platform[3], but the impact on time spent online was not the driving factor. More recently, Facebook tried again in June 2019, releasing a white paper on a new virtual currency (Libra Association 2019) that plans to also cover users of the Whatsapp, Messenger and Instagram platforms.

To explain why virtual currencies may continue to interest social networks such as Facebook, we extend the Gans and Halaburda's model to include two-sided markets (bringing together platform users and firms selling goods and services) and show how platforms may reinforce network externalities by "getting both sides on board".[4]

2 The model

We consider a social network platform where users can interact with their peers. The platform also provides access to digital goods and services sold by firms that have joined the platform.

There are three kind of agents in the model: the users, the firms and the platform. Users allocate their leisure time between productive activities and social network activities. The platform earns revenue by selling advertising to firms, with profits increasing in the num-

[2]For instance, see Facebook's recent white paper (Libra Association 2019).

[3]See `http://adweek.com/socialtime/farewell-facebook-credits/428240`.

[4]See Rysman (2009) for a discussion of two-sided markets.

ber of users and the share of time each user chooses to spend "networking". To enhance user experience, the platform may introduce a virtual currency scheme. Depending on the design, virtual currency tokens may be *acquirable* (bought with state currency or earned through platform activities), *transferable* between users and firms, and *redeemable* for state currency. The platform designs the virtual currency to attract more users and to encourage them to spend more time on the platform, but also to attract more firms to sell their goods and services through the platform.

Users differ in three exogenous characteristics. First, the size of their peer group, which includes users with similar characteristics and determines the extent of network externalities. Second, the user financial margin, meaning the difference between revenue (from offline activities) and basic consumption. Third, users differ in their marginal rate of substitution between online activities and additional offline consumption (in excess of basic consumption).

We do not model the work/leisure time allocation decision. Instead, we assume users have an endowment of Z units of leisure for online activities. User i decides how much time x_i to devote to unremunerated "networking" activities, how much time t_i to devote to remunerated online activities and how much time to devote to extra-offline work (i.e. $Z - x_i - t_i$). In addition, user i decides how many virtual currency tokens θ_i to buy with state currency. User i maximizes utility (1):

$$\mathrm{Max}\ u\left(x_i, t_i, \theta_i\right) = (1 - \delta_i)C_i^{on} + \delta_i C_i^{off}, \tag{1}$$

subject to the leisure endowment constraint,

$$Z \geq x_i + t_i. \tag{2}$$

On the right-hand side of utility (1), the first term is the utility from the time spent on online activities, where δ_i is a preference parameter. It converts the activity on the platform into a consumption-equivalent amount:

$$C_i^{on} = \left\{N_i \cdot \alpha \cdot [1 + e_i(1 - \eta)] - x_i\right\} x_i \tag{3}$$

where N_i is user i's peer group size, α is a parameter common to all users, e_i is the online goods and services obtained with virtual currency tokens and η is the share of e_i that users convert to state currency. Adapting Gans and Halaburda (2015), we assume that the following function converts tokens into goods and services sold by firms active on the platform:

$$e_i = \theta_i \gamma + t_i \phi \tag{4}$$

where γ is the price in tokens for online goods/services and ϕ the wage rate (in online goods/services) for the time spent on remunerated online activities.

The second term on the right-hand side of utility (1) is the utility stemming from C_i^{off} additional offline consumption of a *numeraire*. User i's budget constraint is:

$$(Z - x_i - t_i)\, w_i + W_i = C_i^{off} + \theta_i \mu - e_i \eta, \tag{5}$$

The left-hand side of (5) is user income, where w_i is user i's offline wage rate[5] and W_i his or her financial margin.[6] On the right-hand side of (5), C_i^{off} is the additional offline consumption of the *numeraire*, θ_i is the number of tokens bought at price μ, and η is the share of online goods/services e_i that can be used for additional offline consumption.[7]

The platform sets $\{\gamma, \phi, \mu, \eta\}$ to maximise its profits so these variables are exogenous for platform users. Note from (3) that, as in Gans and Halaburda (2015), the virtual currency scheme enhances user experience on the platform. The value of online goods and services increases with the number of peers, N_i (i.e. there is a network externality). Both δ_i and peer group size N_i are exogenous in our model and reflect what we call user preferences for online activities or "digital" preferences. Lower values of δ_i and higher values of N_i increase the marginal utility of time spent online. Utility function (1) features a constant marginal rate of substitution between additional offline consumption and platform activities (i.e. MRS=$\partial C_i^{on}/\partial C_i^{off} = -\delta_i/(1-\delta_i) = -\Delta_i$), but the marginal utility is decreasing in x_i to ensure a solution for x_i, t_i and θ_i.

Firms sell digital goods and services for online consumption both through the platform and through other channels (not modelled). Sales through the platform must be paid with tokens. For simplicity, we assume that the platform captures the full advertising surplus from the representative firm. However, the firm has an incentive to join the platform as this allows it to sell additional goods and services. The firm's surplus from participating in the platform is given by:

$$\pi_F = (\beta - \eta - f) \cdot \sum_i e_i, \tag{6}$$

where β is the type of the firm, η is the share of tokens that users convert into state-issued

[5]We assume users derive no utility from additional offline leisure, so all time offline (i.e. $Z - x_i - t_i$) is spent working.

[6]The financial margin is $W_i = (T - Z)w_i - C_i$, where T is the time available for work (i.e. 24 hours minus sleep time and offline leisure) and C_i is user i's basic level of consumption.

[7]The variable η is a choice of the platform and therefore, is exogenous for the user. This simplifying assumption reduces the dimensionality of the user problem. For example, η can be considered an expected share of unused tokens. If $\eta = 0$ the platform proposes a virtual currency scheme with non redeemable tokens.

currency, f is a constant fee charged by the platform for every online sale and e_i is defined in equation (4). The platform sets η and f without knowing the firm's type. The platform only knows the distribution of β across firms, which we assume to be uniform between limits bl and ul: $\beta \sim U(bl, ul)$, $bl \geq 0$. Equation (6) implies that firms whose $\beta < \eta + f$ cannot benefit by selling goods and services through the platform.

The platform obtains its revenue from advertising and from the fees that it charges firms who sell goods and services through the platform.[8] Higher online consumption of goods and services e_i raises platform revenue through two channels. First, it increases the number of users and their time online, raising fees and advertising revenue. Second, the advertising revenue rises by a fixed factor κ, representing additional valuable information on users behaviour that is collected by the platform.[9] The introduction of tokens requires the platform to pay a fixed cost K.

For tractability, we assume that the platform knows that a share p of users are characterized by a low marginal rate of substitution δ_i^l, and $1-p$ by a high value δ_i^h. In addition, we assume that the platform knows the distribution of wage rates across users. Platform profits are represented by a linear function of the revenue from different peer groups. Equation (7) consists of three sums, first across peer groups (i), second across the marginal rate of substitution (j, taking two alternative values) and finally across wage rates (continuous):

$$
\begin{aligned}
\pi_P \quad = \quad & \sum_{k=1,..,G} \sum_{j=h,l} \left[r \int_0^{+\infty} x(w|N = N_k, \delta = \delta^j, \Gamma) dFw + \right. \\
& + \mu \int_0^{+\infty} \theta(w|N = N_k, \delta = \delta^j, \Gamma) dFw + \\
& \left. + \left(f \cdot \Pr\left(\pi_F \geq 0\right) + r \cdot \kappa\right) \int_0^{+\infty} e(w|N = N_k, \delta = \delta^j, \Gamma) dFw \right] - K.
\end{aligned} \tag{7}
$$

where, dFw is the probability density function of w conditional on N and δ. The platform sets $\{\gamma, \phi, \mu, \eta, f\}$ to maximise its profits. The technological factor κ is fixed exogenously. For instance, if $\kappa = 0$ then consuming online goods and services bought with tokens does not raise advertising revenue. However, if $\kappa > 0$ advertising revenue increases because the platform can collect valuable information from consumption decisions.[10]

As defined in equation (4), e_i depends on θ_i, although the probability $\Pr\left(\pi_F \geq 0\right)$ does not affect the second term in platform profits. The implied assumption is that users buy

[8] Following Baye and Morgan (2001), the platform does not charge users but only charges firms.

[9] Following studies on ad-blocking technologies (Anderson and Gans 2011, Shiller et al. 2018), we model VCS as a potential revenue enhancer revealing additional valuable information about user preference and behaviour.

[10] We are grateful to Julien Prat for suggesting this improvement to a previous version of the model.

tokens from the platform and acquire goods/services from firms, but firms might fail to pay the transaction fee to the platform.

2.1 User time allocation

We solve the model under three different cases. In the first case, the platform does not allow users to buy goods and services online. In the second case, the platform allows users to exchange state currency for tokens that serve to buy goods and services online. Finally, in the third case, the platform allows users to buy tokens but also pays users in tokens for performing certain online activities.

2.1.1 Case 1: No tokens

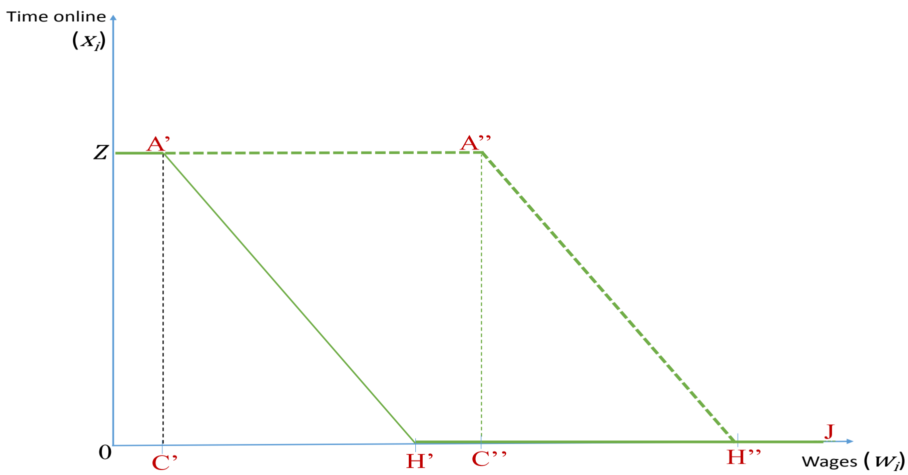
With $\gamma = \phi = \mu = \eta = 0$, solving (1) subject to (2) and (5) yields:

$$x_i^N = \begin{cases} 0 & \text{if } w_i \geq \frac{N_i \alpha}{\Delta_i} & \text{(Inactive user)} \\ \frac{1}{2}\left(N_i \alpha - w_i \Delta_i\right) & \text{if } \frac{(N_i \alpha - 2\,Z)}{\Delta_i} < w_i < \frac{N_i \alpha (1-\delta_i)}{\delta_i} & \text{(Part-time user)} \\ Z & \text{otherwise} & \text{(Full-time)} \end{cases} \tag{8}$$

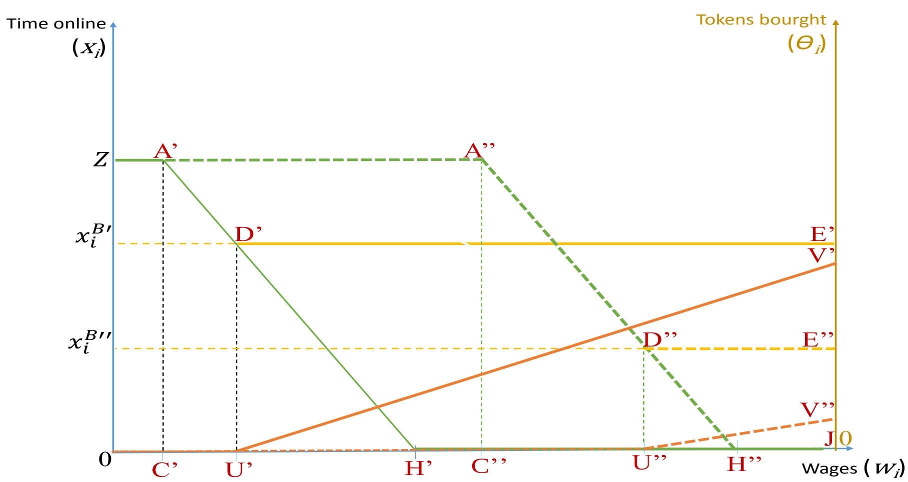
Time spent on the platform depends on user characteristics. The solution is a piecewise continuous function revealing three user types. “Inactive” users do not spend time on the platform, “full-time” users spend all their leisure endowment online and “part-time” users only spend part of it online.

Inactive users are characterized by relatively higher wages, smaller peer groups or a higher marginal rate of substitution between offline consumption and online activities (i.e. -MRS= $\Delta_i = \delta/(1-\delta)$). Figure 1 plots function (8) against the wage, depicting the time spent online by different types of users with two alternative peer group sizes ($N_i' < N_i''$). The time spent online by users with peer group of size N_i' is the set of lines linking points ZA’H’J. The segment ZA’ to the far left corresponds to full-time users. Segment H’J to the far right corresponds to inactive users. In between, the segment linking points A’ and H’ corresponds to part-time users. For users with peer group of size N_i'', the time spent online is the set of dashed lines linking points ZA”H”J. Thus, higher digital preferences, represented by a larger peer group, increase the share of full-time users and reduce the share of inactive users. The impact on the share of part-time users depends on the shape of the wage distribution (conditional on δ), as is formally presented in the next result.

Figure 1: Time spent on the platform in *no VCS* and *tokens for sale* cases



(a) Case 1: no tokens



(b) Case 2: tokens for sale

Notes: $N_i' = N_i''/2$. In case 1, points on the wage axis (abscissa) are: C'$= (N_i'\alpha - 2Z)/\Delta_i$, C''$=$ $(N_i''\alpha - 2Z)/\Delta_i$, H'$= N_i'\alpha/\Delta_i$ and H''$= N_i''\alpha/\Delta_i$. In case 2, points on the wage axis are: U'$=$ $N_i'\alpha/\Delta_i - 2(\mu - \gamma\eta)/[N_i\alpha\gamma(1-\eta)]$ and U''$= N_i''\alpha/\Delta_i - 2(\mu-\gamma\eta)/[N_i''\alpha\gamma(1-\eta)]$. On the time axis (ordinate), point Z corresponds to the leisure time endowment for online activities; $x_i^{B\prime}$ and $x_i^{B\prime\prime}$ refer to the time spent online by token buyers with a group size of N_i' and N_i'', respectively.

The non differentiable points in (8) complicate the derivation of comparative static results. Therefore, we study how changes in user characteristics affect expected time online.

Result 2.1 *Case 1 - No tokens: Comparative statics*

Expected time spent on the platform is higher:

1. *the lower the wage;*
2. *the larger the peer group;*
3. *the lower the marginal rate of substitution between additional offline consumption and online activities.*

Proof in appendix A.

Result 2.1 indicates that higher wages reduce the expected time spent on the platform, raising labour supply. This increases the probability of being a inactive user, who spends zero time on the platform, and lowers the probability of being a full-time user, who spends the full leisure endowment on the platform, while the probability of being a part-time user may increase or decrease. Overall, the substitution effect of higher wages more than compensates the income effect. This leads some part-time users to become inactive users and some full-time users to become part-time users. Through the intensive margin, higher wages reduce time spent online by part-time users.

Result 2.1 suggests that our modelling approach does not allow for cases when the income effect exceeds the substitution effect. In fact, it does not consider changes in the endowment of leisure time for online activities and their effects on labour supply. The next result fills this gap.

For simplicity, the leisure endowment is exogenous and assumed equal for all users. However, a reduction in leisure endowment could reflect increases in financial margins, basic consumption, sleep hours or a reduction in wage rates. In particular, a reduction associated with a decline in wages, could allow the income effect to dominate the substitution effect.

Result 2.2 *Changes in labour supply*

An exogenous increase in user labour supply, which reduces Z, the leisure time available for online activities, reduces the expected time spent on the platform via:

1. *Intensive margin: full-time users spend less time online.*
2. *Extensive margin: the share of full-time users increases while the share of part-time users diminishes (the share of inactive users is unchanged).*

Proof: in appendix A.

The platform increases profits by attracting more users (converting inactive users to part-time users). Result 2.1 indicates that expected time online is lower for high-wage individuals, while it is higher for low-wage users or users with high digital preferences. By selling tokens that allow users to consume goods and services online, the platform attracts new users and encourages all users to spend more time online as we see below.

2.1.2 Case 2: tokens for sale

When the platform introduces tokens for sale, variables γ, μ, η are non-zero although $\phi = 0$ still holds. The following solution assumes that the platform is available to all users, including those who do not buy tokens[11]:

$$x_i^B = \begin{cases} \frac{\Delta_i(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)} & \text{if } w_i \geq \frac{N_i\alpha}{\Delta_i} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)} \qquad \text{(Buyer)} \\ \frac{1}{2}\left(N_i\alpha - w_i\Delta_i\right) & \text{if } \frac{(N_i\alpha-2\,Z)}{\Delta_i} \leq w_i \\ & \text{and } w_i < \frac{N_i\alpha}{\Delta_i} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)} \qquad \text{(Part-time)} \\ Z & \text{otherwise.} \qquad \text{(Full-time)} \end{cases} \tag{9}$$

In Figure 1b, the time spent online is a piecewise continuous function represented by the lines linking points ZA'D'E' if the peer-group is of size N_i', and the points ZA"D"E" if the peer-group is of size N_i''. As in the no tokens case, there are three types of users. However, inactive users become token buyers. In panel 1b of Figure 1 the time spent on the platform by a token buyer is given by the orange lines D'E' for a peer group of size N_i' and D"E" for peer group of size N_i''. User i buys tokens in the amount:

$$\theta_i^B = \begin{cases} 0 & \text{if } w_i \leq \frac{N_i\alpha}{\Delta_i} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)} \\ & \text{(Part- or full-time user)} \\ \frac{\Delta_i}{N_i\alpha\gamma(1-\eta)}\left[w_i + \frac{2(\mu-\gamma\eta)}{[N_i\alpha\gamma(1-\eta)]^2}\right] - \frac{1}{\gamma} & \text{otherwise} \qquad \text{(Buyer)} \end{cases} \tag{10}$$

The first wage condition in (10), which ensures the non-negativity of θ_i, is similar to the one in (9). This means that inactive users in the no tokens case become token buyers increasing platform profits (in Figure 1, users with wages between points H' and J become token buyers). In addition, the wage condition in (9) is not as restrictive as in (8), meaning that the share of part-time users is lower than in the no tokens case, as is clearly visible in Figure 1b. Also from equation (9), it appears that time spent online by token buyers does not depend on their wage (lines D'E' and D"E" are horizontal). However, from (10), higher wage earners will buy more tokens (i.e. lines 0U'V' and 0U"V" in panel 1b of Figure 1). Thus, allowing users to buy tokens increases the utility of time online and provides a way for the

[11] Users that do not buy tokens disregard first order condition (21) (in appendix A) and solve the same optimisation problem as above.

platform to attract users who spend less time online.

In the no tokens case, user characteristics affect time spent on the platform through both extensive and intensive margins. Result 2.1 also applies if tokens are for sale. Changes at the extensive margin act through the share of token buyers.[12] Changes at the intensive margin affect the time token buyers spend on the platform. It is clear from top part of equation (9) that token buyers with larger peer-groups or lower marginal rates of substitution spend less time on the platform. Therefore, individuals with lower wages, larger peer-groups or lower marginal rates of substitution spend more time online because, first, they are less likely to buy tokens and, second, token buyers spend less time online.

From equation (9), part-time users spend more time online if their peer-group is larger or the marginal rate of substitution is smaller, while token buyers spend less time online. This difference reflects the fact that token buyers only spend time online because tokens increase their marginal utility of using the platform. Any increase in marginal utility, other than through buying tokens, will be compensated by a change in the number of tokens bought (from (10) an increase in N_i reduces θ_i), reducing time spent online.

Finally, result 2.2 also applies when tokens are offered for sale. However, changes in the platform choice variables (i.e. γ, μ, η) will have additional effects that are specific to the tokens for sale case. The following result provides comparative statics on the expected time spent online.

Result 2.3 *Case 2 - tokens for sale: Comparative statics*

Expected time spent on the platform is higher:

1. *the higher the price in tokens μ of additional offline consumption;*
2. *the lower the share of tokens converted to state currency η if $\mu/\gamma \geq 1$;*
3. *the lower the price in tokens γ of online goods/services.*

Proof in appendix A.

The second item in result 2.3 is particularly insightful because of the condition on the value in currency of online goods/services obtained with bought tokens μ/γ. A ratio μ/γ higher than one means that one euro of additional offline consumption forgone worths less in terms of online goods/services. In such a case, allowing tokens to be converted into state currency (i.e. $\eta > 0$) logically reduces the expected time spent online. However, this does

[12] Result 2.1 is straightforward because all derivatives keep the same sign. For instance, the derivative of the first wage condition with respect to N_i is positive as in the no tokens case: $\partial\left(\frac{N_i\alpha}{\Delta_i} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}\right)/\partial N_i = \frac{\alpha}{\Delta_i} + \frac{\alpha\gamma(1-\eta)2(\mu-\gamma\eta)}{(N_i\alpha\gamma)^2} > 0$. There is only one additional condition on wages, to ensure the solution remains in the real set: $(w_i)^2 \geq 4\left(\frac{\alpha}{\Delta_i} + \frac{2(\mu-\gamma\eta)}{\alpha\gamma(1-\eta)}\right)$.

not longer hold if the value in currency of online goods/services obtained with bought tokens is lower than one ($\mu/\gamma < 1$). In such a case, the increase in online activities more than compensates the additional offline consumption forgone, which encourages to spend more time on the platform.

If the platform allows tokens to be bought, only high-income users can enhance their online experience by buying tokens. However, below we consider the case where the platform offers tokens to remunerate online activities, which allows low-income users to also access online goods and services. This case can provide additional platform revenue if it reveals valuable information about users (high κ parameter).

2.1.3 Case 3: tokens for sale or earned online

If the platform allows tokens to be earned online as well as bought for state currency, then each user must allocate time on the platform between unremunerated online activities (i.e. x_i) and remunerated online activities (i.e. t_i). Solving (1) subject to (2) and (5) with non-zero values of all platform choice variables $\{\gamma, \mu, \eta, \phi\}$ yields a unique equilibrium if the leisure endowment is above a certain threshold.

$$x_i^E = \begin{cases} \frac{0.5[N_i\alpha(1+\phi Z(1-\eta))-\Delta_i\phi\eta]}{1+N_i\alpha\phi(1-\eta)} & \text{if } w_i \leq \frac{\mu\phi}{\gamma} & \text{(Earner)} \\ \frac{\Delta_i(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)} & \text{if } w_i > \frac{\mu\phi}{\gamma} \text{ and } \frac{\Delta_i(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)} \leq Z & \text{(Buyer)} \end{cases} \tag{11}$$

$$t_i^E = \begin{cases} Z - \frac{0.5}{1+N_i\alpha\phi(1-\eta)}\left[N_i\alpha\left(1+\phi Z(1-\eta)\right) - \Delta_i\phi\eta\right] & \text{if } w_i \leq \frac{\mu\phi}{\gamma} & \text{(Earner)} \\ 0 & \text{if } w_i > \frac{\mu\phi}{\gamma} & \text{(Buyer)} \end{cases} \tag{12}$$

$$\theta_i^E = \begin{cases} 0 & \text{if } w_i \leq \frac{\mu\phi}{\gamma} & \text{(Earner)} \\ \frac{\Delta_i}{N_i\alpha\gamma(1-\eta)}\left[w_i + \frac{2(\mu-\gamma\eta)}{[N_i\alpha\gamma(1-\eta)]^2}\right] - \frac{1}{\gamma} & \text{if } w_i > \frac{\mu\phi}{\gamma} & \text{(Buyer)} \end{cases} \tag{13}$$

We can no longer distinguish user type simply by time spent online, because this now depends on how users acquire tokens: some prefer to buy tokens, others to earn them online, and some do both. The user type depends on the leisure endowment Z, wage, peer-group size and marginal rate of substitution between additional offline consumption and online activities. If Z is sufficiently high, the equilibrium is unique with only two types of user, token earner or token buyer. However, if Z is below a certain threshold Π_i then there is an alternative equilibrium with an additional type of user, token earner-buyer.

Let $\Pi_i = \left(\frac{2\Delta_i(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}\right)\left(\frac{1}{N_i\alpha\phi(1-\eta)}+1\right)+\frac{\Delta_i\eta}{N_i\alpha(1-\eta)}-\frac{1}{\phi(1-\eta)}$, then

$$x_i^E = \frac{\Delta_i\left(\mu-\gamma\eta\right)}{N_i\alpha\gamma(1-\eta)} \qquad \text{if } \frac{\Delta_i\left(\mu-\gamma\eta\right)}{N_i\alpha\gamma(1-\eta)} \leq Z < \Pi_i \qquad \text{(Earner-buyer or Buyer)} \tag{14}$$

$$t_i^E = \begin{cases} Z - \frac{\Delta_i(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)} & \text{if } w_i \leq \frac{\mu\phi}{\gamma} \text{ and } \frac{\Delta_i(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)} \leq Z < \Pi_i \qquad \text{(Earner-buyer)} \\ 0 & \text{if } w_i > \frac{\mu\phi}{\gamma} \qquad \text{(Buyer)} \end{cases} \tag{15}$$

$$\theta_i^E = \begin{cases} \left(\frac{2\Delta_i(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}\right)\left(\frac{1}{N_i\alpha\gamma(1-\eta)}+\frac{\phi}{\gamma}\right) - \\ -\frac{(1+Z\phi)}{\gamma}, & \text{if } w_i \leq \frac{\mu\phi}{\gamma} \text{ and } \frac{\Delta_i(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)} \leq Z < \Pi_i \qquad \text{(Earner-buyer)} \\ \frac{\Delta_i}{N_i\alpha\gamma(1-\eta)}\left[w_i + \frac{2(\mu-\gamma\eta)}{[N_i\alpha\gamma(1-\eta)]^2}\right] - \frac{1}{\gamma} & \text{if } w_i > \frac{\mu\phi}{\gamma} \qquad \text{(Buyer)} \end{cases} \tag{16}$$

The time constraint is binding for low-wage users in equations (11)-(12) and (14)-(15). The wage determines whether a user is a buyer and the leisure endowment determines whether a token earner also buys tokens. In these equations, the wage condition results from the shadow price for additional time online:

$$\lambda_i \geq \delta_i\left(\frac{\mu\phi}{\gamma} - w_i\right).$$

This results from the first order conditions for θ_i, the number of tokens bought, and, t_i the time spent earning tokens (equations (21) and (22) in appendix A). The value in currency of a unit of online goods and services is w_i/ϕ if acquired with earned tokens but μ/γ with bought tokens. The platform controls the value in currency of goods and services paid with bought tokens. Since users with relatively high wages will find buying tokens cheaper than earning them ($w_i/\phi > \mu/\gamma$), they do not value additional time online. Thus, token buyers are characterized by higher wages and a non-binding time constraint ($\lambda_i = 0$)[13]. Conversely, token earners are characterized by low wages and a weakly positive shadow price for time online, meaning that their time constraint is binding.

When tokens can be earned, the leisure endowment for online activities also plays an important role in determining the user type. Figure 2 depicts the solution in two alternative cases: small leisure endowment ($Z < \Pi_i$) in panel 2a and large leisure endowment ($Z \geq \Pi_i$) in panel 2b. In both panels, the x-axis measures the wage level, the left axis time spent on online activities (remunerated and not) and the right axis the amount of tokens bought (which crosses the x-axis at a non-zero value).

In the first equilibrium, which applies whether Z is above or below Π_i, the time spent on non-remunerated online activities is represented by the discontinuous function including segments SS' and NE' in panel 2a. Segment SS' corresponds to the time spent by token earners (equation (11) for wages up to $\mu\phi/\gamma$, noted x_i^E in the ordinates) and segment NE' corresponds to the time spent by token buyers (equation (11) for wages above $\mu\phi/\gamma$, noted x_i^B in the ordinates). The time spent on remunerated online activities is the discontinuous function consisting of segments FF' and QJ (in both panels). Segment FF' corresponds to token earners (equation (12) for wages up to $\mu\phi/\gamma$, noted t_i^E in the ordinates) and segment QJ to token buyers (equation (12) for wages above $\mu\phi/\gamma$). Finally, the line linking points OPVV' (in both panels) represents the number of tokens bought. The segment VV' corresponds to tokens bought by token buyers in the two alternative equilibria (equations (13) and (16) for wages above $\mu\phi/\gamma$). In the first equilibrium, low wage users do not buy tokens.

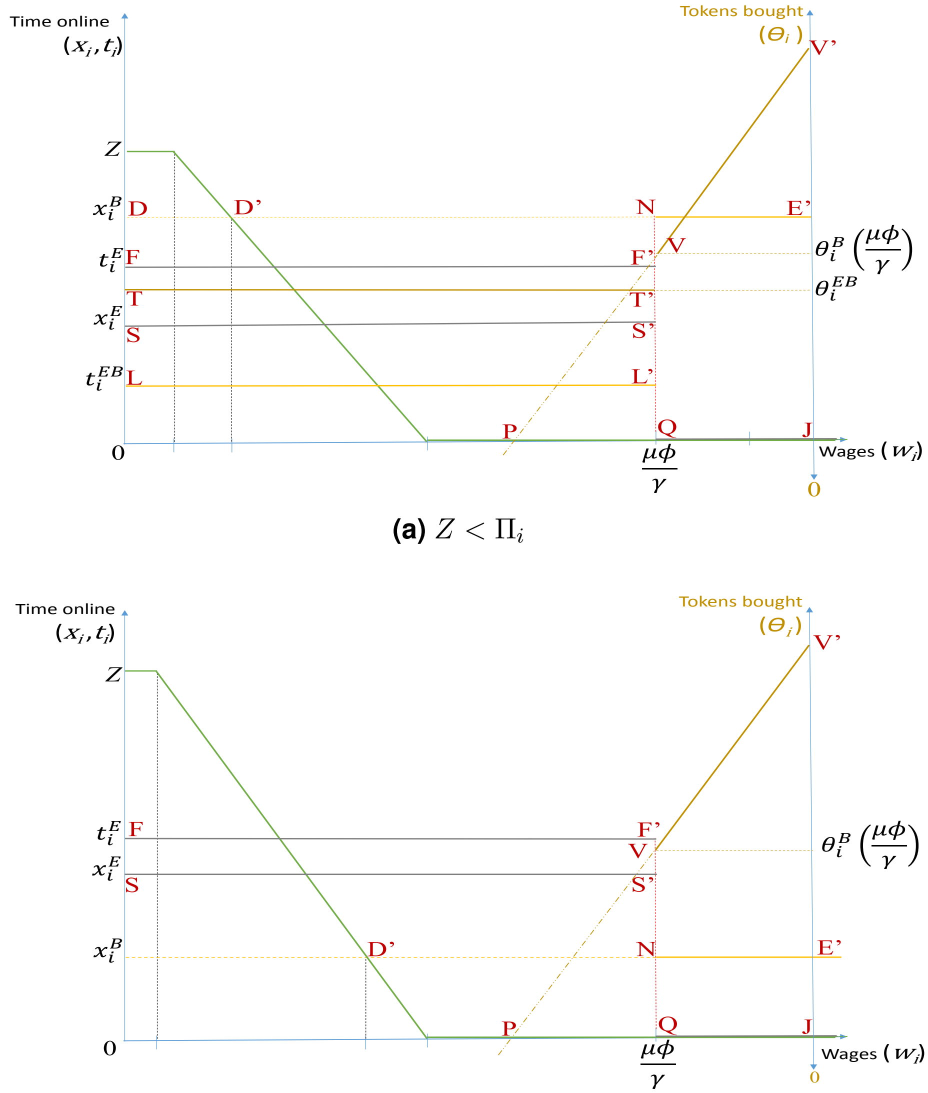
In the second equilibrium (with low Z), low-wage users also buy tokens so that token earners become token earner-buyers. The number of tokens bought is represented by the function consisting of segments TT' and VV'. Segment TT' corresponds to the number of tokens bought by token earner-buyers (equation (16)). The time spent on non-remunerated online activities is represented by the continuous function linking points DD'N in panel 2a. Segment DD'N corresponds to earner-buyer users. The time spent on remunerated online activities by token earner-buyers is the segment LL' in panel 2a. Compared to the first equilibrium, low-wage users spend more time on non-remunerated online activities because they buy tokens. This distinction might serve to select equilibria.

If Z is Π_i or more (panel 2b), token earners spend more time on remunerated online activities. However, if $Z < \Pi_i$ token earners spend less time on non-remunerated online activities than token buyers ($x_i^E < x_i^B$ in panel 2a) , while the opposite is true if $Z > \Pi_i$ ($x_i^E > x_i^B$ in schema 2b). As a result, first order condition (21) for θ_i is not satisfied if $Z > \Pi_i$ and, as in case 2, this condition drops out for token earners.[14] Conversely, first order condition (21) is satisfied if $Z < \Pi_i$ and therefore, low-wage users may buy tokens in

[13]The optimality conditions require a non-negative λ_i. Therefore, users with $w_i > \mu\phi/\gamma$ are token buyers (i.e. $\theta_i > 0$ and $t_i = 0$) even if $x_i^E = Z$.

[14]This is possible because users can participate in the platform whether or not they use tokens.

Figure 2: Time spent on the platform in *no tokens* and *tokens for sale or earned online* cases



(a) $Z < \Pi_i$

(b) $Z \geq \Pi_i$

Notes: The figure assumes that $N_i = N_i'$. In the time axis (ordinate), point Z corresponds to the time endowment for online activities; x_i^E is the time spent by token earners on unremunerated online activities (eq. (11)) and t_i^E is the time spent on remunerated online activities (eq. (12)). For token earner-buyers, the analogous are x_i^B and t_i^{EB}, and θ_i^{EB} is the number of tokens bought. For token buyers, the time spent on unremunerated online activities is also x_i^B.

equilibrium.

Finally, the model suggests that the platform may mitigate the impact of wage differentials on the time spent online by allowing tokens to be bought as well as earned online.

2.2 The platform design choice

In this section we study the platform choice. First, we determine how introducing tokens will affect platform profits. Then, given $\{\mu, \eta, \gamma, \phi, f, r\}$, we identify the VCS design (i.e. tokens for sale only or also earned online) that maximizes profits. However, we do not provide analytical solutions. Instead, we examine how platform profits are affected by changes in the user wage distribution, in the size of peer groups and in user preferences.[15]

The platform only introduces tokens if they generate sufficient profits to cover additional fixed costs. The following result compares platform profits in the no-tokens case to the tokens for sale case.

Result 2.4 *Platform profits in case 1 (No tokens) and case 2 (tokens for sale)*

1. *The platform makes no losses from offering tokens for sale (profits are weakly positive).*

2. *Ceteris paribus, profits from offering tokens for sale are larger:*

   a) *the more negative the skewness of the conditional wage distribution (conditional on peer group size and user preferences);*

   b) *the smaller the peer group N;*

   c) *the greater the marginal rate of substitution between additional offline consumption and online activities (in absolute value) Δ_i;*

Proof in appendix A.

Result 2.4 indicates that, for a given size of the peer group and marginal rate of substitution, an increase in the density mass on high-wages will raise platform revenues from selling tokens. In addition, if users' digital preference are weak (i.e. small peer groups and/or high marginal rate of substitution), then offering tokens for sale becomes more profitable.

The next result compares platform profits with no tokens to profits if tokens can be earned online as well as bought.

Result 2.5 *Platform profits in case 1 (No tokens) and case 3 (tokens earned online or bought)*

[15] By platform profits we mean revenues before deducting the fixed cost of token technology. Changes in user characteristics may make tokens unprofitable after accounting for this fixed cost.

1. *Allowing tokens to be earned online as well as bought generates strictly positive platform profits if $\kappa \geq \Omega$; where, $\Omega = \frac{1}{\phi} - \frac{fPr(B>0)}{r}$.*

2. *If $\kappa < \Omega$, allowing tokens to be earned online generates platform losses in some user groups. Losses tend to increase with a more positive skew of the wage distribution (conditional on N and δ);*

Proof in appendix A.

Parameter κ appears to be a key determinant in the platform decision whether to introduce tokens and in its choice of design. In particular, if $\kappa > \Omega$, platform revenue from a unit of time users spend on remunerated online activities, $\phi[r\kappa + f\Pr(B > 0)]$, more than compensates revenue loss r from a unit of time spent on unremunerated activities. If $\kappa < \Omega$, platform profits from tokens might not be sufficient to cover the additional fixed cost K, as allowing tokens to be earned online as well as bought may generate losses in some user groups. However, the platform may still benefit, if there is sufficient negative skew in the wage distribution. Conversely, if the wage distribution is too positively skewed, the platform would not allow users to earn tokens online but just to bought them with state currency.

The $\kappa \geq \Omega$ case leads to clear-cut results on VCS design. First, the platform always obtains positive profits from allowing tokens to be earned online. Second, if profits cover the fixed cost, the choice between only allowing tokens to be bought and also allowing them to be earned online is mainly determined by the shape of the wage distribution. Tokens for sale only is the preferred option if most of the wage distribution is above $\mu\phi/\gamma$. Otherwise, platforms will also allow tokens to be earned online.

Finally, the composition of Ω suggests a link between the platform design choice and the composition of its revenues. The higher the share of platform revenue from fees, the lower the κ required for strictly positive profits. On the other hand, the higher the share of platform revenue from unremunerated online activities, the higher the κ required for strictly positive profits. For a given κ, allowing tokens to be earned online as well as bought will benefit platforms that rely mostly on transaction fees (that is a small r compared to $f\Pr(B > 0)$). Only allowing tokens to be bought will be preferred by platforms that rely more on collecting and selling user information.

3 Empirical illustration: the case of Luxembourg

We use the Luxembourg component of the EU household survey on Information and Communication Technologies (ICT) (wave 2014 and 2017) to estimate behavioural equations and test the theoretical predictions of result 2.1. In particular, the estimated equations allow us to quantify the impact of various socio-economic characteristics on the time spent on social network platforms. In addition, we estimate the parameters of the wage distribution conditional on digital preferences, which allows us to evaluate platform incentives to introduce a virtual currency based on results 2.4 and 2.5.

The 2014 wave covered 1,521 households weighted to represent 184,194 private households or 414,195 individuals resident in Luxembourg. This wave included specific questions on time spent on some popular social and professional networks[16] but no information on user peer groups. The survey did not ask questions on the use of virtual currency in 2014, but to our knowledge there were no virtual currency on those platforms at that time[17]. The 2017 wave covered 1,517 households, weighted to represent 202,336 private households or 449,175 individuals resident in Luxembourg.

The data provided by Statec contains missing answers. Appendix B describes the data treatments we performed.

3.1 Variable definitions and descriptive statistics

We construct variables on the time spent per week on social network platforms. To test our theoretical hypotheses, we approximate individual digital preferences with a composite indicator constructed by a series of partial regressions to combine variables related to different dimensions of ICT usage.[18]

The indicator considers five interrelated dimensions of individual digital preferences and controls for the role of different user characteristics. First, individual perceptions of Internet as useless or as raising security risks. Second, individual ICT skills. Third, individual connectivity, characterized by the ability to remain connected to the Internet while travelling. Finally, individual online behaviour (shopping and information sharing online). Naturally, individuals need an Internet connection to participate in a platform and individuals who consider Internet a risky or useless tool would be less likely to have Internet access. This is more likely if individual ICT skills are limited.

3.1.1 Digital preferences

Figure 3 plots the empirical distribution of our composite indicator of digital preferences estimated on 414,195 individuals using an Epanechnikov kernel with bandwidth 3.5. By construction, the composite variable is uncorrelated with socio-economic characteristics including age. Negative values of the indicator suggest digital preferences are lower than would be

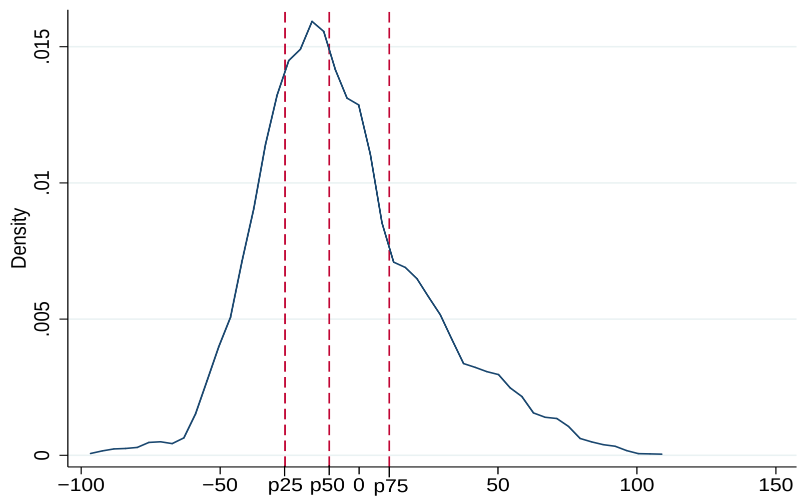
[16]Social networks included Facebook, Google+, Twitter, other. Professional networks included Linkedin, Xing, Viadeo, StudiVZ, Monster.lu, other.

[17]Facebook Credits were phased-out one year earlier.

[18]See Giordana and Guarda (2019) (forthcoming) for a detailed description of this indicator, based on Frisch and Waugh (1933). For an application of this approach to estimate the contribution of different risk factors to individual health outcomes see Jusot et al. (2013) and Deutsch et al. (2018).

expected from the individual's socio-economic characteristics. The red dashed lines are the quartiles of the distribution. We note that the median (p50) takes a negative value, meaning that more than half the population has lower than expected digital preferences. Quartiles p25 and p75 are closer to the median than a normal distribution (i.e. *leptokurtic* distribution). Moreover, the mean is -5.8, above the median, what indicates a slightly positive skewness.

Figure 3: Empirical probability density function of the composite digital preference indicator



Source: Own calculations based on the Luxembourg ICT survey wave 2014 (Statec).

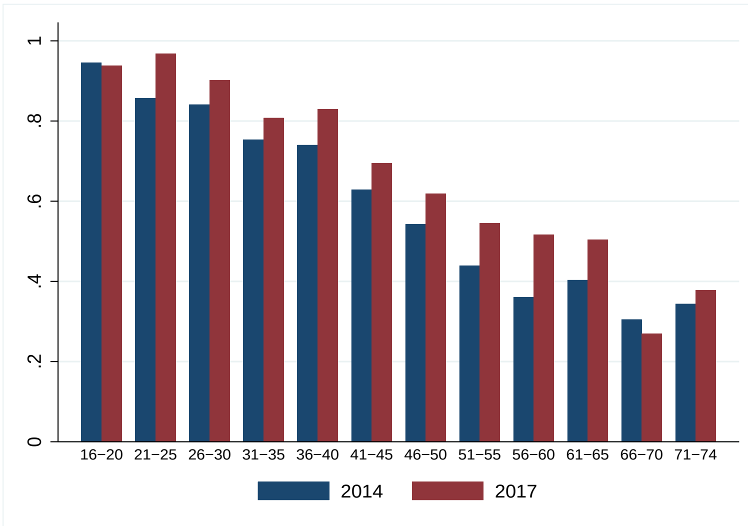
3.1.2 Social network usage

Figure 4 depicts the share of individuals (by age group) who reported using social networks in the three months before the survey. This share declines steadily with age, suggesting a significant age divide. However, the share of older individuals reporting that they use social networks is significantly above zero. Between 2014 and 2017, almost all age groups saw an increase in this share. Overall, it increased from 64% to 70% of those who reported using Internet in the preceding three months (60% to 68% for the whole population).

Figure 5 plots the empirical probability density function of the hours spent per week on social networks. On average, active users spent 5.3 hours per week in 2014 (with a median of 3.1 hours/week and standard deviation of 7.4). However, the mode is clearly zero and more than 28% of individuals with a social network account do not appear to be active[19] sug-

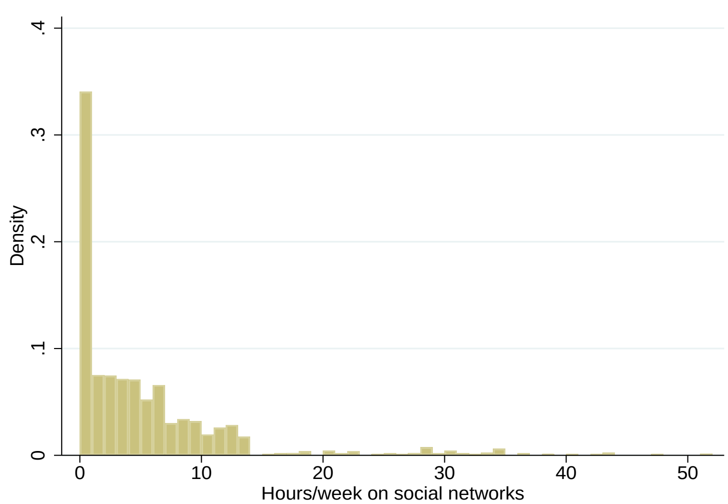
[19]This includes individuals who reported that they used social networks in the three months before the survey but did not know the time involved.

Figure 4: Share of individuals who used social networks in the 3 months before the survey



Source: Own calculations based on the Luxembourg ICT survey wave 2014 and 2017 (Statec).
Notes: Results are weighted.

Figure 5: Empirical probability density function of weekly hours spent on social networks

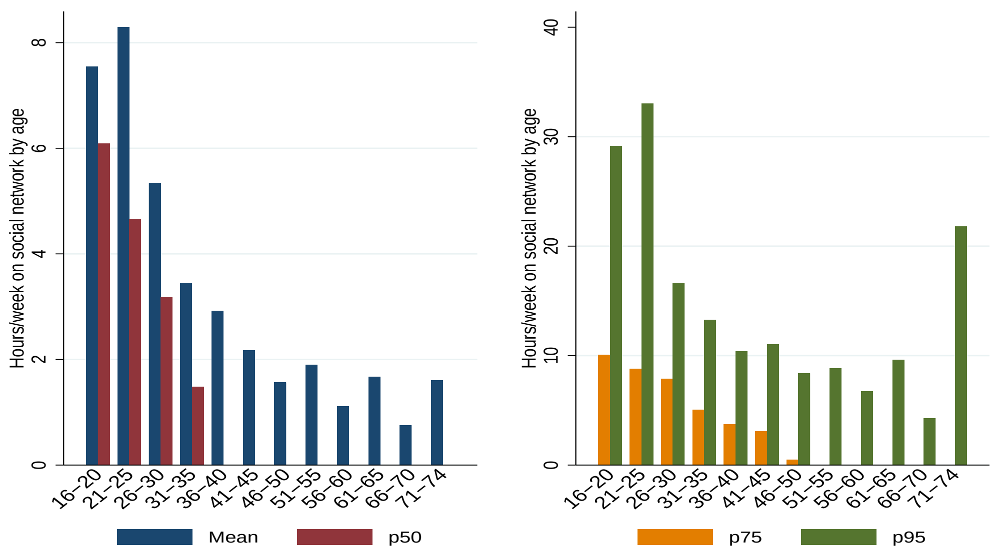


Source: Own calculations based on the Luxembourg ICT survey wave 2014 (Statec).
Notes: Results are weighted.

gesting that weekly hours spent on social networks should be modelled as a left-censored variable.

Figure 6 provides more detail on weekly hours spent on social networks in 2014. All statistics in this Figure tend to decrease along the age axis. The mean is positive in every age group, declinin from more than seven hours/week for those 16-20 years old to less than two hours/week for those 71-74 years old. The median (p50) decreases to reach zero in the group aged 36-40 years. The third quartile (p75 in the right panel of the figure) reaches zero in the group aged 51-55. The 95th percentile also decreases along the age axis but the oldest age group still contains some active individuals spending more than 20 hours/week on social networks.

Figure 6: Mean, Median and selected percentiles of weekly hours spent on social networks in 2014 (by age groups)



Source: Own calculations based on the Luxembourg ICT survey wave 2014 (Statec).
Notes: Results are weighted.

3.2 Empirical strategy and testable hypotheses

To empirically test the theoretical implications concerning platform usage (Result 2.1) and to evaluate the conditions regarding virtual currency design (Results 2.4 and 2.5), we estimate the impact of socio-economic characteristics and digital preferences on: (i) individual use of social network platforms, (ii) the parameters of the conditional wage distribution used in the theoretical model.

To model the time individuals spend *per* week on social networks, we consider a selection model for a left-censored variable with two independent parts: a selection equation (17) and an outcome equation (18).

$$I = \beta^0 \Lambda + \beta^w \cdot w + \beta^{dp} \cdot P + u \tag{17}$$

We estimate two versions of the selection equation. In the first, the binary dependent variable I takes the value one if the respondent used a social network in the three months before the survey. In the second specification, the binary dependent variable one if the respondent has social network accounts but spent zero time on the platforms. We estimate equation (17) using probit specifications (i.e. disturbance term u is normally distributed) where the vector of explanatory variables Λ includes sex, age, nationality, household size, education level, working status (unemployed, student, retired), a binary variable indicating the survey wave and a constant. There are two additional explanatory variables: net monthly income w and P, the composite indicator of individual digital preferences described in section 3.1.

We rely on a generalized linear model of the gamma family to estimate the outcome equation for weekly hours spent on social network platforms. The general specification of the underlying linear equation is as follows:

$$y = \beta_x^0 \Lambda + \beta_x^w \cdot w + \beta_x^{dp} P + u \tag{18}$$

where y is the time spent on the platform and, Λ, w and P, are the same as in the selection equation (17).

To test the theoretical propositions in result 2.1, the coefficients of interest are β^w and β^{dp} from equation (17) and β_x^w and β_x^{dp} from equation (18). In particular, a negative β_x^w and a positive β_x^{dp} would confirm the theoretical predictions. As these effects operate through both the intensive and extensive margins, for inactive users (second specification of equation (17)), a positive β^w and a negative β^{dp} would be consistent with the theoretical signs on the effects of user characteristics.

We rely on a generalized beta distribution (Jenkins 2009) to estimate the parameters of the distribution of income conditional on digital preferences. We focus on a type 2 generalized beta distribution, which has the probability density function:

$$f(y) = \frac{a y^{ap-1}}{b^{ap} B(p,q) \left[1 + (y/b)^a\right]^{p+q}}, \quad y > 0 \tag{19}$$

where a, b, p, q are positive parameters, $B(p,q) = \Gamma(p)\Gamma(q)/\Gamma(p+q)$ is the Beta function, and $\Gamma(.)$ is the Gamma function.

This functional form encompasses widely used parametric models of income, including the Dagum (1977) distribution ($q = 1$) or the Singh-Maddala ($p = 1$) distribution. We use the log-maximum-likelihood procedure implemented in Stata by Jenkins (2014) to estimate these parameters from our composite digital preference indicator.

3.3 Econometric results

We first discuss the estimation results for social network usage (Table 1). Then, we test the predictions of the theoretical model regarding platform user behaviour in the no tokens case (i.e. Result 2.1). Finally, we analyse the conditional income distribution and evaluate the conditions regarding virtual currency design (i.e. Results 2.4 and 2.5).

3.3.1 Social network usage

Table 1 reports the estimation results. The first two columns report the results for equation (17), the selection equation, which explains individual social network usage. In the first column, the dependent variable is whether the respondent used a social network in the three months before the survey. This column combines data from both the 2014 and 2017 surveys. To check for differences across the two waves, we use a dummy to construct interaction terms for several variables. In the second column, the dependent variable is whether the respondent is an inactive user (reports zero time spent on social network platforms).

The three remaining columns in Table 1 report alternative specifications for equation (18), the outcome equation explaining time spent on social network platforms. These are estimated using 2014 data only, because the 2017 wave of the survey did not ask about time spent on social networks.

The coefficients of interest to test result 2.1 are in columns 2 to 5. In the second column, the signs of the coefficients on monthly net income and on digital preferences confirm the theoretical impact operating through the extensive margin (i.e. probability of being an inactive user). The last three columns indicate a statistically significant negative effect of wages and a positive effect of digital preferences. This confirms result 2.1 regarding the impact of user characteristics on time spent online. However, results from the first specification of the selection equation (17) are ambiguous (column 1). While the effect of digital preferences is confirmed (higher preferences raise the probability of using social networks), the effect of monthly net income differs across the two survey waves. This clearly suggests that data compounds at least two different type of users.

Finally, we check whether the composite indicator of digital preferences conveys useful additional information. The estimation reported in column 3 uses age as a proxy for digital preferences, while column 4 uses binary variables to identify the quartiles of the composite indicator. In columns 3 and 4, the estimated coefficients are statistically significant and negative for all age cohorts except for those aged 21-25 and 71-74, which spend more time on social networks than the reference group aged 16-20.[20] In column 4, there are statistically significant differences across the quartiles of the digital preference composite indicator. A Wald test confirms that the composite indicator improves the fit.[21]

3.3.2 Conditional monthly income distribution

Results 2.4 and 2.5 note that platform profits from introducing a virtual currency will depend on the shape of the wage distribution conditional on digital preferences[22]. Result 2.4 also indicates that the gains from introducing tokens for sale are inversely related to digital preferences. In this subsection we study the estimated conditional distribution of monthly net income and discuss the implications for the platform decision whether to introduce virtual currency and whether to allow it to be earned online.

We estimate the parameters of the monthly income distribution assuming a type 2 generalised beta distribution and allowing the parameters to differ across the quartiles of the composite digital preferences indicator. This simple approach is sufficient for illustrative purposes, grouping individuals with similar digital preferences by quartile.

Figure 7 plots the probability density function of monthly income for each quartile of digital preferences based on the estimated parameters.[23] Simple visual inspection confirms that the parametric model provides a good fit for the four conditional distributions. In addition, all four distributions appear to have a similar shape and to be positively skewed.

Table 2 reports several characteristics of the conditional income distributions using the estimated parameters. Mode and mean are not significantly different across quartiles. The income distribution in the first quartile stochastically dominates (at order one) the distribution in the two highest quartiles, but does not dominate the distribution in the second quartile (see Table 2). This suggests that individuals with low digital preference tend to have higher income. In the theoretical model, this would lower their time spent on the platform.

Thus, the estimated conditional income distributions suggest that social network platforms could benefit from introducing virtual currency in the Luxembourg population. Low digital preference individuals are characterized by a high positive skew in their monthly income distribution, which tends to reduce platform revenue from virtual currency. However, their distribution is positioned to the right of the income distributions for individuals in quartiles with higher digital preferences. As reported above, Figure 3 also showed that in 2014

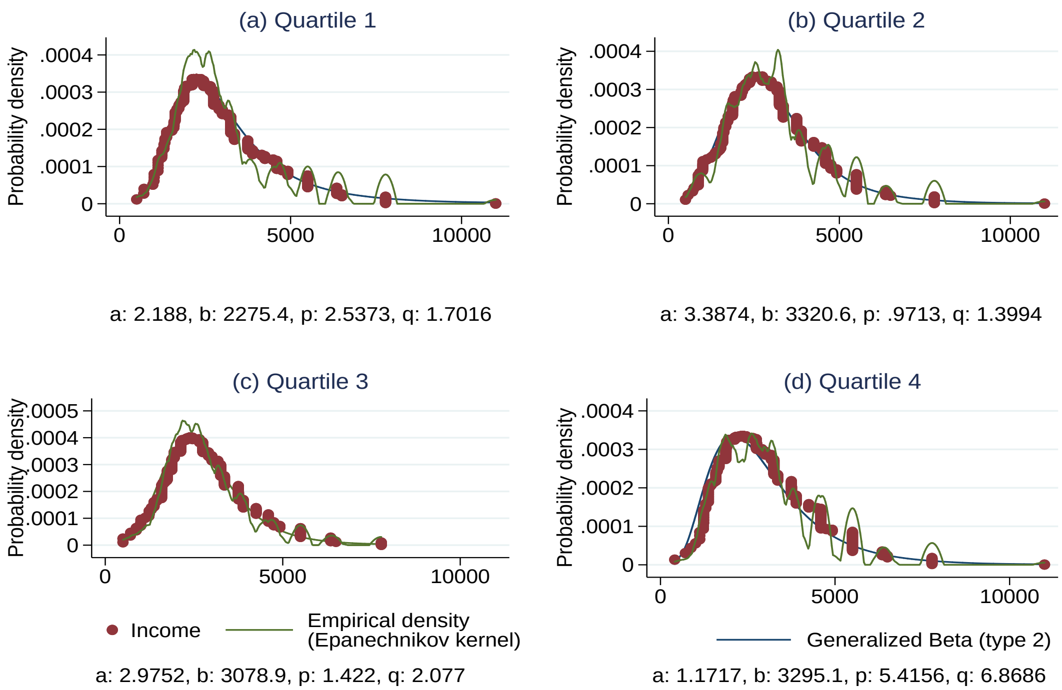
[20] This is consistent with the differences observed in Figure 6.

[21] The null hypothesis is rejected at the highest significance levels: $\chi^2(3) = 126.2$.

[22] Our indicator serves as a proxy for peer group size and marginal rate of substitution between additional offline consumption and online activities.

[23] The estimated parameters are given at the bottom of each panel.

Figure 7: Probability density function of monthly after-tax income by quartiles of the composite digital preference indicator



Source: Own calculations based on the Luxembourg ICT survey wave 2014 (Statec).
Notes: Results are weighted.

more than half of Luxembourg's population was characterized by negative values of the digital preferences indicator. Our theoretical model predicts that in such cases, the introduction of virtual currency would encourage platform usage.

4 Conclusion

In this paper we develop a theoretical model to study how social network platforms decide whether to introduce a virtual currency scheme. In the empirical part, we test benchmark theoretical predictions using data from the Luxembourg component of the EU household survey on Information and Communication Technologies usage.

The theoretical model considers two possible virtual currency designs: *tokens for sale* and *tokens for sale or earned online*. For a each design, we study how the introduction of virtual currency affects user behaviour. Then, we compare platform profits under the two alternatives and find that the platform's incentive to introduce a virtual currency depends on the distribution of income and digital preferences across the population. Finally, our model suggests that platforms whose revenue depends more on collecting and selling user information would only allow tokens to be bought. Platforms whose revenue depends mostly on transaction fees would allow tokens to be bought or earned online since they are less affected by users substituting between alternative online activities.

Our theoretical results shed light on the Libra project recently launched by Facebook. In particular, our analysis suggests that Libra need not have the same features in all markets. The design might differ between developed and developing countries as well as the relative income from collecting transaction fees and selling user information.

Econometric estimates on Luxembourg data confirm theoretical predictions on user behaviour. In particular, we show that high-income and/or low digital preference users spend less time on social network platforms. In addition, we show that individuals with the lowest digital preferences, as measured by our composite indicator, tend to have higher income, which further reduces their time spent online.

We acknowledge that Luxembourg, given its limited population, does not represent a sufficient basis to test the model. However, our empirical analysis still makes at least two original contributions. First, it proposes a well grounded empirical strategy to test our theoretical model. Second, it reveals that even in highly connected economies such as Luxembourg, individual ICT adoption and usage remain heterogeneous.

We plan to extend this work in several directions. First, we need to find an analytical solution for the platform choice between alternative virtual currency designs. This would allow, on the one hand, a more detailed analysis of the two-sided market features of the model and, on the other hand, an analysis of platform competition following Rochet and Tirole (2003). Second, we plan to allow users to save their tokens and perform peer-to-peer payments. Third, the empirical part should incorporate survey data from all EU countries. Finally, we plan to use dynamic microsimulations to assess how population ageing may affect the incentives for social networks to introduce virtual currencies.

A Mathematical appendix

A.1 The user problem: optimality conditions

In addition to the non-negativity constraints for x_i, θ_i, t_i and λ_i, first order conditions (FOCs) for maximizing (1) subject to (2) are:

$$\frac{\partial \mathcal{L}}{\partial x_i} = -\delta_i w_i + (1-\delta_i)\left[N_i\alpha\left(1+(\gamma\theta_i+\phi t_i)(1-\eta)\right)-2x_i\right]-\lambda \leq 0, \;\; x_i\frac{\partial \mathcal{L}}{\partial x_i} = 0 \quad (20)$$

$$\frac{\partial \mathcal{L}}{\partial \theta_i} = \delta_i(\gamma\eta-\mu)+(1-\delta_i)N_i\alpha\gamma(1-\eta)x_i \leq 0, \quad \theta_i\frac{\partial \mathcal{L}}{\partial \theta_i} = 0 \quad (21)$$

$$\frac{\partial \mathcal{L}}{\partial t_i} = \delta_i(\phi\eta-w_i)+(1-\delta_i)N_i\alpha\phi(1-\eta)x_i-\lambda \leq 0, \quad t_i\frac{\partial \mathcal{L}}{\partial t_i} = 0 \quad (22)$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_i} = -x_i-t_i+Z \geq 0, \quad \lambda_i(Z-x_i-t_i) = 0 \quad (23)$$

Given that the utility function is a quasi-concave function of x_i, θ_i and t_i and that the time constraint is a linear function, the solution of the system of equations composed by (20) to (23) maximizes utility.

A.1.1 Deriving equation 8

In case 1, $\gamma = \phi = \eta = t_i = \theta_i = 0$ and the FOCs consist of equations (20) and (23). If the leisure time constraint is not binding, $\lambda = 0$, we obtain from (20):

$$x_i = \frac{1}{2}\cdot\left(N_i\alpha - \frac{w_i\delta_i}{(1-\delta_i)}\right) \quad (24)$$

Substituting (24) in (23), we obtain the bottom wage condition in (8): $w_i \geq (N_i\alpha - 2Z_i)(1-\delta_i)/\delta_i$. If this condition is not satisfied, then from (23), $x_i = Z$ and, from (20), $\lambda_i = -\delta_i w_i + (1-\delta_i)\left[N_i\alpha(1+\gamma\theta_i+\phi t_i)-2Z\right]$. The upper wage condition in (8), $w_i \geq N_i\alpha(1-\delta_i)/\delta_i$, is obtained by solving (24) for the wage rate that ensures a positive x_i.

A.1.2 Deriving equations 9 and 10

In case 2, $\phi = t_i = 0$, $\eta \geq 0$ and $\gamma > 0$. The FOCs consist of equations (20), (21) and (23). If the time constraint is not binding, $\lambda = 0$, we obtain equation (10) by substituting (21) in

(20). Moreover, from (20) we obtain:

$$x_i = \frac{1}{2} \cdot \left(N_i \alpha \left(1 + \gamma \theta_i^B (1-\eta)\right) - \frac{w_i \delta_i}{(1-\delta_i)} \right) \tag{25}$$

The first part of equation (9) results from FOC (21) and is the time spent online by token buyers. The second and third parts of (9) are derived from (25) when $\theta_i^B = 0$.

This solution does not excludes the case where x_i^B for token buyers equals Z (i.e. $\frac{\delta_i(\mu-\gamma\eta)}{(1-\delta_i)N_i\alpha\gamma(1-\eta)} = Z$). All users i with such a combination of N_i and δ_i would be token buyers. Then, substituting $x_i^B = Z$ in (20) yields the number of tokens bought that ensures $\lambda_i = 0$.

A.1.3 Deriving equations (11) to (16)

In case 3, γ, ϕ, η, μ are all different from zero so the FOCs consist of equations (20) to (23). When the time constraint is not binding (i.e. $Z > x_i + t_i$ and $\lambda_i = 0$, which satisfies FOC (23)), the user cannot be both a token earner and a token buyer. From (21), the condition for $\theta_i = 0$ is $x_i < \delta_i(\mu - \gamma\eta)/(1-\delta_i)N_i\alpha\gamma(1-\eta)$. From (22), the condition for $t_i = 0$ if $\lambda_i = 0$ is $x_i < \delta_i(w_i - \phi\eta)/(1-\delta_i)N_i\alpha\phi(1-\eta)$. The comparison of these conditions reveals that $\theta_i = 0$ and $t_i \geq 0$ if $w_i < \frac{\phi}{\gamma}\mu$ (i.e. token earner conditions). Otherwise, $\theta_i \geq 0$ and $t_i = 0$ if $w_i > \frac{\phi}{\gamma}\mu$ (i.e. token buyer condition). However, as previously explained, conditions (21) and (22) also reveal that $\lambda_i > 0$ if $w_i < \frac{\phi\mu}{\gamma}$. It is impossible to obtain for both θ_i and t_i a solution from (20) if $\lambda_i = 0$.

For token earners, equation (11) results from substituting (22) in (20), where $t_i = Z - x_i$ (equation (12)) and $\theta_i = 0$ (equation (13)). Condition (21) is satisfied when $w_i \leq \mu\phi/\gamma$, $\theta_i = 0$ and $Z \geq \Pi_i$, if $x_i \leq \frac{\Delta_i(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}$. Condition (21) is otherwise ignored. The value Π_i is the value of Z that solves θ_i after substituting (22) in (20).

For the token buyer, the time constraint is not binding. We solve x_i (equation (11)) to satisfy FOC (21) and θ_i (equations (13) and (16)) to satisfy FOC (20). Moreover, $t_i = 0$ (equations (12) and 15)) and $\lambda_i = 0$ satisfy FOC (22) because $w_i > \mu\phi/\gamma$.

A token earner-buyer type can appear only if the time constraint is binding (wage is low) and $Z < \Pi_i$. Then, x_i^E (equation (14)) is obtained from (21), which is also the solution for token buyers. If $w_i \leq \phi\mu/\gamma$, conditions (22) and (23) are ensured. The θ_i^E (equation (16)) is obtained from (20) with a condition $Z < \Pi_i$ to satisfy the non-negativity of θ_i.

If $w_i < \phi\eta$ an ill solution can arrive:$x_i = 0$ and $t_i = Z$, which satisfy FOCs (21), (22) and (23). However, FOC (20) is only satisfied under certain condition. For the sake of simplicity, we avoid this additional equilibrium by assuming that the platform sets $\{\mu, \gamma, \phi, \eta\}$ to ensure, for all potential users i, that:

$$Z > \frac{\Delta_i \eta}{N_i \alpha(1-\eta)} - \frac{1}{\phi(1-\eta)} \tag{26}$$

It is straightforward to check that $\delta_i\left(\mu - \gamma\eta\right)/[(1-\delta_i)N_i\alpha\gamma] < Z < \Pi_i$ is consistent with condition (26).

A.2 Proof of Result 2.1

From equation (8), users with lower wages are more likely to be full-time users than those with higher wages, who can be either part-time or inactive users. Moreover, given the conditions in (8), it is straightforward that full-time users spend more time on the platform than other users: $Z > x_i^N(w)$ if $w > (N_i\alpha - 2Z)(1-\delta_i)/\delta_i$. Likewise, part-time users spend more time online than inactive users: $x_i^N(w) > 0$ if $w > N_i\alpha(1-\delta_i)/\delta_i$). Therefore, to prove result 2.1 it is sufficient to prove two statements. First, we prove that the probability of being an inactive user diminishes when there is a decline in the wage rate, the peer-group size or the marginal rate of substitution between additional offline consumption and online activities. Second, given that inactive and full-time users spend a constant time on the platform, we prove that the time spent by part-time users diminishes when the wage rate increases and when there is a decline in the peer-group size or the marginal rate of substitution between additional offline consumption and online activities.

From equation (8), individual i is an inactive user if his or her wage satisfies:

$$w_i \geq N_i\alpha(1-\delta_i)/\delta_i \text{ or } N_i \leq w_i\delta_i/[\alpha(1-\delta_i)].$$

Recall that we assume $\delta_i = \delta^l$ with probability p and $\delta_i = \delta^h$ with probability $1-p$. For the purpose of this proof, we assume that the peer group size is described by a Poisson distribution with mean υ. Therefore:

1. A user with wage w_i is an inactive user with probability:

$$P(N_i\alpha(1-\delta_i)/\delta_i \leq w_i) = p \cdot e^{-\upsilon} \sum_{j=0}^{\frac{w_i\delta^l}{\alpha(1-\delta^l)}} \frac{\upsilon^j}{j!} + (1-p)\cdot e^{-\upsilon} \sum_{j=0}^{\frac{w_i\delta^h}{\alpha(1-\delta^h)}} \frac{\upsilon^j}{j!} \tag{27}$$

   From (27), the lower the wage the lower the probability that a randomly selected individual is an inactive user. From (8), a part-time user spends $x_i^N = 0.5\left(N_i\alpha - w_i\delta_i/(1-\delta_i)\right)$

and $\partial x_i^N / \partial w_i < 0$ for this type of users. Thus, the lower the wage rate, the higher the expected time spent online.

2. A user with a peer-group of size N_i is an inactive user with probability:

$$\begin{aligned} P\left(\frac{w_i \delta_i}{\alpha(1-\delta_i)} \geq N_i\right) &= p \cdot \left(1 - \int_0^{N_i \alpha(1-\delta^l)/\delta^l} f(w|\delta^l) dw\right) + \\ &+ (1-p) \cdot \left(1 - \int_0^{N_i \alpha(1-\delta^h)/\delta^h} f(w|\delta^h) dw\right) \end{aligned} \tag{28}$$

   where, $f(w|\delta)$ is the probability density function of wages conditional on the marginal rate of substitution.

   From (28), the higher the peer-group size the lower the probability that a randomly selected individual be an inactive user. From (8), $\partial x_i^N / \partial N_i > 0$ for part-time users. Thus, the larger the peer-group, the higher the expected time spent online.

3. It is straightforward from (27) that given w_i, a lower marginal rate of substitution reduces the probability of being an inactive user and, therefore, increases expected time online:

$$e^{-\upsilon} \sum_{j=0}^{\frac{w_i \delta^l}{\alpha(1-\delta^l)}} \frac{\upsilon^j}{j!} < e^{-\upsilon} \sum_{j=0}^{\frac{w_i \delta^h}{\alpha(1-\delta^h)}} \frac{\upsilon^j}{j!},$$

   because $\frac{w_i \delta^l}{\alpha(1-\delta^l)} < \frac{w_i \delta^h}{\alpha(1-\delta^h)}$.

   Likewise, given N_i, a lower marginal rate of substitution reduces the probability of being an inactive user and, therefore, increases expected time online, :

$$\left(1 - \int_0^{N_i \alpha(1-\delta^l)/\delta^l} f(w|N_i) dw\right) < \left(1 - \int_0^{N_i \alpha(1-\delta^h)/\delta^h} f(w|N_i) dw\right),$$

   because $N_i \alpha(1-\delta^l)/\delta^l > N_i \alpha(1-\delta^h)/\delta^h$. From (8), $\partial x_i^N / \partial(\delta_i/(1-\delta_i)) < 0$ for part-time users. Thus, the lower the marginal rate of substitution between additional offline consumption and online activities, the higher the expected time spent online by a randomly selected user.

A.3 Proof of Result 2.2

To prove result 2.2, it is sufficient to show that, given N and δ, the expected time users spend online diminishes. The effect through the intensive margin is straightforward because full-time users spend all of Z online. From (8), those with $w_i \leq (N_i\alpha - 2\,Z)(1-\delta_i)/\delta_i$ are full-time users. Thus, the following share of users switches from part-time to full-time type

$$\int_{(N_i\alpha-2\,Z)(1-\delta_i)/\delta_i}^{(N_i\alpha-2\,Z')(1-\delta_i)/\delta_i} f(w|N_i,\delta)dw,$$

and spends less time online as $Z' < Z$ and $Z' < x_i^N\,(N_i\alpha - 2\,Z)(1-\delta_i)/\delta_i + \epsilon)$ for $\epsilon < 2(Z-Z')(1-\delta_i)/\delta_i$.

A.4 Proof of Result 2.3

Given that the time spent online by users other than token buyers are unaffected by the platform choice variables, to prove result 2.3 it is sufficient to show two statements. First, we prove that the probability of being a token buyer increases when the platform choice variables change. Second, we prove that the time spent by token buyers also increases.

The expected time spent online by token buyers is:

$$x_{tb}^B = \frac{\delta_i\,(\mu-\gamma\eta)}{(1-\delta_i)N_i\alpha\gamma(1-\eta)}\int_{\frac{N_i\alpha(1-\delta_i)}{\delta_i}-\frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}}^{+\infty} f(w|N,\delta)dw.$$

Applying Leibniz's rule we obtain:

1. Change in the price of additional offline consumption per token

$$\begin{aligned}\frac{\partial x_{tb}^B}{\partial\mu} &= \frac{2\delta_i\,(\mu-\gamma\eta)}{(1-\delta_i)\left[N_i\alpha\gamma(1-\eta)\right]^2} f\left(\frac{N_i\alpha(1-\delta_i)}{\delta_i}-\frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}\middle|N,\delta\right)+\\ &\quad+\frac{\delta_i}{(1-\delta_i)N_i\alpha\gamma(1-\eta)}\int_{\frac{N_i\alpha(1-\delta_i)}{\delta_i}-\frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}}^{+\infty} f(w|N,\delta)dw > 0\end{aligned}$$

2. Change in the share of unused tokens

$$\begin{aligned}\frac{\partial x_{tb}^B}{\partial\eta} &= -\frac{2\delta_i\,(\mu-\gamma\eta)}{(1-\delta_i)\left[N_i\alpha(1-\eta)\right]^2\gamma} f\left(\frac{N_i\alpha(1-\delta_i)}{\delta_i}-\frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}\middle|N,\delta\right)-\\ &\quad-\frac{\delta_i(\mu-\gamma)}{(1-\delta_i)N_i\alpha\gamma(1-\eta)^2}\int_{\frac{N_i\alpha(1-\delta_i)}{\delta_i}-\frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}}^{+\infty} f(w|N,\delta)dw < 0 \text{ if } \mu<\gamma\end{aligned}$$

3. Change in the price of online goods/services per token

$$\begin{aligned}\frac{\partial x_{tb}^B}{\partial \gamma} &= -\frac{2\mu\delta_i\left(\mu-\gamma\eta\right)}{(1-\delta_i)(1-\eta)(N_i\alpha)^2\gamma^3} f\left(\frac{N_i\alpha(1-\delta_i)}{\delta_i}-\frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}\middle|N,\delta\right)- \\ &\quad -\frac{\mu\delta_i}{(1-\delta_i)N_i\alpha(1-\eta)\gamma^2}\int_{\frac{N_i\alpha(1-\delta_i)}{\delta_i}-\frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}}^{+\infty} f(w|N,\delta)dw<0\end{aligned}$$

The signs of the partial derivatives above prove result 2.3.

A.5 Proof of result 2.4

In case 1, platform profits are:

$$\begin{aligned}\pi_P^{c1} &= \sum_i\sum_{j=h,l}\left[r\cdot\int_0^{+\infty} x_{i,j}^N f(w|N_i,\delta_i^j)dw\right] \\ &= \sum_i\sum_{j=h,l}\left[r\cdot Z\int_0^{(N_i\alpha-2Z)/\Delta_i^j} f(w|N_i,\delta_i^j)dw+\right. \\ &\quad +r\frac{N_i\alpha}{2}\int_{(N_i\alpha-2Z)/\Delta_i^j}^{N_i\alpha/\Delta_i^j} f(w|N_i,\delta_i^j)dw- \\ &\quad \left.-r\cdot\frac{\delta_i^j}{2\left(1-\delta_i^j\right)}\int_{(N_i\alpha-2Z)/\Delta_i^j}^{N_i\alpha/\Delta_i^j} w_i^j f(w|N_i,\delta_i^j)dw\right].\end{aligned} \tag{29}$$

In case 2, platform profits are:

$$
\begin{aligned}
\pi_P^{c2} &= \sum_i \sum_{j=h,l} \int_0^{+\infty} \left[r \cdot x_{i,j}^B + \left[\mu + \gamma \left(f \cdot Pr(\pi_F \geq 0) + r\kappa\right)\right] \cdot \theta_{i,j}^B \right] w_i^j f(w|N_i, \delta_i^j) dw - K \\
&= \sum_i \sum_{j=h,l} \Bigg\{ r \cdot Z \int_0^{(N_i\alpha - 2Z)/\Delta_i^j} f(w|N_i, \delta_i^j) dw + \\
&\quad + r \cdot \frac{N_i\alpha}{2} \int_{(N_i\alpha-2Z)/\Delta_i^j}^{\frac{N_i\alpha}{\Delta_i^j} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}} f(w|N_i, \delta_i^j) dw - \\
&\quad - r \cdot \frac{\delta_i^j}{\left(1-\delta_i^j\right)} \int_{(N_i\alpha-2Z)/\Delta_i^j}^{\frac{N_i\alpha}{\Delta_i^j} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}} w_i^j f(w|N_i, \delta_i^j) dw + \\
&\quad + r \cdot \frac{\Delta_i^j (\mu - \gamma\eta)}{N_i\alpha\gamma(1-\eta)} \int_{\frac{N_i\alpha}{\Delta_i^j} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}}^{+\infty} f(w|N_i, \delta_i^j) dw + \\
&\quad + \left[\mu + \gamma \left(f \cdot Pr(\pi_F \geq 0) + r\kappa\right)\right] \cdot \left[\frac{2\Delta_i^j (\mu - \gamma\eta)}{\left[N_i\alpha\gamma(1-\eta)\right]^2} \int_{\frac{N_i\alpha}{\Delta_i^j} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}}^{+\infty} f(w|N_i, \delta_i^j) dw - \right. \\
&\quad - \frac{1}{\gamma} \int_{\frac{N_i\alpha}{\Delta_i^j} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}}^{+\infty} f(w|N_i, \delta_i^j) dw + \\
&\quad \left. + \frac{\Delta_i^j}{N_i\alpha\gamma(1-\eta)} \int_{\frac{N_i\alpha}{\Delta_i^j} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}}^{+\infty} w_i^j f(w|N_i, \delta_i^j) dw \right] \Bigg\} - K.
\end{aligned} \tag{30}
$$

The difference between π_P^{c2} and π_P^{c1} is:

$$\begin{aligned}
\pi_P^{c2} - \pi_P^{c1} &= \Delta\pi_P^{c2} = \sum_i \sum_{j=h,l} \left\{ \int_{\frac{N_i\alpha}{\Delta_i^j} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}}^{N_i\alpha/\Delta_i^j} r\left(x_{i,j}^B - x_{i,j}^N\right) f(w|N_i,\delta_i^j)dw + \right. \\
&\quad + r\int_{N_i\alpha/\Delta_i^j}^{+\infty} x_{i,j}^B f(w|N_i,\delta_i^j)dw + \qquad (31) \\
&\quad \left. + \left[\mu + \gamma\left(f + r\kappa\right)\cdot \Pr(\pi_F \geq 0)\right] \int_{\frac{N_i\alpha}{\Delta_i^j} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}}^{+\infty} \theta_{i,j}^B f(w|N_i,\delta_i^j)dw \right\} - K \\
&= \sum_i \sum_{j=h,l} \left\{ -r\cdot\frac{N_i\alpha}{2} \int_{\frac{N_i\alpha}{\Delta_i^j} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}}^{N_i\alpha/\Delta_i^j} f(w|N_i,\delta_i^j)dw - \right. \\
&\quad + r\frac{\delta_i^j}{\left(1-\delta_i^j\right)} \int_{\frac{N_i\alpha}{\Delta_i^j} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}}^{N_i\alpha/\Delta_i^j} w_i^j f(w|N_i,\delta_i^j)dw + \\
&\quad + r\frac{\Delta_i^j\left(\mu-\gamma\eta\right)}{\left(1-\eta\right)N_i\alpha\gamma} \int_{\frac{N_i\alpha}{\Delta_i^j} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}}^{+\infty} f(w|N_i,\delta_i^j)dw + \qquad (32) \\
&\quad + \left[\mu + \gamma\left(f\cdot Pr(\pi_F \geq 0) + r\kappa\right)\right]\cdot \left[\frac{2\Delta_i^j\left(\mu-\gamma\eta\right)}{\left[N_i\alpha\gamma(1-\eta)\right]^2} \int_{\frac{N_i\alpha}{\Delta_i^j} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}}^{+\infty} f(w|N_i,\delta_i^j)dw - \right. \\
&\quad - \frac{1}{\gamma} \int_{\frac{N_i\alpha}{\Delta_i^j} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}}^{+\infty} f(w|N_i,\delta_i^j)dw + \\
&\quad \left.\left. + \frac{\Delta_i^j}{N_i\alpha\gamma(1-\eta)} \int_{\frac{N_i\alpha}{\Delta_i^j} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}}^{+\infty} w_i^j f(w|N_i,\delta_i^j)dw \right]\right\} - K.
\end{aligned}$$

It can be shown using equation (9) that the difference $x_{i,j}^{B*} - x_{i,j}^N$ equals zero if $w_i = \frac{N_i\alpha\left(1-\delta_i^j\right)}{\delta_i^j} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}$ and is positive for higher wages. Therefore, the first term of equation (31) is positive. Likewise, it follows from equation (9) that the second term of (31) is positive for wages higher than $\frac{N_i\alpha\left(1-\delta_i^j\right)}{\delta_i^j} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}$. In the same vein, for this range of wages, equation (10) indicates that θ_i^B is positive. Thus, the last term in (31) is weakly positive if $\Pr(\pi_F > 0) \geq 0$. All these prove the first point in result 2.4.

The second point of result 2.4 contains several parts:

a) It is straightforward from equation (31) that the thinner the left tail of the conditional wage distribution, the higher the incremental profit of case 2 with respect to case 1. If the conditional distribution of wages A is more negative skewed than distribution B, we have that distribution A stochastically dominates B in the third order and therefore

$F_A(x|N,\delta) < F_B(x|N,\delta)$, where $F(.)$ is the cumulative distribution function of wages and $x = \frac{N_i\alpha\left(1-\delta_i^j\right)}{\delta_i^j} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}$ is the bottom limit of the finite integrals in (31). This proves our statement. Of course, first order stochastic dominance is a sufficient condition for third order dominance and therefore for our proposition. However, first order stochastic dominance is a more restrictive condition.

We apply Leibniz's rule to the incremental profit in (32) to obtain, after simplification, the effect of changes in variable y:

$$\begin{aligned} \frac{\partial \Delta\pi_P^{c2}}{\partial y} = & \sum_i \sum_{j=h,l} \Bigg\{ r\frac{\partial x_i^{B*}\left(w_i \geq \frac{N_i\alpha}{\Delta_i^j} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}\right)}{\partial y} + \\ & C\frac{\partial \theta_i^{B}\left(w_i \geq \frac{N_i\alpha}{\Delta_i^j} - \frac{2(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}\right)}{\partial y} + \\ & \frac{\partial C}{\partial y}\left[\left(\frac{2\Delta_i^j(\mu-\gamma\eta)}{\left[N_i\alpha\gamma(1-\eta)\right]^2} - \frac{1}{\gamma}\right)\left(1 - F\left(\frac{N_i\alpha}{\Delta_i^j} - 2\frac{(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}|N,\delta\right)\right) + \\ & \frac{\Delta_i^j}{N_i\alpha\gamma(1-\eta)}\bar{w}_i\right]\Bigg\} \end{aligned} \tag{33}$$

where, $C = [\mu + \gamma(r\cdot\kappa + f\Pr(\beta > f + \eta))]$ and $\bar{w}_i = \int_{\frac{N_i\alpha}{\Delta_i^j} - 2\frac{(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}}^{+\infty} w_i f(w|N,\delta)\,dw$.

b) This proof consists in showing that $\frac{\partial \Delta\pi_P^{c2}}{\partial N_i}$ in (33) is negative. We calculate the partial derivatives of x_i^{B*} and θ_i^B with respect to N_i in equations (9) and (10) when $w_i > \frac{N_i\alpha}{\Delta_i^j} - 2\frac{(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}$. These partial derivatives are negative and $\partial C/\partial N_i = 0$, which proves this part of result 2.4.

c) This proof consists in showing that $\frac{\partial \Delta\pi_P^{c2}}{\partial_i^j}$ in (33) is positive, recall that $\Delta_i^j = \frac{\delta_i^j}{(1-\delta_i^j)}$. We calculate the partial derivatives of x_i^{B*} and θ_i^B with respect to A_i^j in equations (9) and (10) when $w_i > \frac{N_i\alpha}{\Delta_i^j} - 2\frac{(\mu-\gamma\eta)}{N_i\alpha\gamma(1-\eta)}$. These partial derivatives are positive and $\partial C/\partial\Delta_i^j = 0$, which proves this part of result 2.4.

A.6 Proof of result 2.5

We focus on the case where the online time endowment is sufficiently loose (i.e. $Z \geq \Pi_i\ \forall i$). Therefore, users decide either buy tokens or earn them (not both). In this case, the platform profits are:

$$
\begin{aligned}
\pi_P^{c3} &= \sum_i \sum_{j=h,l} \left\{ \int_0^{+\infty} \left[r \cdot x_{i,j}^E + \mu\theta_{i,j}^E \right] f(w|N_i,\delta_i^j)dw + \right.\\
&\left. + \int_0^{+\infty} \left(f \cdot Pr(\pi_F \geq 0) + r\kappa\right) e_i^j f(w|N_i,\delta_i^j)dw \right\} - K \\
&= \sum_i \sum_{j=h,l} \left\{ \left[r \cdot x_{i,j}^E + \left(f \cdot Pr(\pi_F \geq 0) + r\kappa\right) \phi t_{i,j}^E \right] \int_0^{\mu\phi/\gamma} f(w|N_i,\delta_i^j)dw + \right.\\
&\left. + \left[rX_{i,j}^E + \left(\mu + \left(f \cdot Pr(\pi_F \geq 0) + r\kappa\right)\gamma\right)\theta_{i,j}^E \right] \int_{\mu\phi/\gamma}^{+\infty} f(w|N_i,\delta_i^j)dw \right\} - K. \quad (34)
\end{aligned}
$$

The difference between π_P^{c3} and π_P^{c1} is:

$$
\begin{aligned}
\pi_P^{c3} - \pi_P^{c1} &= \Delta\pi_P^{c3} = \sum_i \sum_{j=h,l} \left\{ r \int_0^{+\infty} \left(x_{i,j}^{E*} - x_{i,j}^N \right) f(w|N_i,\delta_i^j)dw + \right.\\
&+ \left(f \cdot Pr(\pi_F \geq 0) + r\kappa\right) \phi t_{i,j}^{E*} \int_0^{\mu\phi/\gamma} f(w|N_i,\delta_i^j)dw + \qquad (35)\\
&\left. + \left[\mu + \left(f \cdot Pr(\pi_F \geq 0) + r\kappa\right)\gamma\right] \theta_{i,j}^{E*} \int_{\mu\phi/\gamma}^{+\infty} f(w|N_i,\delta_i^j)dw \right\} - K.
\end{aligned}
$$

More precisely,

$$
\begin{aligned}
\Delta\pi_P^{c3} &= \sum_i \sum_{j=h,l} \left\{ \left[\left(x_{i,j}^E - Z \right) \left[r - \left(f \cdot \Pr(B > 0) + r\kappa\right)\phi \right] \right] \int_0^{(N_i\alpha - 2Z)(1-\delta_i^j)/\delta_i^j} f(w|N_i,\delta_i^j)dw + \right.\\
&+ \left[r\left(x_{i,j}^E - x_{i,j}^N \right) + \left(f \cdot \Pr(B > 0) + r\kappa\right)\phi t_{i,j}^E \right] \int_{(N_i\alpha-2Z)(1-\delta_i^j)/\delta_i^j}^{\Lambda_i^j} f(w|N_i,\delta_i^j)dw + \\
&+ \left[r\left(x_{i,j}^E - x_{i,j}^N \right) + \left(f \cdot \Pr(B > 0) + r\kappa\right)\phi t_{i,j}^E \right] \int_{\Lambda_i^j}^{N_i\alpha(1-\delta_i)/\delta_i} f(w|N_i,\delta_i^j)dw + \\
&+ \left[r x_{i,j}^E + \left(f \cdot \Pr(B > 0) + r\kappa\right)\phi t_{i,j}^E \right] \int_{N_i\alpha(1-\delta_i)/\delta_i}^{\mu\phi/\gamma} f(w|N_i,\delta_i^j)dw + \\
&\left. + \left[r x_{i,j}^E + \left(\mu + \left(f \cdot Pr(\pi_F \geq 0) + r\kappa\right)\gamma\right)\theta_{i,j}^E \right] \int_{\mu\phi/\gamma}^{+\infty} f(w|N_i,\delta_i^j)dw \right\} - K \qquad (36)
\end{aligned}
$$

where $\Lambda_i^j = \frac{N_i\alpha(1-\delta_i^j)}{\delta_i^j}\left[1 - \frac{1+\phi Z(1-\eta)}{1+N_i\alpha\phi(1-\eta)}\right] + \frac{\phi\eta}{1+N_i\alpha\phi(1+\eta)}$.

Result 2.5 contains two parts. From equations (8) and (11), offering tokens for sale or earned online reduces time online in unremunerated online activities for users with wages below Λ_i^j. However, as in case 2, platform losses in advertising revenue due to lower time spent online can be compensated with gains from additional time spent by high-wage users and virtual currency use. In addition, in case 3, platform losses can also be compensated by low-wage users spending time spent on remunerated activities on the platform. This is captured by the first two terms of (36). In the first term of equation (36), revenue from a unit of time of remunerated online activities $\phi(r\kappa + f \cdot \Pr(B > 0))$ compensates revenue loss r from one unit of time of unremunerated activities if $\kappa \geq \frac{1}{\phi} - \frac{f \cdot \Pr(B>0)}{r} = \Omega$. Given that $x_{i,j}^N < Z$ if $w_i^j > (N_i\alpha - 2Z)(1 - \delta_i^j)/\delta_i^j$, the second term of (36) is positive if $\kappa \geq \Omega$. Finally, from equations (8) and (11), the third term of (36) is positive as $x_{i,j}^E > x_{i,j}^N$. Therefore, given that the last two terms of (36) are positive, the first item of result 2.5 is proved.

In the second part of result 2.5, $\kappa < \Omega_i$. In this case, platform revenue from time spent in remunerated activities does not compensate the revenue loss from the reduction in unremunerated activities. Based on equation (36), we showed that platform losses from introducing tokens for sale or earned online are highest among low-wage users if $\kappa < \Omega$. Therefore, the thinner the left tail of the conditional wage distribution, the lower the platform losses. We also showed, based on equations (8) and (11) that the last three terms of equation (36) are positive. Thus, the fatter the right tail of the conditional wage distribution, the higher the platform profits from introducing tokens for sale and earned online.

B Data appendix: variable definitions and data treatment

In this section we define the variables we constructed using survey data and describe the statistical treatments we performed.

B.1 Time spent per week on the platform

This variable combines two questions in the ICT survey (wave 2014) to obtain the total time spent on social network platforms per week. First, we multiply the number of connections per week to a social network platform by the time spent per day on the platform. Then, we sum the time spent online per week across the different social networks platforms covered by the survey.

B.2 Monthly after tax income

The ICT survey asked for the household's approximate after-tax monthly income of the household. In 2014, the survey proposed eleven bins spanning "less than 1500 EUR" to "more than 8000 EUR". In 2017, there were ten bins spanning "less than 2000 EUR" to "more than 8000 EUR". In addition, both waves included a category for no answer. The non-response rate on income was very high in 2014, reaching more than 33% of respondents. In 2017, it was lower, with 24% not responding.

Therefore, we applied a simple imputation, running a least squares regression to predict the income bin of non-respondents using the following explanatory variables (interacted with a year dummy variable): demography (sex, age, nationality, household size), level of education attainment and working status (unemployed, student, retired, employee or self-employed). Estimation results are available upon request.

Then, we defined individual monthly after-tax income by taking the centre of each bin and adjusting for the size of the household (i.e. equivalence scale transformation). Income is not deflated because we include a year dummy interacted with the other explanatory variables.

B.3 Other variables

To avoid losing observations due to missing values we combined some education categories. Moreover, column (2) in Table 1 treats age as a continuous variable, but the estimated coefficient actually indicates the effect of a five-year increase in the age of the individual (movement to the next bin).

C Appendix of tables

Table 1: Estimated coefficients of social network usage models

	(1) Soc.Network	(2) Inactive User	(3) Time(a)	(4) Time(b)	(5) Time(c)
Income	0.0000189***	0.0000115***	-0.0000174***	-0.0000199***	-0.0000165***
	(14.06)	(5.25)	(-8.67)	(-9.91)	(-8.20)
Wave 2014 × Income	-0.0000346***				
	(-15.68)				
Dig.Preferences	0.0118***	-0.00437***		0.00133***	
	(222.35)	(-46.80)		(17.56)	
Q2					0.0590***
					(7.95)
Q3					0.0929***
					(12.74)

Continued on next page

Table 1 – continued from previous page

	(1) Soc.Network	(2) Inactive User	(3) Time(a)	(4) Time(b)	(5) Time(c)
Q4					0.0685***
					(10.20)
Female	0.0716***	-0.257***	-0.140***	-0.139***	-0.138***
	(16.04)	(-45.67)	(-29.83)	(-29.76)	(-29.25)
Wave 2014 × Female	-0.111***				
	(-17.54)				
Foreigner	0.192***	-0.00816	0.0838***	0.0880***	0.0892***
	(40.60)	(-1.42)	(16.65)	(17.49)	(17.66)
Wave 2014 × Foreigner	-0.187***				
	(-27.99)				
Household size	-0.0306***	0.0724***	-0.0376***	-0.0357***	-0.0343***
	(-16.10)	(33.51)	(-19.15)	(-18.27)	(-17.29)
Wave 2014 × HH size	0.0230***				
	(8.77)				
Age		0.0315***			
		(102.76)			
21-25 years	0.554***		0.209***	0.219***	0.217***
	(29.05)		(18.95)	(19.83)	(19.65)
26-30 years	0.00489		-0.132***	-0.153***	-0.146***
	(0.27)		(-11.10)	(-12.87)	(-12.15)
31-35 years	-0.522***		-0.427***	-0.439***	-0.440***
	(-28.35)		(-34.10)	(-35.18)	(-34.77)
36-40 years	-0.484***		-0.379***	-0.395***	-0.393***
	(-25.16)		(-28.57)	(-29.80)	(-29.44)
41-45 years	-0.863***		-0.474***	-0.502***	-0.502***
	(-47.48)		(-35.81)	(-37.78)	(-37.32)
46-50 years	-1.121***		-0.451***	-0.457***	-0.471***
	(-60.95)		(-33.41)	(-33.98)	(-34.12)
51-55 years	-1.373***		-0.205***	-0.218***	-0.228***
	(-75.26)		(-13.12)	(-14.04)	(-14.50)
56-60 years	-1.415***		-0.425***	-0.437***	-0.465***
	(-75.40)		(-24.86)	(-25.62)	(-26.65)
61-65 years	-1.471***		-0.274***	-0.320***	-0.304***

Continued on next page

Table 1 – continued from previous page

	(1) Soc.Network	(2) Inactive User	(3) Time(a)	(4) Time(b)	(5) Time(c)
	(-73.03)		(-12.48)	(-14.57)	(-13.70)
66-70 years	-2.101***		-0.979***	-0.983***	-1.002***
	(-100.07)		(-44.00)	(-44.24)	(-44.64)
71-74 years	-1.845***		0.239***	0.222***	0.201***
	(-75.63)		(6.98)	(6.53)	(5.84)
Wave2014×(21-25 years)	-1.083***				
	(-41.78)				
Wave2014×(26-30 years)	-0.698***				
	(-27.27)				
Wave2014×(31-35 years)	-0.512***				
	(-19.69)				
Wave2014×(36-40 years)	-0.574***				
	(-21.42)				
Wave2014×(41-45 years)	-0.573***				
	(-22.16)				
Wave2014×(46-50 years)	-0.598***				
	(-23.12)				
Wave2014×(51-55 years)	-0.578***				
	(-22.12)				
Wave2014×(56-60 years)	-0.693***				
	(-26.04)				
Wave2014×(61-65 years)	-0.386***				
	(-13.37)				
Wave2014×(66-70 years)	-0.0570*				
	(-1.90)				
Wave2014×(71-74 years)	-0.213***				
	(-6.26)				
Education		0.0487***			
		(30.41)			
Level 2	0.344***		-0.269***	-0.281***	-0.278***
	(30.15)		(-26.36)	(-27.63)	(-27.22)
Level 3	0.293***		-0.146***	-0.159***	-0.150***

Continued on next page

Table 1 – continued from previous page

	(1) Soc.Network	(2) Inactive User	(3) Time(a)	(4) Time(b)	(5) Time(c)
	(32.49)		(-16.67)	(-18.12)	(-17.02)
Level 4	0.166***		-0.211***	-0.211***	-0.214***
	(17.56)		(-21.62)	(-21.70)	(-21.94)
Level 5	0.216***		-0.349***	-0.349***	-0.348***
	(21.95)		(-31.51)	(-31.67)	(-31.37)
Wave2014× L2	-0.441***				
	(-28.34)				
Wave2014× L3	-0.276***				
	(-22.73)				
Wave2014× L4	0.0690***				
	(5.37)				
Wave2014× L5	-0.0792***				
	(-5.71)				
Unemployed	0.555***				
	(24.32)				
Student	0.136***	0.0236**	0.00985	0.00681	-0.00105
	(9.05)	(2.35)	(1.00)	(0.69)	(-0.11)
Wave 2014 × Student	-0.0721***				
	(-3.42)				
Retired	-0.145***	-0.449***	0.154***	0.145***	0.159***
	(-15.37)	(-34.74)	(9.21)	(8.68)	(9.42)
Wave 2014 × Retired	-0.225***				
	(-16.36)				
Wave 2014	0.586***				
	(19.80)				
Cons.	1.207***	-2.161***	2.600***	2.618***	2.544***
	(57.43)	(-123.75)	(164.02)	(165.26)	(154.95)
pseudo R^2	0.229	0.082			
Log lik.	-433444.6	-137184.1	-532399.8	-532255.4	-532318.5
Chi-squared(24)	256962.8	24531.3	14961.0	15399.6	15182.3
N	863370	250541	179437	179437	179437

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Estimated probability distribution function of monthly income after taxes per quartile of the composite indicator of digital preferences

Dig. Preferences:	Q1		Q2		Q3		Q4	
	Qtiles	Cumul. share	Qtiles	Cumul. share	Qtiles	Cumul. share	Qtiles	Cumul. share
1%	893.5	0.0022	742.7	0.0018	839.8	0.0024	766.8	0.0021
5%	1280.3	0.0158	1223.0	0.0148	1256.3	0.0177	1129.7	0.0151
10%	1532.0	0.0371	1529.5	0.0368	1513.7	0.0423	1375.5	0.0360
25%	2046.9	0.1188	2112.0	0.1243	1999.4	0.1362	1889.8	0.1181
50%	2820.4	0.3020	2877.4	0.3222	2637.3	0.3408	2659.4	0.3065
75%	3951.4	0.5531	3842.0	0.5852	3428.4	0.6056	3722.2	0.5675
90%	5520.8	0.7615	5023.7	0.7917	4353.8	0.8080	5040.6	0.7810
95%	6886.2	0.8538	5972.2	0.8778	5057.4	0.8903	6057.2	0.8722
99%	11023.4	0.9540	8608.3	0.9652	6862.1	0.9707	8623.4	0.9650
Parameters								
a	2.188		3.3874		2.9752		1.1717	
b	2275.4		3320.6		3078.9		3295.1	
p	2.5373		0.9713		1.422		5.4156	
q	1.7016		1.3994		2.077		6.8686	
Mode	2237.3		2531.6		2354.2		2102.8	
Mean	3311.1		3154.9		2834.5		3009.4	
St.Dev.	3936.4		3541.9		3092.8		3424.8	
Variance	1.55e+07		1.25e+07		9.57e+06		1.17e+07	
Skewness	1.37e+11		6.63e+10		3.89e+10		5.97e+10	

References

Aaron, M., Rivadeneyra, F., Sohal, S. et al.: 2017, Fintech: Is this time different?: A framework for assessing risks and opportunities for central banks, *Bank of Canada Staff Discussion paper* **10**.

Anderson, S. P. and Gans, J. S.: 2011, Platform siphoning: Ad-avoidance and media content, *American Economic Journal: Microeconomics* **3**(4), 1–34.

Baye, M. R. and Morgan, J.: 2001, Information gatekeepers on the internet and the competitiveness of homogeneous product markets., *American Economic Review* **91**(3), 454 – 474.

BIS: 2018, Cryptocurrencies: looking beyond the hype, Annual Report, Bank for International Settlements, chapter V, pp. 91 – 114.

Camera, G.: 2017, A perspective on electronic alternatives to traditional currencies, *Sveriges Riksbank Economic Review* **1**, 126–48.

Carstens, A.: 2018, Money in a digital age: 10 thoughts, Bank for International Settlements, *speech at Lee Kuan Yew School of Public Policy, 15 November*, Singapore.

Claeys, G., Demertzis, M. and Efstathiou, K.: 2018, Cryptocurrencies and monetary policy, *Bruegel Policy Contribution* **10**.

Cœuré, B.: 2018, The future of central bank money, European Central Bank, *speech at the International Center for Monetary and Banking Studies, 14 May*, Geneva.

Cœuré, B.: 2019a, Digital challenges to the international monetary and financial system, European Central Bank, *speech at the Banque centrale du Luxembourg-Toulouse School of Economics conference on "The Future of the International Monetary System", Banque centrale du Luxembourg, 17 September*, Luxembourg.

Cœuré, B.: 2019b, Introductory remarks to "Digital currencies, focussing on Libra", European Central Bank, *speech at the Committee on the Digital Agenda, Deutscher Bundestag, 25 September*, Berlin.

CPMI: 2015, Digital currencies, *Cpmi papers 137*, Committee on Payments and Market Infrastrutures (CPMI), Bank for International Settlements.

Dagum, C.: 1977, New model of personal income-distribution-specification and estimation, *Economie appliquée* **30**(3), 413–437.

Davoodalhosseini, M., Rivadeneyra, F. et al.: 2018, A policy framework for e-money: A report on bank of canada research, *Bank of Canada Staff Discussion paper* (5).

Demertzis, M. and Wolff, G. B.: 2018, The economic potential and risks of crypto assets: is a regulatory framework needed?, *Bruegel Policy Contribution* **14**.

Deutsch, J., Pi Alperin, M. N. and Silber, J.: 2018, Using the Shapley decomposition to disentangle the impact of circumstances and efforts on health inequality, *Social Indicators Research* pp. 1–21.

ECB: 2015, Virtual currency schemes: a further analysis, *ad-hoc report*, European Central Bank (ECB).

Economides, N.: 1996, The economics of networks, *International journal of industrial organization* **14**(6), 673–699.

Frisch, R. and Waugh, F. V.: 1933, Partial time regressions as compared with individual trends, *Econometrica: Journal of the Econometric Society* pp. 387–401.

Fung, B. and Halaburda, H.: 2014, Understanding platform-based digital currencies, *Bank of Canada Review* **2014**(Spring), 12–20.

Gans, J. S. and Halaburda, H.: 2015, *Some Economics of Private Digital Currency*, University of Chicago Press, pp. 257–276.

Giordana, G. and Guarda, P.: 2019, How digital are we? A measure of individual preferences for online activities, *BCL Working Papers* (forthcoming).

Grym, A.: 2018, Crypto-assets are not money, *Blog post*, Bank of Finland. Accessed 12 July 2019, `https://www.bofbulletin.fi/en/blogs/2018/crypto-assets-are-not-money/`.

He, D.: 2018, Monetary policy in the digital age, *Finance and Development* **55**(2), 13–16.

He, D., Habermeier, K. F., Leckow, R. B., Haksar, V., Almeida, Y., Kashima, M., Kyriakos-Saad, N., Oura, H., Sedik, T. S., Stetsenko, N. et al.: 2016, Virtual currencies and beyond: initial considerations, *Staff Discussion Notes* (SDN/16/03).

Jenkins, S. P.: 2009, Distributionally-sensitive inequality indices and the GB2 income distribution, *Review of Income and Wealth* **55**(2), 392–398.

Jenkins, S. P.: 2014, GB2LFIT: Stata module to fit Generalized Beta of the Second Kind distribution by maximum likelihood (log parameter metric), Statistical Software Components, Boston College Department of Economics.

Jusot, F., Tubeuf, S. and Trannoy, A.: 2013, Circumstances and efforts: how important is their correlation for the measurement of inequality of opportunity in health?, *Health economics* **22**(12), 1470–1495.

Libra Association, M.: 2019, An introduction to Libra: white paper, *White paper*, Libra Association, Zurich.

McKinsey&Company: 2016, Fintechnicolor: The new picture in finance, *Technical report*, McKinsey&Company.

Mersch, Y.: 2018, Virtual currencies ante portas, European Central Bank, *speech at the 39th meeting of the Governor's Club, 14 May*, Bodrum, Turkey.

Mersch, Y.: 2019a, Back to stable, European Central Bank, *speech at Zahlungsverkehrssymposium, Deutsche Bundesbank, 29 May*, Frankfurt am Main.

Mersch, Y.: 2019b, Money and private currencies: reflections on Libra, European Central Bank, *speech at the ECB Legal Conference, European Central Bank, 2 September*, Frankfurt am Main.

Pichler, P., Scherlinger-Brandmayr, A. and Summer, M.: 2018, Digital money, *Oesterreichische Nationalbank Monetary Policy & the Economy* **Q3**, 23–35.

Rochet, J.-C. and Tirole, J.: 2003, Platform competition in two-sided markets, *Journal of the European Economic Association* pp. 990–1029.

Rysman, M.: 2009, The economics of two-sided markets, *The Journal of Economic Perspectives* **23**(3), 125–143.

Shiller, B., Waldfogel, J. and Ryan, J.: 2018, The effect of ad blocking on website traffic and quality, *The RAND Journal of Economics* **49**(1), 43–63.

Stevens, A.: 2017, Digital currencies: threats and opportunities for monetary policy, *National Bank of Belgium Economic Review* **1**, 79–92.

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