Platform quality and competition

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This is a very preliminary work. We have just got access to new data and we plan to estimate again the model. We are also working in improving the estimation method. Moreover, a new theoretical model is under development.

Abstract

The aim of this paper is to explain evidence of unfair practices by online platforms towards business users, particularly SME's. First, using survey data, we show that sellers operating with four different categories of platforms multi-home (marketplaces, app stores, social networks and online advertising). Hence, the appropriate competitive framework is the "competitive bottleneck" model. Second, we develop an empirical model of platform competition adding an additional dimension: service quality. The results indicate that the costs of providing quality to sellers are higher than the costs of providing quality to buyers. These differences may reflect different needs or preferences across groups. While buyers would require simple functionalities sellers would need more sophisticated services. When sellers' multi-home, platforms care more about buyers than sellers and while buyers will get an efficient level of quality, quality to sellers will be "degraded". We argue that this service quality degradation explain unfair trading practices simply because platforms are not willing to invest to take care of sellers.

1 Introduction

Undoubtedly, over the last decades online platforms have become important players in modern economies. As economic and social transactions move to the Internet, online platforms in many areas have emerged as enablers of exchanges between different groups of agents. The main role of online platforms in this context is to facilitate the interaction of these groups. These in turn are characterised by the fact that each group will value the platform all the more when it is largely used by the other group. Hence, individual decisions to join a particular platform generate indirect network effects on agents on the other side. Acting as an intermediary for these transactions, the platform can add value, and capture rents, by contributing to internalise these externalities.

From an economics perspective, it has been long recognized that platforms have the tendency to tip (Caillaud and Jullien, 2001) given by positive cross-group external effects between different groups of participants. However, in several industries more than one platform has positive (and relatively large) market shares. A possible explanation is that platforms offer differentiated services and, therefore, are active in the market (Rochet and Tirole, 2003; Armstrong, 2006). Alternatively, it could be that the indirect network effects are not sufficiently strong to allow one platform to monopolise the exchanges[1].

When platforms compete, the behaviour of each group of participants becomes relevant. If the different sides single-home, -i.e., agents on the different sides join only one of the existing intermediaries- platforms will be responsive to network effects. This means that under single-homing competition, a lost agent in one platform –say a seller- may join the competitor's platform making it more difficult to keep the number of agents in the other side of the platform (buyers) unchanged. In this case, the platform will have to compensate buyers more than a monopolistic platform would do –by reducing the access price, for example- to keep the number of buyers unchanged.

An alternative platform competition context arises when agents in one side multi-home[2]. Multi-homing refers to the decision of the agents on one side of the market to join several platforms at the same time[3]. Multi-homing can happen in every side of the platform, and the literature offers many varied examples[4]. The literature has shown that in a setting where one side is allowed to multi-home while the other group single-homes, the interests of the group that multi-home are ignored by the platform. This is so because its business will ultimately depend on the number of participants on the other side, for which it will have to compete fiercely with other intermediaries. This resulting equilibrium has been characterized as a "competitive bottleneck" (Armstrong, 2006) in which platforms treat favourably the single-homing side, while the multi-homing side has its entire surplus extracted. Multi-homing on one side intensifies competition on the other side as platforms use low prices in an attempt to steer users on the latter side towards an exclusive relationship.

On the other hand, Armstrong and Wright (2007) suggest that when agents on one side multi-home, platforms might offer exclusive contracts to prevent them from multi-homing. Such exclusive contracts can be inexpensive to offer since by tying up one side of the market the platform attracts the other side which reinforces the decision of that side to sign up exclusivity. However, Caillaud and Jullien (2003) show that platforms have incentives to propose non-exclusive services, because with single-homing the incumbent platform needs to set the prices very low to deter any competition. Similarly,

1 See Duch-Brown (2017) for a more detailed account of the interplay of the factors that delineate the market structure of online platforms.

2 The literature so far has only considered the case of full multi-homing, ie, all agents in one side decide to join all available platforms. However, this is an extreme assumption, and intuition (models) considering partial multi-homing would be extremely valuable to understand real multi-homing decisions by agents.

3 It is clear that if one side multi-homes, there is no need for the other side to multi-home as well, since any agent in the single-homing side will find all the multi-homing agents in the platform she decided to join (Armstrong, 2006). Thus, in principle, at most one side multi-homes.

4 Examples range from academic conferences and journals, software, media, shopping malls, payment systems, telecommunications, banking and night clubs. For a detailed discussion of many of these see Armstrong (2002).

they show that multi-homing can improve the efficiency through enhancing the aggregate externality, but may lead to inefficiency in market structure since some platforms may not attract enough agents on the single-homing side.

Due to their nature, in general platforms connect downstream consumers (users) with upstream firms (sellers/producers) in a vertical relationship. For consumers, they are perceived as large sellers in a Business-to-Consumer (B2C) relationship. For sellers, they stand as large buyers, and a Business-to-Business (B2B) link is established. Large and powerful buyers can be found in many markets. For instance, the degree of concentration in the grocery industry has steadily increased in recent years. As the size of retailers has grown larger, attention has mounted over the relationships being established by these large buyers and their suppliers.

In the digital economy, powerful platforms have established themselves as crucial intermediaries for online transactions. As in the more traditional world, some electronic markets have also started to be characterised by strong players that exert a significant pressure on upstream users (sellers or suppliers, the B2B side of the platform). Some of these companies have started to be described as giants using aggressive practices to squeeze their trading partners. As a result, calls for antitrust intervention and regulatory rules to protect suppliers have become increasingly common in the digital world.

In its assessment of online platforms, the European Commission (EC) detected the existence of "unfair" commercial practices imposed by some of these online intermediaries that can be particularly burdensome for small companies. Some of the most relevant practices identified during the EC public consultation on platforms are (i) unfair terms and conditions; (ii) refusal of market access or unilateral modification of the conditions for market access; (iii) promotion of their own products/services; (iv) unfair "parity" clauses; and (v) lack of transparency. When operating a platform, an intermediary has the ability to control the number of traders and the volume of trade of the market. Network effects allow successful platforms to attain large sizes and drive competitors out of the market. These powerful economic actors can potentially abuse their privileged positions and impose unfair terms and conditions on users in some (or all) sides of the market. A legitimate concern –especially from a policy perspective– is to wonder if this phenomenon may be negatively affecting social welfare[5].

These unfair trading practices (UTPs) negatively affect the quality of the service delivered by platforms to their business users (sellers). Service quality can be more important to sellers –particularly SMEs- than to buyers. Most SMEs relying on online platforms consider them essential for their business operations, both for communicating with their customers and for selling products and/or services. Low service quality offered by the platform can have serious consequence for sellers, including reduced sales or reputational damage. Economist have long recognized that quality can be distorted in imperfectly competitive markets since firms will align private marginal benefits to marginal costs while a social planer[6] would consider social marginal costs (Spence, 1975). These distortions represent welfare losses similar to those derived by price distortions.

The literature on two-sided markets has devoted relatively little attention to quality. In a model that allows for two types of externalities, the standard indirect network effect and the externality due to quality considerations, Viecens (2006) shows that the quality level of a platform as a reputation effect can reduce the incentives for multi-homing. Njoroge et al. (2010) analyse online markets in particular, and find that in a game where platforms first choose quality and then compete in prices, the equilibrium involve either maximal or partial differentiation. Ponce (2012) finds conditions under which changes in the quality standards of credit ratings generate quality degradation, with offered quality

[5] Documents and studies supporting these claims can be found at: https://ec.europa.eu/digital-single-market/en/news/comprehensive-assessment-online-platforms.

[6] From a welfare economics perspective, a social planner is an agent that would attempt to attain the best possible result for all parties involved. See, for instance, the Wikipedia entry at: https://en.wikipedia.org/wiki/Social_planner.

below the socially efficient level. Gabszewicz and Wauthy (2014) also propose a model of platform competition where products are also characterised by inter-group externalities. With exogenous symmetry between both sides of the market, they show that platform competition induces a vertical differentiation structure that allows the coexistence of asymmetric platforms in equilibrium. Finally, Ribeiro et al. (2016) analyse quality asymmetries more generally. First, they analyse quality differences among platforms and confirm previous results. Secondly, and more relevant for this paper, they introduce inter-group quality differences. They show that profits for competing platforms increase with the quality gap offered to the two sides.

It is reasonable to think that the different sides of the market differ on their perceptions about quality. Some real world intuition would indicate so. For instance, in the video-game industry we find end-users (gamers) and game developers. It is realistic to assume that the perceived quality of the different platforms (Playstation, X-Box, Wii) is different between the two sides of the market. A similar argument can be made with respect to app stores, where app developers may be essentially worried about the performance of the operating system and the portfolio of services at their disposal to reach end-users. However, end-users may value issues such as the screen-size, the camera resolution and other features of the device, as well as functionalities such as the number of apps available.

As we have seen, the theoretical literature on quality choice by platforms is scarce and incomplete. Although Ribeiro (2015) has endogenised quality and allows for group quality discrimination, it happens in a context where both sides single-home. No paper has analysed quality choice in the context of multi-homing, for instance. In this paper, we assume that the relevant competition model that applies to our empirical exercise is the competitive bottleneck, to which we add the quality dimension. However, our approach is empirical.

The empirical application looks at four platform categories (i) marketplaces; (ii) app stores; (iii) social networks; and (iv) online advertising. First, we show that the majority of the business users in our database multi-home, validating the competitive bottleneck model as the appropriate competitive framework for the analysis. Second, we develop a two-sided market model to capture platforms' quality choices to each side. Our results indicate that, in line with the evidence on poor service quality offered to sellers as identified by the EC public consultation, platforms discriminate on quality among the different groups. Our data indicates that buyers show a greater average marginal valuation for quality than sellers. Hence, platforms offer buyers a level of quality close to the optimal or efficient level. In contrast, and according to the predictions of economic theory, they "degrade" the quality offered to sellers, the side that shows a lower average marginal valuation of quality. This can be interpreted as a "quality bottleneck", in which not only platforms will extract all the sellers' surplus but they will also squeeze them by providing a level of quality below that expected by sellers.

This paper is structured as follows. Section 2 describes the database. Section 3 offers evidence of multi-homing by sellers. Section 4 explains the two-sided market model while section 5 discusses the econometric issues involved. Section 6 presents the results. Section 7 extends the basic results to some counterfactual scenarios. Finally, section 8 offers some conclusions.

2 Data

Market-level data from different sources was assembled for the analysis. First, we obtained survey data on 2553 firms in seven European countries. The survey was carried out in the period November 2016-January 2017. The distribution of firms by country is presented in Table A1 in Annex 1[7]. Firms were asked to indicate if they operate with platforms. Platforms were originally grouped into four different categories (marketplaces, app stores, social network and online advertising). The survey included different numbers of platforms in each category for a total of 49. Some of the platforms are present in more than one category and two or more platforms can be part of the same company. A detailed list of these platforms is included in table A2 in Annex 1[8].

The main purpose of the questionnaire was to gauge the experience of firms when they use platforms for their business operations. In particular, information about the volume of turnover generated via the platforms, or the countries they can be active in via the platforms was collected. In addition, questions about the problems faced by these firms were also included, as well as specificities about the causes of these problems and the perceptions of firms about terms and conditions offered by platforms[9].

This survey provides information about the number of sellers participating in the different platforms in different countries.[10] In addition, it offers information about the problems faced by these firms when dealing with the listed platforms. We use this information to construct an indicator of the quality of the service offered by the platforms to their business users. To do so, we computed the total number of firms per platform and country and deducted the number of firms declaring to have faced a problem with that particular platform. In order to avoid scale issues, we divided the resulting figure by the total number of firms on the platform in the corresponding country, and re-scaled the resulting number to lie between 0 and 10. The higher the value, the higher the perceived service quality of the platform, and viceversa.

The main interest of this paper lies in the analysis of the relationships between platforms and business users. However, in a multi-sided market context, the equilibrium conditions on one side have effects and are determined by the conditions on the other side. In order to capture the buyers' side, we collected additional information for the platforms included in the survey. Data on internet traffic and usage for the selected platforms was obtained from sources such as Alexa and Similarweb, the monthly average of the period November 2016-January 2017. Concretely, data about total internet traffic, unique visitors, country-rank (based on traffic), the average number of daily unique pages visited within the website, the average time spent by visit, and the bounce rate (defined as the percentage of visits to the site that consist of a single pageview) were collected. With this information we are able to characterise the buyers' side of the platforms and hence estimate a full platform model, including both sides[11].

In the empirical section, we will use the information about unique visitors as our measure of demand of buyers. We use the information on country-ranks and average time spent on the corresponding website to build a measure of quality. Concretely, we use the

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7 These numbers guarantee representativeness of the sample at the country level at a 95% of confidence. These numbers are similar to those used in Eurobarometer surveys. However, the relatively low number of sellers may affect the results.

8 Sellers were asked to indicate other platforms they operate with. In a preliminary analysis of these open answers, no other platform was named sufficiently frequently as to be included in the list of main platforms.

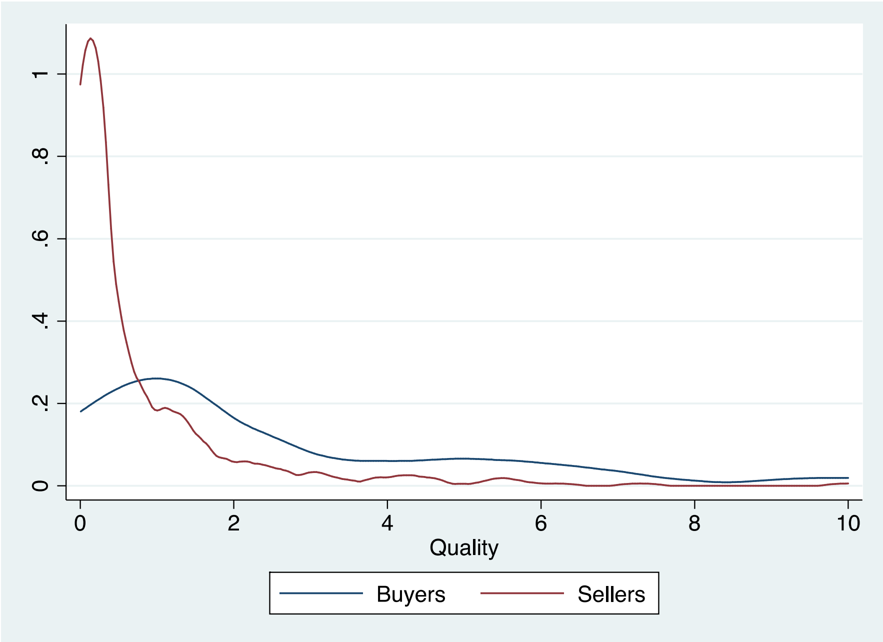
9 Ecorys, 'Business-to-Business relations in the online platform environment', FWC ENTR/300/PP/2013/FC-WIFO, Final Report.

10 Apart from scarce anecdotal evidence, there is hardly any official information about the number of firms using platforms for their business operations. We are not able to specify to what extent these data are representative of the total population or if it includes biases. Hence, we assume it is representative at the country level.

11 We are forced to assume in our empirical exercise that platforms are two-sided but most may be multi-sided. Unfortunately, lack of data does not allow us to be more precise in the empirical exercise. However, we still believe that the model of section 4 gives interesting results to be confirmed by future research.

inverse of the country rank weighted by the time spent on the website, and re-scaled to be in the range of 0-10, to be comparable with the quality measure for sellers. Figure 1 shows the distribution of service quality to both buyers and sellers. The figure shows that sellers' quality has a greater proportion of values close to zero and that for higher levels of quality, the mass of the distribution is always higher for buyers than for sellers.

Figure 1. Distribution of observed quality



Source: own elaboration with data from Similarweb and TNS Panel.

3 Sellers single-home or multi-home?

The nature of competition in multi-sided markets is determined by the decision of the agents in one side to multi-home. As we discussed before, the theoretical predictions about the equilibrium prices and profits for buyers sellers and platforms can vary substantially whether one assumes that both sides single-home or if one of the sides multi-homes. Examples abound on the possibilities for agents on both sides to participate in more than one platform (see Armstrong, 2002).

The business survey at hand offers valuable information on the decision to multi-home by the respondent firms. This source of information also allows for a comparison of the multi-homing decisions by online platform category and by country. Table 1 shows the proportion of sellers that single- and multi-home by category. As the table indicate, the majority of firms' multi-home by joining at least two platforms in the same category.

Table 1. Single-homing vs. multi-homing, by category

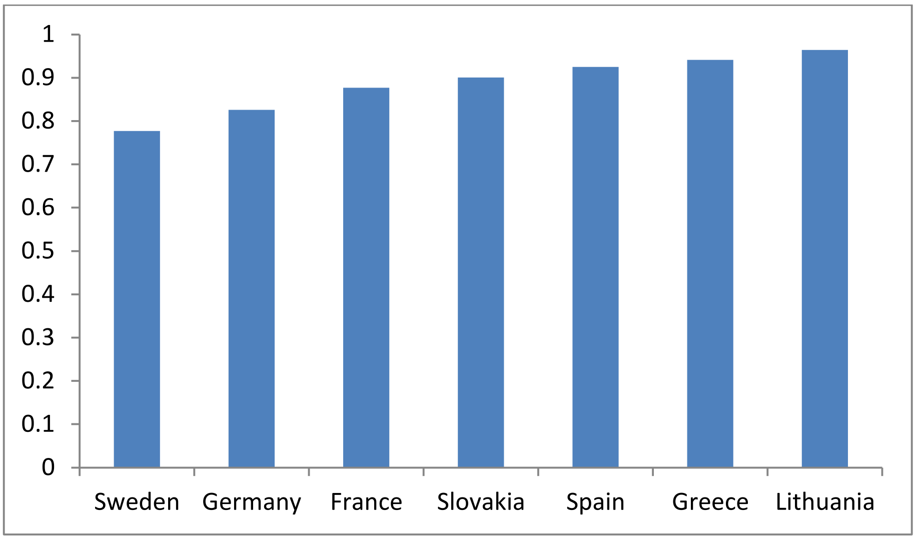
	E-commerce	**Apps**	**Social networks**	**Online advertising**
Single-homing	34.2	46.6	34.9	47.0
Multi-homing	65.8	53.4	65.1	53.0

Source: own elaboration with data from TNS Panel.

The data clearly shows that a big proportion of sellers multi-home, i.e., they operate with several platforms at the same time. More strikingly, looking at the four different categories of platforms considered in this study (marketplaces, app stores, social media and online advertising platforms), 77% of firms are active in at least 2 of them and 35% of firms are active in all four categories. This can be seen at the country level, where the proportion of sellers' multi-homing, when considering all the categories simultaneously, ranges from 78% in Sweden to 96% in Lithuania (Figure 2).

The information provided above indicates that the relevant context for our analysis is the "competitive bottleneck" model (Armstrong, 2006). As explained before, this model studies the resulting equilibrium conditions of competing platforms when the agents in one side multi-home. The model implies that sellers will have their networks benefits extracted fully, while buyers would enjoy a price that is below cost. However, in what follows we will add to this model the quality dimension. Hence, competition among platforms, and the externalities across agents of the different groups will depend not only on the indirect network effects – how each group values the presence of agents of the other group in the platform- but also from the service quality received by each side from the platform.

Figure 2. Multi-homing by country (all categories)



Source: own elaboration with data from TNS Panel.

4 Quality choice in the online platforms ecosystem

The competitive bottleneck model implies that, when sellers' multi-home, platforms will compete fiercely for buyers and will maximize both buyers' benefits and the platform's profits while milking sellers. What about quality? Following the same line of argument, platforms will provide a high quality service to buyers in order to attract them away from competitors while they care little about providing sufficient quality to sellers. Hence, we should expect quality discrimination among the different sides. In this section we describe the model to be taken to data to explore this issue.

We assume there are two groups of agents, buyers (B) and sellers (S), and each group may like or dislike the presence of the other group on platforms. There are J platforms in G categories competing to attract agents from both sides. Since each group of agents accounts for the presence of agents on the other side, the demands of both groups are interrelated, independently of the multi-homing decisions by one group. More formally, let $\mathbf{s} = (\mathbf{s}^b, \mathbf{s}^s)$ be platform demand (expressed in market shares) for groups B and S. Given platforms attributes, $\mathbf{X}^b$ and $\mathbf{X}^s$

$$s_j^b = D_j^b(\mathbf{s}^s, \mathbf{X}^b|\Theta) \tag{1}$$

$$s_j^s = D_j^s(\mathbf{s}^b, \mathbf{X}^s|\Theta) \tag{2}$$

for j=1,…J where D_j^i are continuously differentiable functions and Θ is a set of model parameters to be estimated. The indirect externality is captured by the fact that s_j^i on the left-hand side of equations x and y are elements of $\mathbf{s}^i$ on the right-hand side. Equations (1) and (2) show how the two groups of agents interact through platforms. Any events affecting the membership decisions of group B agents affect the decisions of group S agents as well. However, the effect does not end there since group S decisions in turn affect group B decisions, which in turn affect group S agents' decisions, and so on. This chain of effects is called the feedback loop in the two-sided markets literature and imposes a challenge in empirical estimations, which will be discussed in the next section.

Platform j maximises profits by setting prices (fees) for the two groups, p_j^b and p_j^s. Assuming constant marginal costs c_j^b anc c_j^b, platform j's profits are

$$\pi_j = (p_j^b - c_j^b)s_j^b N^b + (p_j^s - c_j^s)s_j^s N^s$$

and the first order conditions for profit maximisation assuming platforms compete in prices are

$$\frac{\partial \pi_j}{\partial p_j^b} = s_j^b N^b + (p_j^b - c_j^b)\frac{\partial s_j^b}{\partial p_j^b} N^b + (p_j^s - c_j^s)\frac{\partial s_j^s}{\partial p_j^b} N^s = 0$$

$$\frac{\partial \pi_j}{\partial p_j^s} = s_j^s N^s + (p_j^s - c_j^s)\frac{\partial s_j^s}{\partial p_j^s} N^s + (p_j^b - c_j^b)\frac{\partial s_j^b}{\partial p_j^s} N^b = 0$$

where N^i denote the total number of agents for each group. From the above explanation, it is clear that estimating a platform model requires the specification of two separate demand functions, one for each group, and one supply relationship capturing the profit maximising decisions of platforms. The details of each step are described in the following sub-sections.

In our empirical setting, we do not observe prices. In the case of buyers, we are dealing with platforms that do not charge buyers a positive membership or access fee. In the case of sellers, although some fee differences exist across category, there is little variation by category, and in principle all the sellers joining the same platform will have to pay the same fee. This lack of prices, however, requires some assumptions in order to be able to estimate a model.

4.1 The buyers' side

Buyers derive utility by joining a platform that provides both high quality and a large number of sellers. Hence, the conditional indirect utility of individual i in country c from using platform j is assumed to be

$$u_{ijc} = \mathbf{X}_j + \xi_{jc} + \epsilon_{ijc}$$

where $\mathbf{X}_j$ is a multi-dimensional vector of platform characteristics. The term ξ_{jc} captures unobservable platform characteristics. The stochastic term ϵ_{ijc} is assumed to be i.i.d. and to follow a Type I extreme value distribution. It represents unobservable individual-specific tastes.

The data gives a natural partition of the set of platforms into four groups by the type of services these platforms offer to both buyers and sellers: marketplaces, app stores, social networks and online advertising platforms. Out of 49 platforms, 19 operate as marketplaces, 8 are app stores, 12 are social networks and the remaining 10 are online advertising players. These groups give a natural segmentation in the data that allows us to estimate a nested logit model to capture buyers' heterogeneity[12]. The nested logit model allows buyers' preferences to be more highly correlated across groups and thus provides more reasonable substitution patterns than a simple logit.

We thus reformulate the indirect utility function for individual i to be

$$u_{ijc} = q_t^b \beta_b + \alpha_b s_j^s + \xi_{jc} + \zeta_{ig} + (1-\sigma)\epsilon_{ijc}$$

where q_t^b is the quality offered by the platform to buyers, s_j^s the share of sellers who join the platform j, ξ_{jc} represents unobserved demand factors, and ϵ_{ijc} is defined as before. Here, ζ_{ig} represents buyers utility that is common to all platforms in group g. It has been shown that there exists a unique distribution for ζ_{ig} such that $\zeta_{ig} + (1-\sigma)\epsilon_{ijc}$ is an extreme value random variable if ϵ_{ijc} is an extreme value random variable and σ determines the degree of within group correlation of utility (Cardell, 1997). The outside option (j=0) is not to use any platform and its utility is normalised to zero.

With the distributional assumptions on ϵ_{ijc}, the demand equation for buyers is

$$\log(s_j^b) - \log(s_0^b) = q_j^b \beta_b + s_j^s \alpha_b + \sigma \log(s_{j|g}^b) + \xi_j \tag{3}$$

[12] In order to better capture consumer heterogeneity, a random coefficient logit model would be preferred. However, due to the data at hand and the requirements for identification and estimation of such a model, we rely on a nested logit model. We assume that this specification will help us to capture a great deal of buyers' heterogeneity.

where s_0^b denotes the share of the outside option and $s_{j|g}^b$ the within-group market share. Both the service quality and sellers share are endogenous variables that are correlated with unobserved demand factors. The within-group market share is endogenous by construction.

4.2 The sellers' side

Sellers will be willing to join a platform that offers access to a large pool of potential buyers and a high quality service. However, following the competitive bottleneck model (Armstrong, 2006), their decisions to join one platform are independent of their decision to join any other platform as long as their expected benefits of joining are positive.

Sellers are assumed to be heterogeneous. Let λ_i^s identify a group S agent type and assume that it is i.i.d on $U(\lambda_i^s|\vartheta)$. In addition, let q_j^s be the service quality level offered by the platform and s_j^b the proportion of buyers that platform j attracts. Given the cost of participation in the platform, denoted by c_j^s, a type λ_i^s agent will join platform j as long as

$$\pi_j^i = \lambda_i^s q_j^s s_j^b - c_j^s \geq 0 \tag{4}$$

Equation (4) shows that, for the same number of buyers on platform j, group S agents receive different values depending on their type and on the quality received. From the equation it is clear that platform j can compensate quality with more potential buyers to provide the same expected benefit to a type-λ_i^s seller. If quality provision is costly, platforms may have an incentive to degrade quality if they successfully attract more buyers.

If we assume that platforms only know the distribution of λ_i^s, each seller is ex-ante identical and platform j will charge the same access price or fee. In this case, the number of group S agents joining the platform j is determined by

$$n_j^s = \left(1 - U(\lambda_i^s|\vartheta)\right)N^b$$

which is equivalent to

$$s_j^s = \left(1 - U(\lambda_i^s|\vartheta)\right) \tag{5}$$

Equation (5) shows that demand for platform j on the multi-homing side is not a function of other platforms' attributes, so one may conclude that each platform acts as a monopolist towards multi-homing agents. However, platforms still compete indirectly in the multi-homing side through agents on the single-homing side of the market; when a platform changes access costs or attributes on the multi-homing side, it affects demand for other platforms through induced changes in the single-homing side.

Equation (5) can be re-written as

$$s_j^s = \left(1 - U\left(\frac{c_j^s}{q_j^s s_j^b}|\vartheta\right)\right)$$

and assuming that U is the uniform distribution with support on the interval (0,1], that the sellers sensitivity to quality and the proportion of buyers in platform j are given by β_s and α_s respectively, and taking logs, we derive the equation for the demand of sellers:

$$\log(s_j^s) = \mu_g + \beta_s \log(q_j^s) + \alpha_s \log(s_j^b) + e_j \tag{6}$$

which is the specification we take to data. Since the cost to access the platform is unobservable, we will capture it through the constant μ, and e_j is the error term. In the equation, both the service quality and the share of buyers are endogenous variables.

4.3 Supply

Platforms play a two-stage game. In the first stage, they choose the quality of the service they will provide to buyers and sellers. In the second stage, they compete in quantities. Hence, we solve the game by backward induction and the equilibrium concept is sub-game perfection.

In the second stage, platforms compete in quantities. Since we do not observe prices, we assume that platform's profits are proportional to the number of users on both sides:

$$\pi_j^{II} = \theta n_j^b n_j^s$$

this formulation captures the fact that if $n_j^i = 0$, then $\pi_j^{II} = 0$, i.e., that in order to make positive profits platforms have to attract users on both sides, otherwise the level of transactions intermediated by the platform will be zero. Alternatively, platform j profits can be written as

$$\pi_j^{II} = \theta s_j^b N^b s_j^s N^s \tag{7}$$

At this stage, platforms maximize their profits with respect to quantities, i.e., their corresponding shares of buyers and sellers. In the first stage, platforms determine the different levels of quality that maximise their profits. Suppose that the (fixed) cost of choosing a certain combination of qualities is given by $fc(q_i, v_j; \boldsymbol{\gamma})$, where q_i stands for the quality to group i, v_j represents unobservable cost shocks, and $\boldsymbol{\gamma}$ is a vector of parameters. Given the profits derived in the second-stage, in the first stage the problem platform j faces is

$$\pi_j^I = \{\pi_j^{II}(q_i) - fc(q_i, v_j; \boldsymbol{\gamma})\}$$

from equation x we can derive the equilibrium conditions for profit maximisation in the two-stage game

$$\sum \left\{ \frac{\partial \pi_j^{II}}{\partial q_i} + \sum \frac{\partial \pi_j^{II}}{\partial s_j^i} \frac{\partial s_j^i}{\partial q_i} \right\} = \gamma_0 + \gamma_1 q_i + \varrho_j \tag{8}$$

where i=b,s are the qualities to groups B and S respectively, and C is the set of platforms active in country c that compete with platform j. The first term on the left hand side of (8) is the direct impact of increasing quality q_i on platform j on the (variable) profit of platform j. A change in q_i also has an indirect effect on the variable profits of platform j through an impact on the equilibrium number of agents joining the platform in each side, captured by the second term.

4.4 Observed and efficient qualities

The model described so far can be helpful to understand the mechanics of the operation of several platforms and to learn about the valuation of quality and of the strength of the indirect network effect of the different groups of agents joining the platform. However, in order to assess whether the platform is providing the optimal or desired level of quality of each group of agents, we need to take into account one more step.

Following seminal contributions in the economics literature (Spence, 1975; Mussa and Rosen, 1978), market power over quality or quality distortions have to be understood as the difference of the monopolist's choice of product quality and what a social planner would choose. In our context, this means we have to compare the levels of quality that the platforms are providing with those that a social planner would provide. The difference is that platforms choose qualities to maximise their profits. A social planner would select qualities to maximise total social surplus, defined not only as platforms profits, but also the profits of sellers and the consumer surplus of buyers.

Assuming then that total surplus (TS) can be defined as the sum of consumer surplus (CS), sellers' surplus (SS), and the platforms' profits (PS):

$$TS = CS + SS + PS$$

the social planner would choose the two different levels of quality that maximise total surplus, ie:

$$\frac{\partial TS}{\partial q_i} = \frac{\partial CS}{\partial q_i} + \frac{\partial SS}{\partial q_i} + \frac{\partial PS}{\partial q_i} = 0 \tag{9}$$

where i=b,s are the qualities to groups B and S respectively. From the estimation of the demand equation of buyers we can find the corresponding CS, and then obtain the corresponding contribution to the social planner FOC with respect to quality. Similarly, from the estimation of the demand relation of sellers we can derive the second term of the social planner FOC. Finally, from the platforms' profit function we can estimate the third term of the FOC, and then compute the equilibrium values of qualities offered to both sides if the objective would be total surplus maximisation instead of platforms profit maximisation. From equation (9) it is clear that, if the marginal valuation of quality of buyers and sellers is positive, the social planner would choose higher levels of quality than the platforms'. We want to know by how much, and also to identify the differences between buyers and sellers, assuming that the context in which these agents operate with platforms resembles a competitive bottleneck model.

The difference, if any, between the qualities offered by the platforms and the social planner can be interpreted as "quality degradation". However, it could also be the case that the qualities offered by the platform are higher than the socially efficient qualities. In this case, we can talk about "quality upgrading". As explained before, a standard result in the economics literature on quality choice implies that, when there is heterogeneity in the valuation of quality, the quality provided to the group that has the highest valuation is optimal, but the quality offered to the group that has a lower valuation is degraded in order to reach a separating equilibrium.

5 Estimation and identification

In order to estimate the model, first we have to define market size, i.e., the number of agents who can potentially join platforms, for each side of the market. This relative market sizes affect the equilibrium estimates, as explained in the previous section. For estimation, the buyers' total market size is defined as the total number of pageviews by country, averaged over the period November 2016-January 2017. The market size for sellers is defined as the total number of firms per country. Since sellers can multi-home, the number of sellers joining a given platform should be interpreted as market penetration instead of market share.

We estimate the demand of buyers (equation 3), the demand of sellers (equation 6), and the quality cost functions (equations 8) separately, using both a two-stage least square estimator and a GMM estimator. In this last case we use the corresponding equation residuals as the moment conditions. Below we explain the instrumental variables used given that, as we have explained before, many of the variables encounter problems of endogeneity.

The parameters to be estimated include (i) the parameters of the buyers' demand function; (ii) the parameters of the sellers' demand function; and (iii) the cost parameters. There are obvious endogeneity problems in all three equations. Identification of the demand parameters follows the strategy initiated by Berry et al. (1995) by assuming that the average quality levels chosen by platforms in other categories are valid instrumental variables for qualities chosen by platforms in category g. This assumption is largely motivated by the fact that the competitive landscape will be different in each category, and different platforms are active in different categories. Hence, even if quality levels are assumed to be endogenously determined, we postulate that these decisions are independent. However, as platforms face the same demographics on each side of the market in each country, they will take this information into account to decide their profit maximising quality levels. This is particularly so in the case of sellers, given that many of them will multi-home, not only within categories, but also across categories.

6 Results

6.1 Parameter estimates

Demand of buyers Table 2 shows the main coefficients obtained for the demand equation of buyers under two estimation procedures, 2SLS and GMM. In both cases, the three relevant coefficients are statistically significant and have the expected signs. Platform's buyers respond positively to an increase in the quality they receive from the platform. Similarly, buyers respond positively to the number of sellers active in the platform. The estimate of the coefficient of the within-nest share is between 0 and 1, consistent with utility maximisation. Moreover, its value suggests a strong segmentation between the different platform categories.

Table 2. Demand of buyers.

	2SLS	GMM
Quality	0.887***	1.044***
	(0.119)	(0.148)
Sellers	0.0242***	0.0427***
	(0.00571)	(0.0109)
Within-nest share	0.376***	0.289***
	(0.0921)	(0.0900)
Constant	-9.158***	-10.37***
	(0.890)	(1.015)
Observations	343	343
R-squared	0.804	0.740

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Demand of sellers In the sellers' demand estimation, the coefficient on the logarithm of quality and the number of buyers in the platform is statistically significant and with the expected signs. Hence, sellers respond positively to an increase in quality as well as to an increase in the number of potential buyers that join the platform.

Table 3. Demando of sellers.

	2SLS	GMM
Quality	0.152***	0.186***
	(0.0246)	(0.0136)
Buyers	0.0128***	0.00799***
	(0.00195)	(0.00199)
Constant	-0.0278**	-0.0273***
	(0.0129)	(0.00793)
Observations	343	343
R-squared	0.719	0.762

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Supply The estimated distributions of marginal costs of service quality provision to both buyers and sellers at observed quality levels are reported in table 4. The table clearly indicates that the incremental cost of providing one additional unit of quality to buyers is lower than the equivalent increase in the quality provision to sellers. Based on these estimates, the total quality cost function for each group of agents can be reconstructed. As shown in figure 3, for the observed quality levels the total cost of providing quality to sellers is higher than the corresponding cost of providing a similar level of quality to buyers.

Table 4. Quality cost functions estimates.

	Buyers	Sellers
Quality	0.00818***	0.0217***
	(0.00193)	(0.00441)
Constant	0.00658***	0.00437***
	(0.00253)	(0.00160)
Observations	343	343
R-squared	0.432	0.615

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 3. Buyers' and sellers' quality cost functions

Source: own elaboration.

6.2 Observed vs. efficient quality levels

As explained in section 4, the model developed can be used to calculate the level of service quality that a social planner would determine in order to maximise total surplus (defined as the sum of buyers' surplus, and sellers' and platforms' profits). Then, comparing these quality levels with the observed quality levels offered by the different platforms included in the dataset, we can check whether these platforms oversupply or undersupply quality to each group of agents. The results of this exercise are reported in table 5.

Table 5. Observed vs. efficient quality by category.

	Buyers			Sellers		
	Observed	**Efficient**	**Diff*.**	**Observed**	**Efficient**	**Diff*.**
Marketplaces	1.962	2.184	-0.101	0.493	1.263	-0.610
App stores	1.408	1.301	0.082	0.584	1.492	-0.609
Social media	3.783	3.281	0.153	1.255	1.334	-0.059
Online advertising	2.693	3.297	-0.183	0.706	1.934	-0.635
Total	2.462	2.516	-0.021	0.759	1.506	-0.496

* The difference is computed in %. A positive sign indicates quality upgrading while a negative sign can be interpreted as quality "degradation".

Table 6. Observed vs. efficient quality by country.

	Buyers			Sellers		
	Observed	**Efficient**	**Diff.***	**Observed**	**Efficient**	**Diff.***
DE	2.496	2.319	0.077	1.057	1.636	-0.354
ES	2.442	1.943	0.256	1.401	1.774	0.020
FR	2.419	2.561	-0.056	0.677	2.014	-0.664
GR	2.469	2.111	0.170	0.184	1.625	-0.887
LT	2.513	2.035	0.235	0.226	1.910	-0.882
SE	2.443	2.602	-0.061	1.023	1.303	-0.399
SK	2.487	2.706	-0.081	0.597	1.501	-0.602

* The difference is computed in %. A positive sign indicates quality upgrading while a negative sign can be interpreted as quality "degradation".

Table 5 indicates that the observed quality levels are quite close to the efficient ones in the buyers' side while they tend to be considerably lower on the sellers' side. The table also indicates that this is a common result for all the platform categories considered in this paper, with the exception of Social Network platforms, where the level of quality degradation for sellers is relatively low while at the same time the level of quality upgrading for buyers' is the highest. One possible explanation is that in this category, the importance of indirect network effects is lower than in the other categories. In addition, table 6 shows the average results by country, where the results are confirmed.

7 Extensions to the baseline model

In this section we explore alternative scenarios in which platforms can face incentives to quality discriminate between groups. As a baseline, the previous results under the "competitive bottleneck" framework indicated that platforms would offer close to desired quality to the side showing higher valuation for quality while they would offer a lower than desired quality to the side that multi-homes, or that does not use the platform exclusively (sellers). In what follows we present the results of two counterfactual scenarios where the analytical framework is modified and ask what would be the predicted quality offered by the platform and that of a social planner.

7.1 Both sides single-home

When both sides single-home, platforms compete intensively for users located at both sides. If one user in side b (for buyers) moves to a different platform, for instance, this triggers a change in the proportion of buyers in each platform, implying also a change in the intensity of (indirect) network effects. This could trigger a cascade of decisions at both sides that could eventually alter the original distribution of shares at both sides of the market. In the limit, the market would tip on favour of one of the platforms. Hence, under this scenario, platforms have the incentive to offer closed to desire qualities to both sides in order to keep their user base and even attract more users.

Having in mind the baseline scenario, we need to re-estimate the sellers demand, considering now that instead of multi-homing, they are single-homing. This means that we can use a similar specification as the one used for buyers, while buyers demand remains unchanged. The results of the new demand for sellers are shown below in Table 3a. These results indicate that when sellers single-home, their valuation for quality is higher than in the case of multi-homing. However, this valuation is, as in the baseline scenario, lower than the estimated valuation of buyers. Similarly, the magnitude of indirect network effects seems lower than the previous result.

Table 3a. Demand of sellers when both sides single-home.

	2SLS	**GMM**
Quality	0.646***	0.852***
	(0.0675)	(0.189)
Buyers	0.00408***	0.00546***
	(0.000931)	(0.00151)
Within-nest share	0.492***	0.457***
	(0.0523)	(0.0688)
Constant	-5.183***	-5.352***
	(0.232)	(0.323)
Observations	343	343
R-squared	0.873	0.778

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

With the estimated coefficients of Table 3a, and those for buyers from the baseline scenario (Table 2), we can simulate the model and obtain two relevant variables: i) the predicted qualities offered by the platform to both sides, and; ii) the efficient qualities determined by a social planner. The results of this exercise are shown in Table 5a below.

Several results are worth mentioning. First, the qualities for both buyers and sellers are higher under this scenario than under the competitive bottleneck framework.

Importantly, the quality provided to sellers almost triples, while the quality for buyers increases slightly above 20%. However, since buyers still value quality more than sellers, the average quality to buyers is higher than the average quality to sellers. In this sense, even if there is still some quality discrimination between the sides, the table also shows that the average deviation with respect to the optimal qualities (those chosen by a social planner) would be now lower for sellers (a deviation of 9.9%) than for buyers (a deviation of 11.5%). Finally, we observe that the optimal qualities are systematically higher in this scenario than in the baseline scenario. This is mainly due to the fact that on average, the valuation for quality has increased and the internalisation of the network effects along with increased competition at both sides makes quality a relevant feature of platforms.

Table 5a. Predicted and efficient quality by category when both sides single-home.

	Buyers			Sellers		
	Predicted	**Efficient**	**Diff.**	**Predicted**	**Efficient**	**Diff.**
Marketplaces	2.930	3.284	-0.108	1.741	2.127	-0.181
App stores	2.141	2.230	-0.040	1.700	2.149	-0.209
Social media	4.124	4.797	-0.140	2.881	2.854	0.009
Online advertising	2.916	3.373	-0.136	2.141	2.268	-0.056
Total	3.028	3.421	-0.115	2.116	2.349	-0.099

* The difference is computed in %. A positive sign indicates quality upgrading while a negative sign can be interpreted as quality "degradation".

7.2 Both sides multi-home

A situation with the two sides multi-homing is not a very realistic scenario. It has been argued and demonstrated in the literature that if one side multi-homes, there is no need for the other side to also multi-home since an agent in side b, say, will be able to locate any agent in side s when the s-side agents are multi-homing. Hence, since a b-agent will find all the choices from s-agents in a single platform, there are no incentives to join another platform or multi-home. More realistic scenarios would be cases where both sides partially multi-home. This means that some agents single-home and some others multi-home, or that agents are present in some platforms but not all. However, the literature has not tackled this issue appropriately, and certainly there is no empirical evidence.

Despite the lack of realism, we performed a counterfactual scenario assuming that both sides multi-home (in the limit, this could be interpreted as partial multi-homing on both sides). In this case, buyers and sellers will be willing to join a platform that offers access to a large pool of potential sellers/buyers and a high quality service but their decisions to join one platform are independent of their decision to join any other platform as long as their expected benefits of joining are positive.

Similar to the previous case, in this second case we need to re-estimate the demand for buyers when they are assumed to multi-home. Using a similar framework for sellers under the competitive bottleneck framework, we estimated the buyers demand and the results are presented in Table 2a. These results, along with those shown in Table 3, allow us to compute the counterfactual quality measures. First, the results in Table 2a show that, in this scenario, buyers' quality valuation is now **lower** than the corresponding valuation of sellers.

Table 2a. Demand of buyers when both sides multi-home.

	2SLS	GMM
Quality	0.0214***	0.0245***
	(0.00487)	(0.00447)
Sellers	0.0101***	0.0108***
	(0.00386)	(0.00214)
Constant	-0.0529***	-0.0476***
	(0.0123)	(0.00934)
Observations	343	343
R-squared	0.537	0.343

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In this case, the predicted and efficient qualities estimated are very different from the previous scenarios, and are shown in table 5b. Here, we clearly see that the average quality for both buyers and sellers is the lowest of all scenarios. This is due to the fact that, since the decision to join one platform is independent of the decision to join another platform, platforms can do little to attract additional users to both sides. Hence, they do not have incentives to provide higher levels of quality to any side.

Table 5b. Predicted and efficient quality by category when both sides multi-home.

	Buyers			Sellers		
	Predicted	**Efficient**	**Diff.**	**Predicted**	**Efficient**	**Diff.**
Marketplaces	0.420	1.358	-0.691	0.600	1.226	-0.511
App stores	0.608	1.019	-0.403	0.714	1.320	-0.459
Social media	1.347	1.683	-0.200	1.359	1.411	-0.037
Online advertising	0.826	1.606	-0.486	0.949	1.337	-0.290
Total	0.800	1.417	-0.435	0.906	1.324	-0.316

* The difference is computed in %. A positive sign indicates quality upgrading while a negative sign can be interpreted as quality "degradation".

In addition, we also observe that now the average quality provided to sellers is higher than the average quality provided to buyers, due to the fact that under the assumptions of this scenario, sellers value quality more than buyers. Moreover, platforms will be willing to provide higher quality to sellers because it is the side that generates revenues. However, the results indicate that the average qualities offered to both sides are far from the efficient levels of quality a social planner would choose. Since there is no guarantee that by providing more quality, the platform will be able to attract more users to any side, the platform strategy is to minimise costs in the provision of quality and keep it at the lowest level possible. This generates huge deviations of predicted vs efficient qualities in the two sides, more than 40% in the case of buyers and more than 30% in the case of sellers.

Finally, the following table 7 summarises the findings of the different scenarios considered. The most competitive corresponds to the case where both sides single-home, and in that case platforms will have to compete fiercely for users in both sides, since a lost user would weaken the strength of the indirect network effects and could generate a sequence of decisions that could radically alter the shares of users of different platforms. Hence, it is in this scenario where the platforms offer the highest quality to both sides, and where the distortions with respect to the level of quality chosen by a social planner would be the lowest. Clearly, the worst scenario corresponds to a situation where both sides multi-home, since platforms would not have incentives to provide quality at all. Finally, in a competitive bottleneck, buyers get a reasonable level of quality while sellers see their quality degraded.

Table 7. Comparison of the quality provided and efficient in the different scenarios.

	Buyers		**Sellers**	
	Predicted	**Efficient**	**Predicted**	**Efficient**
Competitive bottleneck	2.462	2.516	0.759	1.506
Both sides single-home	3.028	3.421	2.116	2.349
Both sides multi-home	0.800	1.417	0.906	1.324

8 Conclusions

Using survey data, in this paper we first show that sellers operating with four different categories of platforms multi-home. Hence, the appropriate competitive landscape in which these firms operate can be defined as the "competitive bottleneck" model of multi-sided markets (Armstrong, 2006). Second, we develop an empirical model of platform competition and add an additional dimension: service quality. Our aim is to explain evidence on unfair practices by platforms towards SME's, as evidenced by the European Commission, by assuming that these unfair trading practices are the result of under-provision of service quality by platforms.

These results are in line with the economics literature on quality choice. There, a standard result is that the level of quality to the type of agent that values it the most (buyers in our case), is set efficiently, i.e., there are no distortions with respect to the level of quality that a social planner would provide, but the level of quality for the type of user that has a lower value (sellers in our context) is degraded downwards. Moreover, differences in the costs of providing the different quality levels also play a role. We have showed that the costs of providing quality to sellers –as determined by the model- are higher than the costs of providing quality to buyers. These differences may reflect different needs or preferences across groups. While buyers would require simple functionalities associated to search and logical navigation for instance; sellers would need more sophisticated services related to marketing, accounting, transparency in pricing and product listings, to name just a few.

In line with what a standard competitive bottleneck model would suggest, the model presented here finds that when sellers multi-home, platforms will care more about buyers than sellers. Hence, they will provide different levels of quality: buyers will get an efficient level of quality (close to what a social planner would choose) while quality to sellers will be degraded since the platform has not incentives to compete for sellers. By attracting buyers –to whom it offers high quality- it will indirectly attract sellers. Since supplying an additional unit of quality to sellers is more costly (in relative terms) than providing an additional unit of quality to buyers, the platform will maximise profits by strategically degrading quality to sellers.

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Annexes

Annex 1. Data annex

Table A1. Firms by country

Country	N. of firms
Germany	537
France	579
Spain	505
Sweden	516
Lithuania	56
Greece	68
Slovakia	292
Total	2,553

Table A2. List of platforms included in the survey

Marketplaces	App stores	Social networks	Online advertising
Groupon	Google play	facebook.com	Huffington Post
HRS	amazon apps	instagram.com	amazon ad
Kayak	apple.com	linkedin.com	aol.com
allegro.pl	LG	linternaute.com	bing.com
amazon.com	oculus	pinterest.com	dailymotion.com
autoscout24	opera.com	snapchat	doubleclick.com
booking.com	Samsung	tumblr.com	facebook ad
cabify	windowsphone.com	twitter.com	hi-media.com
ebay		viber.com	twitter ad
expedia		vk	yelp ad
fnac		wordpress.com	
immobilienscout24.de		youtube.com	
mytable.es			
spartoo			
trivago			
twago			
uvinum			
yelp			
zalando			