ASSESSMENT OF MARKET POWER IN DIGITAL MARKETS: CONCEPTUAL FRAMEWORK AND EMPIRICAL STRATEGY

By

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ABSTRACT

The rise of digital platforms as a business model and a critical infrastructure for the digital economy is causing increasing trepidation among scholars and competition policy enforcers. In response to concerns about platform dominance, policies that were in place since the 1990s to keep the digital economy free from traditional regulation are being reconsidered. In these discussions, competition is considered an essential mechanism to harness the social and economic benefits of digital platforms, as it serves to attenuate potential risks to innovation, democracy, and to the media industry. This paper contributes to these discussions theoretically and empirically. It addresses some of the challenges of designing comprehensive responses to safeguard and promote competition in digital markets. The focus of the investigation is the assessment of market power in digital markets. First, a conceptual framework is developed, and it is shown that there is a need for new tests in addition to the traditional evaluation of the competitive structure of platform markets. The analysis concludes that to have significant impact in promoting competition in digital markets policy remedies should be enforced jointly on both the user- and supplier sides of the platforms. Second, the article reports results of an online survey experiment with 550 participants. The results suggest that an analysis of user responses to digital ads and data collection procedures would greatly improve the assessments of market power. Overall, this paper develops theoretically and empirically grounded contributions that will help policymakers and regulatory agencies in the design of workable approaches to assess market power in digital markets.

I - INTRODUCTION

Digital technology has transformed people's lives in the last decades. Effects on the way we communicate, work, learn and trade are undeniable. Its enabling effects on competition, investment, and innovation in many industries are also well recognized. On the other hand, the rise of digital platforms as a critical infrastructure and increasingly important business model in the digital economy has been seen with trepidation by a growing number of scholars and competition policy enforcers. Prevailing policies to keep the digital economy free from traditional regulation are being reconsidered.

This paper contributes to these discussions theoretically and empirically. It addresses some of the challenges of designing comprehensive responses to safeguard and promote competition in digital markets. One of the topics investigated is the assessment of market power in digital markets. A conceptual framework is proposed and shows the need for new tests in addition to the traditional evaluation of the competitive structure of platform markets. Also, it was possible to conclude that policy remedies, to have significant impact in promoting competition in digital markets, should be enforced jointly in both user- and supplier sides of the platforms. Furthermore, the results of an online survey experiment with 550 participants suggest that an analysis of user responses to different levels of digital ads and data collection procedures bundled with online services would greatly improve assessments of market power.

During the past decade, traditional instruments of competition policy have been employed. The list of antitrust cases investigating potential, anti-competitive practices of the big, digital platforms such as Google, Facebook, and Amazon, is long and growing. More recently, policy has pivoted to structural responses, exemplified in the approval of the Digital Markets Act (DMA) by the European Union, and the legislative proposals H.R.3816 – *American Choice* *and Innovation Online Act*, under discussion in the U.S. House of Representatives, and S.2992 – *American Innovation and Choice Online Act*, under discussion in the U.S. Senate.

Apart from potential threats to the efficiency of some digital markets, the dominance of a few big techs in the intermediation business is also being associated with broader ailments of a digitally enabled society. For example, platforms are associated with the increased polarization of the political debate in democratic countries (Krämer, 2017; Gillespie, 2018). The promotion of disinformation, and the lack of transparency on news distribution, with harmful consequences to media trust and quality, also seen as a consequence of the weak competitive pressure exerted on incumbent platforms (e.g., Flew and Martin, 2022).

Some authors assert that in the absence of competitive pressure platforms do not undertake sufficient efforts to remedy flaws in the design of the algorithms governing information flows on their networks (Rolnik et al., 2019). Furthermore, effects to data security, personal privacy, and cybercrimes (e.g., piracy on content distribution) have been associated with the lack of competition in the delivery of digital services (Rosen, 2011; Strahilevitz et al., 2019).

Many authors share the view that competition is essential to harness the social and economic benefits of digital platforms with the expectation that this would attenuate potential risks to innovation, democracy, and to the media industry.[1] For example, Mansell and Steinmueller (2020) review the main reasons provided by neoclassical, and institutional

[1] Throughout this paper, competition is conceptualized as a dynamic process of rivalry among suppliers of goods and services for consumers and their attention. This framing is a generalization of traditional models of competition, such as models of perfect competition, duopoly, or monopoly. It builds on early work on monopolistic competition, the notion of workable competition, theories of contestable markets, and more recent approaches to strategic management in digital markets (e.g., Clark, 1940; Schumpeter, 1942; Hayek, 1949; Baumol, Panzar and Willig, 1982; Tirole, 1988; Laffont & Tirole, 1999; Petit & Teece, 2021). In this perspective, suppliers have numerous options to compete, including prices, quantities, quality, and multiple forms of innovation that may introduce new products and services, new production processes, and designs.

economists to intervene in the operation of markets with the goal to promote competition as the most effective check on the behavior of dominant firms. Both frameworks argue that i) the risk of displacement, associated with ii) effective competition pushes market players to a more efficient use of inputs and a more desirable generation of outcomes. The authors suggest that, informed by these traditional economic theories, policymakers around the world increasingly perceive that the potential harms associated with a high level of concentration in the platform economy are sufficiently serious to require a response.

These concerns are examined in this paper with the goal to make theory-based, substantive, and practical contributions to scholarly literature and competition policy practice. Section 2 examines the forms and manifestations of market power when a platform has a dominant position in several digital markets. A conceptual framework is proposed for the assessment of market power in digital markets. The framework builds on recent developments in industrial organization theory to understand competition in two-sided markets with platform intermediaries (e.g., Rochet and Tirole, 2003; Armstrong, 2006), and on applied approaches, particularly the discrete-choice demand modeling approach proposed by Berry (1994) and Nevo (2000).

Then, in Section 3 it is provided empirical grounding for the assumptions made in the conceptual market power model proposed in Section 3. An on-line-based survey experiment with 550 participants is used for this purpose. The analyses of the results show that the size and reach of the platform, as well as users' prior engagement with other digital services provided by the platform, impact users' tolerance for watching ads and sharing information. This suggests that multi-market, incumbent platforms enjoy a competitive advantage that is exogenous to the relevant market under analysis. The information collected through the experiment was analyzed statistically, and the results suggest that the nuisance cost experienced by Internet users that watch ads bundled with videos accessed through well-known, incumbent video streaming services is lower than that experienced on new platforms. The results also show that the level of ad avoidance of users of online video services is inversely related to the number of services the Internet users consume from the same platform (e.g., webmail, web browsing, search, cloud services, etc.).

The research contributes to the design of new competition policy, and regulatory instruments to identify market power of digital platforms that play in several markets. Section 4 concludes the paper by summing up the many ways it pushes the knowledge boundary on market power assessment, and informs policymakers, regulators, and antitrust agencies.

2 – MARKET POWER ASSESSMENT IN DIGITAL MARKETS: CONCEPTUAL FRAMEWORK

This Section examines the conditions under which a need arises to safeguard and promote competition in digital markets. The concentrated structure of several digital markets requires the identification of firms with market power (U.K. Competition and Markets Authority, 2020). However, the methods to assess market power in the context of digital markets are not fully developed and many experts believe that they must be redefined (Scott-Morton at al. 2019). This Section discusses which digital platforms and markets should be targeted by pro-competitive remedies and proposes an original approach to assess market power in digital markets. Prado (2023) brings a review of ground-level concepts pertaining to the platform economy, for those not familiar with the topic. It starts with a review of the main characteristics of the platform intermediation business model. Then it discusses the rise of big digital platforms as dominant players and concludes with an analysis of the risks and benefits of platform dominance in digital markets.

To expand current knowledge and contribute to the definition of policy and regulatory tools to promote competition in digital markets, a conceptual framework is proposed to assess the market power of digital platforms building on discrete choice demand theory. The approach examines the common case where a digital platform has a dominant position in several user-side, digital markets. In a first step, a general utility function of users of digital services is outlined, following the well-known discrete choice demand model setup proposed by Berry (1994). This allows deriving own-demand elasticity functions for digital services. The same approach is used to derive a general utility function and own-demand elasticities of advertisers seeking to purchase ad services from digital platforms, one of the most common supplier-side services provided by digital platforms. Next, functions for the market power of digital platforms are derived from the elasticity functions. Finally, their implications for the definition of relevant markets and the design of competition policy tools and remedies are discussed.

The market power functions found are general in that they are applicable to any two-sided market in which, on the user-side, an intermediate, digital platform supplies digital services (zero-priced or not) bundled with digital ads and data collection procedures. The choice to study the targeted ads market on the supplier side of the platform was made for analytical and practical reasons, because the supply of target ads is a well-known, extremely successful business model exploited by digital platforms. However, the models are applicable to other supplier-side markets without loss of generality.

2.1 Market power conceptual framework

Assume a discrete choice demand setting in which there is a platform $k \in K$ in market $m \in M$ providing one digital service *j* with quality $q_{k,m}$ to internet user $i \in I$. To use the service j, *i* is required to pay the price $p_{k,m}$ to access it, to spend the total time $t_{k,m}$ watching digital ads while using *j*, and to share $d_{k,m}$ amount of information with the platform (e.g., digital traces, demographics, behavioral and psychological characteristics, etc.).[2] In the advertising market $g \in G$, the platform *k* supplies the time gathered from each of its users of *m* to advertiser $a \in A$ at price $r_{k,m,g}$ per impression.[3]

[2] Usually, $p_{k,m}$ is zero in ads-sponsored, digital products/services.
[3] Ad prices are typically expressed as cost per thousand or cost "per *mille*." There are many variants for how digital ads are priced (per impression, per action, per transaction, etc.), although this does not affect the analysis carried out in this paper.

For example, consider Google selling digital ads to advertisers in the United States and reaching YouTube users in Germany. In this case, market *m* is the video-streaming market in Germany, g is the digital ads market of the United States, *i* is an online video user in Germany, *a* is an advertiser in the United States, *j* is YouTube, and *k* is Google. Moreover, Google charges $p_{k,m} = 0$ from *i* to access YouTube but inserts $t_{k,m}$ seconds of ads on its videos and collects $d_{k,m}$ amount of digital traces from its users. Also, Google charges $r_{k,m,g}$ from any advertiser in the United States to deliver digital ads through YouTube to its users in Germany.

User-side Utility Model

Internet user *i* derives utility $U_{i,k,m}$ when it consumes *j* provided by *k* in market *m*.[4] Such utility comes from the value of the quality characteristics of *j*, $q_{k,m}$, which are commonly related to aspects, such as the nature of the content (e.g., audiovisual, text), its theme (e.g., sports, communication, news, games, etc.), its source, its length, etc. (Prasad et al., 2003; Fan et al., 2007; Bounie et al., 2017). For simplicity, the value given to quality characteristics of *j* is assumed to be constant among internet users, as considered in previous studies. Although the preferences of i previously collected by platform *k* in *M* may also impact the quality of some digital services, this depends on how customizable the service is, what information is collected, and the existence of consistent, previous interactions between the user and the platform.

The amount of digital ads bundled with *j*, $t_{k,m}$, is well documented in the literature of online advertisement economics as a source of disutility to digital content consumers (De Corniere and Taylor, 2014). This disutility is dependent on the user's nuisance cost of watching ads, α, generally assumed by the literature to be constant among all internet users after

[4] Because each platform *k* is assumed to provide one digital service *j*, the subscript *j* is dropped in equation 2.1.

controlling for their personal preferences and socio-economic conditions (Dukes and Gal-Or, 2003; Prasad et al. 2003; Papies at al. 2011; Acquisti and Spiekermann, 2011; Zhang and Sarvary, 2015; Bounie et al., 2017).[5] The homogeneity assumption of α among all internet users and platforms is further discussed and relaxed in the next subsection, where I argue that the size and reach of the platform k in digital markets M also affect the user's nuisance cost of watching ads experienced by the platform users.

The level of information (length and diversity) collected from i while she consumes j, $d_{k,m}$, is also considered in the literature a source of disutility, dependent on a nuisance cost of data collection, β, assumed, for now, to be constant among all internet users and platforms. However, evidence was found that internet users generally would not be able to have a sense of this disutility, and therefore it would have no impact on consumption decisions (Tucker, 2012; Strandburg, 2013). However, recent improvements in the transparency of privacy policy among digital platforms and other internet suppliers may have resulted in an increase of the importance of privacy issues among internet users (Martin, 2018; Johnson et al., 2018; Wang and Herrando, 2019). Finally, consumer i derives disutility of paying $p_{k,m}$ to access j, dependent on her price responsiveness, γ, also assumed, for now, to be constant among all internet users and platforms. The homogeneity assumptions of β and γ are also relaxed in the next subsection.

Equation (2.1) models the overall utility $U_{i,k,m}$, which also includes unobservable factors related to product j of platform k ($\xi_{k,m}$) that also have an impact on $U_{i,k,m}$, as well as an error term $\varepsilon_{i,k,m}$. Equation (2.2) expresses the mean utility function, which is independent of users'

[5] Tucker (2012) argues that consumers derive some benefit from being well informed about products that they most likely have interest in purchasing. However, such benefit generally is not sufficient to make positive the total utility they derive from spending time on ads, because they originally want to consume a digital content or service, not an ad.

heterogeneity and thus is only a function of the characteristics of the digital service provided by platform *k* in market *m*.

$$U_{i,k,m} = q_{k,m} - \alpha t_{k,m} - \beta d_{k,m} - \gamma p_{k,m} + \xi_{k,m} + \varepsilon_{i,k,m} \tag{2.1}$$

$$\delta_{k,m} = q_{k,m} - \alpha t_{k,m} - \beta d_{k,m} - \gamma p_{k,m} + \xi_{k,m} \tag{2.2}$$

Now let us consider $s_{k,m}$ the market-share of *k* in market *m*. Assuming that $\varepsilon_{i,k,m}$ is identically and independently distributed according to a Type I extreme value distribution, Berry (1994) and Nevo (2000) showed that $s_{k,m}$ can be expressed in the classic *logistic* form as the probability that user *i* consumes *j* provided by *k*, given that she derives the mean utility $\delta_{k,m}$ from this choice.

$$s_{k,m} = \frac{\exp(\delta_{k,m})}{1+\sum_{k=1}^{K}\exp(\delta_{k,m})} = \frac{\exp(q_{k,m}-\alpha t_{k,m}-\beta d_{k,m}-\gamma p_{k,m}+\xi_{k,m})}{1+\sum_{k=1}^{K}\exp(q_{k,m}-\alpha t_{k,m}-\beta d_{k,m}-\gamma p_{k,m}+\xi_{k,m})} \tag{2.3}$$

Writing the market-share of *k* in *m* helps us to derive the own-demand elasticities of internet users with respect to *k*'s level of digital ads, level of information collected, and price, as shown in equations (2.4), (2.5) and (2.6), respectively. The intuition behind the own-demand elasticities is that assuming α, β, and γ are constant among users and platforms, the bigger the market-share of *k* in *m*, the more inelastic is its demand to variations in $t_{k,m}$, $d_{k,m}$, and $p_{k,m}$. Because market-power is usually measured by the Lerner Index as the inverse of own-demand elasticity $(-1/\eta)$ (Lerner, 1934), one may easily investigate market power of platform *k* in market *m* by exploring how market-share of *k* respond to variations in the levels of digital ads, information collected, or the access price associated with each of them.

$$\eta_{k,m}(t_{k,m}) = \frac{\partial s_{k,m} t_{k,m}}{\partial t_{k,m} s_{k,m}} = -\alpha t_{k,m}(1 - s_{k,m}) \tag{2.4}$$

$$\eta_{k,m}(d_{k,m}) = \frac{\partial s_{k,m} d_{k,m}}{\partial d_{k,m} s_{k,m}} = -\beta d_{k,m}(1 - s_{k,m}) \tag{2.5}$$

$$\eta_{k,m}(p_{k,m}) = \frac{\partial s_{k,m} p_{k,m}}{\partial p_{k,m} s_{k,m}} = -\gamma p_{k,m}(1 - s_{k,m}) \tag{2.6}$$

Such results reassemble the idea behind the Small but Significant and Non-transitory Increase in Price (SSNIP) test – a conceptual tool used extensively in competition policy and regulation to define a relevant market and assess market power.[6] However, they are extended here to assess market power in markets where the product is zero-priced, which is the case in most digital markets. For such markets, our model suggests that price can be replaced by the level of digital ads, or the extent of information collected and bundled with *j*, because both are also sources of disutility and have an impact on *k*'s market share. For example, equation (2.4) allows us to expect that a platform *k* that has 80% of market-share ($s_{k,m}$) in a user-sided digital market *m* is expected to lose four times fewer users if it doubles the time its users must spend viewing targeted ads, when compared with a smaller platform with only 20% of market-share.

Leveraging market power across user-side, digital markets

So far, the proposed model borrowed from existing advertisement economics literature, which assumes the nuisance costs α, β, and γ are constant among users and platforms, to build

[6] The SSNIP test was first introduced in 1982 by the U.S. Department of Justice Merger Guidelines and has been used also by competition authorities in Europe since the early 1990s. It aims to identify markets in which a hypothetical monopolist can impose profitable increases in price (above competitive levels). Coate and Fisher (2008) provide theory and practical details about the test and its applications.

a framework for assessing market power of digital platforms in ad-sponsored, two-sided markets. Although the conclusions we have reached still hold when we relax these assumptions,[7] an important result is found when we model nuisance costs dependent on the size and reach of platform *k*. It is plausible to assume that when *i* consumes many other services from a big platform *k* in markets other than *m*, her wider engagement with *k*, and previous awareness about *k*'s quality standards and functionalities make her switching cost higher than when *k* is a new platform for *i*. Consequently, user *i* would be more tolerant to an increase in the time she needs to spend watching ads in *k* when *k* is a big digital platform, than when k is a small platform. The same rationale also applies to an increase in the level of user information collected by *k*.

As a practical example, this assumption suggests that an internet user who consumes many services from Google, such as Gmail, Google Drive, Google Maps, Google Chrome, and Google Search would accept watching more digital ads on YouTube than on a smaller, unknown platform. Section 3 of this paper provides empirical evidence that supports such an assumption. Analyzing online video users' response to ads in an experiment with two platforms (a big and a small platform), showed that users are more tolerant to watch digital ads and share information in a big platform, when compared to when they are accessing a small one.

To model such platform heterogeneity and thus analyze its implications for the assessment of the market power, let us consider the nuisance costs α_k, β_k, and γ_k, which are marginal disutilities, now dependent on platform *k*. To differentiate well-known, multi-market platforms from smaller ones, it the variable $S_{k,-m}$ is used, a function of $n_{k,-m}$ the likely level of

[7] Berry et al. (1995) and Nevo (2000) show that when the heterogeneity of consumers' tastes (their nuisance cost or sensitivity) is considered, own-demand elasticities are still negatively related to the level of prices and the inverse of firms' market-share ($1 - s_{k,m}$), integrated throughout a distribution of consumer tastes.

engagement of *k* with *i.* First, a platform present in more digital markets is more likely to have a wider engagement with user *i*, who may consume more than one digital service from *k*. As discussed earlier, a wider engagement leads to a higher switching cost, and consequently to a higher tolerance of end users to increased levels of $t_{k,m}$, $d_{k,m}$, and $p_{k,m}$. So, it is expected that the marginal disutilities α_k, β_k, γ_k, and $n_{k,-m}$.

In addition to being present in many markets, having big market-shares in these markets is an important characteristic of *k* that supports assuming a high engagement between platform *k* and the user *i*. For example, a platform *k* present in several digital markets, and with great market shares in most of them (e.g., Google, Apple, or Amazon) would be more likely to have a wider engagement with consumer *i* than a platform which is present in many digital markets, but with little market shares on all or most of them. To capture such features, the total level of market shares of *k* in all the markets other than *m* where it is present is modeled by the simple sum of all the market shares, $\sum s_{k,-m}$.

Another important factor to consider when modeling the potential level of engagement of *i* with platform *k* is how the market shares of *k* are distributed around the $n_{k,-m}$ digital markets other than *m* where it is present. For example, consider Platform 1 with 80% market share in market A, 20% in market B, and 50% in market C. Now consider Platform 2 with 75% market share in market D, and 75% in market E. Now consider that Platforms 1 and 2 compete in another market (e.g., market F), subject to market power assessment by competition authorities. Which platform is more likely to have a wider engagement with consumer *i* of market F, an internet user which, most likely, also consume digital services in all the other markets (A to E)? It is reasonable considering that, even though the total market shares $\sum s_{k,-m}$ of both platforms on markets A to E are equal (in this case, 150%), Platform 1 may be engaged with *i* in three digital services other than *j*, while Platform 2 only in two other digital services. This difference should lead to a higher switching cost (and tolerance to disutilities) of *i* with respect to Platform 1 than to Platform 2 on market F. This characteristic can be captured by a simple interaction between the number of markets where *k* is present other than *m*, and the total market shares of *k* in markets other than *m*, $n_{k,-m}.\sum s_{k,-m}$.

Finally, we assume that the marginal increase of $S_{k,-m}$ as a response of an increase in the interacted term $n_k.\sum s_{k,-m}$ should be decrescent with increases in $n_{k,-m}.\sum s_{k,-m}$. This can be explained by the fact that most internet users are not present or active in all digital markets, as digital services usually compete for the users' online time. Based on this, and in the fact that the level of engagement between *i* and *k* should be a non-negative variable, $S_{k,-m}$ is modeled as the natural logarithm of one plus the product between the number of different digital markets where *k* is present other than *m*, and the sum of *k*'s market-shares in all user-side digital markets other than *m* ($S_{k,-m} = \ln(1 + n_{k,-m}\sum s_{k,-m})$). Equations (2.7), (2.8) and (2.9) provide general forms of the marginal disutilities α_k, β_k, and γ_k dependent on $S_{k,-m}$.

$$\alpha_k = \alpha_0 - \alpha_1 S_{k,-m} = \alpha_0 - \alpha_1 \ln(1 + n_{k,-m}\sum s_{k,-m}) \text{ with } \alpha_k \geq 0 \text{ for } \forall\ S_{k,-m} \qquad (2.7)$$

$$\beta_k = \beta_0 - \beta_1 S_{k,-m} = \beta_0 - \beta_1 \ln(1 + n_{k,-m}\sum s_{k,-m}) \text{ with } \beta_k \geq 0 \text{ for } \forall\ S_{k,-m} \qquad (2.8)$$

$$\gamma_k = \gamma_0 - \gamma_1 S_{k,-m} = \gamma_0 - \gamma_1 \ln(1 + n_{k,-m}\sum s_{k,-m}) \text{ with } \gamma_k \geq 0 \text{ for } \forall\ S_{k,-m} \qquad (2.9)$$

The interpretation of the equations above is the following. The disutilities, or nuisance costs experienced by *i* when she has to spend $t_{k,m}$ of her time watching ads, or has to share $d_{k,m}$ of her private information, or has to pay $p_{k,m}$ to access and use *j* in market *m* are lower the bigger the digital platform *k*, as the switching cost (and tolerance) of *i* is assumed to be higher with platforms whose which she is more engaged in other digital markets. This implies that internet users would be more tolerant of spending time watching ads and having their information collected from incumbent digital platforms then from new entrants into market *m*. Consequently, an incumbent platform *k* can sustain profitable levels of $t_{k,m}$, $d_{k,m}$ and $p_{k,m}$ above the competitive equilibrium and proportional to its size and reach in the digital economy. Equations (2.10), (2.11) and (2.12) show how the level of market power $\Omega_{k,m}$ of digital platform *k* in market *m* can be leveraged by the extent of *k*'s presence in other digital markets.

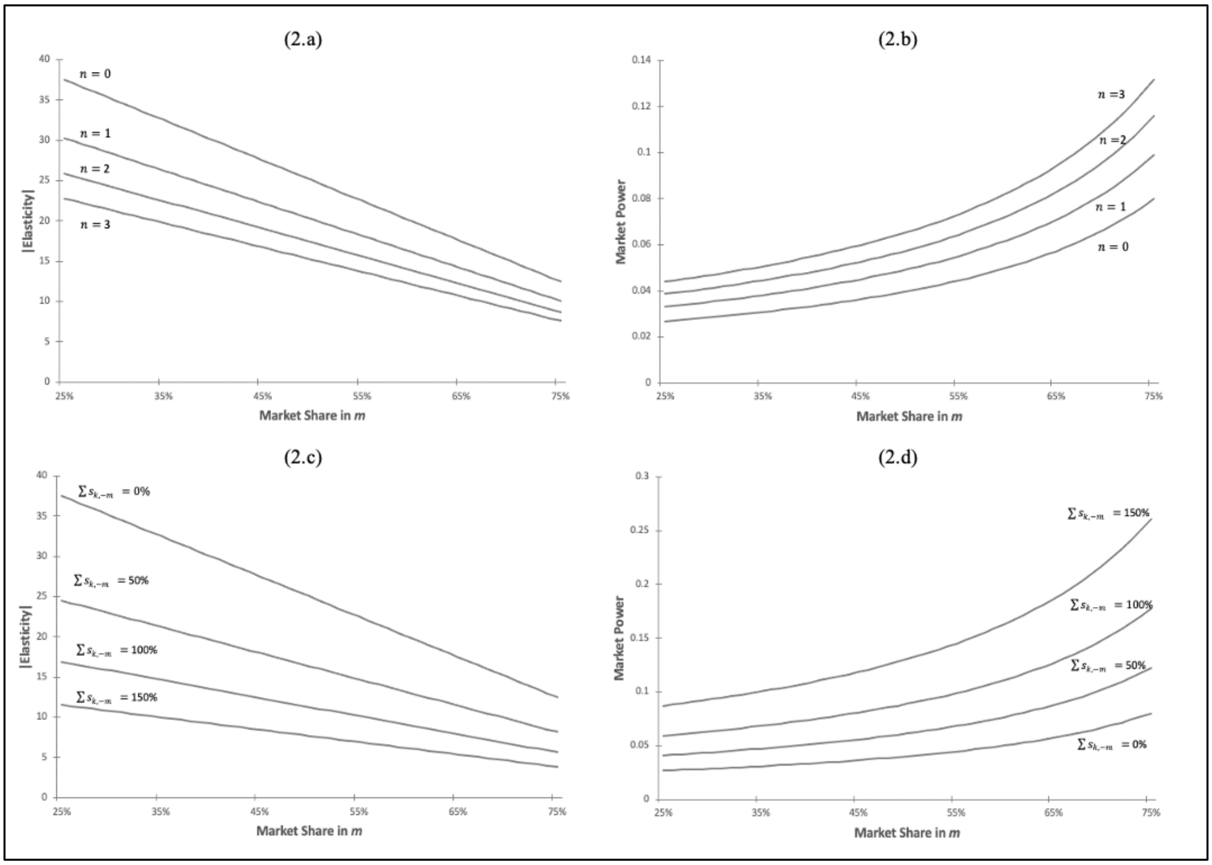
$$\Omega_{k,m}(t_{k,m}) = \frac{-1}{\eta_{k,m}(t_{k,m})} = \frac{1}{[\alpha_0 - \alpha_1 \ln(1 + n_{k,-m} \sum s_{k,-m})]\; t_{k,m}(1 - s_{k,m})} \tag{2.10}$$

$$\Omega_{k,m}(d_{k,m}) = \frac{-1}{\eta_{k,m}(d_{k,m})} = \frac{1}{[\ln(1 + n_{k,-m} \sum s_{k,-m})\,] d_{k,m}(1 - s_{k,m})} \tag{2.11}$$

$$\Omega_{k,m}(p_{k,m}) = \frac{-1}{\eta_{k,m}(p_{k,m})} = \frac{1}{[\gamma_0 - \gamma_1 \ln\,(1 + n_{k,-m} \sum s_{k,-m})\,] p_{k,m}(1 - s_{k,m})} \tag{2.12}$$

The equations above allow us to conclude that the greater the presence of platform *k* not only in *m* but also in digital markets other than *m*, the more inelastic is its demand with respect to any increase in $t_{k,m}$, $d_{k,m}$, or $p_{k,m}$, and, thus, the greater its market power is in digital market *m*. Figure 2.1 illustrates such effects, showing that, assuming α_1, β_1 or γ_1 greater than zero, the bigger the number of different digital markets other than *m* where the platform *k* is present ($n_{k,-m}$), and the bigger its total market-share in those markets ($\sum s_{k,-m}$), the lower its own-demand elasticity in *m* and the bigger its market power. Indeed, we can see in the figure that a platform with great presence in other markets but low market-share in *m* may even have a lower own-demand elasticity and a bigger market power in *m* when compared with a platform with a bigger market-share in *m* but without presence in other digital markets.

Figure 2.1 – Elasticity and market power plots in market *m*



Source: Author.

Such results show that the dominant position of an incumbent digital platform in other markets can be leveraged to market *m*, allowing the incumbent platform to sustain higher levels of ads, data collection procedures, and prices when compared with small platforms. A second conclusion is that when a big digital platform is the newcomer in a digital market, instead of competing in terms of the levels of quality, ads, data collection procedures, and price, such a platform may set the same levels chosen by its competitors and still gain a market share.

The implications of such results to set effective regulatory remedies to foster competition in digital markets is further discussed in Prado (2023). However, it is important to note that, if the competition authority wants to analyze simultaneously the market power of a big digital platform in all the user-side markets where *k* is present, a general equilibria approach would be preferable. The market models derived in this Section apply for analyzing market power in just one digital market *m* at once, what is generally acceptable, as this is the most common practice in competition policy and regulation procedures.

Advertiser-side Utility Model

Advertisers, framed herein as buyers in the supplier side of the intermediation platform *k*, derive utility from purchasing digital ads and having their products and services efficiently exposed to the platform users most likely to pay for them. Such utility is a function of the visibility of the advertisement minus the price the advertiser pays for it (Bonnie et al., 2017). Consider the advertising market $g \in G$, where the platform *k* supplies a unit fraction of the time $t_{k,m}$ of i to advertiser *a* at price $r_{k,m,g}$. The utility of advertiser *a* can be modeled as a function of the quality of the digital ad offered by platform *k* in market *m* ($\sigma_{k,m}$), and the price that the platform *k* charges in geographic market *g* to show the ad of *a* to user *i* in market *m* ($r_{k,m,g}$).

The quality of the digital ad referred here ($\sigma_{k,m}$) is not related to the content characteristics of the ad, as the advertiser generally provides the ad to be distributed by the platform. Rather, it is related to the ability of platform *k* effectively targeting the ad towards potential consumers of *a* in market *m*. In this sense, $\sigma_{k,m}$ might be dependent, among others, on the market share of platform *k* in *m* ($s_{k,m}$), as the greater the universe of users of platform *k* in market *m*, the greater the chances of the platform finding relevant consumers for the products and services that *a* seeks to advertise. Moreover, $\sigma_{k,m}$ might be also dependent on the amount and diversity of information that platform *k* collects from its users in market *m* and in all other user-sided markets where k is present ($D_k = d_{k,m} + d_{k,-m}$). In fact, a platform with more data of its end users might achieve better accuracy predicting potential customers of a's products and services.

It is important to also note that, intuitively, $r_{k,m,g}$ would depend on $\sigma_{k,m}$, because high quality digital ads may have high production costs. However, because the platform business model creates high economies of scale and scope for the intermediary platforms (Crémer et al., 2019), we assume here that $r_{k,m,g}$ is exogenously defined by the platform according to the level of competition it faces in the ads market g. $U_{a,g,k,m}\xi_{k,m}U_{a,g,k,m}\varepsilon_{a,g,k,m}$

$$U_{a,g,k,m} = \sigma_{k,m} - \phi r_{k,m,g} + \xi_{k,m} + \varepsilon_{a,g,k,m} \tag{2.13}$$

$$\sigma_{k,m} = \theta_0 + \theta_1 D_k + \theta_2 s_{k,m} \tag{2.14}$$

$$U_{a,g,k,m} = \theta_0 + \theta_1 D_k + \theta_2 s_{k,m} + \xi_{k,m} - \phi r_{k,m,g} + \varepsilon_{a,g,k,m} \tag{2.15}$$

Like the scenario described in the previous Subsection, let us consider $s_{k,g}$ the market-share of platform k in market g. As shown by Berry (1994) and Nevo (2000) for discrete-choice demand models, assuming that $\varepsilon_{a,g,k,m}$ is identically and independently distributed according to a Type I extreme value distribution, $s_{k,g}$ can be expressed in its classic logit form of equation (4.16), which represents the probability that advertiser a chooses ads from k knowing the average utility derived from the ads provided by k. It is important to note that a discrete-choice demand setting like this one has certain limitations to model the behavior of advertisers, as several of them multi-home to reach more group of users in different platforms. On the other hand, given the current concentrated structure of many user-side, digital markets, and the rising costs of digital ads campaigns, most publishers and advertisers may opt to advertise in one, wide-reaching platform instead of multi-homing (Loeb, 2021; Johnson, 2022).

Equations (2.17), (2.18), (2.19) and (2.20) provide the derived, own-demand elasticities of *a* with respect to the level of information D_k that platform *k* collects from its users in markets M, as well as to its user-side market-share $s_{k,m}$ and price $r_{k,m,g}$.

$$s_{k,g} = \frac{\exp\left(\theta_0+\theta_1 D_k+\theta_2 s_{k,m}-\phi r_{k,m,g}+\xi_{k,m}\right)}{1+\sum_{k=1}^{K}\exp\left(\theta_0+\theta_1 D_k+\theta_2 s_{k,m}-\phi r_{k,m,g}+\xi_{k,m}\right)} \quad (2.16)$$

$$\eta_{k,g}(D_k) = \frac{\partial s_{k,g} D_k}{\partial D_k s_{k,g}} = D_k\left(1-s_{k,g}\right)[\theta_1-\theta_2\beta s_{k,m}(1-s_{k,m})] \quad (2.17)$$

$$\eta_{k,g}(D_k) = \frac{\partial s_{k,g} D_k}{\partial D_k s_{k,g}} = D_k\left(1-s_{k,g}\right)[\theta_1-\theta_2(\beta_0-\beta_1 S_{k,-m})s_{k,m}(1-s_{k,m})] \quad (2.18)$$

$$\eta_{k,g}\left(s_{k,m}\right) = \frac{\partial s_{k,g} s_{k,m}}{\partial s_{k,m} s_{k,g}} = \theta_2 s_{k,m}(1-s_{k,g})] \quad (2.19)$$

$$\eta_{k,g}\left(r_{k,m,g}\right) = \frac{\partial s_{k,g} r_{k,m,g}}{\partial r_{k,m,g} s_{k,g}} = -\phi r_{k,m,g}(1-s_{k,g})] \quad (2.20)$$

The derived own-demand elasticity functions presented in equations (2.17), (2.19), and (2.20) provide important insights for the identification of platforms with market power in the market of advertisement. Equation (2.17) shows us that the higher the market-share of a platform among users of market *m*, the more inelastic is its demand among advertisers of market *g* with respect to a decrease in the level of information D_k that *k* has from its internet users. Similar, and more important, the larger *k*'s market-share is among advertisers on market *g*, the more inelastic is its demand for decreases in D_k and the larger its market power among advertisers. These results suggest that asymmetric measures aimed at reducing the market power of digital platforms on the ads market should also focus on reducing concentration in market *m*, because the high market-share of the platform in that user-side market plays a key role in lowering its own-demand elasticity in market g.

Furthermore, when we allow β to vary across platforms (see equation 2.18, where I plugged equation 2.8 to equation 2.17), such asymmetric measures should address reducing the market power of platform k not only in the user-side market m but in all user-side markets where k is dominant. Moreover, equations (2.19) and (2.20) show that the larger k's market-share among advertisers of market g, the more inelastic its demand with respect to variations in the price $r_{k,m,g}$ or in the level of market-share k holds among internet users of m. Hence, an approach like the SSNIP test could also be applied by competition authorities in the ads market to identify platforms with market power. Indeed, one could assess the impact on the demand for digital ads of platform k in response to a small but significant non-transitory increase in the level of information that the platform has from its users, or the amount of market-share it has on m, or even in the price of the digital ads offered by k in market g.

The implications of these results for the design of effective regulatory remedies to promote competition in the supply of digital ads are further discussed in Prado (2023). For example,

3 – MARKET POWER ASSESSMENT IN DIGITAL MARKETS: AN EMPIRICAL STRATEGY

Recent competition policy research suggests a need to reconceptualize the tools used to identify market power in digital markets (Scott Morton at al., 2019). Section 2 proposed a conceptual framework for the assessment of market power, aimed at informing policy decisions as to which digital platforms and markets require pro-competitive remedies. A critical point of that framework is whether the disutility of users associated with ads and their privacy concerns vary between incumbent platforms and new platforms (see equations 2.7 and 2.8).

This Section reports the design and findings of an empirical investigation of the assumption that internet user's nuisance costs due to ads and collection of personal data, and consequently the market power of a platform in one digital market are also a function of its presence and shares in other digital markets. The study analyzes responses of internet users to different levels of advertising and different data collection strategies employed by platforms in the online video market. The research combines an experimental design and survey methods to investigate whether internet users tolerate higher levels of digital ads and data collection procedures in online video services when they are provided by well-known, big digital platforms, rather than by smaller platforms.

3.1 Measuring the nuisance costs of digital ads and data collection procedures

Inserting advertisements into media content is a well-known revenue-generation strategy that has been used by traditional newspapers and TV broadcasters for decades. In these traditional media outlets, users of a geographic region are indiscriminately targeted by the same ads, which are a predictable part of the content to be consumed (Logan, 2013). According to the same author, on digital services users are more concerned about having to spend their time watching ads due to an expectation of consuming only the content of interest. The research on the economics of online advertising shows that digital ads inserted in video streaming services, like YouTube, are a source of disutility for consumers (Acquisti and Spiekermann, 2011; Zhang and Sarvary, 2015).

Frade et al. (2021) provides a comprehensive review of studies that identify effects of digital ads on media consumers. Among other results, the reviewed studies show a clear negative impact of in-stream ads on a user's utility from consuming online video services. Such effects are found to vary according to several ad-related factors, like format (e.g., in-stream, banner, etc.), size, duration, position (e.g., at the beginning or at the middle of a video), level of congruence with the main content, etc. These negative effects also depend on user-related factors, like the level of previous engagement of the user with the service, gender, users' content preferences, her country and cultural background, age, etc. (Joa et. al, 2018; Duffett et al., 2019). In contrast, the research literature thus far has typically assumed that the effects of in-stream, digital ads are constant with respect to the characteristics of the digital service provider (Papies at al. 2011; Bounie et al., 2017).

To quantify the tolerance of media users to digital ads, several studies have relied on the scales measuring user ad avoidance proposed by Cho and Cheon (2004). Based on previous studies reported by Vakratsas and Ambler (1999), these authors assume that consumers respond to advertisement stimuli in three ways: cognition, affect, and behavior. Also, they show empirical evidence which confirms previous theoretical claims, found in the psychology, marketing, and communications scholarship, that users avoid advertisement on the Internet due to perceived goal impediment, perceived ad clutter, and prior negative experiences. Based on this theoretical framework, the authors proposed a survey instrument to measure the level of ad avoidance, categorized in three different types (cognitive, affective, and behavioral), as well as its three causal attributes.

However, more than measuring the responses of an online video user *i* to digital ad *j*, our main objective is understanding whether, and in which extent these responses vary with the size and reach of the digital service provider, and with the level of previous engagement of the user with the platform. Equation 3.1 and 3.2 below present the relationships we are interested in estimating empirically.

$$RESP_{i,j} = w(PLAT_i, AD_j, ATTR_i) \tag{3.1}$$

$$RESP_{i,j,PLAT} = g(ENG_{i,PLAT}, AD_j, ATTR_i) \tag{3.2}$$

PLAT identifies the platform providing the service, AD a set of characteristics of the advertisement (e.g., duration, position, etc.), ATTR represents attributes of the user (e.g., age, gender, country of origin, etc.), and ENG a set of variables that captures the level of engagement between the user and the platform service provider in markets other than the online video services. Finally, *RESP* captures the set of alternative outcome response variables by online video users to advertisement already reviewed (e.g., cognitive, affective, or behavioral ad avoidance, ad clutter, etc.).

In Section 2, we have assumed that tolerance of users to data collection procedures is also dependent on the size and reach of platform service provider, and on the level of engagement of the user with the platform in other markets (see Equation 2.8). Thus, *RESP* also contains a set of variables proposed by Baek and Marimoto (2022) that capture online video users' responses to data collection procedures performed by platform service providers. These variables measure how comfortable a user is when her information is collected, the importance of privacy to the user, her level of concern with how personal information is stored, and with the risk of the platform misusing or sharing personal information without her consent. More details on the scales used to measure such variables are provided in the following subsection.

3.2 Empirical strategy: experiment design, survey instrument, and data summary

This sub-section details how the experiment was designed and implemented to empirically measure the responses of online video users to digital ads and data collection procedures. In addition, the experiment was designed to investigate how the variation in the size of the platform service provider, or the level of engagement between the user and the provider, affect users' responses. After discussing the experiment design, survey approach, and sampling strategies used, a summary of the data collected is presented.

The experiment used a 2 x 4 design: 2 conditions for market share in the online video market: high vs. low (between variation) x 4 conditions for message repetition, with different sizes of ads and positions in the main content (within variation). A convenience sample of 550 participants[8] recruited through an online panel of general, U.S.-based internet users, was used. Participants first provided basic information on their socio-economic, demographic, and cultural background, their tastes for several types of video content (e.g., sports, cooking, etc.), and their level of engagement with several digital platforms in the market of online videos, and in another markets. Also, they were asked to answer questions to measure users' perceptions regarding the

[8] The selection of participants among those that voluntarily opted to participate in the experiment (seeking for some sort of compensation) followed the objective of achieving geographic, gender, and age quotas representative of typical U.S. internet user.

size and reach of several digital platforms and online videos services, and their level of engagement with digital platforms in different markets. This was important to guarantee that the perceptions of the users regarding the size and reach of each platform were coherent with their actual market shares and multi-market present. Details of the survey instrument can be found on Prado (2023).

Then, participants were randomly split into two groups, A and B. Participants assigned to group A were asked to watch four videos of less than 2 minutes, including ads of different lengths (5, 15, and 30 seconds), and inserted at different positions in the videos (beginning, and middle). The setting gave the impression that the videos were accessed via a well-known video streaming platform (YouTube). Participants randomly assigned to group B were asked to watch the same four videos, but in a setting that gave the impression that the videos were being accessed through an unknown, small video streaming platform (Zen Videos, a brand that was created just for the experiment). After watching each of the four videos, participants of both groups were asked to answer questions designed to measure their cognitive, affective, and behavioral ad avoidance.[9] They were also asked about the importance of privacy to them and about their concerns related to data collection procedures, storage, and the risks of data misuse or sharing. Table 3.1 presents a description of the variables assessed with the survey experiment.

[9] Other responses that cause the ad avoidance, like perceived goal impediment, and perceived ad clutter, were also captured in the survey. As these variables are not relevant to this research, these results were omitted.

Table 3.1 – Description of the variables

Variable Name	Abbreviation	Description
Responses to digital ads		
Overall Ad Avoidance	adavoid	Overall ad avoidance, calculated by the sum of adavoid_affect, adavoid_behav, and adavoid_cog
Ad Avoidance - Affective	adavoid_affect	Average participant's responses to the following two statement: "When I watch a video like this on a video streaming platform like YouTube/ZenVideos, I hate the ads." "When I watch a video like this on a video streaming platform like YouTube/ZenVideos, it would be better if there were no ads." (Strongly disagree = 0; Disagree = 1; Neutral = 2; Agree = 3; Strongly Agree = 4)
Ad Avoidance - Behavior	adavoid_behav	Participant's response to the following statement: "When I watch a video like this on a video streaming platform like YouTube/ZenVideos, I skip the ads if it is possible." (Strongly disagree = 0; Disagree = 1; Neutral = 2; Agree = 3; Strongly Agree = 4)
Ad Avoidance - Cognitive	adavoid_cog	Participant's response to the following statement: "When I watch a video like this on a video streaming platform like YouTube/ZenVideos, I intentionally do not pay attention to the ads." (Strongly disagree = 0; Disagree = 1; Neutral = 2; Agree = 3; Strongly Agree = 4)
Responses to data collections procedures		
Overall Privacy concerns	privacy	Overall privacy, calculated by the sum of priv_collect, priv_import, priv_misuse, priv_safestor, and priv_share
Data collection	priv_collect	Participant's response to the following statement: "I feel uncomfortable when my information is collected without permission." (Strongly disagree = 0; Disagree = 1; Neutral = 2; Agree = 3; Strongly Agree = 4)
Privacy concerns	priv_import	Participant's response to the following statement: "Privacy concerns play an important role in my choice." (Strongly disagree = 0; Disagree = 1; Neutral = 2; Agree = 3; Strongly Agree = 4)
Misuse of data	priv_misuse	Participant's response to the following statement: "I feel concerned about misuse of my personal information." (Strongly disagree = 0; Disagree = 1; Neutral = 2; Agree = 3; Strongly Agree = 4)
Data storage	priv_safestor	Participant's response to the following statement: "I believe that my personal information will not be safely stored." (Strongly disagree = 0; Disagree = 1; Neutral = 2; Agree = 3; Strongly Agree = 4)
Data sharing	priv_share	Participant's response to the following statement: "I believe that my personal information will be afterwards shared without permission." (Strongly disagree = 0; Disagree = 1; Neutral = 2; Agree = 3; Strongly Agree = 4)
Digital ad characteristics		
Ad duration	ad_dur	Duration of the digital ad, in seconds

Ad position	ad_pos	Position of the digital ad inside the video (0 = beginning, 1 = middle)
Streaming platform	str_plt	Streaming platform (0 = Zenvideos; 1 = YouTube)
Participant attributes		
Taste for sports videos	sports	Frequency in which participants watch sports videos. (Never = 0; Rarely = 1; Sometimes = 2; Frequently = 3; Very Frequently = 4)
Perception of YouTube size in context	pu_f_YouTube	Level of perception of how many users YouTube has among family and friends of participants. (Very few = 0; few = 1; some = 2; many = 3; very many = 4)
Perception of YouTube size	pu_YouTube	Level of perception of how many users YouTube has. (Very few = 0; few = 1; some = 2; many = 3; very many = 4)
Importance of ads duration	imp_ads	Level of importance of duration of ads to decision on streaming platform. (Not at all Important = 0; Low Important = 1; Neutral = 2; Important = 3; Very Important = 4)
Importance of previous experience	imp_exp	Level of importance of previous experience to decision on stream platform. (Not at all Important = 0; Low Important = 1; Neutral = 2; Important = 3; Very Important = 4)
Importance of price	imp_pric	Level of importance of price to decision on streaming platform. (Not at all Important = 0; Low Important = 1; Neutral = 2; Important = 3; Very Important = 4)
Importance of privacy	imp_priv	Level of importance of privacy to decision on streaming platform. (Not at all Important = 0; Low Important = 1; Neutral = 2; Important = 3; Very Important = 4)
Importance of quality	imp_qual	Level of importance of quality to decision on streaming platform. (Not at all Important = 0; Low Important = 1; Neutral = 2; Important = 3; Very Important = 4)
Age Group	age_gr	Age group of the participant (1 = 18-34; 2 = 35-54; 3 = 55+)
Gender	gend	Gender (1 = Male; 2 = Female; 4 = Other)
Region	geo	Geographic region of US where participant lives (1 = Midwest; 2 = Northeast; 3 = South; 4 = West)
Country	nation	Country where the participant grew up
Race	race	Race of the participant
Income	income	Income range, in U.S. dollars (< 29999 = 0; 30000 to 59999 = 1; 60000 to 99999 = 2, 100000 to 149999 = 3, >150000 = 4)
Engagement with Google and YouTube		
Engagement with Google	n_serv_goog	Number of Alphabet/Google services used by the participant other than YouTube (Google Maps, Images, News, Chrome, Gmail, Search, and Drive)
Engagement with YouTube	subs_youtube	Participant is a subscriber of YouTube (0 = No; 1 = Yes)
Usage of YouTube	u_youtube	Level of participant's use of YouTube monthly. (Never = 0; Rarely = 1; Sometimes = 2; Frequently = 3; Very Frequently = 4)

Tables 3.2 and 3.3, and Figure 3.1, provide summary statistics and the distribution of the participants' responses to digital ads and data collection procedures. The summary statistics are shown for all participants, as well as separately for each of the two groups of participants randomly selected to watch the videos in the platforms ZenVideos or YouTube. It is also reported the results of t-tests performed to conduct a preliminary assessment of the existence of statistically significant differences in the mean responses of each of the two groups. The p-values presented in the last column of both tables suggest that the means of all types of participants' responses to digital ads, and of some types of responses to data collection procedures, are different for the two groups. Conclusions based on these differences require a more rigorous statistical investigation, which we will report later in this Section.

Table 3.2 – Responses to digital ads – summary statistics

Experimental observations	All (N=2,200)				Str_plt: ZenVideos (N=1,004)				Str_plt: YouTube (N=1,196)				t-test (Ho: diff = 0)
Variables	**Mean**	**Std Dev**	**Min**	**Max**	**Mean**	**Std Dev**	**Min**	**Max**	**Mean**	**Std Dev**	**Min**	**Max**	**p-value**
adavoid	6.933	3.176	0	12	7.227	3.167	0	12	6.687	3.163	0	12	0.0001
adavoid_affect	2.296	1.119	0	4	2.395	1.103	0	4	2.214	1.126	0	4	0.0001
adavoid_behav	2.610	1.177	0	4	2.685	1.187	0	4	2.547	1.166	0	4	0.0060
adavoid_cog	2.027	1.239	0	4	2.146	1.242	0	4	1.926	1.228	0	4	0.0000

Table 3.3 – Responses to data collection procedures – summary statistics

Experimental observations	All (N=550)				Str_plt: ZenVideos (N=1,004)				Str_plt: Youtube (N=1,196)				t-test (Ho: diff = 0)
Variables	**Mean**	**Std Dev**	**Min**	**Max**	**Mean**	**Std Dev**	**Min**	**Max**	**Mean**	**Std Dev**	**Min**	**Max**	**p-value**
privacy	14.91	3.993	1	20	15.00	4.078	1	20	14.83	3.919	1	20	0.3279
priv_collect	3.013	1.101	0	4	3.068	1.041	0	4	2.967	1.148	0	4	0.0318
priv_import	3.055	0.954	0	4	3.120	0.959	0	4	3.000	0.947	0	4	0.0034
priv_misuse	3.122	0.956	0	4	3.088	0.991	0	4	3.151	0.926	0	4	0.1247
priv_safestor	2.760	1.029	0	4	2.737	1.027	0	4	2.779	1.031	0	4	0.3381
priv_share	2.960	0.985	0	4	2.988	0.968	0	4	2.936	0.998	0	4	0.2210

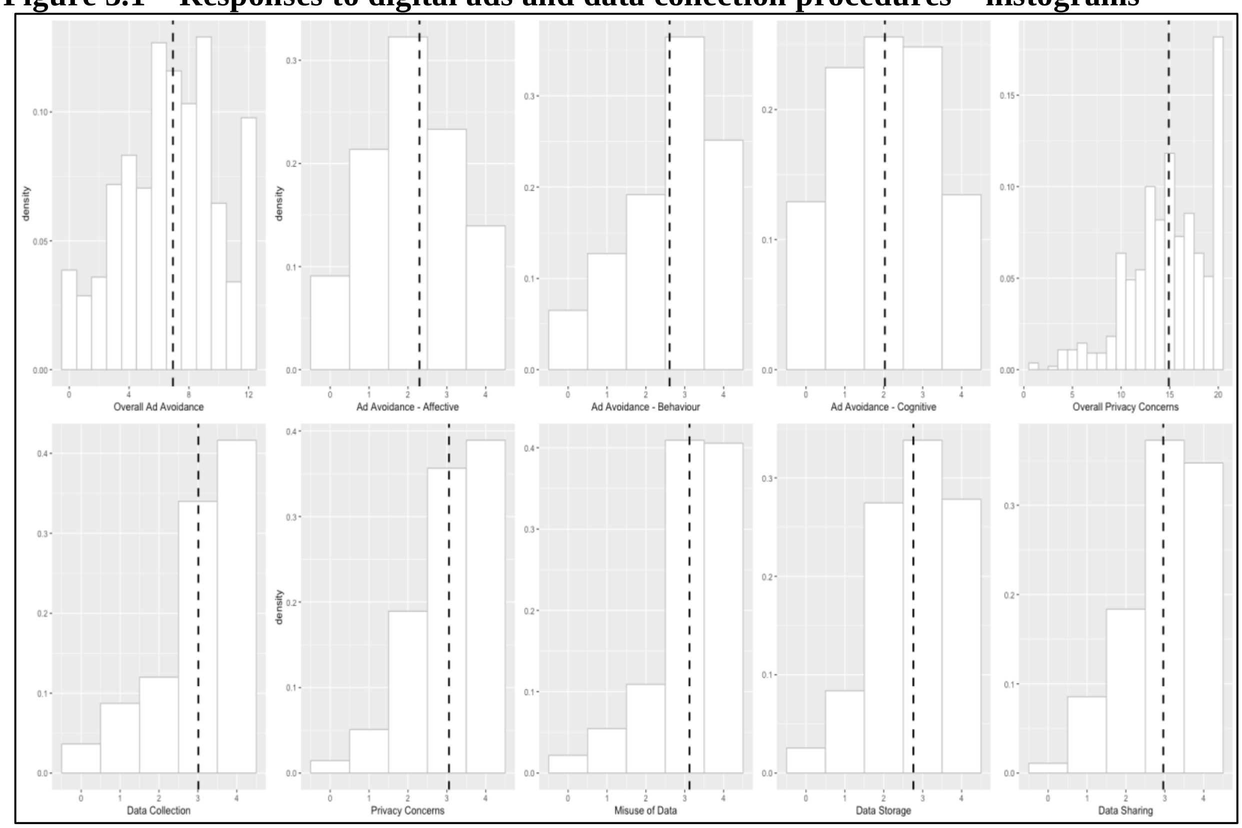
Table 3.4 – Participants' attributes and engagement – summary statistics

Number of participants	All (N=550)				Str_plt: ZenVideos (N=256)				Str_plt: Youtube (N=299)				t-test (Ho: diff = 0)
Variables	**Mean**	**Std Dev**	**Min**	**Max**	**Mean**	**Std Dev**	**Min**	**Max**	**Mean**	**Std Dev**	**Min**	**Max**	**p-value**
Participant attributes													
sports	1.220	1.356	0	4	1.243	1.337	0	4	1.201	1.372	0	4	0.466
pu_f_youtube	2.967	1.209	0	4	2.996	1.183	0	4	2.943	1.230	0	4	0.307
pu_youtube	3.529	0.771	0	4	3.526	0.688	0	4	3.532	0.835	0	4	0.859
imp_ads	2.615	1.074	0	4	2.622	1.077	0	4	2.609	1.072	0	4	0.781
imp_exp	2.796	0.979	0	4	2.849	0.999	0	4	2.753	0.961	0	4	0.022
imp_pric	3.284	0.872	0	4	3.299	0.830	0	4	3.271	0.906	0	4	0.455
imp_priv	3.020	1.030	0	4	3.024	0.990	0	4	3.017	1.062	0	4	0.871
imp_qual	3.347	0.828	0	4	3.375	0.806	0	4	3.324	0.845	0	4	0.158
Engagement with Google and YouTube													
n_serv_goog	4.435	1.918	0	7	4.442	1.832	0	7	4.428	1.988	0	7	0.863
subs_youtube	0.716	0.451	0	1	0.721	0.449	0	1	0.712	0.453	0	1	0.651
u_youtube	2.589	1.413	0	4	2.570	1.368	0	4	2.605	1.449	0	4	0.556

Table 3.5 – Participants' demographic attributes – summary statistics

Number of participants	All (N=550)	Str_plt: ZenVideos (N=256)	Str_plt: Youtube (N=299)
Variables	%	%	%
Participant attributes			
age_gr (18-34)	30.5	30.7	30.4
age_gr (35-54)	31.6	30.7	32.4
age_gr (55+	37.8	38.6	37.1
gend_male	46.0	44.6	47.2
gend_female	53.3	54.6	52.2
gend_other	0.7	0.8	0.7
geo_midwest	19.8	20.3	19.4
geo_northeast	19.5	21.1	18.1
geo_south	39.8	39.4	40.1
geo_west	20.9	19.1	22.4
nation_usa	97.5	97.6	97.3
nation_nonusa	2.5	2.4	2.7
race_white	75.6	80.1	71.9
race_asian	5.3	4.8	5.7
race_latino	4.5	3.6	5.4
race_black	7.1	5.6	8.4
race_others	7.5	6.0	8.7
income (< 29999)	24.3	26.4	22.5
income (30000 to 59999)	32.5	29.3	35.2
income (60000 to 99999)	27.0	24.8	28.9
income (100000 to 149999)	11.1	13.4	9.2
income (>=150000)	5.1	6.1	4.2

Figure 3.1 – Responses to digital ads and data collection procedures – histograms



Tables 3.4 and 3.5 show summary statistics of the attributes of participants, and for their level of engagement with Google and YouTube. The statistics are shown for all participants, as well as separately for the participants of each of the two groups. They mainly suggest that participants' attributes do not differ significatively among the groups. Indeed, the p-values reported in Table 3.4 show that it is not possible to reject the null hypothesis that the mean attributes of both groups of participants are equal, but for variable *imp_exp*[10]. Furthermore, a comparison of the demographic characteristics of the participants of both groups, shown in Table 3.5, corroborates the close similarity between them. These summary statistics confirm the success of the randomization procedure adopted in the experiment to assign participants between the two platforms (ZenVideos and YouTube), with the aim of avoiding strong, statically significant differences in their personal treats.

Summary statistics shown in Table 3.4 for the participants' perception of YouTube size, and their level of engagement with the online video service, and its parent digital platform (Google[11]), also confirm that participants widely perceive and use them as a major player in the online videos market, with a lot of users in the U.S. and among participants' family and friends. Participants of both groups consume on average four digital services provided by Google other than the YouTube service (e.g., Google Maps, Google Chrome, etc.). These results are important to our empirical design, which proposed to compare how the participants' responses to digital ads and data collection procedures vary between a major online video service (YouTube) and a

[10] Although the mean value of *imp_exp* differ between the two groups of participants, this unwanted characteristic of the sample does not interfere on the results of the analysis of the effect of the size and reach of the platform on the participants' responses to digital ads and data collection procedures, reported later in this Section. This is because, in the estimation models used (see equations 5.3 and 5.4), we control for the effects of this variable on the participants' responses.

[11] Technically, the digital platform is named as Alphabet, but it is more widely known among participants simply as Google. For this reason, the research used the term "Google" to refer for this platform in the survey.

small one (ZenVideos), as well as with the level of participants' engagement of the platform service provider.

3.3. Estimation models

This section specifies the estimation models used to identify associations between the size and reach of the online video platform provider, as well as the level of engagement of an internet user with the platform in other digital markets, and her tolerance to watch digital ads and have their data collected by the platform. As previously shown in this Section, internet users' responses should be related to attributes of the platform, of the digital ad, as well as of the users themselves (see Equations 3.1 and 3.2).

Through the survey experiment already detailed in this Section, online video users $i \in \mathrm{I}$ were exposed to four videos with one different digital ad $j \in \mathrm{J}$ inserted in each, of duration ad_dur_j and inserted in the position ad_pos_j of the videos. Then, four types of online video users' responses to digital ads were obtained: $adavoid\_affect_{i,j}$, $adavoid\_behav_{i,j}$, $adavoid\_cog_{i,j}$, and $adavoid_{i,j}$, which is the overall sum of the three types of ad avoidance measured. Also, the responses of online video users to data collection aspects were gathered and modeled by the variables $priv\_collect_i$, $priv\_import_i$, $priv\_misuse_i$, $priv\_safestor_i$, $priv\_share_i$, and $privacy_i$, which is the overall sum of the five aspects of privacy concerns measured, detailed in Tables 3.1 and 3.3.

The main objective of the estimation procedure was to investigate potential associations between variations in the online videos' platform str_plt_i used, and the users' levels of ad avoidance and concerns about privacy aspects. A second objective was to identify potential associations between the level of engagement of the users with the platform provider in other digital markets, captured by the variable $n\_serv\_goog_i$, and the level of users' tolerance to ads and data collection procedures.[12]

As suggested by the literature reviewed earlier in the Section, and considering the data collected by the survey experiment, we control for the effect of variations on the platform and on the level of engagement between the user and the platform in other markets. Also, we control variations in attributes of the digital ads, as well as by several other attributes of the participants. The full list of control variables, denoted as the vector of variables $\boldsymbol{ATTR}_i$, is detailed in Tables 3.1, 3.4, and 3.5. Equations (3.3) and (3.4) below present the estimation models used.

$$RESP_{i,j}^{v} = \varepsilon_i \exp\left(\alpha^v + \beta_0^v str\_plt_i + \beta_1^v ad\_dur_j + \beta_2^v ad\_pos_j + \boldsymbol{ATTR}_i \boldsymbol{\gamma}^v\right) \tag{3.3}$$

$$RESP_{i,j,str\_plt=1}^{v} = \epsilon_i \exp\left(\delta^v + \theta_0^v n\_serv\_goog_i + \theta_1^v ad\_dur_j + \theta_2^v ad\_pos_j + \boldsymbol{ATTR}_i \boldsymbol{\omega}^v\right) \tag{3.4}$$

In equations (3.3) and (3.4), $RESP_{i,j}^{v}$ may be either of the nine response variables already detailed, with the superscript v indicating each one. The exponential functional form is the most popular specification when the response variables receive only zero or strictly positive values, and follow an exponential, or a normal distribution (see Figure 3.1). The use of a simple, linear model in this case would suffer from allowing negative outputs of the estimated model, what would be inconsistent with the data observed (Wooldridge, 2010, page 723 and 724).

The coefficients of interest are β_0^v, and θ_0^v, the semi-elasticities of $RESP_{i,j}^{v}$ and $RESP_{i,j,str\_plt=1}^{v}$ with respect to str_plt_i and $n\_serv\_goog_i$. In other words, they measure the

[12] As the platform ZenVideos were created only for the survey experiment, this secondary assessment was made only with participants who were assigned to watch the videos on Google's YouTube.

average marginal effect on the level of online video users' ad avoidance and concerns with data collection procedures associated with variations in the size and reach of the platform service provider, and in the level of engagement between the user and the platform.

This empirical approach has some intrinsic limitations. First, our data do not allow us to control all the characteristics of the ads that may affect users' tolerance to them. For example, platforms with bigger engagement with the end users can customize the ads shown to each user based on the data collected, to make the ads more interesting for the users. Also, our data does not allow us to control all the users and platform attributes, like time-varying factors, which may affect the users' responses. Examples are cases of data breaches, which may affect user's concerns to privacy issues in the following months, and improvement in the quality of the video content offered, or in the service interface of each platform, which may make users more, or less tolerant to ads and data collection procedures. The implications of such limitations on our empirical approach to the interpretation of the estimation results are discussed in the following sub-section.

3.4. Empirical Results

Table 3.6 and 3.7 show results of the estimation of the models specified by equations (3.3) and (3.4), respectively, using the data collected on the survey experiment already described in this Section. Table 3.6 reports estimates for the impact of the streaming platform on the types of ad avoidances that were measured. Table 3.7 reports estimates for the impact of the level of engagement of participants with Google in other markets, on the types of ad avoidances measured only among the participants who watched the videos and digital ads on YouTube. Columns (1), (4), (7), and (10) of both tables report estimates calculated using the traditional Poisson quasi-maximum likelihood estimator (QMLE). This procedure gives estimates of the effects of each independent variable on the mean value of the output variable, or, in other words, how the mean value of the ad avoidances measured varies with variations on each independent variable included in the models.

However, one would expect that the effects of variations in the digital platform, and in the level of engagement between the participant and the platform in other markets, on the ad avoidances measured are different among participants with high or low ad avoidance. For example, the effect of variations in the streaming platform, or in the level of engagement with the platform, may be lower for online video users that have low levels of ad avoidance, when compared with those more sensitive to digital ads. If this was true, the estimated partial effects of variations in explanatory variables on the mean value of the ad avoidances might mask different effects in different segments of the ad avoidance distribution.

To investigate the effects of the relevant covariates on features of the ad avoidance distribution other than the mean (for example, in different quantiles), a quantile regression (QR) estimator was used (Wooldridge, 2010). In these estimations, instead of using the exponential models specified in equations (3.3) and (3.4), we use linear model specifications with log-transformed dependent variables, to allow caparison between the resulting estimates and those obtained using the Poisson QMLE estimator. These estimates are reported in Table 3.6 and 3.7 for the quantiles 25% and 75%.

Finally, and for brevity, estimates of just five out of the eighteen control variables used in the estimations are reported in the table. They are the two attributes of the digital ads (ad duration and ad position), and three of the sixteen participant attributes (usage of YouTube, taste for sports, and importance of ads). Table I.1 in the Appendix I of this paper reports the estimates of all the eighteen control variables used in the analysis reported in column (1), as an example, to allow the review of the full list of same control variables included in all the estimations reported in Tables 3.6 and 3.7.

The results show a negative, statistically significant association between platform size and all types of ad avoidance. In other words, the results suggest that the higher the size, or the market share of the platform, the lower a user's ad avoidance or nuisance cost to digital ads, even after controlling for digital ads attributes and participant's attributes. The mean overall ad avoidance of the survey participants who watched the videos on the incumbent platform (YouTube) is 6.55% lower than of the participants who watched through the small platform (ZenVideos), with results statistically significant at the 1% level, and with a 95% confidence interval of [-10.3%, -2.76%]. These results are also consistent for all three types of ad avoidances that were investigated. Mean affective ad avoidance is 6.2% lower for YouTube users, while the mean behavioral ad avoidance is 4.13% lower, and the mean cognitive ad avoidance 10% lower. The results support the assumption made in Section 3 of this paper that participants' nuisance costs of watching ads are lower the higher the size and reach of the platform (see Equation 3.7).

The investigation of the effects of platform variation on the quantiles of the ad avoidances distributions suggests that the impact is higher in magnitude for participants with high levels of ad avoidances. Although the effects on the quantiles 25% and 75% of the overall ad avoidance do not differ significatively with respect to the effect on the mean (7.59% and 5.10%, respectively), the results are quite different for the three types of ad avoidances analyzed in separate. The effect of platform variation on the 25% quantile of all the three types of ad avoidances are not statistically different than zero, while the 75%

quantile of the affective ad avoidance, and of the behavioral ad avoidance are 5.69% and 4.62% lower, respectively, among participants who watched the videos through the YouTube platform, when compared to those that watched through ZenVideos.

Table 3.6 – Results of the Poisson estimation – Effects of variance on the streaming platform

Dependent variable	Ad Avoidance			Affective Ad Avoidance		
Model	(1)	(2)	(3)	(4)	(5)	(6)
Method	P-QLME	QR25%	QR75%	P-QLME	QR25%	QR75%
Str. Platform	-0.0655***	-0.0759**	-0.0510***	-0.0620***	-0.0251	-0.0569***
	(0.0193)	(0.035)	(0.0167)	(0.0204)	(0.0307)	(0.0171)
Ad duration	-0.0048***	-0.0074***	-0.0039***	-0.0053***	-0.0053***	-0.0030***
	(0.0014)	(0.0022)	(0.0012)	(0.00147)	(0.00198)	(0.00115)
Ad position	0.207***	0.296***	0.157***	0.255***	0.313***	0.182***
	(0.0248)	(0.0364)	(0.0206)	(0.0261)	(0.0365)	(0.0237)
Use of YouTube	-0.0506***	-0.0695***	-0.0271***	-0.0550***	-0.0835***	-0.0336***
	(0.0105)	(0.0179)	(0.0092)	(0.0112)	(0.0156)	(0.0083)
Taste for sports	-0.0788***	-0.108***	-0.0538***	-0.0821***	-0.0996***	-0.0517***
	(0.0096)	(0.0188)	(0.0078)	(0.0102)	(0.0169)	(0.0080)
Import. of Ads	0.0536***	0.0577***	0.0505***	0.0636***	0.0847***	0.0613***
	(0.0115)	(0.0173)	(0.0093)	(0.0123)	(0.0159)	(0.0093)
Observations	2120	2048	2048	2120	2000	2000

Dependent variable	Behavioral Ad Avoidance			Cognitive Ad Avoidance		
Model	(7)	(8)	(9)	(10)	(11)	(12)
Method	P-QLME	QR25%	QR75%	P-QLME	QR25%	QR75%
Str. Platform	-0.0413**	0.0463	-0.0462***	-0.100***	-0.0786	0.0000
	(0.0193)	(0.0349)	(0.0134)	(0.0265)	(0.0727)	(0.0151)
Ad duration	-0.0039***	-0.0059**	-0.0025***	-0.0056***	-0.0004	0.0000
	(0.0014)	(0.0026)	(0.0009)	(0.0019)	(0.0053)	(0.0009)
Ad position	0.154***	0.172***	0.0963***	0.221***	0.0658	0.0000
	(0.0251)	(0.0436)	(0.018)	(0.034)	(0.0964)	(0.0214)
Use of YouTube	-0.0278***	-0.0345*	-0.00598	-0.0746***	-0.0781*	0.0000
	(0.0106)	(0.0187)	(0.00765)	(0.0139)	(0.0408)	(0.00873)
Taste for sports	-0.0758***	-0.0892***	-0.0471***	-0.0792***	-0.0888***	0.0000
	(0.00957)	(0.0172)	(0.00595)	(0.0131)	(0.0339)	(0.00945)
Import. of Ads	0.0514***	0.0808***	0.0521***	0.0454***	0.0707**	0.0000
	(0.0111)	(0.0219)	(0.00782)	(0.0162)	(0.0348)	(0.00806)

Observations	2120	1978	1978	2120	1840	1840

Columns report results of Poisson QLME estimations of the effects of variations of explanatory variables on the mean of the output variables, as well as on their 25% and 75% quantiles.

For quantile regression estimates reported, outcome variables were log transformed.

Robust standard errors are reported in parentheses.

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

The partial effects of some digital ads and participant attributes on ad avoidances are also interesting to discuss. For example, although the effects of an increase in the ad duration on the levels of ad avoidance are negative (between 0.3% and 0.6% for each additional second), the greater the relevance of ads duration to the participant's decision on which streaming platform to use, the greater the participants ad avoidance levels. A reasonable explanation to these incongruent results is that although the participants consider that longer ads impede them to consume the relevant content, longer ads may have more room to catch the user's attention and interest. However, these results are not conclusive, as only three ad durations were tested in this experiment (5s, 15s, and 30s).

Digital ads placed in the middle of the videos are associated with a 15.4% higher mean overall ad avoidance than when the ads are placed at the beginning of the video, confirming early studies already reviewed in this Section. This effect is even greater for the mean affective ad avoidance, which is 25.5% higher for ads placed in the middle of the ad. In another interesting result, ad avoidances are consistently lower the higher the frequency of participants usage of YouTube, suggesting that the previous experience with a digital ads based online videos platform reduces the harm of ads to internet users regardless of the platform, a result also consistent with the literature reviewed. Finally, the negative associations found between the taste for sports videos (the theme of all the four videos watched by each participant), and the ad avoidance levels suggest that the interest of the user to the video content attenuates the disutility generated by the ads.

Table 3.7 brings results estimated only among participants who watched the videos on the YouTube platform. The objective of performing these estimations was to assess the effects on the levels of ad avoidance that can be associated with the participants' level of engagement with YouTube's parent platform, Google, in other digital markets. The estimation methods were the same used in the models reported in Table 3.6, as well as the control variables. Results found for the control variables were omitted for brevity.

Table 3.7 – Results of the Poisson estimation – Effects of engagement with Google in other markets

Dependent variable	Ad Avoidance			Affective Ad Avoidance		
Model	(1)	(2)	(3)	(4)	(5)	(6)
Method	P-QLME	QR25%	QR75%	P-QLME	QR25%	QR75%
Number of Google Services	-0.0212***	-0.0299***	-0.0206**	-0.0102	0.0051	-0.0165**
	(0.0078)	(0.0112)	(0.0080)	(0.0084)	(0.0157)	(0.0073)
Observations	1136	1089	1089	1136	1060	1060

Dependent variable	Behavioral Ad Avoidance			Cognitive Ad Avoidance		
Model	(7)	(8)	(9)	(10)	(11)	(12)
Method	P-QLME	QR25%	QR75%	P-QLME	QR25%	QR75%
Number of Google Services	-0.0303***	-0.0535***	-0.0187***	-0.0214*	-0.0176	-0.0346***
	(0.0079)	(0.0128)	(0.0054)	(0.0111)	(0.0237)	(0.0053)
Observations	1136	1050	1050	1136	965	965

Estimations were performed only among participants who watched the videos on the YouTube platform.
Columns report results of Poisson QLME estimations of the effects of variations of explanatory variables on the mean of the output variables, as well as on their 25% and 75% quantiles.

For quantile regression estimates reported, outcome variables were log transformed.

Robust standard errors are reported in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

The reported estimates suggest that the higher the number of digital services consumed by participants from Google (other than YouTube), the lower their level of ad avoidance. The mean overall ad avoidance of participants is 2.12% lower for each other digital service the participant consumes, with the results statistically significant at the 1% level, and a 95% confidence interval of [-3.65%, -0.58%]. Similar results are found for the mean affective ad avoidance, behavioral ad avoidance, and cognitive ad avoidance, which are 1.02%, 3.03%, and 2.14% lower for each other digital service consumed, respectively. These results also corroborate the assumption made in Section 2 of this paper that the participants' nuisance costs of watching ads (their tolerance to ads) is lower the higher the level of engagement between the platform and the participant in other digital markets.

Analyzing the results of the quantile regressions, is it possible to also note that, although the effect of a higher participant – platform engagement on 25% and 75% quantiles of the overall ad avoidance are virtually the same (-2.99% and -2.06%, respectively), some important variation is found for the three different types of ad avoidances. For the affective ad avoidance, and the cognitive ad avoidance, the effects of the level of engagement on quantile 25% are not statistically different than zero, while are highly statistically significant on quantile 75% (-1.65% and 3.46%, respectively). On the other hand, the effect on quantile 25% of the behavioral ad avoidance is almost three times higher than the effect on quantile 75% (-5.35%, and -1.87%, respectively), suggesting that no strong conclusions can be made by comparing the effects on the different segments of the ad avoidances' distributions.

Table 3.8 shows results of the Poisson QLME estimation of the effects of platform, and engagement variations on the mean participants' responses regarding data privacy concerns. In the estimation models (1) to (6), the explanatory variable of interest is the streaming platform in which the participant watched the videos. In the other models, this explanatory variable is replaced by the one which measures the number of Google digital services used by the participant other than YouTube. Also, models (7) to (12) were estimated using only data of participants that used the YouTube platform in the experiment. For all models, the same control variables included in Table I.1 were used, but the variables which capture attributes of the digital ads (ad duration, and ad position). The exclusion of these two variables was done because the privacy related survey is administered once per participant, and so the answers do not vary with the attributes of the ads.

Table 3.8 – Results of the Poisson estimation – Effects of platform and engagement on privacy concerns

Dependent variable	Overall Privacy	Data collection	Privacy concerns	Misuse of data	Data storage	Data sharing
Model	(1)	(2)	(3)	(4)	(5)	(6)
Str. Platform	-0.0074	-0.0385**	-0.0322**	0.0281**	0.0213	-0.0156
	(0.0110)	(0.0157)	(0.0127)	(0.0128)	(0.0160)	(0.0143)
Observations	2120	2120	2120	2120	2120	2120
Model	(7)	(8)	(9)	(10)	(11)	(12)
Number of Google Services	-0.0113***	-0.0005	-0.0032	-0.0014	-0.0312***	-0.0215***
	(0.0041)	(0.0059)	(0.0055)	(0.0045)	(0.0061)	(0.0055)
Observations	1136	1136	1136	1136	1136	1136

Columns report results of Poisson QLME estimations of the effects of variations of explanatory variables on the mean of the output variables.

The same control variables included in Table III.1 are presented in all the twelve models reported in this table, but the variables which capture attributes of the digital ads (ad duration, and ad position), as the privacy related survey is administered once per participant, after her have watched all the videos.

Robust standard errors are reported in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

The estimates reported in Table 3.8 suggest that the higher the size and reach of the platform, and the level of engagement between the platform and the user in other digital markets, the lower the user's privacy concerns. Although the overall data privacy concerns of the experiment participants are note related to the platform they used, the level of harm created when participants' data is collected without permission is 3.85% lower among participants which used the YouTube platform, when compared to those who used ZenVideos, a result statistically significant at the 1% level.

Participants who used the YouTube platform reported a lower importance of data privacy concerns for their choice of platform. Their levels of concern about misuse of personal data were 3.22% and 2.81% lower. On the other hand, no statistically significant effects were found for the effects of platform variation on participants' concerns with data storage and sharing. Furthermore, we found that the overall privacy concerns of the experiment participants who were assigned to use the YouTube platform are 1.13% lower for each digital service they use from Google other than YouTube. The effect is even higher for the participants' concerns about the risk that personal information might not be safely stored, or shared without permission, which are 3.12% and 2.15% lower per each other Google digital service used.

3.5. Discussion

The results of the survey experiments suggest that the higher the size, or the market share of a digital platform, the lower the ad avoidance and the privacy concerns of their users, after controlling for the attributes of the participants and of the digital ads. A deeper investigation of the effects of platform variation on quantiles of the ad avoidance distributions allowed us to conclude that this association is higher in magnitude for participants with high levels of ad avoidance. Also, the results of our survey experiment suggest that the higher the number of other digital services of the same digital platform consumed by an online videos user, the lower their levels of ad avoidance and data privacy concerns with respect to that platform.

These results provide empirical grounding for the assumptions made in Section 2 about the proportionally inverse relationship between the user's nuisance cost to digital ads and data privacy concerns, and the market share of the platform and the number of other markets where the platform is present (see Equations 2.7 and 2.8). However, some limitations of this research should be recognized. First, our experimental design just included two platforms, a well-known incumbent, and an unknown, small platform created just for the experiment. This set up does not allow us to control for characteristics of digital platforms other than their market share. Differences in the participants ad avoidance and data privacy concerns for each platform may not be as significant if YouTube were compared with a middle-sized platform, or with a group of platforms of different market sizes. Further research should investigate such relationships with a wider set of platforms.

Also, the relationship between the level of engagement of users with the platform in other markets, and their responses to digital ads and data privacy concerns should be investigated for platforms other than Google, to allow further generalization of the results. Finally, it is important to note that the experiment design focused on investigating the nature of the reactions of online video users to digital ads (in video format). Although this is a common case set up to represent users' daily interactions with digital ads and data collection procedures, the investigation of these relationships in other ads-based services, like social media and search engines, for example, should be done before generalizing our results to the entire digital economy.

Despite of these limitations, the results of the survey experiment generated theoretically and methodologically robust findings to establish a possible path for policymakers and competition authorities that are investigating the channels through which big digital platforms may exploit their market power. It reveals scenarios in which platforms could earn supra-normal profits by collecting more than the optimal level of data and inserting more than the optimum level of digital ads. Along with the conceptual models proposed in Section 2 of this paper, these empirical results suggest that big, multi-market digital platforms can collect more data and insert more ads on their digital services, because their end users are more tolerant to these strategies than the users of smaller, or single-market platforms. An above-equilibrium level of digital ads and data collection procedures may reduce the utility that the end users could attain in a competitive scenario. It should also represent a competitive advantage for incumbent big techs, which can hardly be overcome by market-specific, competition policy and antitrust remedies.

On the other hand, our results may also suggest that concentration in some digital markets is welfare-enhancing. For example, keeping the level of ads and data collection procedures the same throughout the online videos' platforms, these sources of disutility would generate less harm to the welfare of end users if a big, multi-market incumbent dominated the market, than if it is served equally by several platforms under perfect competition. The conclusion has implications for the adoption of ex ante versus ex post competition policies to promote competition for the incumbent, digital platforms, as discussed in Prado and Bauer (2023).

This research may also inform competition authorities on the design of tools to assess market power, and to delineate the boundaries of relevant, digital markets. For example, empirical investigations of end user responses (in terms of ad avoidance and privacy concerns) to small increases in the level of digital ads inserted, or in the level of data collected or shared by a digital platform could use this approach.

4 – CONCLUDING REMARKS AND FUTURE WORK

This paper made original contributions to the research literature on platform economics. Building on recent developments in applied industrial organization theory, regulatory economics, and econometric methods, it expands the knowledge frontier of market power assessment in digital markets. The first contribution is the development of a conceptual framework for the assessment of market power in situations when large digital platforms are present in several, interrelated digital markets. This scenario poses several challenges to traditional methods of market power assessment, which typically rely on market-specific approaches.

A second contribution is the design and implementation of a theoretically and methodologically robust, empirical path for policymakers and competition authorities investigating the channels through which big digital platforms may exploit their market power. A survey, experimental research design was used to assess the relationship between online video platforms size and multi-market presence, and the tolerance of their users to digital ads and data collection procedures.

The proposed conceptual framework for market power assessment revealed the weaknesses of the prevailing approaches to market power analysis, which pay too little attention to multi-market presence. The conceptual analysis showed that market-specific, pro-competitive remedies may not assure enough incentives to entry digital markets. Incumbent platforms that are present in several digital markets experience a more inelastic demand with respect to variations in the level of digital ads, data collection, and price of their digital services. To capture these characteristics of platform markets with large players, a multi-market, coordinated analysis is needed. Big digital platforms will have to be targeted by pro-competitive remedies in all markets in which they are present at once.

Furthermore, the results of the online survey experiment suggest that a high market-share, and multi-market presence, make end users more tolerant to digital advertisements and data collection procedures embedded in most of their digital services. This frees large multi-market platforms to embed an above-equilibrium level of digital ads and data collection procedures in their services. On one hand, this may reduce the utility that the end users could attain in a competitive scenario. It should also represent a competitive advantage for incumbent big techs, as it would reduce the likelihood that their end users switch to smaller competitors even when those offer services with less ads and data collection (two well-known sources of disutility for end users). On the other hand, these results may also suggest that concentration in some digital markets is welfare-enhancing, as these sources of disutility would generate less harm to the welfare of end users if the market were dominated by a big, multi-market incumbent platform, than if it is served equally by several platforms under perfect competition.

These findings contribute to the current debate on methodologies to objectively measure the market power of digital platforms that do not charge a price from users. Section 2 of this paper showed that, when the users' nuisance costs of watching ads depend on the level of their engagement with the platform in other digital markets, a relationship suggested by the results of this experiment, the assessment of market power should consider the platform position in all markets where the platform is present. Also, the results shed additional light on the mechanisms through which big digital platforms can leverage their market power across several digital markets, as well as help informing the debate on how to assess market power in the digital economy and which sort of regulatory remedies could be effective to foster competition.

Finally, although this work has addressed a range of relevant topics that have advanced knowledge boundaries on platform economics and policy, several areas would benefit from additional research. For example, in the investigation of the influence of platforms size, and multi-market presence, on the nuisance costs of end users to digital ads and data collection procedures, further research should investigate such relationships with a wider set of platforms, to allow one controlling for a greater variety of characteristics of digital platforms.

Also, future research may expand the experiment to investigate the relationship between the level of engagement of users with the platform in other markets, and their responses to digital ads and data privacy concerns for platforms other than Google, to allow further generalization of the results. In the same vein, although online video platforms are a common case set up to represent users' daily interactions with digital ads and data collection procedures, the investigation of these relationships in other ads-based services, like social media and search engines, for example, should contribute to allow generalizing our results to the entire digital economy.

BIBLIOGRAPHY

Acquisti, A., and Spiekermann, S. (2011). Do interruptions pay off? Effects of interruptive ads on consumers' willingness to pay. Journal of Interactive Marketing, 25(4), 226-240.

Armstrong, M. (2006). Competition in two-sided markets. The RAND Journal of Economics, 37(3), 668–691.

Baek, T. H., and Morimoto, M. (2012). Stay away from me. Journal of advertising, 41(1), 59-76.

Baumol, W. J., Panzar, J. C., and Willig, R. D. (1982). Contestable Markets and the Theory of Industry Structure. Harcourt Brace Jovanovich.

Berry, S. T. (1994). Estimating Discrete-Choice Models of Product Differentiation. The RAND Journal of Economics, 25(2), 242. https://doi.org/10.2307/2555829

Bounie, D., Valérie, M., and Quinn, M. (2017). Do you see what I see? Ad viewability and the economics of online advertising. Ad Viewability and the Economics of Online Advertising. Available at https://www.lcii.eu/wp-content/uploads/2017/02/Bounie-Morrisson-Quinn-Ad-viewability-and-the-economics-of-online-advertising.pdf

Cho, C.-H., and Cheon, H. J. (2004). Why Do People Avoid Advertising on the Internet? Journal of Advertising, 33(4), 89–97. https://doi.org/10.1080/00913367.2004.10639175

Clark, J.M. (1940). Toward a concept of workable competition. American Economic Review, 30(2), 241-256.

Crémer, J., Montjoye, Y.-A. de, Schweitzer, H. and Directorate-General for Competition - European Commission (2019). Competition policy for the digital era. Retrieved from http://publications.europa.eu/publication/manifestation_identifier/PUB_KD0419345ENN

De Corniere, A. and G. Taylor (2014). Integration and Search Engine Bias. Rand Journal of Economics, pp. 576-597.

Duffett, R., Petroșanu, D. M., Negricea, I. C., and Edu, T. (2019). Effect of YouTube marketing communication on converting brand liking into preference among millennials regarding brands in general and sustainable offers in particular. Evidence from South Africa and Romania. Sustainability, 11(3), 604. https://doi.org/10.3390/su11030604

Dukes, A., and Gal–Or, E. (2003). Negotiations and exclusivity contracts for advertising. Marketing Science, 22(2), 222-245.

Fan, M., Kumar, S., and Whinston, A. B. (2007). Selling or Advertising: Strategies for Providing Digital Media Online. Journal of Management Information Systems, 24(3), 143–166. https://doi.org/10.2753/MIS0742-1222240305

Flew, T., and Martin, F. R. (Eds.). (2022). Digital platform regulation: Global perspectives on Internet governance. Palgrave Macmillan.

Frade, J. L. H., de Oliveira, J. H. C., & Giraldi, J. D. M. E. (2021). Advertising in streaming video: An integrative literature review and research agenda. Telecommunications Policy, 45(9), 102186.

Gillespie, T. (2018). Custodians of the Internet: Platforms, Content Moderation, and the Hidden Decisions That Shape Social Media. Yale University Press.

Hayek, F. A. (1949). The meaning of competition. In F. A. v. Hayek (Ed.), Individualism and economic order. Routledge.

Joa, C. Y., Kim, K., and Ha, L. (2018). What makes people watch online in-stream video advertisements? Journal of Interactive Advertising, 18(1), 1–14. https://doi.org/10.1080/15252019.2018.1437853

Johnson, L. (2022). Here's How much ads cost on Google, Meta, Amazon, TikTok, and Snap. Business Insider. Available at https://www.businessinsider.com/digital-ad-prices-are-skyrocketing-in-2022-2

Johnson, V. L., Kiser, A., Washington, R., and Torres, R. (2018). Limitations to the rapid adoption of M-payment services: Understanding the impact of privacy risk on M-Payment services. Computers in Human Behavior, 79, 111–122. https://doi.org/10.1016/j.chb.2017.10.035

Krämer, B. (2017). Populist online practices: the function of the Internet in right-wing populism, Information, Communication & Society, 20:9, 1293-1309, DOI: 10.1080/1369118X.2017.1328520

Laffont, J.-J., and Tirole, J. (1999). Competition in telecommunications. MIT Press.

Lerner, A. P. (1934). The Concept of Monopoly and the Measurement of Monopoly Power. The Review of Economic Studies. 1 (3): 157–175. doi:10.2307/2967480

Loeb, W. (2021). The Rising Costs of Digital Advertising Will Force Spending Shifts. Forbes - Business - Retail. Available at https://www.forbes.com/sites/walterloeb/2021/08/04/rising-costs-of-digital-advertising-will-force-spending-shifts/?sh=2a2612245a7c

Logan, K. (2013). And now a word from our sponsor: Do consumers perceive advertising on traditional television and online streaming video differently? Journal of Marketing Communications, 19(4), 258–276. https://doi.org/10.1080/13527266.2011.631568

Mansell, R., and Steinmueller, W. E. (2020). Advanced introduction to platform economics. Edward Elgar Publishing.

Martin, K. (2018). The penalty for privacy violations: How privacy violations impact trust online. Journal of Business Research, 82, 103–116. https://doi.org/10.1016/j.jbusres.2017.08.034

Nevo, A. (2000). A Practitioner's Guide to Estimation of Random-Coefficients Logit Models of Demand. Journal of Economics & Management Strategy, 9: 513-548. https://doi.org/10.1111/j.1430-9134.2000.00513.x

Papies, D., Eggers, F., and Wlömert, N. (2011). Music for free? How free ad-funded downloads affect consumer choice. Journal of the Academy of Marketing Science, 39(5), 777-794.

Petit, N., and Teece, D. J. (2021). Innovating big tech firms and competition policy: Favoring dynamic over static competition. Industrial and Corporate Change, 30(5), 1168-1198.

Prado, T. S. (2023). Digital Platform Economics: Essays on Innovation Effects, Assessment of Market Power, and Policy Approaches to Promote Competition. Ph.D. Dissertation, Michigan State University. Available at https://quello.msu.edu/wp-content/uploads/2023/04/Prado-2023_Dissertation.pdf

Prado, T. S., and Bauer, J. M. (2023). Safeguarding Competition in Digital Markets: A Comparative Analysis of Emerging Policy and Regulatory Regimes. Working Paper available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4137588

Prasad, A., Mahajan, V., and Bronnenberg, B. (2003). Advertising versus pay-per-view in electronic media. International Journal of Research in Marketing, 20(1), 13–30. https://doi.org/10.1016/S0167-8116(02)00119-2

Rochet, J.-C., and Tirole, J. (2003). Platform Competition in Two-Sided Markets. Journal of the European Economic Association, 1(4), 990–1029. https://doi.org/10.1162/154247603322493212

Rolnik, Guy, Julia Cagé, Joshua Gans, Ellen Goodman, Brian Knight, Andrea Prat, Anya Schiffrin, and Prateek Raj (2019). "Protecting journalism in the age of digital platforms." Committee for the Study of Digital Platforms Media Subcommittee. Chicago: Stigler Center for the Study of the Economy and the State. University of Chicago Booth School of Business.

Rosen, J. (2011). The Deciders: The Future of Privacy and Free Speech in the Age of Facebook and Google. Fordham Law Review, 80, 1525.

Schumpeter, J. A. (1942). Capitalism, socialism, and democracy. Harper.

Scott-Morton, F. M., Bouvier, P., Ezrachi, A., Jullien, B., Katz, R., Kimmelman, G. , Melamed, A. , Morgenstern, J. (2019). Committee for the Study of Digital Platforms: Market Structure and Antitrust Subcommittee - Report. Stigler Center for the Study of the Economy and the State, University of Chicago Booth School of Business, Chicago.

Strahilevitz, L., Cranor, L. F., Marotta-Wurgler, F., Mayer, J., Ohm, P., Strandburg, K., and Ur, B. (2019). Committee for the Study of Digital Platforms: Privacy and Data Protection Subcommittee - Report. Stigler Center for the Study of the Economy and the State, University of Chicago Booth School of Business, Chicago.

Strandburg, K. J. (2013). Free Fall: The Online Market's Consumer Preference Disconnect. University of Chicago Legal Forum: Vol. 2013, Article 5. Available at: http://chicagounbound.uchicago.edu/uclf/vol2013/iss1/5

Tirole, J. (1988). The theory of industrial organization. MIT Press.

Tucker, C. E. (2012). The economics of advertising and privacy. International journal of Industrial organization, 30(3), 326-329.

U.K. Competition and Markets Authorithy (2020). Online platforms and digital advertising: Market study final report. Competition and Markets Authority. Retrieved on December 3, 2020, from https://www.gov.uk/cma-cases/online-platforms-and-digital-advertising-market-study#final-report

Vakratsas, D., and Ambler, T. (1999). How advertising works: what do we really know? Journal of marketing, 63(1), 26-43.

Wang, Y., and Herrando, C. (2019). Does privacy assurance on social commerce sites matter to millennials? International Journal of Information Management, 44, 164–177. https://doi.org/10.1016/j.ijinfomgt.2018.10.016

Wooldridge, J. M. (2010). Econometric analysis of cross section and panel data. Cambridge, MA: MIT press.

Zhang, K., and Sarvary, M. (2015). Differentiation with user-generated content. Management Science, 61(4), 898-914.

APPENDIX I – Detailed results of Section 3

Table III.1 – Detailed results of the Poisson QMLE estimation of Column (1) of Table 3.6

adavoid	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
str_plt	-.0655011	.019306	-3.39	0.001	-.1033403	-.027662
ad_dur	-.0048435	.0014064	-3.44	0.001	-.0075999	-.0020871
ad_pos	.2070461	.0248098	8.35	0.000	.1584199	.2556724
subs_youtube	.116159	.0282533	4.11	0.000	.0607836	.1715344
u_youtube	-.0505706	.0105045	-4.81	0.000	-.071159	-.0299822
pu_f_youtube	.0116169	.0106669	1.09	0.276	-.0092899	.0325237
pu_youtube	.0236212	.0168932	1.40	0.162	-.0094889	.0567313
sports	-.0788173	.0095553	-8.25	0.000	-.0975454	-.0600893
imp_ads	.0535514	.0115054	4.65	0.000	.0310013	.0761015
imp_exp	.0016677	.0118263	0.14	0.888	-.0215113	.0248468
imp_pric	.0664898	.0141676	4.69	0.000	.0387218	.0942577
imp_priv	-.0222188	.0108596	-2.05	0.041	-.0435033	-.0009343
imp_qual	-.0734795	.0160553	-4.58	0.000	-.1049473	-.0420117
income	.0231692	.0093817	2.47	0.014	.0047814	.0415569
age_gr	-.0314532	.0139117	-2.26	0.024	-.0587197	-.0041867
race						
Asian	.109571	.0809186	1.35	0.176	-.0490265	.2681685
Asian,Native Hawaiian or Pacific Islander	.0960317	.1592086	0.60	0.546	-.2160115	.4080749
Black or African American	-.030089	.0779579	-0.39	0.700	-.1828837	.1227057
Black or African American,Latino	-.0579398	.2589279	-0.22	0.823	-.5654292	.4495497
Latino	.1772357	.0747539	2.37	0.018	.0307208	.3237506
Latino,Asian	.1989512	.0983831	2.02	0.043	.0061238	.3917786
Native Hawaiian or Pacific Islander	.3562757	.0913122	3.90	0.000	.1773072	.5352443
Other	.0489011	.1537629	0.32	0.750	-.2524686	.3502708
Prefer not to answer	.1431566	.0879639	1.63	0.104	-.0292494	.3155626
White	.0305923	.0662318	0.46	0.644	-.0992196	.1604041
White,American Indian or Alaska Native	.220239	.0875579	2.52	0.012	.0486286	.3918494
White,Asian	.2618206	.1595607	1.64	0.101	-.0509126	.5745537
White,Black or African American	.131516	.0932413	1.41	0.158	-.0512335	.3142656
White,Black or African American,Latino	-.070353	.1461655	-0.48	0.630	-.3568321	.2161261
White,Latino	.0714063	.0857227	0.83	0.405	-.0966071	.2394196
White,Latino,Asian	.4822007	.0743771	6.48	0.000	.3364242	.6279772
nation						
Costa Rica	.1262486	.1718244	0.73	0.462	-.2105211	.4630183
France	-.2531809	.2294836	-1.10	0.270	-.7029605	.1965986
Hong Kong (S.A.R.)	.4448648	.198426	2.24	0.025	.0559571	.8337726
India	.8022957	.1679194	4.78	0.000	.4731796	1.131412
Japan	-.4601647	.2807529	-1.64	0.101	-1.01043	.0901009
Pakistan	.3084094	.1803354	1.71	0.087	-.0450414	.6618602
Romania	.4177145	.1676398	2.49	0.013	.0891464	.7462825
South Africa	.7809846	.1668423	4.68	0.000	.4539796	1.10799
Sweden	-.26322	.2424458	-1.09	0.278	-.7384051	.211965
Switzerland	.5772171	.1759776	3.28	0.001	.2323073	.9221268
United States of America	.3307438	.1636515	2.02	0.043	.0099929	.6514948
Viet Nam	-1.154727	.3137694	-3.68	0.000	-1.769703	-.53975
gend						
Male	.0771906	.02182	3.54	0.000	.0344242	.1199569
Other	-.1793482	.100364	-1.79	0.074	-.3760579	.0173616
geo						
Northeast	-.0764974	.0301095	-2.54	0.011	-.135511	-.0174838
South	-.1352174	.0258645	-5.23	0.000	-.1859109	-.0845238
West	-.0430671	.0278556	-1.55	0.122	-.097663	.0115289
_cons	1.609217	.1908386	8.43	0.000	1.23518	1.983253