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IFN Working Paper No. 1550, 2026

# **What is the Value of Attention? Supply and Demand Estimation of Attention in a Mobile App Setting**

Johan Orrenius

# What is the value of attention? Supply and demand estimation of attention in a mobile app setting

Johan Orrenius <sup>\*†</sup>

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## Abstract

I study the digital market for attention in a freemium mobile game where users choose between paying with money or by watching 30-second video ads. Using unique event-level data, I estimate consumers' supply elasticity of attention. In the aggregate, a one percent higher price increases the share of users watching videos as a payment by 2.2 percent. A substantial part is due to individual heterogeneity in tastes. When accounting for individual heterogeneity, the elasticity reduces to 0.5. The individual elasticities vary throughout the day, peaking in the evening. Complementing the unique data on each play made by users, I use data on the revenue to the gaming company from showing ads. The data is on an individual and daily level, allowing me to match the individual supply elasticity with the revenue from showing ads to the same individual. I find advertisers pay more to show ads to individuals who are less likely to use ads as their payment method. The effect is stronger among Android users than iOS users.

**Keywords:** Attention, Mobile games, Value of time

**JEL Codes:** D12 ,D83, J22, L82,

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# 1 Introduction

Consumers' attention is the hard currency of the digital economy. Consumers often pay for digital products with their attention by watching ads, rather than paying with money. The consumers' attention is then sold to advertisers through a real-time online auction.<sup>1</sup> The advertisers' demand for consumers' attention can be easily estimated, as it is sold in these markets. However, understanding consumers' disutility from spending time watching ads will allow us to find the supply of attention and understand other aspects of the advertisement-driven digital economy, as consumer supply, optimal pricing, and the effect of policy.

In this paper, I answer the research question: What is consumers' valuation of their attention? And what are the implications for the digital economy? I use a freemium product to understand users' tradeoffs between "paying" with attention and paying with money, and then estimate the elasticity of attention in monetary terms. By matching estimates of users' valuation of attention with the revenue from showing that user an ad, I investigate the efficiency of the attention market.

I study the value of attention in the context of a mobile game, where users are exposed to advertisements. In the literature, watching advertisements is an activity that requires attention (e.g., [Anderson & Jullien \(2015\)](#), [Newman \(2015\)](#)).<sup>2</sup> I elicit the Willingness to Pay to Avoid (WTPA) a 30-second video advertisement (*video*) in a mobile game and use it as my empirical measure of the value of attention.

In the mobile game, an individual can choose between paying with attention or with an in-game currency (*coins*). Mobile games are, to my knowledge, the only setting where the choice of payment method between money and watching ads is a choice to the consumer for each unit of the good they purchase, allowing for the estimation of their WTPA outside of a lab setting. Players are presented with two adjacent buttons: one for paying with *coins* and the other for watching an ad (*video*). The price in *coins* varies between situations, but the price in attention is always watching one *video*, establishing a relative price between *coins* and *video*. I can thus estimate consumers' supply elasticity of attention. Using panel data from individual purchases, I decompose the effect of price on payment method into within- and between-individual effects and examine differences throughout the day.

I find the elasticity of attention with respect to money to be 2.2 when considering the entire population. That is, an increase in the cost of paying with money by one percent leads to an increase in the usage of *video* as a payment method by 2.2 percent. Accounting for the considerable individual variation in the use of *video* to pay for the

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<sup>1</sup>The combined revenue from mobile apps globally is 300 billion Euros. Of these 300 billion Euros, 80 are revenues from advertisements in mobile games ([Statista 2024](#)).

<sup>2</sup>Similarly, practitioners such as the UK Competition and Markets Authority use the term in ([U.K. Competition and Markets Authority 2020](#)).

game with an individual fixed effects specification, the elasticity drops to 0.5. I find higher elasticities during afternoons and evenings than during mornings. Using a modeling approach, I estimate the Willingness to Pay to Avoid a 30-second ad to be 0.15 Euros, which amounts to 18 Euros per hour.

I establish a statistically significant correlation between the cost advertisers incur to reach an individual and that individual's valuation of their attention. A one-standard-deviation increase in the share of video used by the individual corresponds to a decrease of 0.15 standard deviations in the revenue from showing that individual a *video*.

I study the behavior of mobile game users in the trivia game QuizDuel.<sup>3</sup> The game is developed by MAG Interactive, known for its knowledge-based games, including quizzes and word puzzles. The data consists of users from France, Germany, and Sweden, spanning 9 weeks in the fall of 2022. The data records every payment made by users and the payment method used, either *video* or *coins*.

In addition to analyzing players' behavior, I study the gaming company's revenue from advertising. In the standard freemium setting, such as modeled in Sato (2019), consumers pay a monthly subscription fee to remove all ads during a month. However, in my setting, the consumer pays to remove a single ad, a payment model called micro-payments. Micro-payments enable me to match the average revenue from ads shown to a specific individual within a specific time period (the demand for attention) with that individual's payment behavior in the same time period (the supply of attention). This framework enables me to investigate the efficiency of the attention market.

Freemium products, such as this game, often have a substantial share of customers who never spend cash on the service. Such behavior can either indicate a low valuation of attention in general or a specific preference in the game setting.<sup>4</sup> Therefore, I focus on analyzing individuals who have made at least one payment with real money in the game. I will, however, analyze the main specification, including all types of players, as a robustness check. This group is referred to as converters in the industry and is the term I will use throughout the paper. Thereby, I can tie the estimates to real money.

Like goods, time is scarce, and consumers must choose how to allocate it. When spending time on an activity, the consumer forgoes other activities, creating an opportunity cost. When Becker formalized the value of time framework in his seminal paper (Becker 1965), he emphasized that the value of time is context-dependent. The value of time is different when you watch an ad versus waiting for the bus. At first glance, watching the 30-second *videos* studied in this paper can be seen as giving up time, but

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<sup>3</sup>Within the trivia category, it is one of the most popular games on both Apple's App Store and Google Play, from <https://www.similarweb.com/> accessed on the 6th of May 2024

<sup>4</sup>One example would be a mental rule to never pay, in order not to get addicted to the game.

it is better characterized as requiring attention.<sup>56</sup>

The value of attention varies by how much time and focus an individual spends on the ad, as well as the information transferred by the ad. Video advertisements emphasize the time component of consumers' valuation of attention further. By understanding consumer valuation of their attention in a video setting, we can also understand their valuation of time in our mobile setting.

We spend 4.8 hours each day on our phones.<sup>7</sup> Given that the day only has a limited amount of time, mobile use crowds out other economic activities, and the valuation of time spent online is therefore relevant not only in itself but also for the economy in general.

Advertisers are interested in converting consumers' attention into sales in the short or long run. Therefore, consumers' attention, not time, is valuable to the advertiser. My conceptual approach to measuring attention is that when watching the *video*, the users sell their attention on the attention market. Advertisers then buy the attention. Thus, we can study both supply and demand behavior in the attention market.<sup>8</sup> With this approach, my setting is different from the subscription structure, which is the most prevalent in freemium services. As my payments correspond to the removal of one ad, not all ads in a month, I can better match the supply and demand of attention.

I contribute to the literature in three main ways. First, the main contribution of this paper is to present a novel method for empirically estimating consumers' supply elasticity of attention in the digital economy. Using unique observation-level data from individual purchases in a mobile game, I can also consider individual heterogeneity. My estimation shows that attention has an elasticity of 2.2 when considering the entire population. Accounting for the large individual variation in the use of *video* to pay for the game with a fixed effects specification, the elasticity drops to 0.5.<sup>9</sup> The difference speaks to the heterogeneity of the player group and the varying intensity of play. Empirical estimates of the supply of attention are scarce. For example, previous literature has leveraged users' substitutability between services to empirically study consumers' supply of attention (Aridor 2025, Srinivasan 2023) or has studied the supply of attention in a subscription setting (Brynjolfsson et al. 2024, Goli et al. 2025). I complement these measures by presenting elasticities in monetary terms for avoiding one ad, which can be used as input in other models of the digital economy (Goolsbee

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<sup>5</sup>Watching a *video* interrupts your digital activity; it does not exclude any other activity, but reduces the attention you can spend on other activities, which is close to the definition of attention in psychology. In psychology, the lexicographic definition is: "Attention, in psychology, the concentration of awareness on some phenomenon to the exclusion of other stimuli" (McCallum 2022)

<sup>6</sup>Attention can also be a way to think about workers' productivity, see (Caplin, Andrew 2023).

<sup>7</sup>On average, individuals globally spend 4.8 hours on their phones per day (Data.ai 2023).

<sup>8</sup>An analogy is the labor market, where attention can be seen as labor, supplied by individuals and demanded by companies.

<sup>9</sup>On par with the intensive labor supply elasticity (Cahuc et al. 2014).

& Klenow 2006, Ghose & Han 2014).

Enache *et al.* (2023) employed a similar mobile app setting to investigate the effect of price increases on app usage and attention as a payment method, but at an aggregate level. However, I can decompose the aggregate effect into within- and across-individual effects. Such understanding of the distribution over individuals gives empirical inputs to models for pricing in the digital economy, such as the freemium model (Sato 2019) and purchases in online settings (Shiller & Waldfogel 2011)

Second, I can utilize heterogeneity in consumer valuation of attention to address the value of time literature, following Becker (1965). I find a higher price sensitivity during afternoons and evenings, in contrast to the literature on the value of waiting time (Buchholz *et al.* 2025, Goldszmidt *et al.* 2020), which finds a higher sensitivity during mornings.

Third, I match the supply of attention with the demand for attention, measured as the revenue from showing an ad. My results show that the price advertisers pay for consumers' attention is negatively correlated with the valuation individuals place on it. The digital economy is often a two-sided market as explored in the seminal theoretical paper by Roche & Tirole (2003). Other more recent extensions in a digital economics context are (Rysman 2009, Spulber 2019). By matching supply and demand and identifying a correlation, I provide empirical support for a largely theoretical literature.

The attention market is a type of information market as studied by Bergemann & Bonatti (2019). The impact of data access and privacy in the digital market is well understood, as demonstrated in (Bian *et al.* 2022, Aridor *et al.* 2025, Cheyre *et al.* 2023). Access to data on users enables targeted advertising, making their attention more valuable. I find that the relationship between users' supply valuation and demand for their attention, as measured by revenue, is stronger in Android than in iOS. Apps in Android have more data access than in iOS. The difference between Android and iOS indicates that there is an effect on data access in a novel way. Noteworthy is also how much smaller the average revenues from ads are compared to the estimated value of attention.

Other descriptions of the digital economy are highlighted by (Einav & Levin 2014, Athey *et al.* 2018, Yin *et al.* 2014, Ghose & Han 2014, Goolsbee & Klenow 2006, Allcott *et al.* 2020). I study a specific and growing part of the digital economy: the mobile game market. My estimates also complement other measures of attention, such as eye tracking in marketing research (Wedel 2017).

The paper proceeds as follows: In Section 1.2, I describe the setting and present descriptive statistics. In Section 1.3, I build a conceptual framework for the supply-side valuation of attention. In Section 1.4, I then estimate supply-side elasticities along different heterogeneity dimensions and match the supply-side individual behavior with

the demand for attention, measured as the revenue from showing an ad. In Section 1.5, I relate my findings to the ongoing policy debate on the digital economy. Then I conclude in Section 1.6.

## 2 Setting and Data

### 2.1 Setting

The setting is the trivia mobile game QuizDuel, developed by MAG Interactive. Each *game* is a sequence of 3 or more questions within one of multiple categories, such as history, geography, or cooking, in the language of your choice. My research utilizes data from France, Sweden, and Germany, where the game is popular and has a large user base.

To start a new game or progress after failing, players make payments. I refer to payment situations as *situations*, where the player can choose to pay with *coins* or *video*. The *coins* are the in-game currency, and the *video* is a 30-second-long rewarded video. The *video* option is displayed to the player before they progress, and they must click on it and watch it to receive the reward to continue playing, hence the name. I examine three different *situations*: Arena, StarStreak, and Pay to Continue, where the first two are games, and the last one is a feature in StarStreak that allows you to continue playing, even if you fail. The relative price of the *coin* to the *video* differs in various *situations*, and I will use this difference to estimate the elasticities between *coins* and *video*.

In all *situations*, the price if you pay with *coins* is different, as presented in Table 1, but the price if you pay by watching a *video* is always only one video. Players are gifted starts that are disregarded in the analysis<sup>10</sup> as they vary between the different *situations*. The variation in the relative price will be used to identify the elasticities between *coins* and videos.

The practical way the different payment methods are displayed to the player is presented in Figure 1, where they pay in either *coins* or *video*.

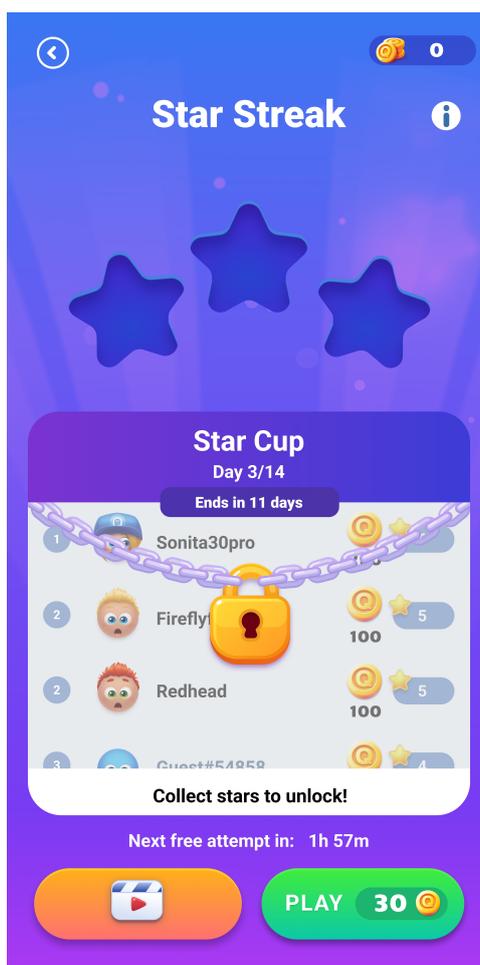
Before spending *Coins* in the game, they need to be purchased through the in-game store at an exchange rate. The exchange rate refers to the cost of *coins* in real money, and the relative price refers to the price for a *situation* in *coins* the player pays instead of watching a *video*. The exchange rate is approximately 1 Euro for 110 *coins*. The exchange rate will vary by country, operating system, and how many *coins* you buy.<sup>11</sup>

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<sup>10</sup>Each player gets some free plays per day, or daily rewards in the ticket currency. I, therefore, exclude the first plays in tickets, corresponding to the numbers rewarded.

<sup>11</sup>In the game, *coins* come in two different variations: coins and tickets, with the conversion rate that one ticket is 10 coins. Tickets are used to start the Arena *situations*, whereas the other two require coins. For consistency, I use the term *coins* and refer to the value in coins, as it is also the main currency you

Figure 1: A *situation*, where you would enter StarStreak



Notes: The screen facing the player when they want to play the game StarStreak. The player can pay with *coins* or *video*.

## 2.2 Data

The dataset is a record of all plays by individuals, as well as all transactions of coins for a sample of individuals. Throughout the paper, I will distinguish between converters and non-converters. Converters are individuals who made at least one purchase with real money in the game, either before or during the period studied. Non-converters are defined as the rest. The sample was selected to cover all individuals in France, Germany, and Sweden who are converters and a 10% sample of the players who are non-converters. The restriction was at the data provider's request to make the data extraction feasible.

The raw sample delivered consists of 144,773 individuals who used the QuizDuel app during the period of the 4<sup>th</sup> of September to the 5<sup>th</sup> of November in 2022. Some players who opened the app did not play any of the *situations* I study and are therefore

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buy with real money. Hence, the focus on the *situations* StarStreak, and Pay to Continue is warranted, to not contaminate my estimates with the different *coins*.

Table 1: Price to play a game in the different *situations*

Situation	Price in <i>coins</i>	Value in Euro
StarStreak	30	0.3
Pay to continue	25	0.25
Arena	10	0.1

Notes: The table presents the price to play a game in the different *situations*. The price is in *coins* and the value in Euro.

not included. The restriction of any play gives us a total of 97,461 individuals.

For the main specification, I restrict myself to converters and *situations* where *coins* in the main variant is the currency, giving me a total of 24,224 players. In the appendix, I use a specification including non-converters and *situations* when tickets are used.

To choose the sample in a transparent way, I accessed raw data from the game, but at a different time period. Different specifications were tested, all on a separate dataset. The process was used to reduce the risk of selecting the sample that gave the desired results while also understanding the data and testing the feasibility of different specifications. The iterative process resulted in the choices above.

The restrictions above make the sample less representative of the entire population of players. However, they aim to estimate the effect on the population that is of economic interest. By excluding individuals who never pay with money, I aim to capture the intensive margin of the supply elasticity, rather than contaminate the estimates with the well-documented zero-pricing effect (Newman 2015, Shampanier *et al.* 2007).

The decision to pay for a freemium product is influenced by many non-economic factors that do not relate to one's marginal willingness to pay to avoid ads. Including that large part of the sample would bias the results by allowing the extensive margin of paying at all to drive the results. The extensive margin is also of interest, but it would reduce the external validity of the economic interpretations.

Note that the exploratory analysis and choice of specification for this decision were done before access to the final raw sample.

In the dataset on revenues from advertisements to the gaming company, each observation is the average revenue from showing ads to a unique player. The data is available for a sub-sample of the players. For 18 days from the 19<sup>th</sup> of October to the 5<sup>th</sup> of November, I have the hourly average revenue to MAG from advertisers per individual. For the 13<sup>th</sup> to 26<sup>th</sup> of September, I instead have the daily average revenue from advertisers per individual. As not all individuals appear in both periods, I will aggregate the data to a daily average in the main specification. I then matched the

average revenue with the share of videos used by individuals on that date and the individual supply elasticity. This results in two datasets, one cross-sectional with one observation per individual. Having one observation per individual allows for matching the estimated individual elasticities with the average revenue. The other dataset is an unbalanced panel on the individual time date level, allowing for estimating the correlation between the share of video and average revenue per day using the within-individual variation.

## 2.3 Descriptive statistics

Table 2 shows summary statistics. The statistics are averages per individual of the individuals in the sample. Note that the median and mean of the variables differ to a large degree, indicating a skewed distribution. It is common knowledge in the industry that individual usage is heavy-tailed distributed.

Table 2: Summary statistics of the main sample

Statistic	Mean	Median	SD	Min	Max
Plays per individual	93.81	12	241.42	1	3063
Plays per individual and day	4.27	2.29	5.03	1	50.17
Share video	0.72	0.91	0.39	0	1

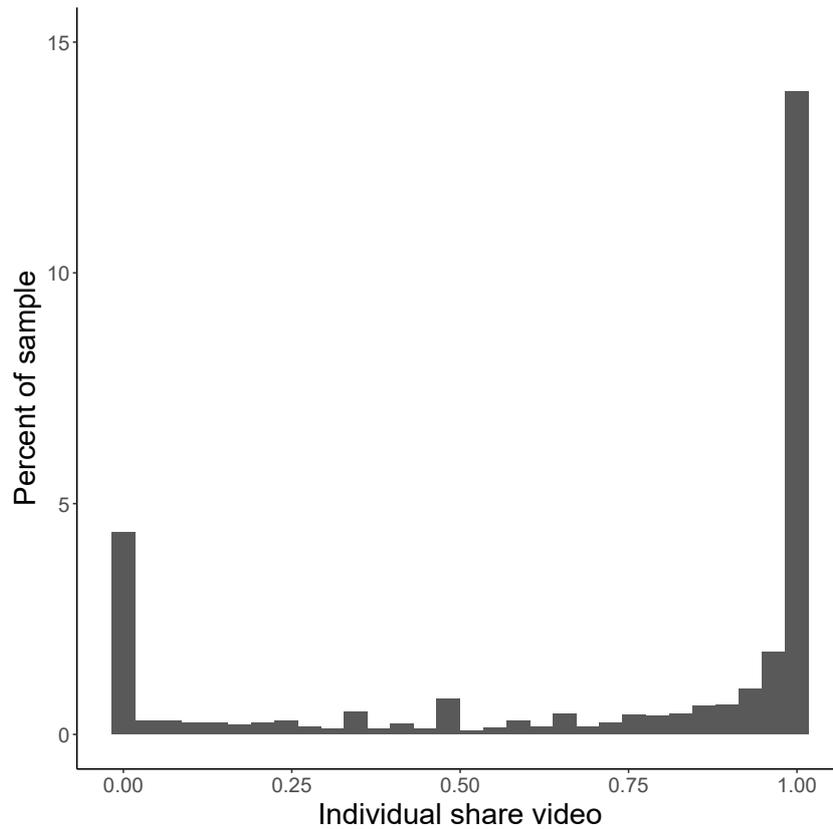
Notes: The table presents summary statistics of the individuals of the main sample. It is the total number of plays over the entire time period, the number of plays per active day, as well as the total share of videos as a payment method, per individual.

I first examine the individual variation in the share of *situations* paid with *video* for converters in Figure 2. A large number of individuals who only pay with *video*, corresponding to the value 1 in Figure 2, can be explained by either an extremely low valuation of one’s attention or a behavioral mechanism, where the individual has a mental rule to not buy anything in the game.<sup>12</sup> The large peak in zero usage of videos for converters can be seen as the opposite, a large valuation of their attention for converters.

I present data split by the platform and country in Table 3. Here, I include non-converters as well to illustrate the selection and to motivate the heterogeneity analysis over the groups. The two different platforms have a similar number of users, both in general and in shares that are in the sub-sample of converters. In the different countries, on the other hand, we see substantial differences. Germany is responsible

<sup>12</sup>As converters have spent money in the game, it might be counter-intuitive that they do not use money as a payment method, but they do not necessarily have to spend *coins* in the period, only buy them at some point historically.

Figure 2: Usage of *video*



Notes: This graph shows the distribution of the individuals in the sample by their average share of video as a method of payment.

for about 80% of the number of users, but the share of converters is different in the countries, varying from 55% in Sweden to 32% in France.

Table 3: Summary statistics of converters in different subgroups

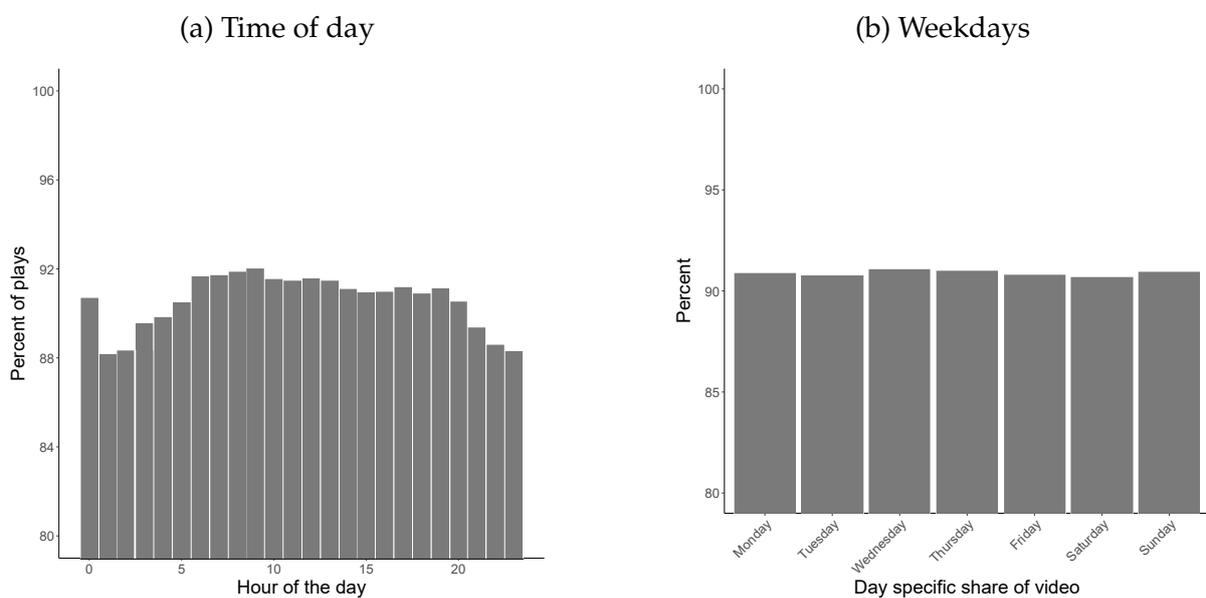
Selection	N	Share Video	Num converters	Percentage converters
iOS	22050	0.930	11812	53.6
Android	27172	0.947	12807	47.1
Germany	40006	0.942	20162	50.4
Sweden	5792	0.931	3288	56.8
France	3555	0.948	1203	33.8
All	49024	0.736	24485	49.9

Notes: The table presents summary statistics of the different sub-samples that are used in the heterogeneity analysis.

In Figure 3, I examine the variation in the share of *video* payment over time and see that there is a slightly higher share of video usage during midday in comparison to early mornings and evenings. The pattern can be rationalized by considering a typical individual in my sample as the normal 9-to-5 worker. The increase in the share of *video*

aligns well with the start and end of regular office hours. However, the raw means do not take into account individual heterogeneity when individuals play or value. The time heterogeneity can then be explained by certain hours when individuals commute, which aligns with the increase in the number of plays seen in Figure 4a. Another obvious explanation is that individuals have different valuations during leisure time, but multiple other factors can be at play. However, a clear rationalizable pattern cannot be seen over the days of the week, where the differences are minimal. I will expand on these stylized facts in the supply-side elasticities estimation in Section 4.1, where I will be able to take the individual differences into account.

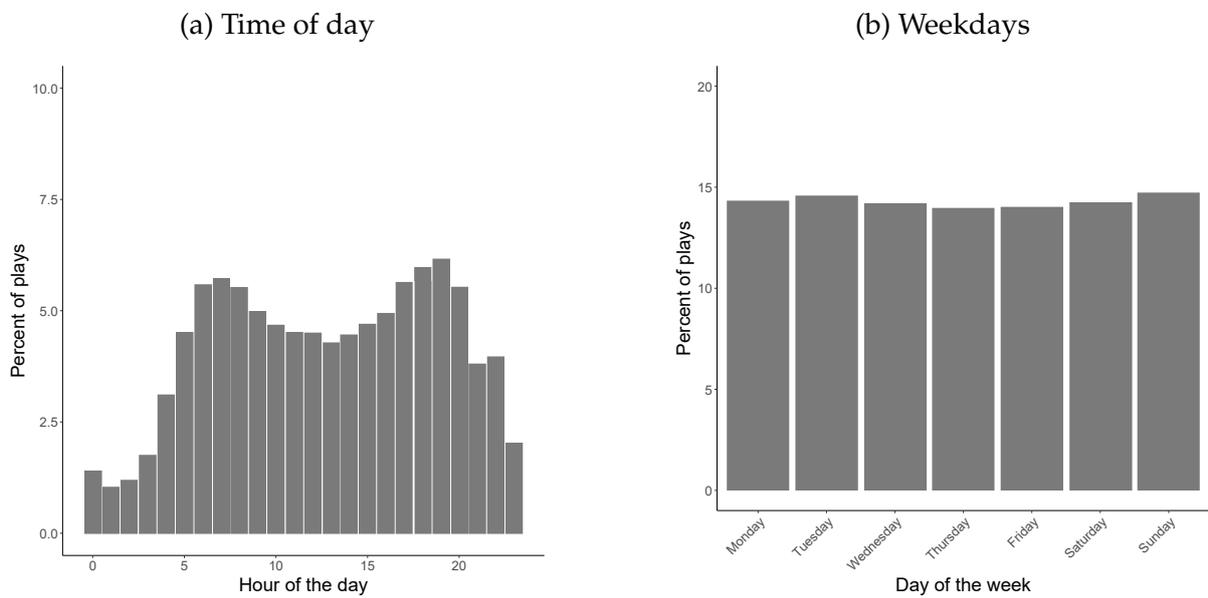
Figure 3: Share of *video* usage for different time periods for converters



Notes: The graphs show the share of video as a payment method for the different time periods.

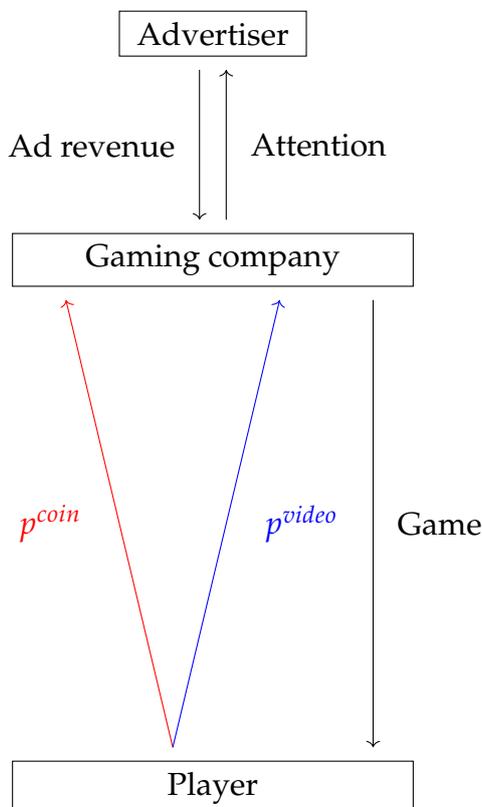
When we turn to Figure 4, we see a more pronounced heterogeneity. Noteworthy is, however, that the spikes in the number of plays do not correspond to the share of plays done by *video*.

Figure 4: Number of plays for different periods in the converters sample



### 3 Conceptual framework

Figure 5: The digital market for attention



Notes: The figure illustrates the digital market for attention with its three actors, the player, the gaming company, and advertisers. The player interacts with the gaming company by playing the game. Before they play, they pay the gaming company either in *coins* or in attention by watching *video*. The price in *coins* is decided by the gaming company. The player then receives the game. If they pay with *coins*, the interaction is finished. If they pay attention, the gaming company sells the player's attention to advertisers. The sale takes place in a live auction where the players' characteristics are put up for sale, and advertisers buy their attention algorithmically through an intermediary.

The market described in Figure 5 is the market for attention, and is the focus of this paper. The value of attention to the individual is defined here as the Willingness to Pay to Avoid (WTPA) a 30-second advertisement. To understand the WTPA, we focus on the first interaction depicted in Figure 5, namely, the player's choice of payment method, which we will use to estimate the WTPA.

To rationalize that the same player pays using both *coins* and *video* as payment methods, we treat  $p^{video}$  as a random variable,  $P^{video}$ . The underlying distribution of  $P^{video}$  is  $F^{video}(\cdot)$ . I assume that individuals only differ in the first moment of the distribution. We can then denote the individual distribution as

$$F_i^{video}(\cdot) = F^{video}(\cdot) + \gamma_i.$$

The individual  $i$  is about to pay for the game. We index the game  $j$ . We assume that  $P_{ij}^{video} \in F_i^{video}(\cdot)$ , i.e. the distribution is time-invariant. Before the choice of payment, the individual draws  $P_{ij}^{video}$  from which realizes to  $p_{ij}^{video}$ . Now faced with the payment options of *coins* and *video*, the individual compares  $p_{ij}^{video}$  with  $p^{coin}$  and chooses the cheaper payment method. They will then compare the cost of paying with the utility of playing, and only play if the cheaper payment method gives a positive surplus. The gaming company sets  $p^{coin}$  in advance, but it varies depending on the *situation*. It is the variation in  $p^{coin}$  that is the identifying variation that we will use to estimate the distribution  $F^{video}(\cdot)$ .

## 4 Empirical results

### 4.1 Supply side of attention

#### 4.1.1 Identification strategy

To identify the supply-side elasticity of attention, I rely on one main assumption. The assumption is that individuals' choice of payment method is solely determined by the cost in *coins* once they make a payment. The prices in *coin* from Table 1 in Section 2 might steer individuals to play different games, as they are cheaper in *coins* but once they play and make a payment there is nothing intrinsic about the *situations* themselves, causing the individual to choose a *video* as the payment method. Conditionally on making a payment, the prices can be seen as plausibly exogenous.

Even if the rich digital setting seems perfect for first-degree price discrimination, the company has opted out of this due to complexity and the fear of a backlash from players.<sup>13</sup> Second-degree price discrimination is, however, present as there are different prices for different situations. This might sort individuals with different WTPA into different games and be a threat to identification when we run the simple OLS regression. By including individual fixed effects, we remove the variation between individuals in their WTPA, and the remaining variation comes from the same individual using different payment methods in the different *situations*, when they face different prices.

#### 4.1.2 Estimation

More technically, the price in *coins* is fixed for each *situation*  $g$ .<sup>14</sup> As it does not vary over individuals and time, we are interested in the consumer response to different

<sup>13</sup>The assumption is made after discussions with the gaming company. They have not examined and optimized the prices for the different *situations* systematically.

<sup>14</sup>This is done for the main sample. In A, I do the same analysis, including the times the payment method is used for tickets, with qualitatively the same results.

prices. The fixed price is the tool that the price setter, the gaming company, could use to optimize revenue today. The supply elasticity of the population as a whole is what affects company revenue, and to estimate it, I regress the usage of *videos* on the price  $P_g$ . The sample is the *situations* that individual  $i$  encounters at instance  $j$  of *situation*  $g$ , where  $video_{igj} = 1$  if the payment was a *video* and  $video_{igj} = 0$  if the payment was in *coins*.  $P_g$  is the price in coins of the *situation*, even if the payment is made using video. I first estimate the coefficients with ordinary least squares, which is analogous to a linear probability model. I also report a logit specification in [A](#), with qualitatively the same results.

$$video_{igj} = \alpha + \beta \cdot P_g + \gamma_i + \theta_h + \lambda_d + \mu_w + \epsilon_{igj} \quad (1)$$

In [Table 4](#), Column (1), we see that the OLS estimate of the coefficient on price is large. An increase in the *coins* price by one *coin*<sup>15</sup> increases the share of *videos* by seven percentage points (p.p.). The simple OLS explains 26% of the variance, indicating a strong explanatory power.

I also include individual  $i$ , hour  $h$ , weekday  $d$ , and week  $w$  Fixed Effects as  $\gamma_i$ ,  $\theta_h$ ,  $\lambda_d$ , and  $\mu_w$ , in [Equation 1](#). The coefficient shrinks to a fourth when individual fixed effects are introduced in [Column \(2\)](#) and the variance explained by the price alone is now only 4%. The differences imply that the large effects are across individuals rather than within individuals.

The standard errors are clustered at the *situation*  $\times$  individual level. In [A](#), I also estimate the model on the entire sample, i.e., including the non-converters.

[Table 5](#) explores whether there are systematic differences in the response to price between the three different countries and the two different operating systems. The lack of variation between platforms in the sub-sample analysis is noteworthy. Previously, it was common wisdom that iOS users were richer and behaved differently than Android users, see eg [Gotz et al. \(2017\)](#). My results indicate that this is not the case in this setting. A plausible explanation is the increased quality of Android phones, making selection less due to the price of the phone. The differences between the countries are minor in magnitude. France deviates but consists of the smallest sample, as well as the country with the smallest share of converters.

The elasticities corresponding to [Table 4](#) and [5](#) are calculated by taking the  $\frac{\Delta \ln(video)}{\Delta \ln(P)}$  change at the mean and shown in [Figure 6](#). On aggregate, attention is an elastic good, but when taking individual fixed effects into account, it becomes an inelastic commodity. The aggregate estimate corresponds to an extensive margin, with the price variation affecting who plays, whereas the estimate with the individual fixed effects corresponds to an intensive margin.

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<sup>15</sup>0.01 Euro

Table 4: Main regression results

Model:	video	
	OLS (1)	FE (2)
<i>Variables</i>		
Constant	-1.12*** (0.047)	
Price	0.070*** (0.002)	0.019*** (0.0003)
Dep var mean	0.909	0.909
Percent	7.73	2.06
<i>Fixed-effects</i>		
userid	NO	YES
weekday	NO	YES
hour	NO	YES
week	NO	YES
<i>Fit statistics</i>		
Observations	2,252,465	2,252,465
R <sup>2</sup>	0.25728	0.74776
Within R <sup>2</sup>		0.04385
Individuals	24,224	24,224

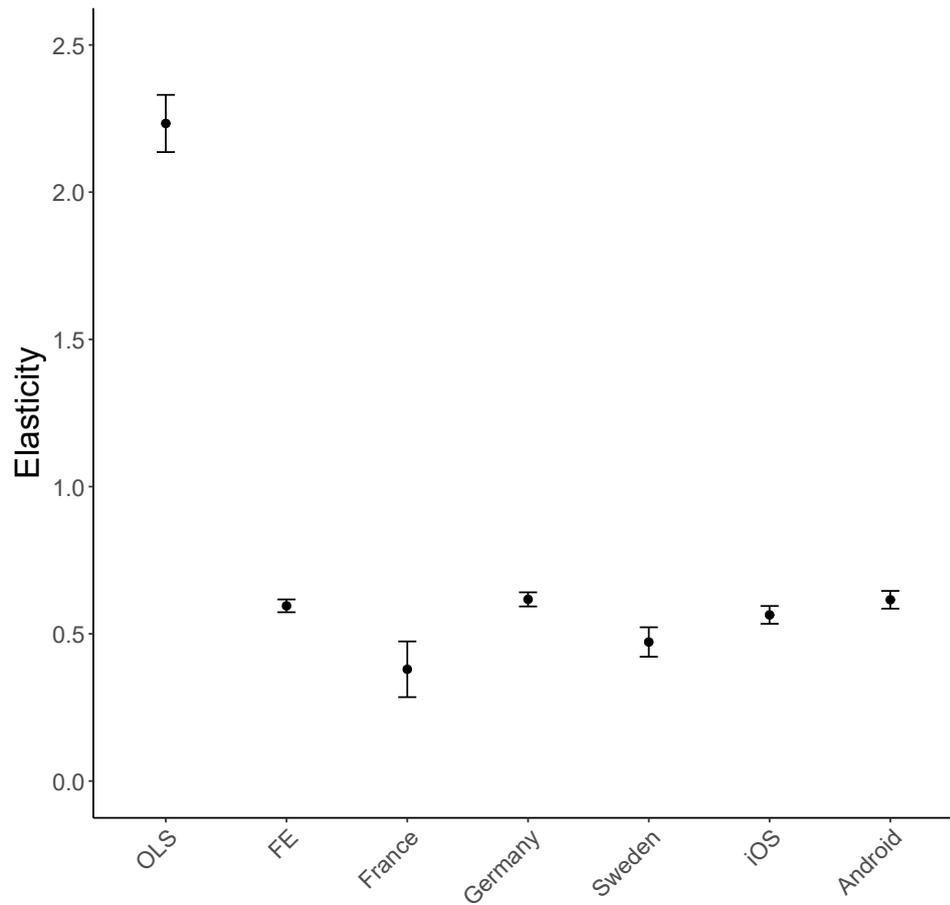
Notes: Clustered (Individual-Price) standard-errors in parentheses. Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1. This table reports the results from the main regression. The dependent variable is whether the payment is made with *videos*, and the independent variable is the price. The dependent variable mean is the average share of video usage in the sample.

Table 5: Main regression, different selections

Model:	France (1)	Germany (2)	video Sweden (3)	iOS (4)	Android (5)
<i>Variables</i>					
Price	0.012*** (0.002)	0.019*** (0.0004)	0.015*** (0.0008)	0.018*** (0.0005)	0.019*** (0.0005)
Dep var mean Percent	0.932 1.31	0.909 2.13	0.898 1.64	0.902 1.96	0.913 2.13
<i>Fixed-effects</i>					
userid	YES	YES	YES	YES	YES
weekday	YES	YES	YES	YES	YES
hour	YES	YES	YES	YES	YES
week	YES	YES	YES	YES	YES
<i>Fit statistics</i>					
Observations	82,437	1,969,591	200,437	899,304	1,353,161
R <sup>2</sup>	0.75720	0.74557	0.76632	0.76315	0.73622
Within R <sup>2</sup>	0.02463	0.04640	0.02886	0.03931	0.04702
Individuals	1,191	19,933	3,268	11,619	12,605

Notes: Clustered (Individual-Price) standard-errors in parentheses. Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1. This table reports the results from the main regression. The dependent variable is whether the payment is made with *videos*, and the independent variable is the price. The dependent variable mean is the average share of video usage in the sample. The sample is split by country and platform.

Figure 6: Elasticities corresponding to the main regression results.



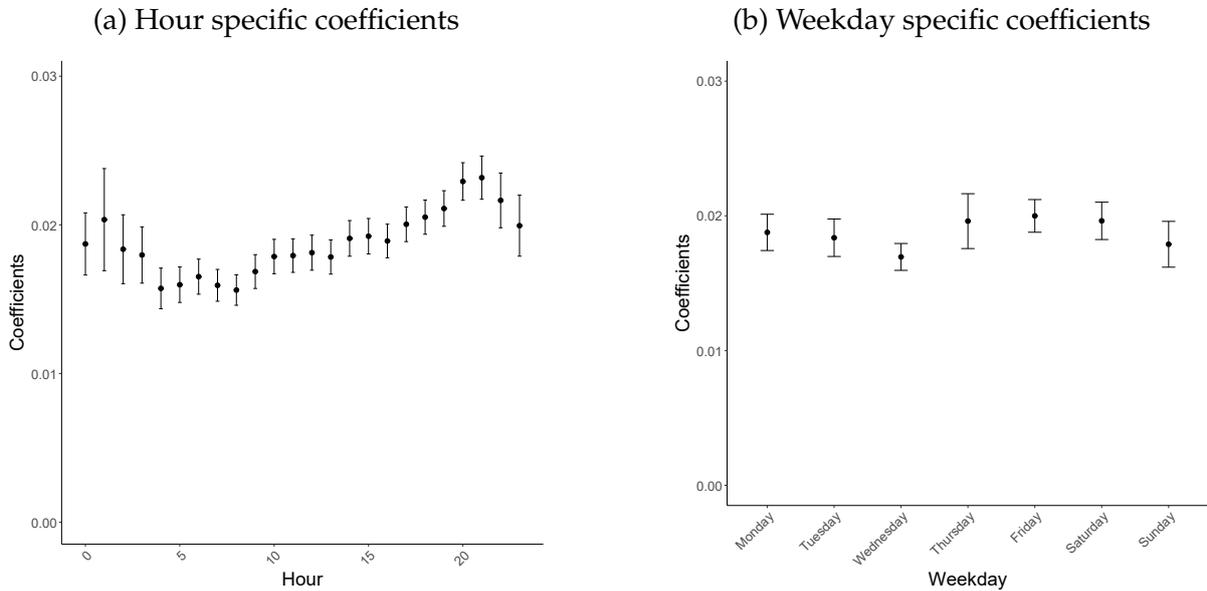
Notes: These estimates are the elasticities of the price of *videos* on the share of *videos* used. The estimates are derived from the coefficients in Table 4 and 5. The elasticities are calculated at the mean. The error bars are the 95% confidence intervals. The confidence intervals are derived with the delta method.

Next, I investigate the time of day and weekday heterogeneity in price sensitivity. We estimate the analog of Equation 1 but with time-of-day interactions in Equation 2.

$$video_{igj} = \alpha + \sum_{t=0}^{23} \beta_t \cdot \mathbb{1}(t) \times P_g + \mu_i + \gamma_t + \epsilon_{igj} \quad (2)$$

The results are displayed in Figure 7a. Here we see a clear increase in the price sensitivity during the evening when accounting for different individuals playing at different times. For the day of week heterogeneity, we see no significant differences. The heterogeneity in valuation over the day is also present in other related literature, such as the value of waiting time in the paper by (Buchholz *et al.* 2025) on cab-waiting times. (Buchholz *et al.* 2025) find a higher valuation of time in the mornings and during the day, whereas I see a heterogeneity between our two papers that highlights the context-specificity of the value of time, indicating that it is about the context-specificity of the value of time, and that they are not externally valid in other settings. The result could indicate shirking at the workplace, as the elasticities are lower during traditional work hours, even if the weekday similarities do not support such a mechanism. The findings suggest a new avenue for price discrimination based on the time dimension.

Figure 7: Heterogeneity over time in the estimated coefficients



Notes: This figure shows the coefficients that correspond to Equation 2 for the hour of the day and the same for weekdays. Standard errors are clustered by user and price and then derived with the delta method.

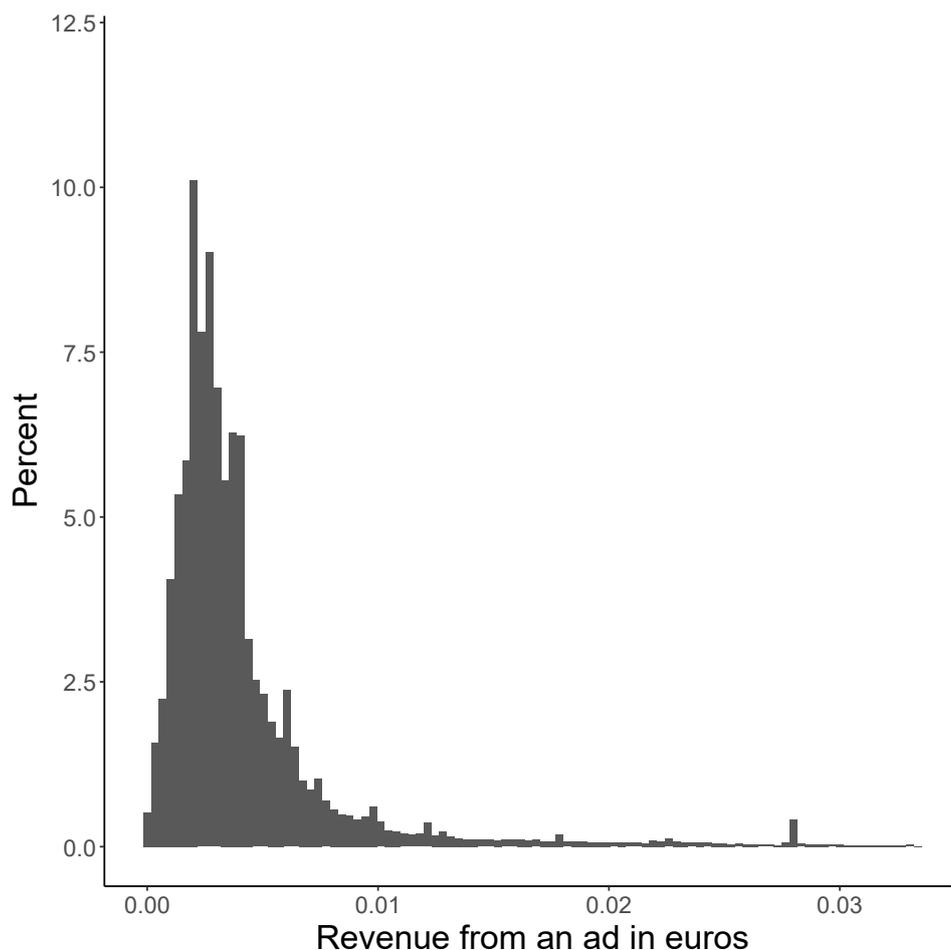
## 4.2 Demand for attention

To understand both sides of the attention market, I match the results of individual users' behavior with revenue for the gaming company from showing *video* ads to that

individual. The data I have is the average revenue for the gaming company, showing a specific individual's *video* over a particular time period. To decide which *video* is shown, a real-time auction is held. Different platforms have varying auction systems, and the bidding process may differ accordingly. The ad shown is most often the one that paid the most for that specific slot, but the ad platform can take other factors into account, such as the relevance or quality of the *video*. The process is not transparent, and especially small advertisers might have more problems targeting the correct group. See the report "Online platforms and digital advertising" (U.K. Competition and Markets Authority 2020) for a more detailed description of how the advertisement market works technically.

The average revenues from the ads in my sample are displayed in Figure 8. The graph is trimmed at the 99<sup>th</sup> percentile. The median revenue is 0.004 Euro, and the mean revenue is 0.006 Euro, per 30-second *video*.

Figure 8: The distribution of revenues from advertising



Notes: The distribution shown is the average revenue the gaming company gets from showing an ad to a specific user on a specific day. The distribution is winsorized at the 99<sup>th</sup> percentile. The mean revenue is 0.006 Euro, and the median revenue is 0.004 Euro, per 30-second *video*.

Figure 9 shows the raw correlation between the individual's share of *video* usage to pay for a feature, with the average revenue for the gaming company.<sup>1617</sup> The stylized fact that the attention of individuals with higher shares of *video* usage at a specific time fetches a lower revenue on the attention market indicates that the market can match demand with supply. Contributing factors can be that advertisers want to target individuals who are big spenders, which implies individuals with a low *video* share. Such an explanation would mean that the effect is solely driven by individual variation. Another rationalization is the evidence that the price of advertisement is higher when the consumer is hard to reach, as documented by [Gentzkow et al. \(2024\)](#).

To estimate the correlation between revenue from showing *videos* and the usage of *video* by individuals, I first use the data formatted as a cross-section, where each observation is an individual and the value is the average within that individual, and apply Equation 3. I then use a panel structure where the data is at an individual-by-date level, and the values are averages for each date and Equation 4. This is due to the data availability as described in Section 2. In both specifications, I control for the average number of ads.

$$\text{Ad revenue per video}_i = \alpha + \beta \cdot \text{Share video}_i + \nu \cdot \text{Nr of Ads}_i + \epsilon_i \quad (3)$$

$$\text{Ad revenue per video}_{it} = \alpha + \beta \cdot \text{Share video}_{it} + \nu \cdot \text{Nr of Ads}_{it} + \gamma_i + \epsilon_{it} \quad (4)$$

All coefficients are standardized to compensate for the non-intuitive levels of the revenue from showing *video*. In Table 6, Columns (1) and (4), I use the cross-sectional data and Equation 3, but in Column (4), I use individually estimated supply elasticities instead of the share of *videos*. An individual with a one standard deviation higher share of videos as their average payment method generates a 0.15 standard deviation lower revenue from showing ads. When using the estimated individual elasticities, the value drops to 0.08. Note, however, that the elasticities are estimated, and that the uncertainty of the estimated elasticities is not taken into account.

In Columns (2) and (3), I use the panel structure and Equation 4. In Column (3), the individual fixed effects,  $\gamma_i$ , are included but not in Column (2). When using the panel structure without individual fixed effects, a one standard deviation higher share of videos as a payment method generates a 0.09 standard deviation lower revenue from showing ads. When including the fixed effects, the coefficient drops to 0.007. All coefficients are significant at the 1% level.

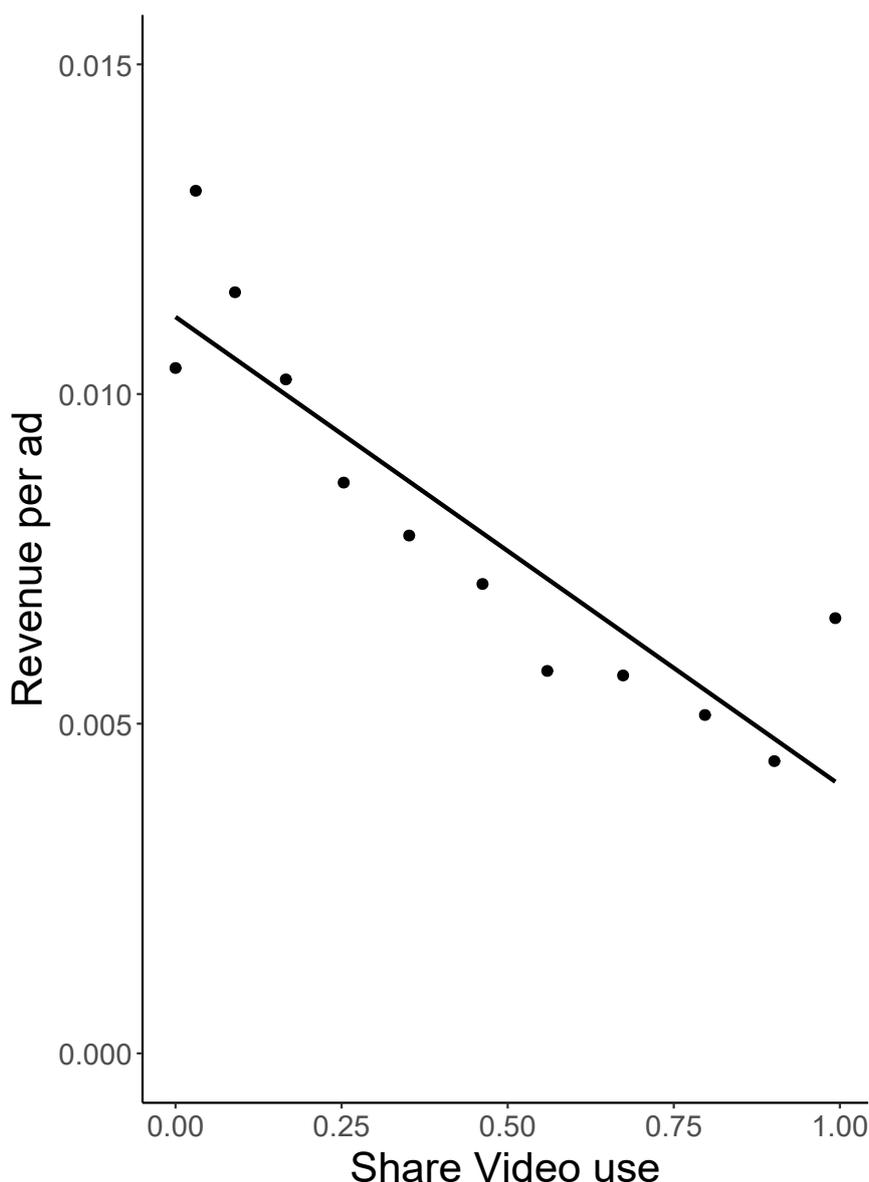
From this exercise, we see that the relationship between an individual's value on the ad market and their own valuation of their attention is significant and negative,

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<sup>16</sup>I use the share of video instead of individually calculated elasticity, which I use to validate the relationship. As the elasticities are estimated and cannot be calculated for all individuals, using them as the main specification would reduce power.

<sup>17</sup>The data is in the panel form with one observation per day and individual.

Figure 9: Demand-side relationship between average revenue and user *video* usage.



*Notes:* This figure shows the relationship between the share of *videos* used by individuals and the average revenue the gaming company gets from showing an ad to that individual as a binscatter plot. On the y-axis, we have the revenues as in Figure 8, and on the x-axis, we have the share of *videos* usage. The dataset is of a panel structure. The line is the simple OLS regression.

meaning that individuals with a low valuation are worth less on the ad market. The correlation is slightly stronger in the cross-sectional data than in the panel data. When including the individual fixed effects, the coefficient decreases by a magnitude.

In the specifications, I include the standardized number of videos shown to the individual.<sup>18</sup> The marginal return to advertisers of showing the same ad to the same

<sup>18</sup>This is measured as the average number of videos shown to individual  $i$  during time period  $t$ , i.e., per day in the panel and during the entire sample in the cross-section.

individual can decrease due to how the market is set up. The correlation between the number of ads and revenue is negative; an increase of one standard deviation in the number of ads will decrease the ad revenue by 0.098 standard deviation. The effect is slightly smaller than that of the share of video, indicating that the decreasing marginal revenue is present.

Comparing Columns (2) and (3), we see that including the individual fixed effects decreases the coefficient of the share of *video* effect by a magnitude, but only halves the coefficient on the number of ads. Such a pattern indicates that the share of video characterizes the revenue from individuals in general, whereas the decrease in marginal revenue from showing one more ad also seems to happen on a daily level.

Table 6: The relationship between revenue and usage of videos

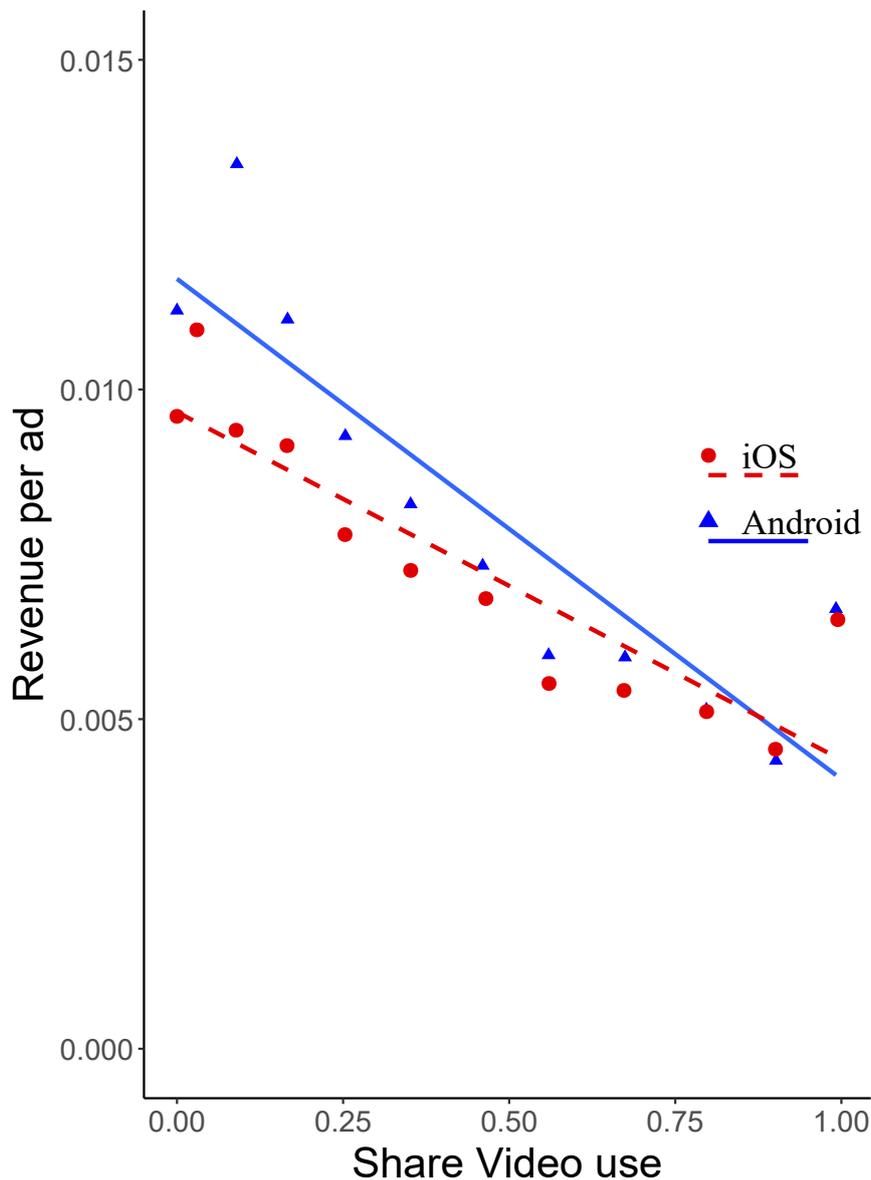
Dependent Variable: Model:	Expected profit per ad			
	(1)	(2)	(3)	(4)
<i>Variables</i>				
Constant	-0.0466*** (0.0039)	-0.0731*** (0.0029)		-0.2016*** (0.0044)
Share Video	-0.1493*** (0.0041)	-0.0934*** (0.0028)	-0.0066*** (0.0008)	
Nr of Ads	-0.0974*** (0.0042)	-0.0556*** (0.0013)	-0.0237*** (0.0005)	-0.0686*** (0.0042)
Elasticity				0.0812*** (0.0041)
Level of data	Cross-section	Panel	Panel	Cross-section
<i>Fixed-effects</i>				
userid	NO	NO	YES	NO
<i>Fit statistics</i>				
Observations	58,770	994,045	994,045	23,151
R <sup>2</sup>	0.04029	0.02253	0.83715	0.03005
Within R <sup>2</sup>			0.00595	

Notes: Clustered (Individual) standard-errors in parentheses. Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1. This table shows the results from the regression of the revenue from showing ads to individuals on the share of *videos* used by the individual for three different specifications. The dependent variable is the revenue from showing ads to the individual. The independent variable is the share of *videos* used by the individual. In Columns (1) and (4), the data is a cross-section with every observation representing one individual. In Column (2), the data is on a panel structure where each observation is a date, and Column (3) includes individual fixed effects.

Further of interest is the difference between the platforms iOS and Android as seen in Figure 10. Here we see that the revenue from ads to Android users is higher and

that the relationship between *video* usage and the revenue of the ad is stronger in the Android platform. This indicates a higher revenue for advertisers to reach paying Android users at various levels and larger price discrimination. A natural interpretation of the relationship is that Android users are more valuable than iOS users.

Figure 10: iOS vs Android: Demand-side relationship between average revenue and user *video* usage



Notes: This figure illustrates the relationship between the share of *videos* used by individuals and the average revenue the gaming company receives from displaying an ad to that individual, presented as a bin-scatter plot, for the two different platforms separately. On the y-axis, we have the revenues as in Figure 8, and on the x-axis, we have the share of *videos* usage. Both are aggregated on the individual timed day level. The line is the simple OLS regression.

The platform heterogeneity is investigated in Table 7. Using the specification from

## Equation 5

$$\begin{aligned}
& \text{Ad revenue per video}_i \\
& = \alpha + \beta_1 \cdot \text{Share video}_i + \beta_2 \cdot \text{iOS}_i + \beta_3 \cdot \text{Share video}_i \times \text{iOS}_i \\
& + \nu \cdot \text{Nr of Ads}_i + \epsilon_i.
\end{aligned} \tag{5}$$

The same sample as in Column (1) of Table 6. In Column (1) I include a platform effect and in Column (2) interact the platform variable with the share of *videos* and find the result that iOS users are cheaper to show ads to and that the correlation between their usage of *videos* and the revenue to show the ad is smaller, confirming the results seen in Figure 10.

Table 7: Controls and platform heterogeneity

Dependent Variable:	Expected profit per ad			
Model:	(1)	(2)	(3)	(4)
<i>Variables</i>				
Constant	-0.0433*** (0.0053)	-0.0429*** (0.0053)	-0.0699*** (0.0042)	
Share Video	-0.1495*** (0.0041)	-0.1570*** (0.0054)	-0.0957*** (0.0040)	-0.0045*** (0.0011)
Nr of Ads	-0.0977*** (0.0042)	-0.0975*** (0.0042)	-0.0556*** (0.0013)	-0.0237*** (0.0005)
iOS	-0.0076 (0.0080)	-0.0073 (0.0080)	-0.0084 (0.0054)	
Share Video × iOS		0.0170** (0.0080)	0.0060 (0.0053)	-0.0056*** (0.0016)
Level of data	Cross-section	Cross-section	Panel	Panel
<i>Fixed-effects</i>				
userid	NO	NO	NO	YES
<i>Fit statistics</i>				
Observations	58,770	58,770	994,045	994,045
R <sup>2</sup>	0.04030	0.04037	0.02257	0.83715
Within R <sup>2</sup>				0.00599

Notes: Clustered (Individual) standard-errors in parentheses. Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1. This table shows the results from the regression of the revenue from showing ads to individuals on the share of *videos* used by the individual for two different specifications. The dependent variable is the revenue from showing ads to the individual. The independent variable is the share of *videos* used by the individual. Columns (1) and (2) use the cross-section dataset, and Columns (3) and (4) use the panel dataset. In Column (1), the platform and country are added as controls, and in Column (2), the platform interacted with the share of *videos* used. Column (3) estimates the interacted version on the panel dataset, and Column (4) includes individual fixed effects.

In 2021, Apple introduced its App Tracking Transparency Framework. The policy severely limited the data that could be shared between apps on the iOS platform. Previous research has shown that after the introduction, iOS apps reduced reliance on ads for monetization (Cheyre *et al.* 2023), indicating such an effect. The privacy effect is also observed in other aspects of mobile apps by Bian *et al.* (2022), who find a reduction in the use of apps that share a lot of individual data after the introduction of easy-to-read privacy labels. Furthermore, Bian *et al.* (2022) also finds that stock markets reacted negatively to stricter privacy measures, as companies that provide data-intensive apps experienced a decline in market value.

The attention market of advertisement is a market for information, as reviewed by Bergemann & Bonatti (2019). Better targeting will enable more effective price discrimination, resulting in higher value for advertisers. The difference in data sharing between iOS and Android is the most plausible rationalization of the difference in revenue relations.

## 5 Policy implications

The digital economy is a growing part of the economy, with large tech companies like Google and Facebook controlling much of the digital advertising market. Digital service providers are price-takers in the advertiser market. The pricing choices of digital service providers, in our case the gaming company, depend on the revenue from the advertisement market for the attention of their users, as well as the willingness to pay to avoid an ad,  $p^{video}$  of the users. Regulation or policy intervention, such as GDPR, the Digital Markets Act, and different antitrust cases ([FTC v. Facebook, Inc. 2021](#), [United States Department of Justice 2020, 2023](#)), will affect advertisement revenues for digital service providers. The dynamic impact of such policy interventions will require us to understand consumers' willingness to pay to avoid an ad,  $p^{video}$ .

If, for example, the company faces a decrease in revenue from ads on the market, the company will change its prices in *coins* to re-optimize its revenue. Whether they increase or decrease their prices will depend on the distribution of willingness to pay to avoid ads,  $F_i^{video}(p^{coin})$  of the users. The high elasticity I estimate in Section 4.1 on the aggregate level, together with the relatively large revenue from coins compared to ads, indicates that the company will decrease the price of *coins* to increase the number of plays with *coins*.

One proposal put forward is a digital ads tax ([Acemoglu & Johnson 2024](#), [Romer 2021](#)). The aim of such a tax could be to use the revenue to fund public goods or simply as a Pigouvian tax to reduce the harm from the usage of digital content. Most designs of such a tax will reduce revenue for the digital service provider, which in turn will change their design choices. How to design such a tax is an open question and depends on the aim of the policy.

In my setting, I can predict such a response. We treat Figure 5 in section 3 as a two-sided market. In my setting, I can model the design choices of the digital service provider, the gaming company.

Here follows how my setting could be used to study such a tax:

Let us set up an optimization problem for the gaming company. Within the app, the gaming company is a monopolist, ie, they are the only provider of trivia games to the players. They set  $p^{coin}$  optimally. In the advertiser market, they are price takers and will optimize revenue from ads and user payments. The profit function is set up in Equation 6. Here  $\Pi_G$  is the profit of the gaming company,  $k$  is the number of plays, and  $j$  is the instance of the plays.  $0.7 \cdot p^{coin}$  is the revenue from a play in coins.<sup>19</sup>  $p_j^{Ad}$  is

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<sup>19</sup>App store/Google play takes about 30% of all in-app purchases.

the revenue from showing an ad instead of the instance of play  $j$ .

$$\Pi_G = \sum_{j=1}^k \left( 0.7 \cdot p^{coin} \cdot (1 - F_i^{video}(p^{coin})) \right) + p_j^{Ad} \cdot F_i^{video}(p^{coin}) \quad (6)$$

The number of plays  $k$  will be endogenous and depend on the willingness to pay to avoid,  $F_i^{video}(p^{coin})$ , and so will the payment method, both of which are important for the revenue. The individual player plays according to the design choices as explained in Section 3 and maximizes equation 7.

$$U_{iT}(k) = \sum_{j=1}^k \left( u_i(j) - \overline{w_{iT}} - p_{iT}^{video}(k) \cdot F_i^{video}(p^{coin}) + p^{coin} \cdot (1 - F_i^{video}(p^{coin})) \right) \quad (7)$$

Given some  $u_i(j)$  and  $F_i^{video}(p^{coin})$ , one could plug in the data we have on  $p_j^{Ad}$  to the theoretical optimal price. This price will depend on  $p_j^{Ad}$  and determine the number of plays, payment method, and thereby consumer surplus,  $v_{ij}$ . Conceptually, a tax that decreases revenue from ads will also decrease the possibility for price discrimination. This will lower the price in *coins* as well and increase the consumer surplus, while decreasing the amount of ads shown, thereby decreasing tax revenue.

This model is only a partial equilibrium as it does not include the demand for attention, but could be used as an input in such a model.

## 6 Conclusion

The consumer valuation of their attention and time is fundamental to understanding the advertisement-based digital economy. In the mobile game setting, attention is elastic on the aggregate, but inelastic within an individual. My novel investigation into consumers' willingness to pay to avoid *video* advertisements provides novel insights into the supply side of the attention market, allowing me to describe both individual heterogeneity and time heterogeneity.

The results indicate that the willingness to pay to avoid advertisements is of the same magnitude as other measures of the value of time, while also exhibiting different time heterogeneities, which suggests the context-dependence of the value of time. Furthermore, the price advertisers pay for consumers' attention correlates with the value the individual places on their attention. Still, the price paid is only a fraction of the monetary value individuals put on their attention.

Optimal pricing implied by the data would primarily involve individual price set-

tings; however, as individual pricing may be perceived as unfair to individuals, time-dependent pricing might be an option to optimize profits for the gaming company. As optimal pricing depends on both supply-side behavior and revenues from advertisement, the impact of policies that change the revenues from advertisement needs to take into account consumers' valuation of their attention. Presently, both antitrust cases ([FTC v. Facebook, Inc. 2021](#), [United States Department of Justice 2020, 2023](#)) and proposed digital ads taxes ([Acemoglu & Johnson 2024](#), [Romer 2021](#)) are ongoing policy questions that would affect the advertising market. My novel estimates will help understand the effects of such policies in a dynamic setting. To build a model that can empirically answer questions about policy implications, further work is needed.

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## A Tables

Table 8: All prices and logit

Model:	video			
	OLS (1) OLS	FE (2) OLS	Logit (3) Logit	Logit FE (4) Logit
<i>Variables</i>				
Constant	-0.249*** (0.002)		-18.3*** (0.371)	
price	0.040*** (0.0001)	0.005*** ( $8.28 \times 10^{-5}$ )	0.752*** (0.014)	0.630*** (0.009)
Dep var mean	0.571	0.571	0.909	0.909
Percent	7.07	5.41	218.0	182.7
Individuals	45,303	45,303	24,224	24,224
<i>Fixed-effects</i>				
userid	NO	YES	NO	YES
weekday	NO	YES	NO	YES
hour	NO	YES	NO	YES
week	NO	YES	NO	YES
<i>Fit statistics</i>				
Observations	4,119,071	3,960,334	2,252,465	1,743,334
Squared Correlation	0.60238	0.70453	0.25728	0.74010
Pseudo R <sup>2</sup>	0.64427	-2.0833	0.34423	0.73632
BIC	2,097,569.7	-4,280,693.4	901,760.2	457,409.6

Notes: Clustered (Individual-Price) standard-errors in parentheses. Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1. The table presents the alternative specification where all prices are included and a logit specification. Both with and without fixed effects. The dependent variable is the use of video.

Table 9: Weighted regression with all individuals

Model:	video			
	OLS (1)	Interaction (2)	FE (3)	FE Interaction (4)
<i>Variables</i>				
Constant	0.696*** (0.006)	-1.12*** (0.047)		
price	0.010*** (0.0002)	0.070*** (0.002)	0.005*** ( $8.28 \times 10^{-5}$ )	0.019*** (0.0003)
Non-converter		1.93*** (0.047)		0.109 (2,296.1)
price $\times$ Non-converter		-0.064*** (0.002)		-0.015*** (0.0003)
Dep var mean	0.974	0.974	0.974	0.974
Percent	1.02	7.21	0.464	1.91
Individuals	48,598	48,598	48,598	48,598
<i>Fixed-effects</i>				
userid	NO	NO	YES	YES
weekday	NO	NO	YES	YES
hour	NO	NO	YES	YES
week	NO	NO	YES	YES
<i>Fit statistics</i>				
Observations	3,960,334	3,960,334	3,952,507	3,952,507
R <sup>2</sup>	0.02389	0.12889	0.53542	0.53825
Within R <sup>2</sup>			0.00826	0.01430

Notes: Clustered (Individual-Price) standard-errors in parentheses. Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1. The table presents the alternative specification where all individuals are included. It is weighted according to the sampling probabilities. Further, the interactions are such that the price coefficient corresponds to the effect on converters and the interaction term corresponds to the effect on non-converters. Both with and without fixed effects. The dependent variable is the use of video.