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

Johan Orrenius *

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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 consumer's supply elasticity of attention. In the aggregate, a one percent higher price increases the share of payments by users watching videos 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. Finally, I estimate the willingness to pay to avoid a 30-second ad to 0.15 euros. By considering the time component of the ad, we get a value of time of 18 euros per hour. This is of similar magnitude to previous estimates of consumers' valuation of time.

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 instead of paying with money. The consumers' attention is then sold to advertisers through a real-time online auction.[1] The advertiser's demand for consumers' attention can easily be estimated as it is sold in these markets. However, to understand all aspects of the advertisement-driven digital economy we also need to understand consumers' disutility from spending time watching ads

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. Additionally, I develop a model to estimate the monetary price of attention and the implications of policy changes in the attention market on the digital economy.

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)).[2] 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*). 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 across-individual effects and explore differences over 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 large individual variation in the use of *video* to pay for the 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 0.15 Euro, which amounts to 18 Euros an hour.

I establish a statistically significant correlation between advertisers' cost 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 0.2 standard-deviation in the revenue from showing that individual a *video*.

I study the behavior of mobile game users in the trivia game QuizDuel.[3] The game is

[1]The combined revenue from mobile apps globally is 300 billion Euros. Of these 300 billion Euros, 80 are revenues from advertisement in mobile games (Statista, 2024)

[2]similarly by practitioners such as the UK competition and markets authority in (CMA, 2020).

[3]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

developed by MAG Interactive, known for knowledge-based games such as quizzes and word puzzles. The data consists of users from France, Germany, and, Sweden and spans 9 weeks in the fall of 2022. The data records every payment the users make 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. The micro-payments allow me to match the average revenue from ads shown to a specific individual in a specific time period (the demand for attention) with that individual's payment behavior in that specific time period (supply of attention). This framework allows me to investigate how efficient the attention market is.

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 very low valuation of attention generally or a specific preference in the game setting.[4] Therefore, I focus on analyzing individuals who have paid at least once with real money in the game. This group is called converters in the industry and is the term I will use throughout the paper. Thereby, I can tie the estimates to real money.

I finally propose a simple model that estimates users' Willingness to Pay to Avoid the ads and matches that to the price revenue from advertisement. The model also motivates why the same individuals use *video*s and *coins* within the data. Using this framework, I relate the results to the ongoing policy debate on the digital economy with proposals such as antitrust regulation and a digital tax on advertisers.

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 if you watch an ad or wait for the bus. At first glance, watching the 30-second *videos* studied in this paper can be seen as giving up time, but is better characterized as requiring attention. [5][6]

This 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.[7] 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.

[4]One example would be a mental rule to never pay, in order to not get addicted to the game.

[5]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)

[6]Attention can also be a way to think about workers' productivity, see (Caplin, Andrew, 2023)

[7]On average, individuals globally spend 4.8 hours on their phones per day (Data.ai, 2023).

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. The attention is then bought by advertisers. Thus, we can study both supply and demand behavior in the attention market.[8] 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 way to empirically estimate 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.[9] The difference speaks to the heterogeneity of the player group and that the intensity of play is different depending on your valuation of attention. Empirical estimates of the supply of attention are scarce. For example, the previous literature has leveraged the users' substitutability between services to empirically study consumers' supply of attention (Aridor, 2023; Srinivasan, 2023; Yuan, 2020) or have been done for a subscription setting (Brynjolfsson *et al.* , 2024). I complement these measures by presenting elasticities in monetary terms, which can be used as input in other models of the digital economy (Goolsbee & Klenow, 2006; Ghose & Han, 2014).

Enache *et al.* (2022) used a similar mobile app setting to study the price increase effect on the usage of apps, and on attention as a payment method, but on 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 use heterogeneity in the consumer valuation of attention to speak to 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.* , 2022; Goldszmidt *et al.* , 2020) who find a higher sensitivity during mornings. Using a modeling approach I estimate the Willingness to Pay to Avoid of 0.15 Euro for a 30-second ad which aggregates to 18 Euros an hour. My results of the Willingness to Pay to Avoid is of the same magnitude as other estimates of the value of time (Verbooy *et al.* , 2018) find 16 Euros in a leisure time estimation and the value of the travel time literature ranges from 6 Euros to 30 Euros (Shires & de Jong, 2009) depending on the means of travel. It also lines up with the median take-home wage in my sample countries.

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'

[8] An analogy is the labor market, where attention can be seen as labor, supplied by individuals and demanded by companies.

[9] On par with the intensive labor supply elasticity (Cahuc *et al.* , 2014)

attention is correlated with the valuation by the individuals. 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 finding a correlation I give empirical support to a mostly theoretical literature.

The attention market is a type of information market as studied by Bergemann & Bonatti (2019). The effect of data access and privacy in the digital market is well understood as shown in (Bian *et al.* , 2022; Aridor & Che, 2024; Cheyre *et al.* , 2023). Access to data on users makes their attention more valuable. I find that the relationship between supply valuation and demand revenue in Android, which has more data access, is stronger than in iOS. The difference between Android and iOS indicates that there is an effect of 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) and 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 (M Wedel, 2017).

The paper proceeds as follows: In Section 2, I describe the setting and present descriptive statistics. In Section 3 I build a conceptual framework for the supply-side valuation of attention. In Section 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 5, I propose a model to back out a Willingness to Pay for individuals' attention, and in Section 6 I estimate the model. In Section 7 I relate my findings to the ongoing policy debate on the digital economy. Then I conclude in Section 8.

2 Setting and Data

2.1 Setting

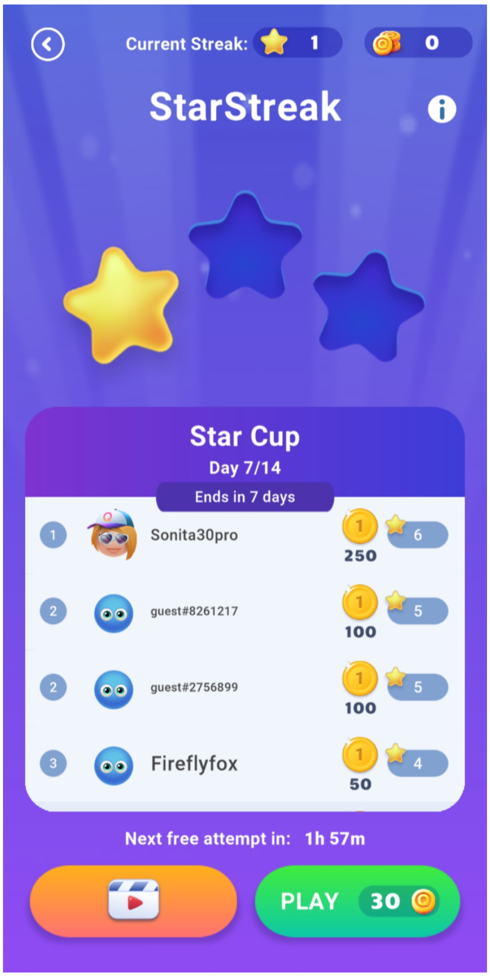
The setting is the trivia mobile game QuizDuel from MAG Interactive. Each *game* is a sequence of 3 or more questions within one of multiple categories such as history, geography, or cooking in the language of your choice. My research utilizes data from France, Sweden, and Germany, where the game is 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 shown to the player before they progress and they need to click on it and watch it to get the reward to play, thus 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 keep playing, even if you fail. The relative price of the *coin* to the *video* is different in the different *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[10] 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*.

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*.

Before spending *Coins* in the game they need to be purchased through the in-game store with 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.[11]

[10] 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.

[11] In the game, *coins* come in two different variations qoins (sic) and tickets, with the conversion rate that one ticket is 10 coins. Tickets are used to start the Arena *situations*, whereas the two others require qoins (sic). For consistency, I use the term *coins* and refer to the value in qoins (sic), as it is also the main currency you 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 *coins*	Value in Euro
StarStreak	30	0.3
Pay to continue	25	0.25
Arena	10	0.1

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 dataproviders 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^{th} of September to the 5^{th} of November in 2022. The period was chosen such that the price change by Apple analyzed in Section 4.3 was in the middle of the period and there are few major holidays during the timeperiod. Some players who opened the app did not play any of the *situations* I study and are therefore 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 $24,485$ players. In the appendix, I use a specification including non-converters and *situations* when tickets are used.

To choose the sample I accessed raw data from the game but at a different time period. Different specifications were tested, all on a different 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. 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^{th} of October to the 5^{th} of November, I have the hourly average revenue to MAG from advertisers per individual. For the 13^{th} to 26^{th} 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.

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-tail distributed.

Table 2: Summary statistics of the main sample

Statistic	Mean	Median	SD	Min	Max
Plays per individual	93.813	12	241.421	1	3063
Plays per individual and day	4.273	2.286	5.027	1	50.167
Share video	0.716	0.975	0.390	0	1

Notes: The table presents summary statistics of the individuals of the main sample. It is total number of plays over the entire time-period, The number of plays per active day as well as teh 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 that only pay with *video*, corre to the value 1in 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.[12] 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 including non-converters as well to ilustrate 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 share that are in the sub-sample of converters. In the different countries on the other hand we see substantial differences. Germany is responsible for about 80% of 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

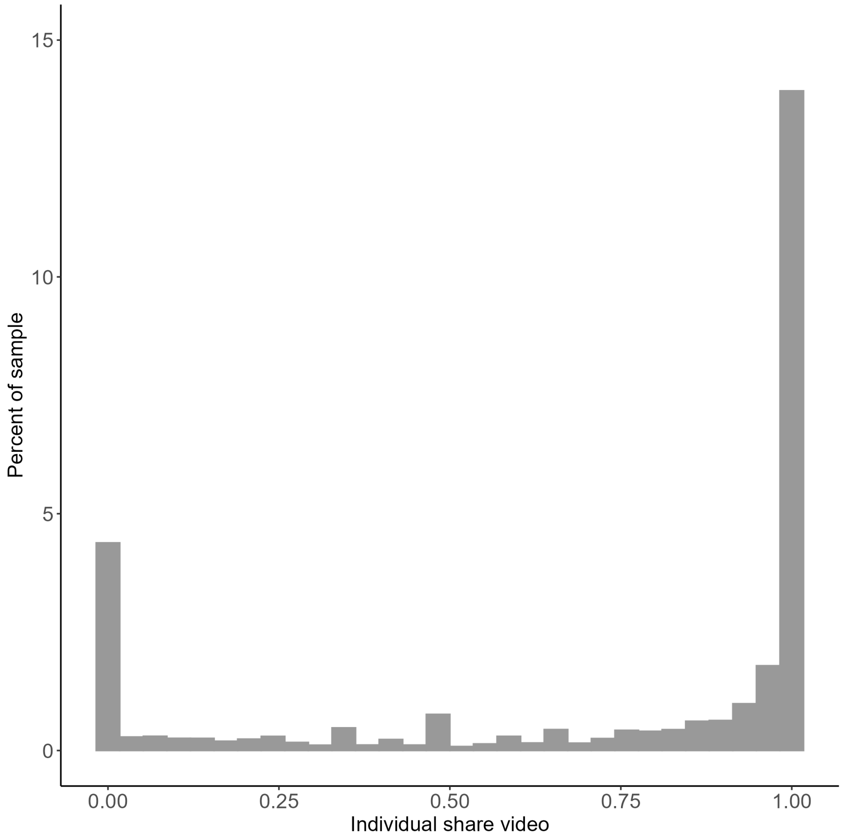
Selection	N	Share Video	Num converters	Percentage converters
ios	22050	0.930	11812	53.6
android	27172	0.947	12807	47.1
Germany	40006	0.942	20162	50.4
Sweden	5792	0.931	3288	56.8
France	3555	0.948	1203	33.8
All	49024	0.736	24485	49.9

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 high share of video usage during the midday in comparison to early mornings and

[12] 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*



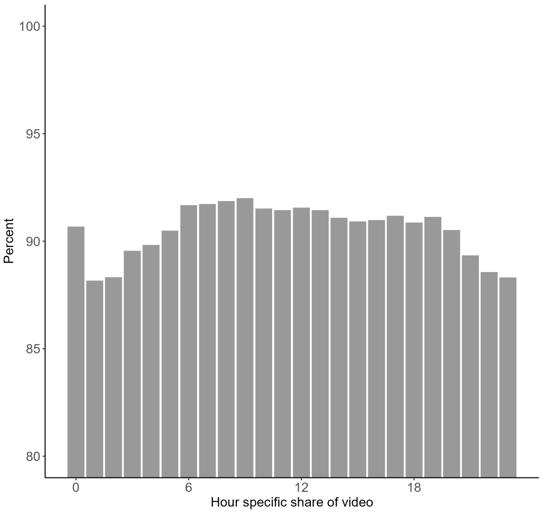
*Notes:*This graph shows the distribution of the individuals in the sample by their average share of video as a method of payment.

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 valuation. 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 can not 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.

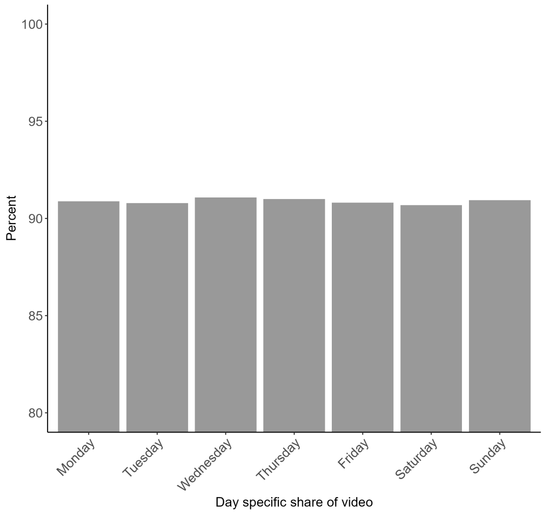
When we turn to Figure 4 we see a more pronounced heterogeneity. Noteworthy is however that the spikes in the number of plays do not correspond to the share of plays done by *video*.

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

(a) Time of day



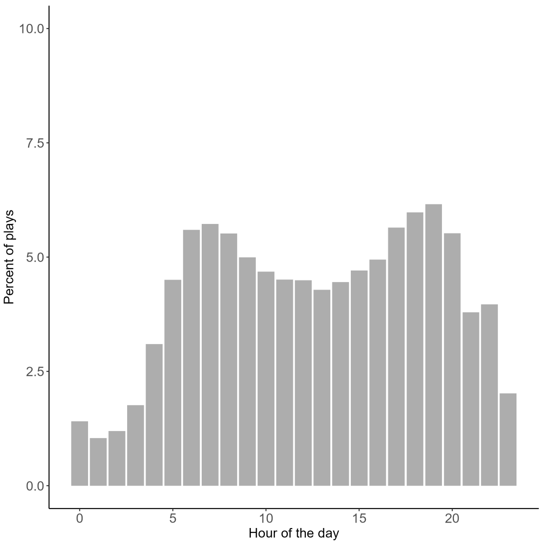
(b) Weekdays



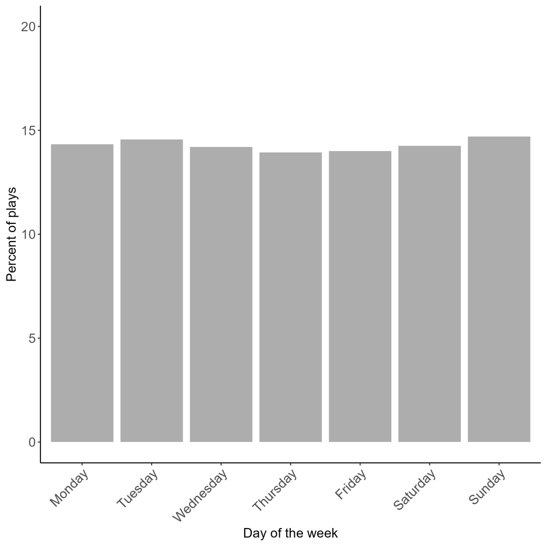
Notes: The graphs show the share of video as a payment method for the different time periods.

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

(a) Time of day



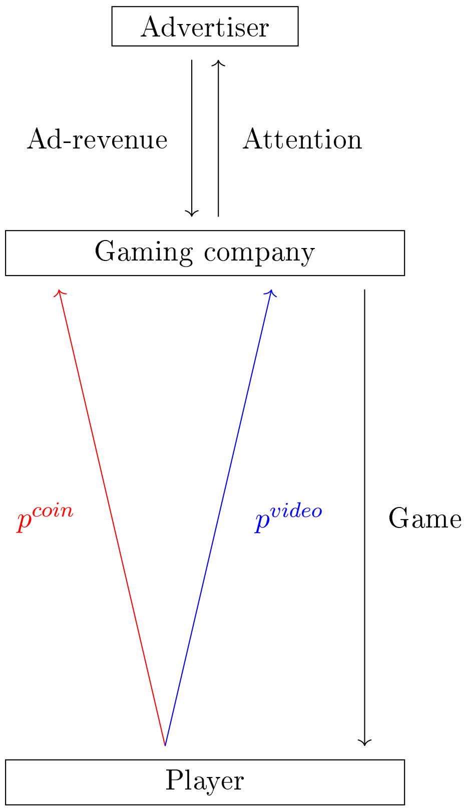
(b) Weekdays



Notes: The graphs show the number of plays for the different time periods.

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 set by the gaming company. They then receive the game. If they pay with *coins* the interaction is finished. If they pay with attention, the gaming company sells the attention of the player to advertisers. This is done 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 that is studied in this paper. The value of attention to the individual is here defined as the Willingness to Pay to Avoid(WTPA) an ad of 30 seconds. The framework will be formally modeled in Section 5. To understand the WTPA, we focus on the first interaction of Figure 5, ie the choice of payment method of the player 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 instances individual i is about to pay for the game are denoted j. We assuem that $P_{ij}^{video} \in F_i^{video}(\cdot)$ and therefore time-invaiant. 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. p^{coin} is set by the gaming company in advance, but different for different *situations*. 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 some assumptions. Firstly, the prices in *coin* from Table 1 in Section 2 are seen as plausibly exogenous.

The assumption implied is that individuals' choice of payment method is solely determined by the relative prices and that there is nothing intrinsically of the *situations* themselves causing the individual to choose a payment method. The assumption is made after discussions with the data provider. They have not examined and optimized the prices for the different *situations* systematically. To complement the analysis I will in Section 4.3 use an exogenous shock to the exchange rate between money and *coins*. The price shock is announced by Apple only a few days before the implementation and the gaming company has no control over the timing. They also did not change the price of coins in the game.

4.1.2 Estimation

More technically, the price in *coins* is fixed for each *situation* g.[13] As it does not vary over individuals and time, we are interested in the consumer response to different 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 Appendix A, with qualitatively the same results.

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

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* [14] increases the of share of *videos* with 7 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 γ_i, θ_h, λ_d, and μ_w, in Equation 1. The coefficient shrinks to a fourth when individual fixed effects are introduced in

[13] This is done for the main sample. In Appendix A I do the same analysis including the times the payment method is tickets, with qualitatively the same results.

[14] 0.01 Euro

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.

Table 4: Main regression results

	video	
	OLS	FE
Model:	(1)	(2)
Variables		
Constant	-1.12***	
	(0.047)	
price	0.070***	0.019***
	(0.002)	(0.0003)
Dep var mean	0.909	0.909
Percent	7.73	2.06
Fixed-effects		
userid		YES
weekday		YES
hour		YES
week		YES
Fit statistics		
Observations	2,252,465	2,252,465
R^2	0.25728	0.74776
Within R^2		0.04385
Individuals	24,224	24,224

Clustered (userid-price) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

Notes: This table reports the results from the main regression. The dependent variable is if 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 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 small in magnitude. France deviates but consists of the smallest sample as well as the country with the smallest share of converters.

Table 5: Main regression, different selections

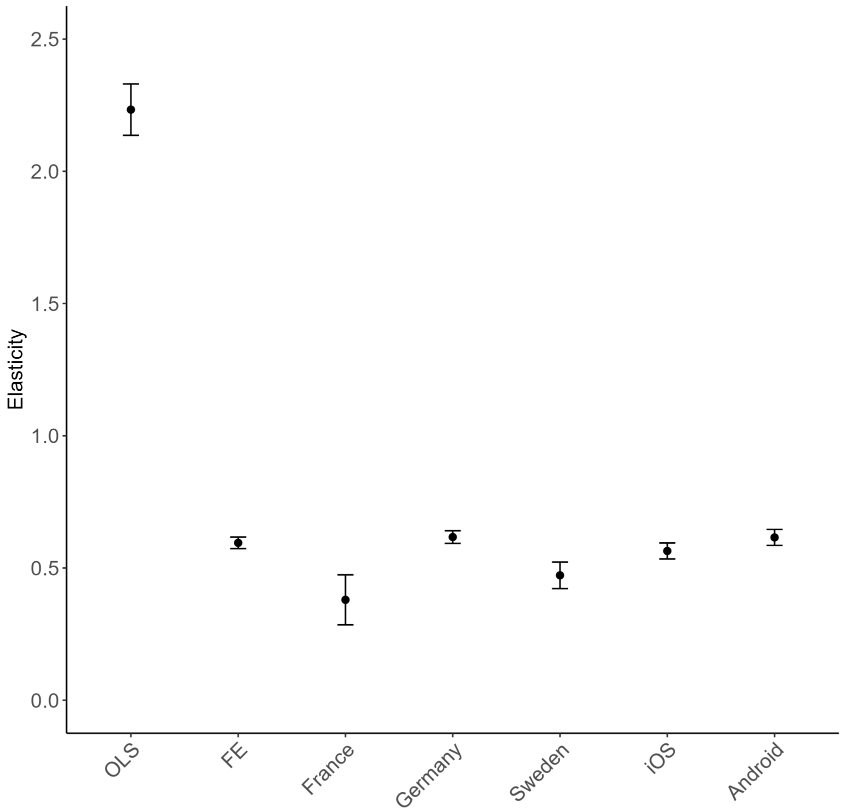
Model:	France (1)	Germany (2)	video Sweden (3)	iOS (4)	Android (5)
Variables					
price	0.012***	0.019***	0.015***	0.018***	0.019***
	(0.002)	(0.0004)	(0.0008)	(0.0005)	(0.0005)
Dep var mean	0.932	0.909	0.898	0.902	0.913
Percent	1.31	2.13	1.64	1.96	2.13
Fixed-effects					
userid	YES	YES	YES	YES	YES
weekday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

Clustered (userid-price) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

Notes: This table reports the results from the main regression. The dependent variable is if 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.

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 the 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.

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^{th} 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.

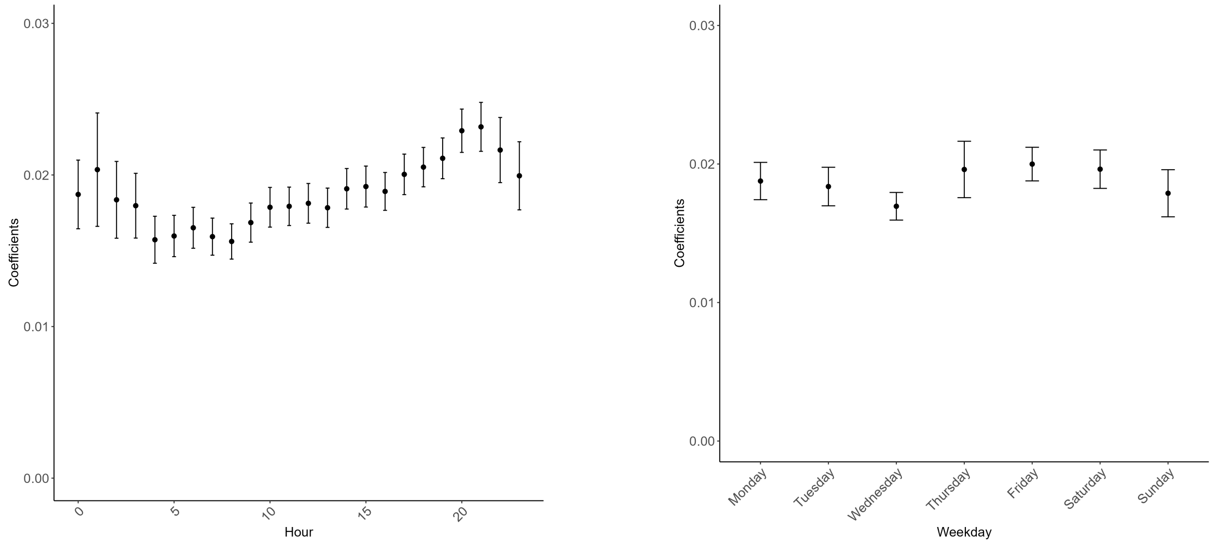
$$video_{igj} = \alpha + \sum_{t=0}^{23} \beta_t \cdot \mathbb{1}(t) \times P_{gt} + \mu_i + \gamma_t + \epsilon_{igj} \tag{2}$$

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. 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.* , 2022) on cab-waiting times. (Buchholz *et al.* , 2022) find a higher valuation of time in the mornings and during the day, whereas I find a higher valuation of time in the afternoon and evenings.

The difference in the heterogeneity between our two papers stresses the point 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. For the day of week heterogeneity we see no significant differences.

Figure 7: Heterogeneity over time in the estimated coefficients

(a) Hour specific coefficients (b) Weekday specific coefficients



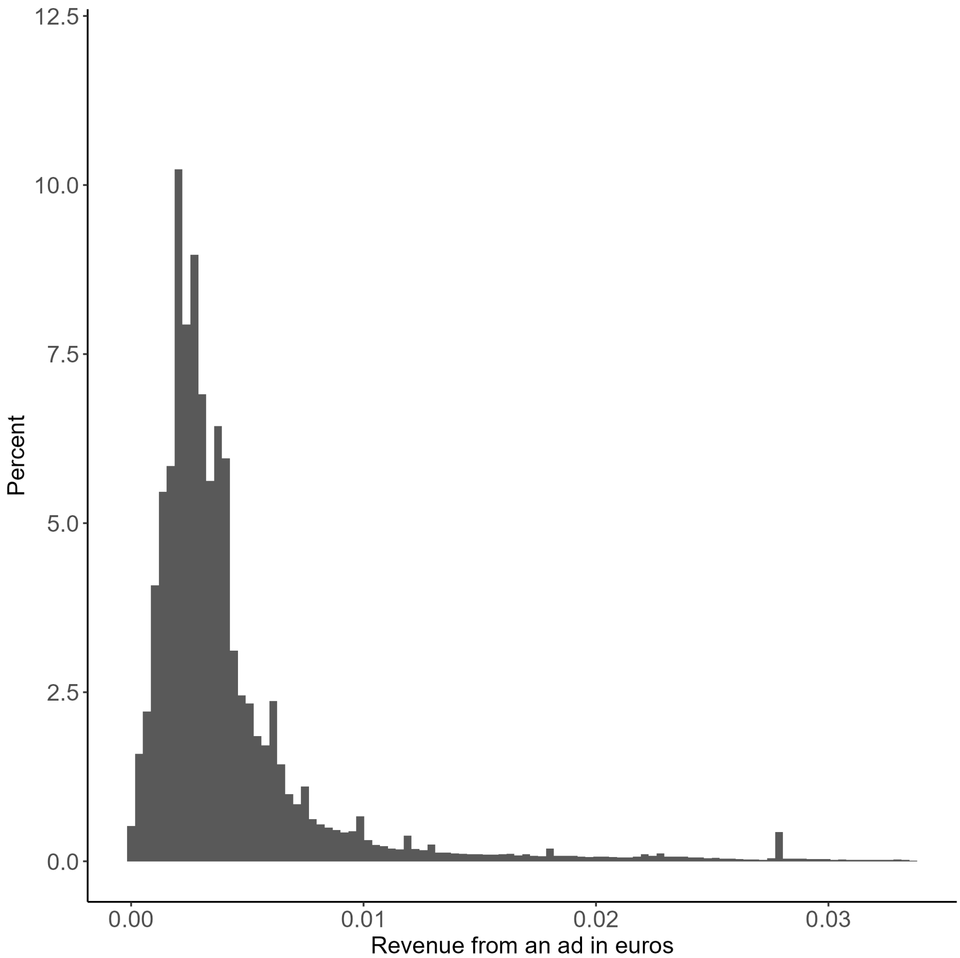
Notes: This figure shows the coefficients that corresponds to equation 2 for the hour of the day and the same for weekdays. Standard errors are clustered as in on user and price and then derived with the delta method.

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 to show a specific individual *video* in a specific time period. To decide which *video* is shown a real-time auction is held. Different platforms have different auction systems, and the bidding process may differ. 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" (CMA, 2020) for a more detailed description of how the advertisement market works technically.

The revenues from the ads in my sample are displayed in Figure 8. The graph is trimmed at the 99^{th} percentile. The median revenue is 0.004 Euro and the mean revenue is 0.006 Euro.

Figure 8: The distribution of revenues from advertising

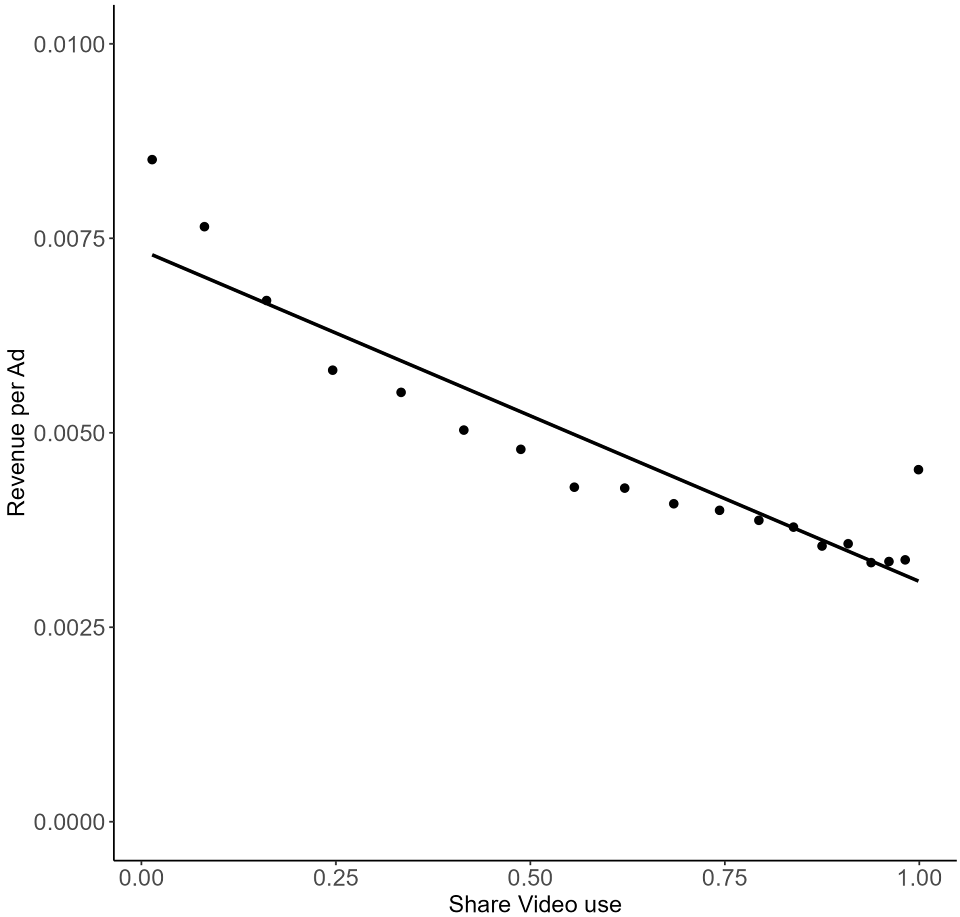


Notes: The distribution shown is the average revenue the gaming company gets from showing an ad to a specific user on a specific day. The distribution is winsorized at the 99^{th} percentile. The mean revenue is 0.006 Euro and the median revenue is 0.004 Euro.

In Figure 9, the raw correlation between the individual's share of *video* usage [15] to pay for a feature, with the average revenue for the gaming company. 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 imply that the effect is solely driven by individual variation.

[15] Variation is on the level of for each different user, for each day of the time period.

Figure 9: Demandside relationship between average revenue and user *video* useage



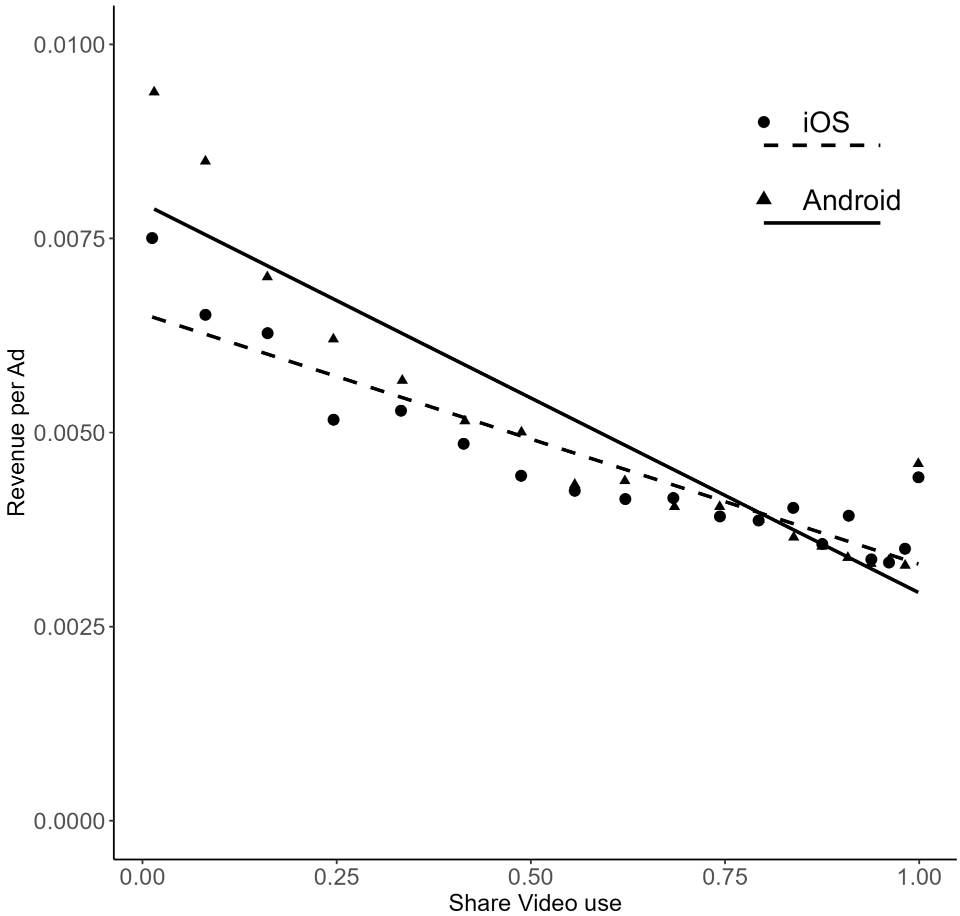
Notes: This figure shows the relationship between the share of *videos* used by individuals and the average revenue the gaming company gets from showing an ad to that individual as a binscatter. On the y-axis we have the revenues as in Figure 8 and on the x-axis we have the share of *videos* usage. Both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

Further of interest is the difference between the different platforms as seen in Figure 10. Here we see that the ads to Android users cost more, but also that the relationship between *video* usage and the revenue of the ad is stronger. This indicates a higher revenue for advertisers to reach paying Android users in levels as well as larger price discrimination. A natural interpretation of the relationship is that Android users are more valuable than IOS users. Such a small difference is not economically significant, but the results can be interpreted as a rebuttal to the former industry knowledge that IOS users are richer and more valuable users.

Another rationalization is that Android shares more of the users' data with advertisers, after the introduction of Apple's App Tracking Transparency Framework in 2021. The attention market of advertisement is to some extent a market for information, as reviewed by Bergemann & Bonatti (2019). Better targeting will allow for better price discrimination making the value to advertisers higher. After the introduction, IOS apps reduced reliance on ads for monetarization (Cheyre *et al.* , 2023), indicating such an effect. The privacy effect is also seen in other aspects of mobile apps, such as in Bian *et al.* (2022) who find a reduction in the use of apps that share lots of individual data after the introduction of easy-to-read privacy labels. Further, Bian *et al.*

(2022) also find that stock markets reacted negatively to such stricter privacy measures, for companies that were exposed to data-intensive apps.

Figure 10: IOS vs Android: Demandside relationship between average revenue and user *video* useage



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, 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.

To estimate the correlation between revenue from showing *videos* and the usage of *video* by individuals I apply Equation 3 and report the estimated coefficients in Table 6.

$$\text{Ad revenue per video}_{it} = \alpha + \beta \cdot \text{Share video}_{it} + \gamma_i + \epsilon_{it} \tag{3}$$

All coefficients are standardized to compensate for the non-intuitive levels of the revenue from showing *video*. In Table 6, Columns (1) and (2) I aggregate the numerical value of the share of *videos* to different levels. In Column (1) the share of *videos* watched by individuals and the revenue from showing ads are aggregated on the individual level, i.e. one individual is one observation. In Column (2) the share is instead aggregated on the individual$\times$ date level. Column (3) is aggregation on an individual $\times$ date level and includes the fixed effects γ_i. From this exercise we see that the relationship between the value of an individual on the ad market and their own valuation of their attention is significant and negative, meaning that individuals with a low valuation are worth less on the ad market. The correlation is stronger when the data is aggregated on the individual level, indicating that the targeting is done on the individual level, which is further supported by the decrease when individual fixed effects are added.

Table 6: The relationship between revenue and usage of videos

Dependent Variable:	Expected profit per ad			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	0.2984***	-0.0521***		0.1575***
	(0.0073)	(0.0006)		(0.0083)
Share Video	-0.2081***	-0.0852***	-0.0023**	
	(0.0064)	(0.0006)	(0.0008)	
Elasticity				0.1038***
				(0.0060)
Level of data	Per individual	Per individual and date	Individual FE	Elasticity
Fit statistics				
Observations	68,607	1,781,100	1,781,100	23,452
R^2	0.01500	0.01041	0.69166	0.01241
Within R^2			1.16×10^{-5}	

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

Notes: 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 column (1) the aggregation is on the individual level, in column (2) the aggregation is on the individual$\times$ date level, which corresponds to Figure 9, and in column (3) the aggregation is on the individual$\times$ date level and includes individual fixed effects.

The platform heterogeneity is investigated in Table 7. Using the specification from Equation 4

$$\text{Ad revenue per video}_i = \alpha + \beta_1 \cdot \text{Share video}_i + \beta_2 \text{iOS}_i + \beta_3 \text{Share video}_i \times \text{iOS}_i + \epsilon_i \qquad (4)$$

and 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.

4.3 Difference in Difference

As described payment is done in two steps. First *coins* are bought, and then they are used to pay for features. The amount of money paid for a coin is called the exchange rate, to distinguish it from the price of the feature. The dataset is chosen so that there is a sharp increase in the

Table 7: Controls and platform hetrogenity

Dependent Variable:	Expected profit per ad			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	0.3530***	0.3388***	0.1905***	0.1896***
	(0.0093)	(0.0096)	(0.0107)	(0.0107)
Share Video	-0.2123***	-0.2518***		
	(0.0064)	(0.0087)		
iOS	-0.1257***	-0.0865***	-0.0822***	-0.0797***
	(0.0135)	(0.0147)	(0.0169)	(0.0169)
Share Video × iOS		0.0887***		
		(0.0130)		
Elasticity			0.1042***	0.1150***
			(0.0060)	(0.0081)
iOS × Elasticity				-0.0246**
				(0.0122)
Fit statistics				
Observations	68,607	68,607	23,452	23,452
R^2	0.01624	0.01691	0.01340	0.01357
Adjusted R^2	0.01622	0.01687	0.01332	0.01345

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

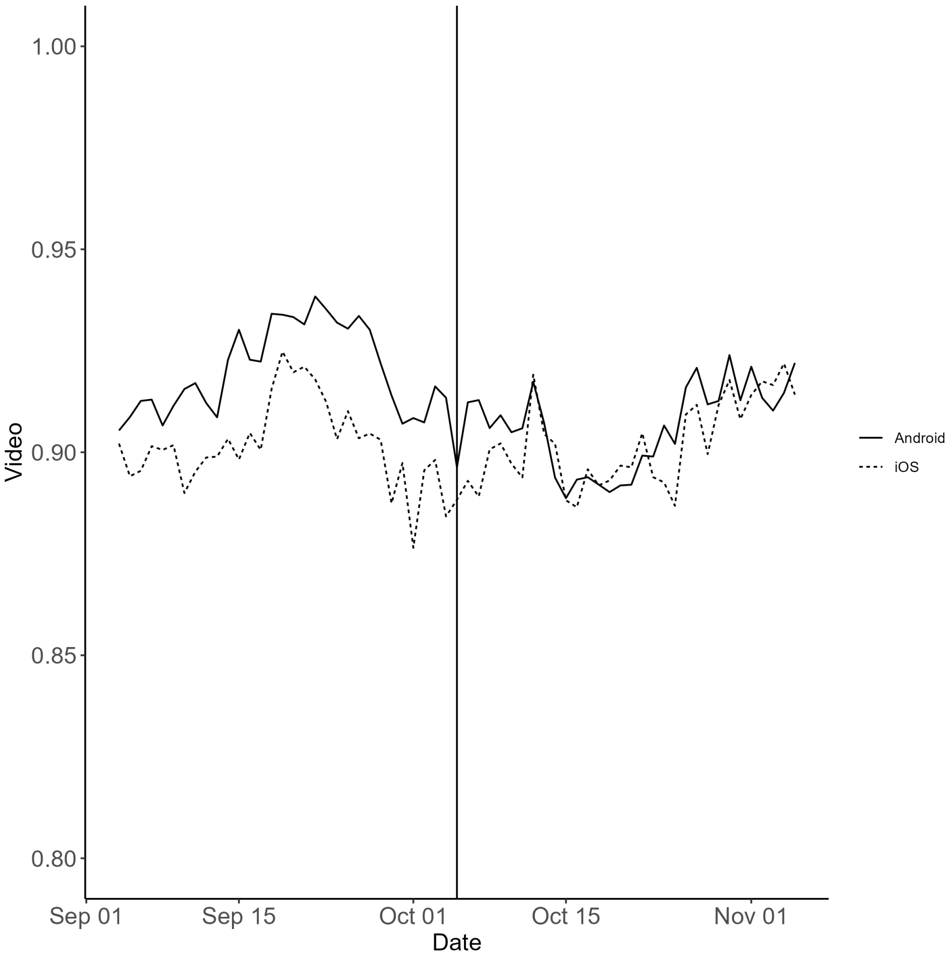
Notes: This table shows the results from the regression of the revenue from showing ads to individuals on the share of *videos* used by the individual for two different specifications. The dependent variable is the revenue from showing ads to the individual. The independent variable is the share of *videos* used by the individual. The aggregation is on the individual× date level. In column (1) the platform and country are added as controls, and in column (2) the platform interacted with the share of *videos* used, corresponding to Figure 10

exchange rate between money and *coins* on October 6th for IOS. The method follows (Enache *et al.* , 2022), who looked at conversion rates using an earlier increase in the exchange rate. Exogenity can be established as the policy was announced by the platform (IOS), not the gaming company, and the gaming company did not change its own pricing in response to the change within the data period.

The increase is for IOS but not for Android. Generally, the cost to consumers is structured such that *coins* can be bought in tiers. The lowest tier is 110 *coins*, the next 600 *coins*. Before the change the price for the lowest tier was 0.99 Euro and after it was 1.19 Euro in IOS. Generally, the exchange rate increase was between 20 and 25%, depending on the amount you bought for. In contrast, the exchange rate in Android was 1.09 Euro during the entire period. I will therefore estimate the effect of the exchange rate increase on the general usage of *videos* in a Difference in Difference setup.

In Figure 11 we see that the usage of *videos* is higher in Android than in IOS before the price change. Visually, the usage co-move in the pre-period, indicating that the parallel trend assumption holds.

Figure 11: Average *video* use over time, IOS vs Android



Notes: This figure shows the average share of *videos* used by individuals in the sample over time. The sample is split by platform. The vertical line indicates the time of the price change in iOS. The preperiod, even if noisy shows no indication of the parallel trend assumption being violated.

In Table 8 we see that there is a positive effect of the exchange rate increase on Rewarded video, following the documented effect from Enache *et al.* (2022) that *coins* and *videos* are complements. Interestingly the effect disappears with individual fixed effects in Column (2), indicating that it is mainly due to the exit and entry of different players. In Columns (3) and (4) I use the sample of nonconverters as a placebo test. They have never used money in the game and should therefore not have a reaction to the price change. We there see an point estimate that is about 5% of the effect on the converters, and not statistically significant.

Table 8: Price of coin change

Dependent Variable:	video			
	Payer		Non-payer	
Model:	(1)	(2)	(3)	(4)
Variables				
post × treat	0.013***	0.0002	0.0007	0.0006
	(0.0008)	(0.002)	(0.0004)	(0.0006)
Fixed-effects				
userid		Yes		Yes
date		Yes		Yes
Fit statistics				
Observations	2,252,465	2,252,465	1,707,869	1,707,869
R^2	0.00065	0.73656	0.00373	0.41370
Within R^2		7.78×10^{-5}		3.66×10^{-5}

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table shows the Difference in Differences results from the ios price change on the price of coins. In column (1) we see the effect of the price change on the share of *videos* used. In column (2) we see the effect when individual fixed effects are added. In column (3) we see the effect on the non-converters and in column (4) the effect on the non-converters with individual fixed effects.

The acts of buying coins and then spending them in the game are different. The implied elasticity by Column (1) of Table 8 is 0.065. It corresponds to the extensive margin. The implied intensive elasticity is insignificant and close to zero following Column (2). When comparing elasticity from the purchasing stage estimated here with the usage of coins elasticities from above, we have a difference in magnitudes. The difference is striking and speaks to the different processes of purchasing of the *coins* and spending of *coins*. The structure is imposed by the entire ecosystem of the platform. The magnitudinal differences in my results can both be explained by behavior that is the result of the setup of payments itself. But another rationalization on how the behavioral processes of buying coins and spending them are different, which in turn is why the structure is set up the way it is, by the platforms.

Enache *et al.* (2022) find an elasticity of the price increase on video use of 0.473, with aggregate data. Even if it is larger by a magnitude than my extensive margin results my estimates are inside their confidence intervals. The differences can be due to either the statistical power differences or more fundamental differences, such as the difference in the apps we study or the population of players in the different apps.

As the effect is a functional zero when considering the intensive margin, I indicate that results in Enache *et al.* (2022) are mainly due to the exit and entry of different players from buying coins in total.

5 Model

In addition to the elasticities estimated previously, I will also estimate the price of attention, or as I formally define it, the willingness to pay to avoid advertisement (WTPA).

Expanding on the conceptual framework from Section 3, I propose a model that rationalizes two empirical observations: individuals use both *video* and *coins* as methods of payment, and individuals do not play the game in infinity. I model individual behavior, which corresponds to the supply side of the market for attention. The model has two purposes. First, it will allow me to estimate the WTPA or price of attention to a numerical value. I will also do so for the distribution of individuals. Second, it lays the groundwork to consider individuals' consumption decisions in response to changes in the price to play in *coins*. Using as few assumptions as possible the model allows me to estimate a numerical value for the price of attention. My modeling approach is the following:

I assume that for a time-period T there are J instances of potential playing, j, ordered such that the marginal utility is decreasing in j. The individual i has the utility u_{ij} from playing the game at instance j. The cost to play in *coins*, p^{coin}, is set by the gaming company. It is fixed from the perspective of the individual. The cost in attention is a random variable, P_{ij}^{video}. I assume that it is individual and instance dependent, and measured in *coins*. P_{ij}^{video} corresponds to the individual's willingness to pay to avoid (WTPA) a *video* in instance j.

5.1 Setup

To formalize the problem, we set up a decision problem for the individual i. For the time-period T, the individual will have J instances at which she can potentially play the game. After the time-period T, the utility is reset and the individual starts anew. On the individual level, I formally define the cost of attention in coins for the individual i and instance j ($j \in J$) as the random variable P_{ij}^{video}. P_{ij}^{video} is drawn independent and identical distributed from the distribution $F_i^{video}(\cdot) = F^{video}(\cdot) + \gamma_i$ where γ_i is the individual deviation in mean from the aggregate distribution. The distribution $F_i^{video}(\cdot)$ is stationary, i.e. does not vary over j and therefore not over time. In the estimation, I will first consider the distributions $F^{video}(\cdot)$. For the heterogeneity, I will go back to the individual specification, $F_i^{video}(\cdot)$.

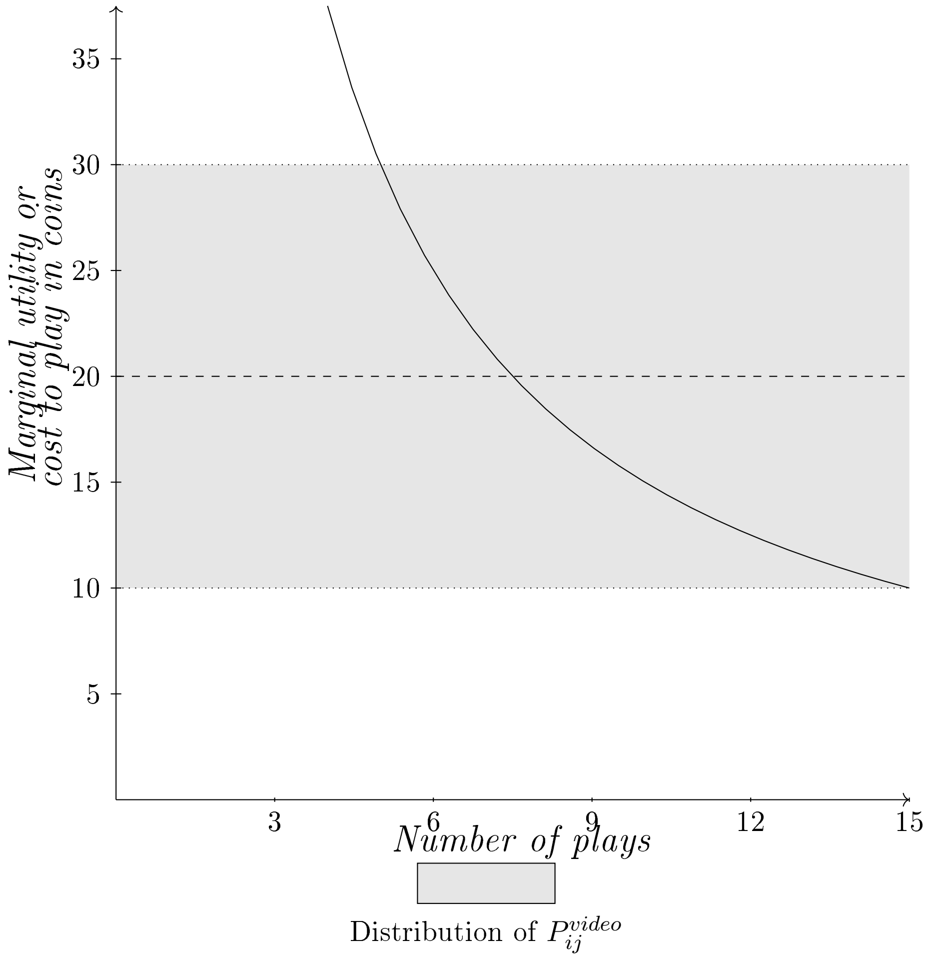
The individual has a decision problem where she chooses her action in the following way. In the beginning of each instance $j \in J$ she draws P_{ij}^{video} IID from $F_i^{video}(\cdot)$. The random variable P_{ij}^{video} is realized before she acts according to equation 5. The cost of playing the game for individual i at instance j using *video* is the realization of P_{ij}^{video}, p_{ij}^{video}. The actual cost of playing the game, c_{ij} depends on if the realization is higher or lower than the price to play using coins, p^{coins}:

$$c_{ij} = \min\{p^{coin}, P_{ij}^{video}\}$$

Finally the individual i's surplus at instance j is $V_{ij} = u_{ij} - P_{ij}$.

$$\text{Action} = \begin{cases} \text{Do not play} & \text{if} \quad u_{ij} < c_{ij} \\ \text{Play with } \textit{coins} & \text{if} \quad u_{ij} \geq c_{ij} \ \& \ p^{coin} \leq p_{ij}^{video} \\ \text{Play with } \textit{video} & \text{if} \quad u_{ij} \geq c_{ij} \ \& \ p^{coin} > p_{ij}^{video} \end{cases} \tag{5}$$

Figure 12: An example of how the cost and marginal utility can change over the number of plays in a day.



The shades area corresponds to a uniform distribution of P_{ij}^{video}. The dashed line is p^{coin}, as well as the mean of the uniform distribution. The black line is the decreasing marginal utility function.

The individual utility will vary over j. Note that the realization of the cost of attention varies over j but the distribution is stationary. The most conceptually appealing framework would be for the utility also to be a random variable, but for tractability, I use a deterministic utility function. Instead, I order the instances from the highest to the lowest utility for $j \in J$.

Next, we construct an arbitrary example that illustrates the mechanisms of the model. We look at Figure 12. Marginal utility is represented by the black line $u_{ij} = \frac{150}{j}$ and the distribution of P_{ij}^{video} is $F_i(\cdot) = U(10, 30)$, which is indicated by the shaded area. The fixed cost in *coins* is $p^{coin} = 20$, the dashed line.

Individuals will only play if $u_{ij} > c_{ij}$, as seen in Equation 5. The variation of the individual's utility for the potential instances J is a function of j, ie $u_{ij} = u_i(j)$ and are ordered as decreasing in $j, u_i(j+1) < u_i(j)$. The demand is then the sum of the marginal utilities of the games played for J,

$$U_{iJ}(k) = \sum_{j=1}^{k} u_i(j)$$

We will then estimate the expectation of the individual WTP to avoid a *video*, $\widehat{p_i^{video}}$.

To describe the number of plays done with *coins* and *video* we have the total number of plays times the share of plays with *coins* and *video*. We want to describe the number of plays done with *coins* and *video* as functions of the price of play in coins. The probability that $P_i^{video} < p^{coin}$ is $F_i^{video}(p^{coin})$ and the probability that $P_i^{video} > p^{coin}$ is $1 - F_i^{video}(p^{coin})$. Given these probabilities, we can express the expected number of plays with *coins* and *video* as functions of the price of play in coins. We also need the probability of playing at all. It depends on j and is represented by $\max\{\mathbb{1}(u_{ij} \geq p^{coin}), F_i^{video}(u_{ij})\}$.

In expectation, the total number of plays is then the product of $\max\{\mathbb{1}(u_{ij} \geq p^{coin}), F_i^{video}(u_{ij})\}$ and J. To get the number of plays in coins we multiply with $1 - F_i^{video}(p^{coin})$ and to get number of plays with *video* we multiply with $F_i^{video}(p^{coin})$.

Each J is treated separately so that the utility function is reset each J. Agents maximize their surplus over instances J which in expectation is equivalent to choosing the number of games to play. This choice I call k, such that $k = \underset{k \in J}{\arg\max} V_{iJ}(k)$ with

$$V_{iJ}(k) = \sum_{j=1}^{k} \left(u_i(j) - \left(p_{ij}^{video} \cdot F_i^{video}(p^{coin}) + p^{coin} \cdot (1 - F_i^{video}(p^{coin})) \right) \right).$$

The maximization can intuitively be thought of as the individual keeps playing until marginal utility decreases below cost:

$$u_i(k) = p_{ij}^{video}(k) \cdot F_i^{video}(p^{coin}) + p^{coin} \cdot (1 - F_i^{video}(p^{coin})). \tag{6}$$

Equation 6 I call the stopping condition.

For an example, we turn to Figure 13. The marginal utility function here is once again $u(j) = \frac{150}{j}$, and $p_{coins} = 20$. $P_{ij}^{video} \in F_{video}^{i}(\cdot) = U(10, 30)$ is a uniform distribution, ie the same as in Figure 12. In the dotted area, the player does not play, in the area with vertical lines the player pays with *coins* and in the area with horizontal lines, the player pays with *video*. In this example, the player will play at least until $j = 7$, as the utility is larger than p^{coin} up until then. The choice of payment depends on if $p_{ij}^{video} \geq p^{coin}$. After $j = 7$, more plays might happen, if p_{ij}^{video} below the further $u_i(j)$, but no more payments with *coins*.

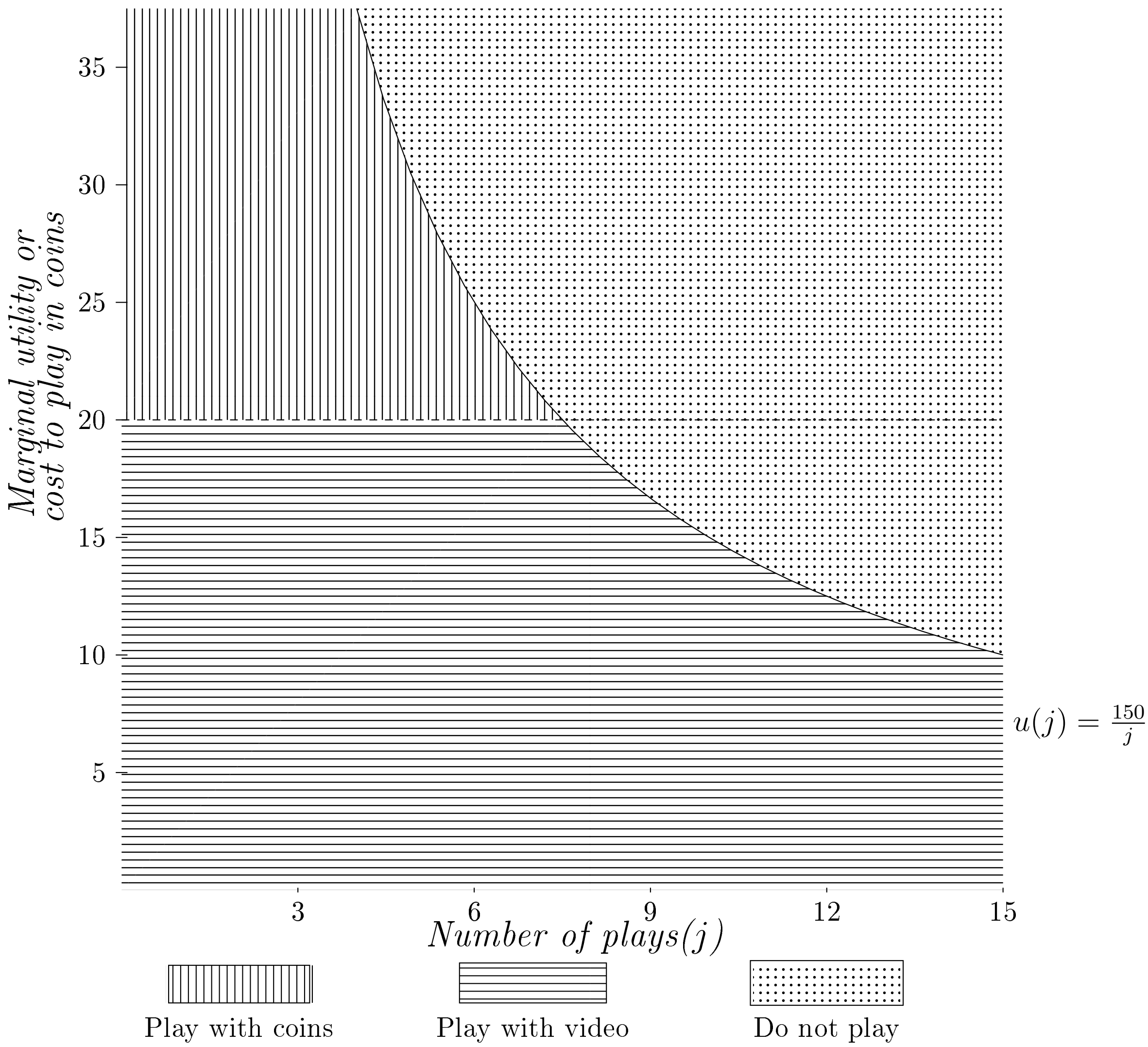
6 Estimation of the value of attention

To estimate the cost of attention to individual i, P_i^{video}, I use data from the two games(instances) Starstreak (SS) and Arena(A). They both follow the stopping condition in Equation 6 separately. Let us first assume that the utility form for the games, (u_{iJ}^{SS}, u_{iJ}^{A}) can vary in their functional form. The cost in coins is different between the games according to Table 1 and fixed, $p_A^{coin}, p_{SS}^{coin}$.

First I set the stopping condition for both games, SS and A. This is for time period covering instances J

$$u_{iJ}^{SS}(k^{SS}) = p_{iJ}^{video} \cdot \frac{video_{iJ}^{SS}}{k^{SS}} + p_{SS}^{coin} \cdot \frac{coin_{iJ}^{SS}}{k^{SS}}.$$

Figure 13: The different areas around which an individual will play



The different areas correspond to the different actions the player can take, according to Equation 5. The player has the utility $u(j) = \frac{150}{j}$. Note that the payment choice only depends on p_{ij}^{video}.

$$u_{iJ}^{A}(k^{A}) = p_{iJ}^{video} \cdot \frac{video_{iJ}^{A}}{k^{A}} + p_{SS}^{coin} \cdot \frac{coin_{iJ}^{A}}{k^{A}}$$

Here k^A and k^{SS} are the numbers of games played in the two different games during J and $video_{iJ}^{SS}$, the number of payments in SS for individual i in J. $video_{iJ}^{A}$, $coins_{iJ}^{SS}$, $coins_{iJ}^{A}$ follow the same pattern. I then divide the SS condition with the A condition.

$$\frac{u_{iJ}^{SS}(k^{SS})}{u_{iJ}^{A}(k^{SS})} = \frac{p_{iJ}^{video} \cdot \frac{video_{iJ}^{SS}}{k^{A}} + p_{SS}^{coins} \cdot \frac{coins_{iJ}^{S}}{k^{SS}}}{p_{iJ}^{video}(k^{A}) \cdot \frac{video_{iJ}^{A}}{k^{A}} + p_{A}^{coins} \cdot \frac{coins_{iJ}^{A}}{k^{A}} -}.$$

The aim is to estimate $\overline{p_i^{video}} = \mathbb{E}_T(P_i^{video})$. The ratio $\frac{u_{iJ}^{SS}(k^{SS})}{u_{iJ}^{A}(k^{SS})}$ is denoted du_{iJ}. I rewrite to get a closed-form expression for $\overline{p^{video}}$:

$$\overline{p^{video}_{iJ}} = \frac{10du_{iJ}\frac{coins^{A}_{iJ}}{k} - 30\frac{coins^{SS}_{iJ}}{k^{SS}}}{\frac{video^{SS}_{iJ}}{k^{SS}} - du_{iJ}\frac{video^{A}_{iJ}}{k^{A}}}.$$

I estimate du_{iJ} using a functional form of $u_i(j)$. For tractability we make the ansatz :

$$\sum_{j=1}^{k} u_i(j) = \eta_i \ln(k) \implies du_{iJ} = \frac{\eta_i^{SS}}{\eta_i^{A}} \frac{ln(\frac{k^{SS}}{k^{SS}-1})}{\ln(\frac{k^{A}}{k^{A}-1})},$$

which corresponds to logarithmic demand. The anzats allow for a different functional form of the utility function in the two games. As non-converters can be modeled as having a distribution with an upper bound strictly smaller than 10, they face the same price in both games and play until the marginal utility of the two games is the same, ie $du_{iJ} = 1$.

Then

$$\frac{\eta_i^{A}}{\eta_i^{SS}} = \frac{ln(\frac{k^{SS}}{k^{SS}-1})}{\ln(\frac{k^{A}}{k^{A}-1})}$$

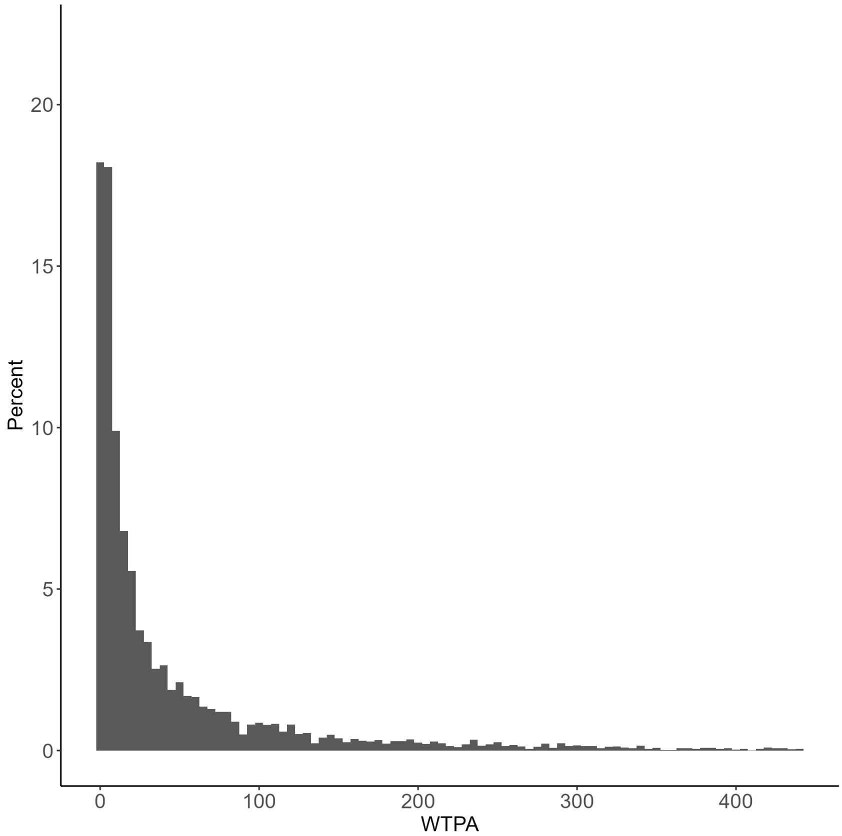
holds for non-converters, and if $\frac{\eta_i^A}{\eta_i^A SS}$ is the same for converters and non-converters, we can calibrate the fraction on non-converters. For the non-converters the average numerical value $\frac{\eta_i^A}{\eta_i^A SS} = 1.38$ which gives the average of$du_{iJ} = 1.24$ for converters. Taking the average for the entire converter sample we get the estimate $\overline{p^{video}}$ is the mean of $Fvideo$:

$$\overline{p^{video}_{iJ}} = \frac{10\frac{coins^{A}_{iJ}}{k^{A}} * du_{iJ} - 30\frac{coins^{SS}_{iJ}}{k^{SS}}}{\frac{video^{SS}_{iJ}}{k^{SS}} - \frac{video^{A}_{iJ}}{k^{A}}du_{iJ}}.$$

With aggregation over the converter's sample, and T is one day the estimate is: $\overline{p^{video}} = 15.9$ coins. Using the in-game exchange rate $\overline{p^{video}} \approx 0.15$ Euro.

We can also estimate the price individually, p_i^{video}. Then I assume the common η for all individuals to estimate $\overline{p_i^{video}}$. The distribution of $\overline{p_i^{video}}$ is plotted in Figure 14, trimmed at the 2.5^{th} and 97.5^{th} percentile.

Figure 14: Individual price heterogeneity



Notes: This figure shows the distribution of individual willingness to pay to avoid an ad. It is trimmed at the 95th percentile. Each observation is an individual.

We can see the characteristics of the distribution in Table 9. Noteworthy is once again the skewness of the distribution. It indicates how price discrimination could be used to increase revenue. But as mentioned in the previous section, direct price discrimination has not been implemented in part due to the risk of consumer backlash.

Table 9: The distribution of individuals WTPA

Mean	Median	SD	P10	P25	P75	P90
45.79	14.85	72.91	1.23	3.97	53.08	129.83

Notes: This table shows the characteristics of the distribution of individuals WTPA. Each observation is an individual.

7 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 anti-trust cases (FTC, 2021; United states Department of Justice., 2020; DoJ, 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 their prices in *coins* to reoptimize their revenue. If they increase their prices 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 in *coins* to increase the number of plays with *coins*. But to get an accurate prediction we cannot rely on the reduced form result only. Instead, we need to estimate the distribution of $F_i^{video}(p^{coin})$ from the model in Section 5 as done in Section 6.

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 7. Here Π_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[16]. p_j^{Ad} is the revenue from showing an ad instead for the instance of play j.

$$\Pi_G = \sum_{j=1}^{k} \left(0.7 \cdot p^{coin} \cdot (1 - F_i^{video}(p^{coin})) + p_j^{Ad} \cdot F_i^{video}(p^{coin}) \right) \tag{7}$$

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 important for the revenue. The individual player plays according to the same model as in Section 5 and maximizes equation 8.

$$U_{iT}(k) = \sum_{j=1}^{k} \left(u_i(j) - \left(u_{iT}(k) = p_{iT}^{video}(k) \cdot F_i^{video}(p^{coin}) + p^{coin} \cdot (1 - F_i^{video})(p^{coin}) - \overline{w_{iT}} \right) \right) \tag{8}$$

Given given some $u_i(j)$ and $F_i^{video}(p^{coin})$ one could plug in the data we have on p_j^{Ad} to thet a theoretical optimal price. This price will depend on p_j^{Ad} and determine the number of plays,

[16]The operating system takes about 30% of all in-app purchases.

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.

8 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* advertisement gives novel insights into the supply side of the attention market, by allowing me to describe both individual heterogeneity and time heterogeneity.

The results say willingness to pay to avoid advertisement is of the same magnitude as other measures of the value of time, while also having different time heterogeneities speaks to the context-dependence of the value of time. Further, the price advertisers pay for consumers' attention is correlated with the valuation the individual puts on their attention, but the price paid is only a fraction of the monetary value players put on their attention.

Optimal pricing implied by the data would include mainly individual price settings, but as individual pricing might be seen 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 anti-trust cases (FTC, 2021; United states Department of Justice., 2020; DoJ, 2023) and proposed digital ads taxes (Acemoglu & Johnson, 2024; Romer, 2021) are ongoing policy questions that would affect the market of advertisement. My novel estimates will be useful in understanding the effects of such policies in a dynamic setting. To build a model that can answer the questions of policy implications empirically, further work is needed.

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A Tables

Table 10: Weighted regression with all individuals

	video			
	OLS	Interaction	FE	FE Interaction
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	0.696***	-1.12***		
	(0.006)	(0.047)		
price	0.010***	0.070***	0.005***	0.019***
	(0.0002)	(0.002)	(8.28×10^{-5})	(0.0003)
free_userTRUE		1.93***		0.108
		(0.047)		(2,191.9)
price × free_userTRUE		-0.064***		-0.015***
		(0.002)		(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
Fixed-effects				
userid			YES	YES
weekday			YES	YES
hour			YES	YES
week			YES	YES
Fit statistics				
Observations	3,960,334	3,960,334	3,960,334	3,960,334
R^2	0.02389	0.12889	0.55346	0.55618
Within R^2			0.00826	0.01430

Clustered (userid-price) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

Notes: 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.

Table 11: All prices and logit

	video			
	OLS	FE	Logit	Logit FE
Model:	(1)	(2)	(3)	(4)
	OLS	OLS	Logit	Logit
Variables				
Constant	-0.249***		-18.3***	
	(0.002)		(0.371)	
price	0.040***	0.005***	0.752***	0.630***
	(0.0001)	(8.28×10^{-5})	(0.014)	(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
Fixed-effects				
userid		YES		YES
weekday		YES		YES
hour		YES		YES
week		YES		YES
Fit statistics				
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^2	0.64427	-2.0833	0.34423	0.73632
BIC	2,097,569.7	-4,280,693.4	901,760.2	457,409.6

Clustered (userid-price) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

Notes: 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.