International Journal of Industrial Organization 88 (2023) 102945

Contents lists available at ScienceDirect

International Journal of Industrial Organization

journal homepage: www.elsevier.com/locate/ijio

Demand for in-app purchases in mobile apps—A difference-in-difference approach[☆]

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ARTICLE INFO

Article history:
Received 16 August 2022
Revised 28 February 2023
Accepted 8 March 2023
Available online 17 March 2023

JEL classification:
D43
L13
L82

Keywords:
Freemium
Demand estimation
Mobile app markets
Platforms

ABSTRACT

Using five "freemium" mobile app games on six European markets we examine the effect of price changes on conversion rate, number of users and viewing of rewarded videos. Our difference-in-difference estimation relies on games being available on both the Apple and Google platforms with price changes on only one platform. Our main identification comes from exogenous adjustments of Apples prices in 2021. Own-price elasticities of conversion are in the -1 to -4 range. Watching of rewarded videos decreases as in-app prices decrease with an average elasticity of around 0.5, but overall play is not affected by changes in-app prices.

1. Introduction

"Little can be said about the functioning of a market without a quantitative assessment of demand." Berry and Haile (2021, page 1)

Mobile apps are increasingly shaping how we consume goods and services. By 2021 the average American spent around four hours per day on mobile devices and globally mobile apps generated 170 billion USD of in-app sales and 300 billion USD in ad spending.[1] Consumers overwhelmingly access mobile apps via either Apple's or Google's app store and the rapid growth of mobile apps since the introduction of smartphones in 2007 have put markets for mobile apps at the center of many ongoing policy discussions.[2] The power of platforms relative to content developers (as exemplified by legal action

☆ Financial support from Jan Wallander and Tom Hedelius Stiftelse is gratefully acknowledged. We are grateful to conference audiences at Civica (EUI), SIDE (Palermo), SWERIE (Stockholm), to the editor (Frank Verboven) and to two anonymous referees for valuable comments. Wiklander is CFO and director of Data and Analytics at MAG Interactive that provided the data. Beyond this the authors have no interests to declare.

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[1] Data.ai (2022, p 3).

[2] A user whose device runs on Apple's Ios operating system is typically constrained to download apps via Apple's app store and a user of a device with Android's operating system is typically constrained to download apps via the Google play store. For simplicity we simply refer to Apple and Google in

https://doi.org/10.1016/j.ijindorg.2023.102945

involving e.g. Apple and Epic Games)[3] and how mobile platforms should be regulated (e.g. the Digital Markets Act in the EU) are but two examples of such discussions.

While many mobile apps are free to download, sales revenue from in-app purchases (a so called “freemium” business model) is often an important source of revenue.[4] Freemium is a common business strategy, used by for instance many game developers and other firms operating in digital markets, such as Dropbox and Spotify. Despite its ubiquity, the economics and marketing literature on this business model is still very limited.[5]

Thus, mobile apps are an increasingly important market that is partly shaped by rules set by two platforms and with many app developers using a model for pricing that has seen relatively little research so far. This paper aims to increase our understanding of demand for in-app purchases on mobile apps. We use data for five games across six European markets (France (FR), Germany (DE), Great Britain (GB), Italy (IT), Netherlands (NL) and Sweden (SE)). All the games that we examine are word-based puzzle games with *Wordbrain* as an illustrative name and supplied by Sweden-based app developer MAG Interactive.[6]

We highlight three contributions. First, we provide a detailed description of pricing and demand for these apps. For a novel market where such details are typically hidden behind the corporate veil we expect this to be a useful description for others wanting to understand these markets. Second, we provide some of the first estimates of the price sensitivity of demand for in-app purchases in mobile apps, finding own-price elasticities of conversion in the -1 to -4 range. In so doing we also rely on institutional detail and rich data to show how a difference-in-difference approach can be used to estimate demand responses to price changes in these markets and overcome challenges faced by a more standard approach. A final contribution to highlight regards the estimation of the elasticity of substitution between two ways of paying for in-game benefits: time (watching rewarded videos) and money (making in-app purchases). We find that the two ways of paying are substitutes with an average elasticity of around 0.5.

Let us expand somewhat on each of these three contributions. First, relying on user-level data for one of the games we document that the revenue distribution across users is very skewed, and further, that in-app purchases are a key source of revenue for the firm. To fix ideas we also present a simple model of differentiation by the opportunity cost of time that we apply to the freemium decision problem of the firm. We further note that mobile app developers are not free to set any price in the Apple app store and instead a developer chooses a pricing ”tier” for each product. In the U.S. the lowest tier is USD 0.99 and the next tier is USD 1.99 and the local currency prices in the markets that we examine are rough equivalents of these prices. We show that prices are very stable and further document that there are only small price differences between the same item on the Apple and Google platforms.

For the second contribution we note that a key input into analysis of any market is the response of demand to changes in price. Standard estimation of the elasticity of demand relies on variation in prices to trace out quantity responses, where the researcher needs to take care to identify price changes that are not endogenous to quantity - i.e. price changes that are not just a response to changes in demand (see for instance Berry and Haile (2021)). A typical estimation strategy is to use instrumental variables which affect the optimal price but have no independent effect on demand. Mobile app markets present a difficulty in that a standard form of instruments, that rely on marginal cost shocks, are not well suited since marginal costs of apps are close to zero and not linked to input prices.

We note that institutional features of the Apple platform facilitates estimation of demand responses to price changes. First, in non-U.S. markets Apple occasionally adjusts the local currency price of the respective tiers. With several million apps on each platform these price changes are plausibly exogenous from the perspective of an individual app developer. These changes are typically non-trivial and occur only on the Apple platform. Second, a typical app appears in identical versions on both the Apple and Google platforms which suggests that users on the other platform can act as a control group.

Fig. 1 illustrates the latter point by graphing the daily number of users of one of the games (*W1*) across the six national markets for each of the platforms. Visually the aily number of users move in tandem to a remarkable degree and it appears clear that the two series hold up well against a “parallel trends” assumption – plausibly the same demand shocks that affect the number of players of this particular game on Iphones in a country a particular day are having a very similar effect on the number of players of the same game using an Android phone in the same country and day.

The third contribution that we highlight, the elasticity of substitution between time and money, is a question of interest with many applications in economics. In these games consumers can choose to pay with money or by watching a short rewarded video gives an unusually clean setting for valuing time. Our estimated elasticity (.5) is on the low side compared to findings from other fields (e.g. macroeconomics and travel cost analysis) and we highlight that only a very small share of consumers make in-app purchases. Our model predicts that the customers who are affected on the margin by the changes in price are those that have a relatively high opportunity cost of time and, thus, have a relatively low tendency to switch to a more time-consuming way of playing if prices of in-app purchases increase.

this paper to denote the respective eco-system of operating systems and app stores. Competition & Markets Authority (2022) provides a comprehensive overview of these two eco-systems.

[3] See for instance “Apple wins a court battle with Epic Gamessort of”, The Economist, September 18, 2021.

[4] Techjury (2022) for instance reports that around half of app revenue comes from in-app purchases.

[5] See e.g. Shi et al. (2019), Sato (2019) or Boudreau et al. (2022) for exceptions and Kumar (2014) for an overview of some of the issues.

[6] See e.g. https://www.maginteractive.com or the annual report (MAG Interactive (2022)) for further description of the company and the games.

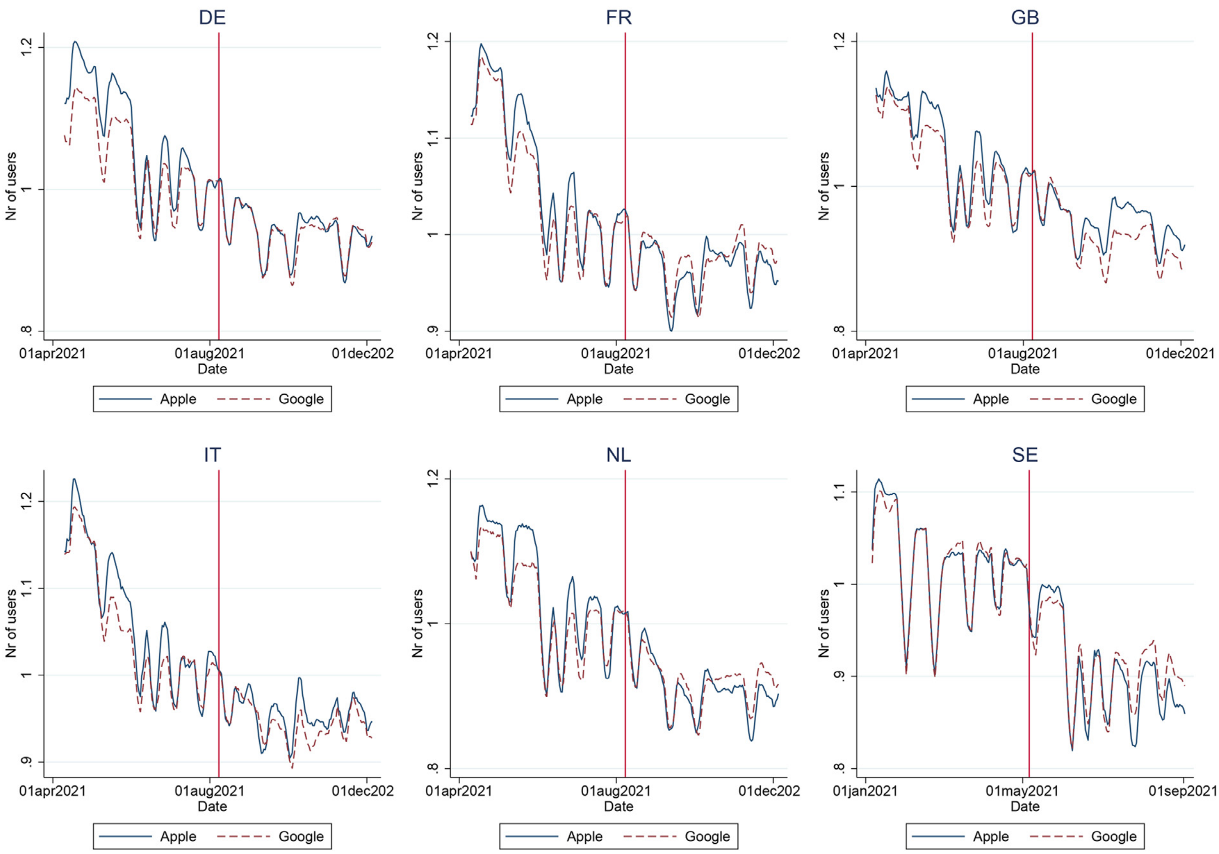

Fig. 1. The number of users per day of *W1* in six European countries surrounding price changes in Apple. The figure shows the daily number of users for 120 day windows on either side of a price decrease in Apple on six European countries. The timing of price decreases illustrated by vertical bars and number of users per day and platform are seven-day moving averages, normalized so that number of users for 30 days prior to the price change set to 1.

The economic literature on mobile apps is still in its infancy but can be seen as a part of a growing literature on digital markets with important strands empirically examining welfare effects of digital consumption (see, e.g., Allcott et al. (2022)) and theoretical work examining competition between platforms (see, e.g., Rochet and Tirole (2003)); Calvano and Polo (2021) provide a broad overview of research focusing on digitalized markets. Most closely related to ours are a set of articles that estimate how demand for mobile apps depends on observable characteristics of those apps, for instance establishing that the number of downloads increase with higher ratings, with the availability of an in-app purchase option, with greater visibility in the mobile app platforms and with version updates (see e.g. Ghose and Han (2014), Comino et al. (2019) or Ershov (2022)). Another strand of the literature focuses on user retention, again the estimation strategy that we propose has not been explored and research has focused on identifying and retaining the most valuable customers (see e.g. Gu et al. (2022)).

2. Data and description of the games

2.1. The data set

We have access to comprehensive daily country×platform level data on five games from the six European markets mentioned above from January 1, 2017 until February 9, 2022.[7] Reporting details of revenue and linking them to individual games is sensitive for MAG and therefore the names of the games are anonymized and we term them *W1-W5*. All the games are word-based and focus on intellectual challenge. They are thus examples of an important subcategory of games for mobile apps, word games, where well known games include Wordscapes, Wordle or indeed MAG-supplied games like Ruzzle and Wordbrain.[8] For these games we observe, at the daily level, for each country, game and platform the number of

[7] For the purposes of this paper we originally also had access to data for the five games for Australia, Canada, Denmark, Norway, South Africa and Turkey. South Africa and Turkey were excluded because of sparsity of in-app purchases for several of the games and the other countries were dropped because there were no in-sample changes in the Apple pricing tiers.

[8] See e.g. https://apps.apple.com/us/charts/iphone/word-games/7019 for additional examples in this category.

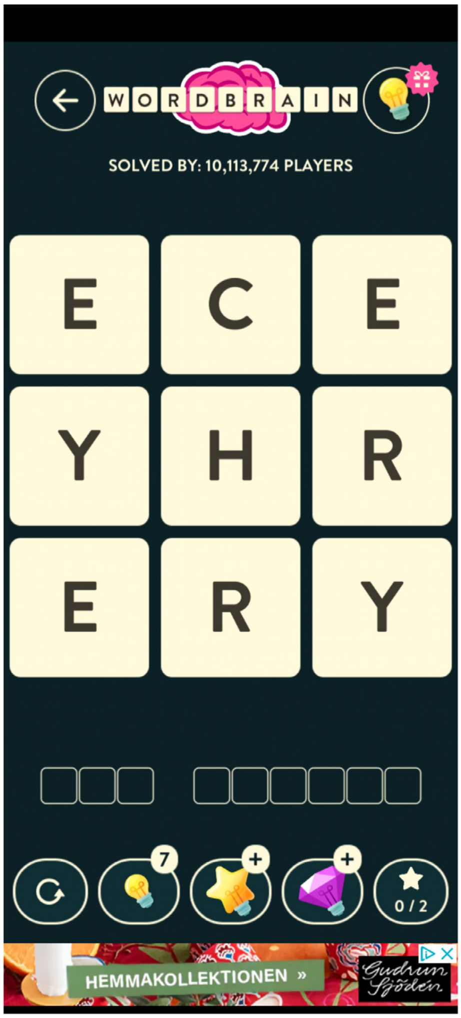

Fig. 2. A screenshot from *Wordbrain*. The figure shows a screenshot from an early stage game in *Wordbrain*.

users, the number of in-app purchases, and the number of rewarded videos watched to the end. Separate price files provide daily (by country, platform and game) number of purchases of different items and their respective prices. In regression work below we will focus on the number of users, conversion (number of in-app purchases/users) and videos (number of rewarded videos watched/users) at the daily country×game×platform level.

As explained below, our main identification strategy relies on changes in Apple's pricing tiers to estimate the elasticities of in-app purchases, of number of videos watched and of usage with respect to price. We estimate these on a subset of the full data, using event windows that span a period of 120 days before and after Apple's changes of pricing tiers. The normalized series for these event windows that we use for estimation are available in a replication package, Enache et al. (2023).

Summary statistics for non-normalized data to aid understanding of the market will to some extent rely on earlier observations as more current, non-standardized, data are sensitive for the firm to share. In addition, to describe some patterns of a freemium business model we use individual-level data (anonymized) from *W2* from two national markets (France and US) on revenue (from advertising and from in-app purchases) for all users that downloaded the respective game during a seven-day period.

2.2. A description of the games

All the five games of study are casual word-based puzzle games and Fig. 2 presents an example of a typical screen faced by the player in one MAG game, *Wordbrain*. The player should solve the puzzle, in this very early stage of the game using the nine letters on top to form two words at the bottom of the screen.[9] All the five games have a freemium structure such

[9] In the case illustrated the words are "eye" and "cherry".

Table 1
Summary statistics: A snapshot of daily averages across games and countries.

Game	Apple Users	Google Users	Apple Conversion	Google Conversion	Apple Videos	Google Videos
Germany						
W1	2802.50	3119.58	0.46	0.44	5.07	6.39
W2	931.37	2117.71	1.15	0.64	1.94	2.12
W3	1029.93	1331.44	0.42	0.53	2.46	2.87
W4	389.73	982.70	1.25	1.25	0.68	0.64
W5	9018.08	20158.83	0.53	0.46	5.72	6.72
Great Britain						
W1	14926.64	5384.06	0.80	0.84	4.53	5.79
W2	3989.08	1812.48	1.10	1.26	1.66	2.02
W3	3841.16	1747.96	0.94	1.01	2.16	2.75
W4	850.84	1180.10	2.43	1.21	0.31	0.27
W5	5105.09	4227.96	0.66	0.61	4.58	4.82
Sweden						
W1	4880.90	2020.48	0.70	0.37	5.86	6.98
W2	1371.18	1226.44	1.36	0.82	1.97	1.83
W3	2272.63	1151.20	0.54	0.41	2.47	2.97
W4	4969.88	4801.24	1.06	1.52	0.46	0.54
W5	2484.45	1689.95	0.75	0.68	4.71	5.35

Summary statistics for five games supplied by MAG interactive for full year of 2019. Users is the average number of daily users for the respective game and platform, Conversion is average of number of purchases/users and videos is average number of rewarded videos seen/users.

that the game is free to download and to play but the user encounters some advertising.[10] Hints and other features that facilitate play can be obtained via in-app purchases or via actively choosing to play rewarded videos. The rewarded videos typically take 20 to 30 seconds and, if they are played to the end, result in rewards that can be used in the game.

The in-app products on offer via videos or purchases are with few exceptions a set of hints that make solving the respective puzzle easier. As such the in-app purchases are essentially consumption goods.[11]

2.3. Summary statistics on the games

To provide a snapshot of differences across games and platforms Table 1 presents some summary statistics for three countries (where we have selected Germany as an example of the euro zone).[12] We see differences between countries, for instance *W5* has relatively many users in Germany whereas *W1* has relatively many users in Great Britain. Conversion rates, measured as the number of in-app purchases in a day over the number of users in a day, are mostly in the 0.5 to 1.25 range whereas the ratio of videos to users are tends to lie between 2 and 7. We see some differences across games, for instance *W2* has a relatively high conversion rate whereas *W1* and *W5* tend to have relatively high number of videos watched in relation to number of users. The differences between platforms are limited but we postpone a deeper discussion of differences across platforms until Section 5.1, where we examine the parallel trends assumption that is key for a difference-in-difference analysis.

3. A closer look at the freemium business model

The games supplied by MAG are free to download and then revenue is made from advertising and from sales of in-app items. Such a “freemium” business model is common for mobile apps. In this section we first provide a snapshot of user-level revenue where the key take-away is that that sales of in-app items are a key component of revenue, even if relatively few users make in-app purchases. We then present a simple model of demand and profit maximization in a freemium setting.[13] The purpose of the model is to provide some structure for the later empirical analysis and generate predictions in a simple and transparent way.

[10] See Lambrecht et al. (2014) for an overview of different revenue models for digital goods.

[11] This is in contrast to some other games where for instance an especially fancy avatar could be thought of as investment good. The one in-app purchase that can be thought of as an investment good in the current context is the purchase of ad-free play. This represents a very small share of purchases only, as we discuss in Section 6.1.

[12] Because of company secrecy we do not present non-normalized data for the very recent period and hence use 2019. Qualitative patterns are broadly stable across the years.

[13] We are grateful to an anonymous reviewer for pointing to the value of clearly spelling out the choice set of consumers and the optimization problem of the firm.

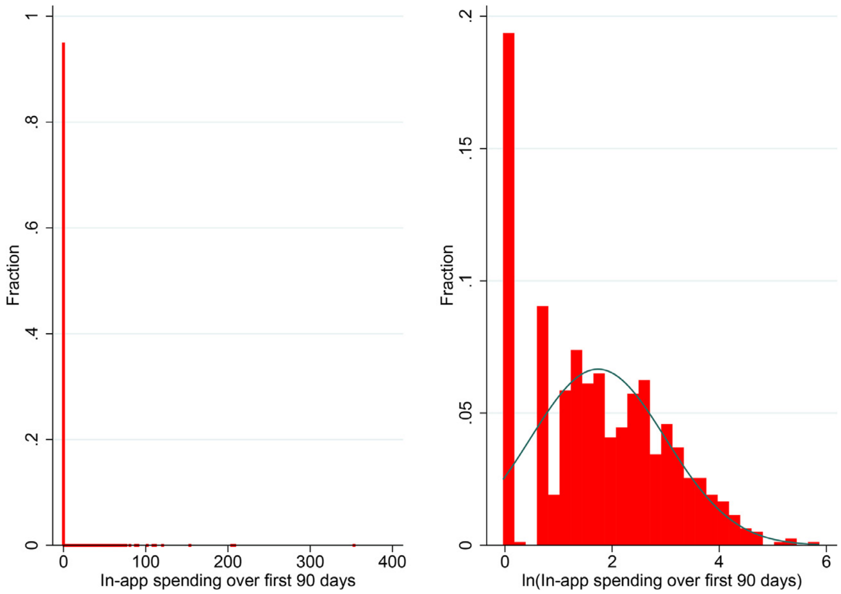

Fig. 3. Distribution of in-app spending for French users of *W2*, first 90 days after download. The left panel reports a histogram of in-app spending in *W2* across consumers over 90 days following download. All users for *W2* from France that downloaded the game during a seven day period in January 2017. The right panel reports the histogram of the natural log of the same data with a log-normal distribution overlaid.

Table 2
Summary statistics of user level data for *W2*.

Market	(1) ARPU (with adv.)	(2) Advert.Rev. /Total Rev. (%)	(3) Paying users /Total users(%)	(4) ARPPU	(5) N. Users
Apple France	1.50	8.17	5.21	26.42	4089
Google France	1.38	9.14	4.99	25.12	15,741
Apple US	3.44	8.22	9.38	33.70	13,880
Google US	3.49	7.20	10.15	31.87	9713

The table shows key metrics for users of the game *W2* from MAG Interactive for France and US. Columns (1) and (4) in US dollars (USD). Calculated for the first 90 days following download for cohort that downloaded during a week of January 2017.

3.1. A view into revenue with user level data

To highlight some features of a freemium business model this subsection uses individual-level data (anonymized) from *W2* from two national markets (France and US) and analyze the platform on which they were downloaded separately. Qualitative patterns are representative for the other games and time periods. We observe daily data on revenue (from advertising and from in-app purchases) for all users that downloaded the game during a seven-day period in January 2017 and observe their use for 90 days following the initial download.

Fig. 3 reports histograms where each unit of observation is the cumulative in-app spending by one player who downloaded the game in France for the first 90 days after download. The left panel reports a histogram of total in-app spending for all the customers that spent at least some time playing. The spike at zero shows that the overwhelming majority of players do not make any in-app purchases. On the other hand, some players are spending substantial amounts and to ease visualization the right panel reports the histogram of the natural log of the same data with a log-normal distribution overlaid, which appears to provide a good fit in the right tail.[14]

Table 2 presents some key statistics that are commonly used for mobile apps. The first column presents average revenue per user (ARPU) in US dollars (USD). This is simply total revenue from the respective cohort (country and platform) divided by the number of users in that cohort. As seen, it is around 1.5 to 3.5 USD with higher values for the US. Column (2) presents the advertising share of revenue and as seen it is in the range of 7–10%. Column (3) presents the share of customers that make at least one in-app purchase during these 90 days, and as seen this is around 5% in France and around 10% in the US.

[14] The right tail of a log-normal distribution is often difficult to distinguish from a power-law distribution and this is thus a clear indication of the importance of extreme observations (see e.g. Eeckhout (2009)). In contrast, the left tail is not well described by the log-normal, there are too many consumers that just make a handful of purchases.

The combined picture of columns (2) and (3) is thus that 5–10% of customers account for around 90% of revenue. Judging from discussions in the industry, such a pattern is common and column (4) presents the revenue (excluding advertising) divided by the number of customers who make at least one purchase (average revenue per paying user, ARPPU). Dividing revenue by the share of paying users (ARPPU) rather than all users (ARPU) thus yields a substantially higher figure, for the US around 30 USD rather than around 3.5 USD per user. All the revenue figures (columns 1 to 4) suggest limited differences between platforms within a country, but non-trivial differences between countries. The final column presents the number of customers that downloaded the game and spent at least some time playing.

3.2. A simple model of differentiation by the opportunity cost of time applied to freemium mobile apps

An important source of inspiration for our model is the work by Sato (2019), who examines the optimal menu of prices for access, and prices of advertising, of a two-sided platform. He establishes conditions under which a freemium business model with only two services is optimal, that is to only offer a basic version that is fully financed by ads and an ad-free version that is paid for by fees. It is a rich model in which the price of advertising is endogenous.

The model that we sketch in the following is a simple application of a model of vertical product differentiation in the tradition of Shaked and Sutton (1982). We use the framework to fix ideas, which we qualitatively also expect to hold in richer settings. We consider a provider of a product sold on a mobile app which takes the actions of all other apps as given, such that we can effectively treat the maximization problem as that of a monopolist. Assume that there is a continuum of players with unit mass and where income $Y_i \in [0, 1]$ follows a uniform and continuous distribution. Let V denote the intrinsic utility of playing the game.[15] Consumers can either pay a price p to purchase items in the game or play the free version of the game and be exposed to advertising videos. Watching the ad carries a disutility cost of ω that is interacted with income, reflecting the opportunity cost of time. The net utility of a consumer with income Y_i is therefore given by

$$U_i = \begin{cases} V - p, & \text{if make in-app purchase} \\ V - \omega Y_i, & \text{if choose free version} \\ 0, & \text{if don't play} \end{cases} \tag{1}$$

Individuals will make an in-app purchase rather than use the free version if the following holds:

$$V - p \geq V - \omega Y_i.$$

Denote by $\widetilde{Y}$ the income for the marginal consumer that is indifferent between the two options and we immediately find that

$$\widetilde{Y} = \frac{p}{\omega}.$$

High income players will choose to pay, their demand being given by[16]

$$D_H = 1 - \frac{p}{\omega}$$

and demand for the free version is given by

$$D_L = \frac{p}{\omega}.$$

The app provider's profits (Π) depend on the fraction of consumers that choose to pay versus only using the free version, as well as on the prices of in-app purchases and of ads, p_a. It also depends on fixed costs F but we let the profit function incorporate the fact that serving an additional customer is essentially zero.

$$\Pi = p\left(1 - \frac{p}{\omega}\right) + p_a\left(\frac{p}{\omega}\right) - F.$$

To fully solve the model we would need to make explicit assumptions about how the price of ads depends on the number of users and the value of those users to the advertisers.[17] While we have disregarded consumer choice between different games we should also note that with many thousands of games available the advertising price is likely to be largely exogenous – this is one important difference between the setting that we examine and that studied by Sato (2019).

[15] As argued we sketch as simple a model as possible to capture key features of the setting. For instance in our model the intrinsic utility is independent of how the good is paid for, which matches the setting well. In a richer model of vertical differentiation, which would provide a better match of some other freemium examples such as Spotify, the paid version would carry intrinsic valuation V_H and the free V_L with $V_H > V_L$. The paid version of Spotify for instance allows the user to save playlists and listen offline. Similarly, for greater realism one could consider non-uniform distributions of income (or of the opportunity cost of time).

[16] We implicitly assume that $\omega > p$. Thus, the profit maximizing price is low enough that at least some consumers prefer to pay with money rather than with time.

[17] Note that we have simplified the setting by not modeling two different platforms, something that would be trivial to do as the Google platform is essentially just a replication of the Apple platform with the proviso that income distribution and fees from Apple and Google may differ. Modeling of optimal prices should however take into account the institutional rules applied by the platforms that we explain further below.

Table 3
Price tiers and prices in euros for *W1* in Apple in Euro Zone (Germany, France, Italy, Netherlands) surrounding 2021 price change.

Tier	Price pre-change	Price post-change	Share of purchases pre-change	Share of purchases post-change
1	1.09	0.99	66.36	62.92
4	4.49	3.99	15.02	20.29
5	5.49	4.99	1.34	0.80
10	10.99	9.99	5.23	4.39
15	16.99	14.99	12.05	11.59

Prices and share of purchases in the period pre-change (120 days before August 8, 2021) and post-change (120 days after August 8, 2021) in the different tiers on Apple in *W1* in the euro zone (Germany, France, Italy, Netherlands).

He models the decision problem of a two-sided platform like Spotify or Youtube whereas we study the decision problem of a mobile app provider who is but one of very many on a platform.

That said, the setting above clarifies how profits for the firm depends on both in-app prices and on ad prices. In the empirical section we examine three predictions that come out of this framework. The first prediction that we examine is that an increase in the in-app price lowers the share of paying customers, something that holds in the model since

$$\frac{\partial D_H}{\partial p} = -\frac{1}{\omega} < 0.$$

The second, linked, prediction that we examine is that an increase in price increases the share of customers that choose the free version and "pay" by watching videos. This is easily established by noting that

$$\frac{\partial D_L}{\partial p} = \frac{1}{\omega} > 0.$$

A third observation is that if the market is covered we also note that the total number of users is unaffected by p – it only affects the margin between making an in-app purchase and only using the free version.

4. Pricing of in-app items on mobile apps

4.1. Prices on the Apple platform

At the time of study app developers are not free to choose prices in Apple's app-store.[18] Instead developers choose a "tier" for each product. The lowest available tier is USD 0.99, the next tier is USD 1.99 and so forth at discrete intervals. By choosing a tier a firm chooses that tier in all countries in which it is distributing the app. Consumers in the countries that we study see these tier prices in local currency and they are roughly equivalent to the USD prices when expressed in common currency.

While the USD price of different tiers hasn't changed since the introduction of the app store in 2008 occasionally there are changes in other countries. In our sample period there is one such change for France, Germany, Great Britain, Italy and Netherlands around August 8, 2021 and two similar changes in Sweden (price increase on October 6, 2019 and price decrease on May 6, 2021). These are announced a couple of days in advance by Apple with similar language in each case. For instance the August 2021 changes were announced on August 3, on Apple's news feed for App developers (https://developer.apple.com/news/) "When taxes or foreign exchange rates change, we sometimes need to update prices on the App Store in certain regions and/or adjust your proceeds. In the next few days, prices of apps and in-app purchases (excluding auto-renewable subscriptions) on the App Store will decrease in... " As explained below, our main demand estimation will examine event windows surrounding these price changes.

Table 3 presents the tiers used in one game, *W1*, and the respective prices for the period before and after the August 2021 price decrease. The different tiers correspond to different number of hints that can be used to facilitate play in the game. Purchases are concentrated in the lower priced tiers, something that also holds for the other games that we study (corresponding tables are found in the Online appendix, Tables IA.1-IA.4).

4.2. Pricing on the Google platform and stability of prices over time

All the five games are available in identical versions on Google. Pricing policy on Google offers more leeway for developers but, as we document below, price differences between platforms are low and prices are very stable on both platforms.

[18] Competition & Markets Authority (2022) provides an accessible description of many aspects of mobile app markets. Note however that as of December 6, 2022 Apple announced that they would gradually be implementing changes during 2023, intending to offer more flexibility to app developers (https://www.apple.com/newsroom/2022/12/apple-announces-biggest-upgrade-to-app-store-pricing-adding-700-new-price-points/). To what extent this will be changing practices remains to be seen at the time of writing.

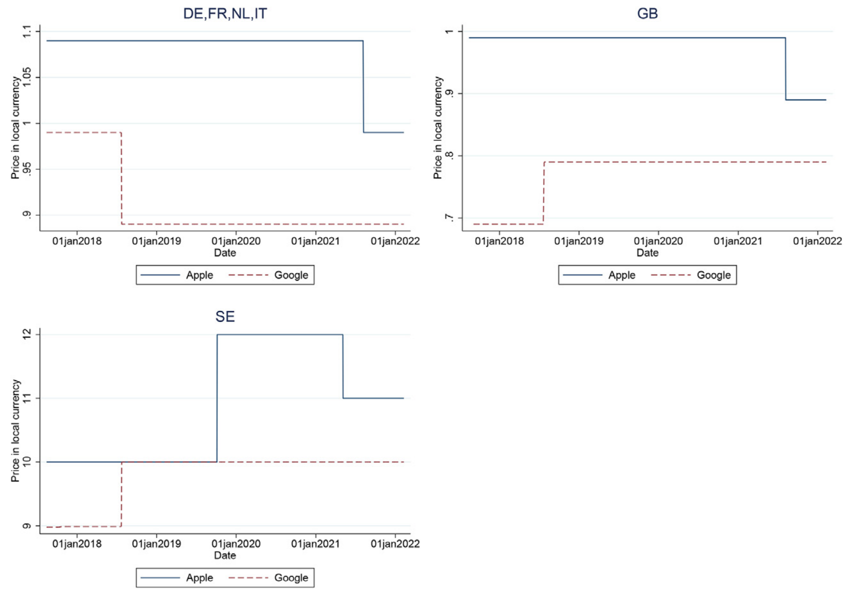

Fig. 4. An example of local prices: A tier 1 product in *W1* in six European countries 2017–2022 The figure shows the price in local currency of a tier 1 product in *W1*.

To illustrate price developments Fig. 4 shows the price for a tier 1 item in *W1*, in the relevant markets. The price changes of this item in July 24, 2018 in Google are idiosyncratic and due to policy in MAG, whereas the changes in Apple prices are all due to policy changes in Apple, where the local price of different tiers are changed.

The great stability of prices may at first be surprising to an economist. One explanation, from the perspective of an app developer, is that Apple's policies preclude any minor price changes. For instance, in the euro zone, the three lowest possible price points during the first four years of the study are euros 1.09, 2.29 and 3.49. For a simple thought experiment consider first a firm that initially has a profit maximizing price close to 1.09 euros. Since this is the lowest price tier, the firm will not be able to charge a lower price in response to shocks. On the other side, shocks that would trigger a price increase would need to be large enough for the firm to want to more than double its price, from 1.09 to 2.29 euros. Even in the absence of such institutional details it is a stylized fact that prices across many differentiated goods markets are rigid, see e.g. Nakamura and Steinsson (2013) for a survey. We can also note that marginal cost changes due to changing input prices, that are key for motivating price changes in many goods markets, are of little importance for mobile apps. Finally, there is evidence that prices at particular pricing points like 0.99 cents are more rigid (Basu (1997), Levy et al. (2011); Levy and Young (2004) provide a striking example of the "nickel coke" where the price of a Coca-Cola bottle was rigid at 5 cents for more than 70 years.

The later demand estimation focuses on the August 2021 price changes in Apple. While Fig. 4 showed that prices for one product were stable we could in principle imagine that MAG changed tiers for some other products and/or that prices on Google changed. For the period surrounding the August 2021 price change there are no such changes and we use Fig. 5 of average prices in *W1* in France to illustrate.[19]

The average prices used for the comparison in Fig. 5 are weighted by the average share of each different item's share of purchases for each game, country and platform in the 120 days before the price change. To aid interpretation prices have been normalized so that average price in Apple at the start of the period equals 100. Average price in Google is similarly normalized but also adjusted to reflect level differences in the average price. Hence, at the start of the period depicted in Fig. 5, the average price in Google is about 2% higher than the average price in Apple. This difference in average price between platforms potentially reflect differences in the relative weight given to different items as well as price differences for the same item. As we shall see shortly the latter are mostly small and the differences in average prices across platforms that we see in Fig. 5 are thus mainly the result of different shares of consumption accruing to the different items in a game across countries. In this case Google users of *W1* in France have a slightly larger share of purchases of higher priced items compared to Apple users.

We now show that price differences for the same item across platforms are low. We first exemplify by Fig. 6 which plots prices on the Apple platform against the price of the identical item on the Google platform for all the items sold in the five games in the euro zone before and after the August 2021 price decrease in Apple. Clearly, if prices are on the 45-degree line they are equal. We see some differences between the platforms and also see that for a given price in Apple, some different

[19] Figures IA.1-IA.4 in the Online appendix illustrate that the same price stability holds also for the other games in the study.

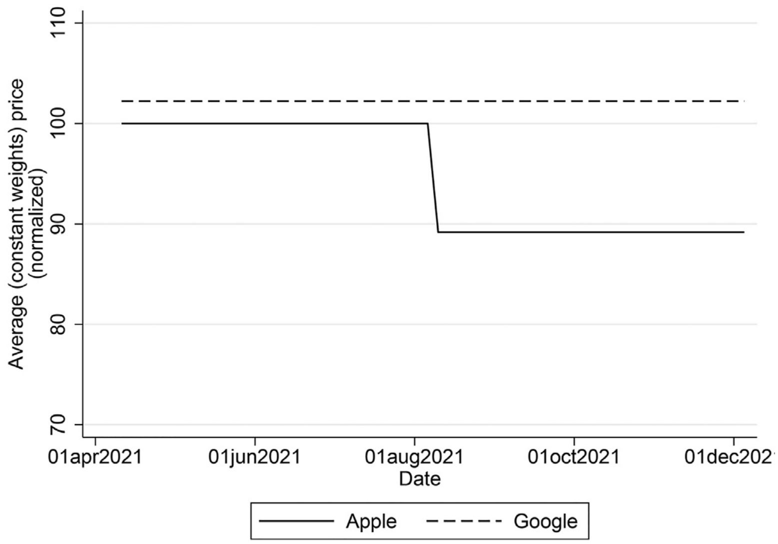

Fig. 5. Average (constant weights) prices in *W1* surrounding August 2021 price changes in France. Average (constant weights) prices in *W1* surrounding August 2021 price changes in France. Weights reflecting each item's share of purchases in 120 days before the price change. Normalized so that average price in Apple in April 2021 equal to 100 and average price in Google normalized to reflect level difference in April 2021.

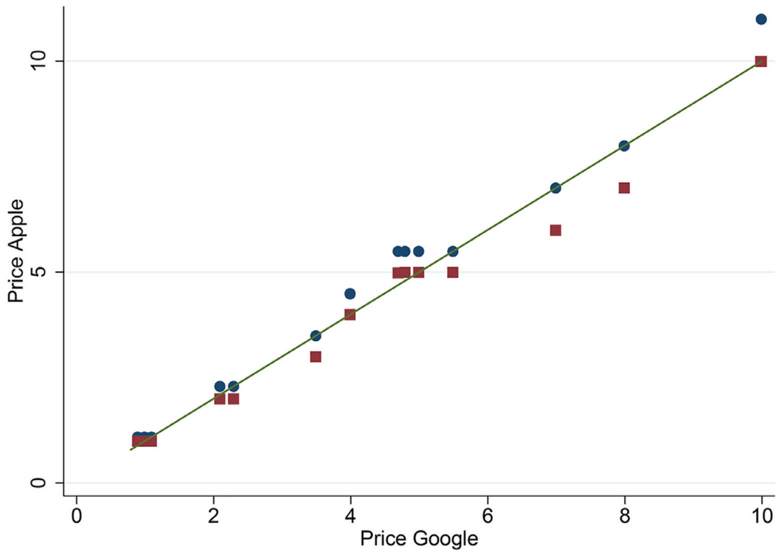

Fig. 6. An example of price differences for identical items: Euro zone before (circles) and after (squares) the August 2021 price change in Apple. Prices for items in five games in the euro zone (DE, FR, NL, IT) on Apple and Google platforms surrounding the August 2021 price decrease on the Apple platform.

prices on Google are sometimes chosen. For instance the Apple tier 1 price of Euro 1.09 has the same item on Google priced at 0.89, 0.99 and 1.09. Nevertheless the main impression from Fig. 6 is that price differences between platforms are small.

To complement the visual evidence we note also consider the percentage price difference for identical items on Apple and Google before and after the August 2021 price decrease on Apple. On average, across all the items, price is about 5% higher on Apple before the price change and 5% lower after the price change.[20]

5. Empirical model: Difference-in-difference estimation of demand for mobile apps

In the following we estimate the effect of the price changes discussed above on in-app purchases, videos watched and overall play in the five games from MAG for which we have data. To capture purchases we follow convention in the industry and use "conversion rate" as the main outcome variable of interest, the number of in-app purchases of game g on app store

[20] See Table IA.5 in the online Appendix for the full distribution.

s in country c on day t divided by the number of users of that game on that same platform×country×day. The daily number of users are denoted as $users_{cgst}$ and the average number of videos watched are defined as total number of rewarded videos seen in a day divided by the number users that day: $videos_{cgst}$.

We focus on event windows surrounding price changes, mainly on the Apple platform. We use an indicator variable to capture variables on the Apple platform and a variable *post* to capture periods after the price change in the respective country. We use windows of 120 days before and after the respective price change as an estimation window. A window of approximately four months on each side of the price change allows us to follow developments over a substantial post-change period but the qualitative results are not sensitive to the length of the estimation period (the maximum possible window for the August 2021 price changes given the end of the data set is around 180 days). We estimate regressions where we pool all countries and games as well as separate regressions for each game. The regressions that we estimate are thus of the form (for a pooled regression)

$$ln(q_{cgst}/users_{cgst}) = \alpha + \gamma_{gc} + \theta_t + Apple_{cst} + Apple_{cst} \times post + \epsilon_{cgst} \quad (2)$$

where γ_{gc} are fixed effects for each game×country combination (replaced by a country fixed effect in game-level regressions) and θ a day fixed effect. In some regressions we will instead examine a price change of one product on the Google platform and in those cases the indicator variable for Apple in Equation (2) is replaced with an indicator variable for Google.

5.1. Discussion of identification assumptions

Let us now discuss the institutional aspects that lead us to use difference-in-difference estimation to estimate the effect of price changes. In many cases we would expect a price change to come in response to a change, or expected change, in demand. As noted, the change in the local price on the Apple platform is decided by Apple however and common for all apps in a given country and we therefore view it as exogenous from the perspective of the game developer. We noted above that there are no other price changes in the event window than the ones that are a direct result of Apple's change of local prices of the different pricing tiers.[21] In the full sample there are occasions where an item changes price however and we also consider an idiosyncratic change by the app developer in one game on the Google platform. Clearly the assumption of an exogenous price change is less tenable in that case, even if a large discrete price change on the same day in several markets suggests that endogeneity concerns are limited (see Fig. 4).

Demand is affected not only by price but also by a multitude of demand shocks. As illustrated by the number of users in Fig. 1, the number of users of *W1* on the two platforms track each other extremely closely. This is an indication that they are buffeted by the same shocks. Figures IA.5-IA.8 in the Online Appendix show that the same pattern broadly holds for the other games as well. In their thinking on the reasons for the remarkably high comovement MAG distinguishes between external and internal factors. The external factors that drive patterns include day-of-the-week patterns, national holidays and data limits on mobile usage that are renewed monthly.[22] Such factors are expected to have very similar effects across the two platforms.

Internal factors can be advertising campaigns and various in-game events – limited time campaigns with for instance additional features meant to drive user engagement or specific content related to some fund raising campaign. For instance, during October 2021 such events included special ocean-themed gaming events linked to a United Nations initiative[23] and a one day event in the UK where all revenue from UK games is donated to a charity.[24] MAG generally sets up the events identically across the Apple and Google platforms such that the internal factors are also likely to have similar effects across the two platforms. New versions of games are another possible internal factor that can drive demand. There are no such new versions in the event windows that we examine.

One may also have noted in Fig. 1 that the number of users were declining over the event window surrounding the 2021 price decreases in Apple. We have not tried to determine the precise causes for this but note that several of these games are considered as "evergreens" for MAG and are not on a general downward trend (MAG Interactive (2022)). If anything, the evidence points to the value of having users on Google as a control group when Apple users are treated since the sources of various demand shocks are somewhat opaque to the econometrician.

Conversion rates in the two platforms typically also track each other closely prior to price changes, even if the level of comovement is less striking than for the number of users. We exemplify with conversion rates for *W1* in Fig. 7 and conversion rates for the other games are reported in Figures IA.9-IA.12 in the Online Appendix.[25] Estimation of treatment

[21] Concerns about how difference-in-difference estimators are affected by staggered treatment has been the focus of much recent research (see, e.g., De Chaisemartin and d'Haultfoeuille (2020)). The timing of treatment in our case study, with all Apple prices affected at the same time, implies that such concerns are mute in our setting.

[22] It is not uncommon for mobile subscriptions to for instance include 10 GB of free data per calendar month.

[23] https://www.maginteractive.com/media/news-and-press-releases/2021/mag-collaborates-with-un-environment-initiative-playing-for-the-planet/, accessed February 12, 2023.

[24] https://www.maginteractive.com/media/news-and-press-releases/2021/mag-supports-the-charity-fundraiser-one-special-day-for-the-fifth-year-in-a-row/, accessed February 12, 2023.

[25] Broadly speaking conversion rates are more variable in smaller markets and idiosyncracies play a greater role. While one could set different thresholds on the number of purchases needed for inclusion in the sample we have opted for the simple policy of including all the six national markets for all the five games.

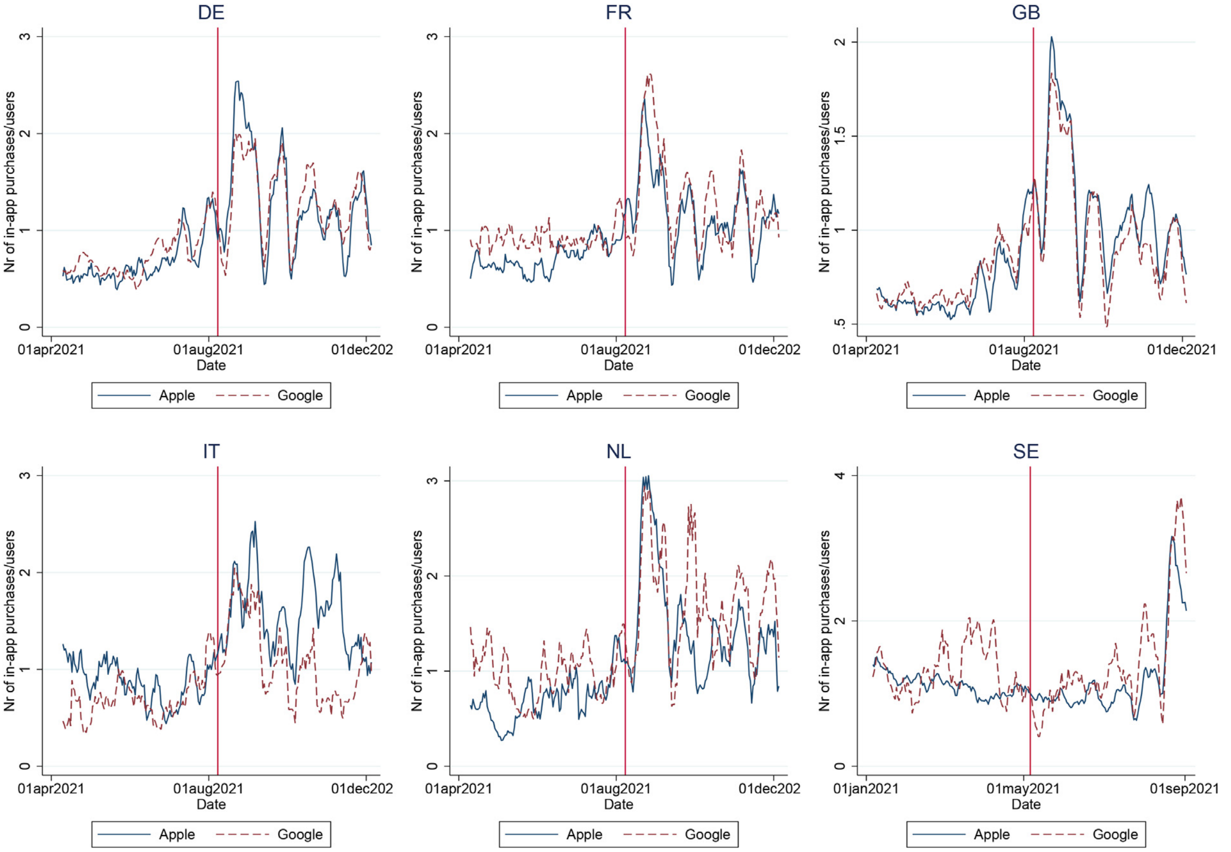

Fig. 7. Conversion rate per day in *W1* in six European countries surrounding price changes in Apple The figure shows the daily number of in-app purchases/number of users for 120 day windows on either side of a price changes in Apple on six European countries. The timing of price changes illustrated by vertical bars and number of users per day and platform are seven-day moving averages, normalized so that daily number of in-app purchases/number of users for 30 days prior to the price change set to 1.

effects, that also includes pre-treatment indicator variables (reported in the Online Appendix), indicates that there are no statistically significant pre-trends between the two platforms.

It is common for app developers to multihome, to supply their apps on both platforms (see e.g Bresnahan et al. (2014) for an analysis). A highly ambitious report by the British Competition Authority, (Competition & Markets Authority (2022, p. 121)) cites Apple as stating that “popular and successful app developers almost universally choose to multi-home, that is, make their apps available on both Android and Apple devices.” As discussed, this is the case for all the games supplied by MAG.

At the same time, multihoming in the sense that the same consumer uses both an Android and an Ios smart phone is likely to be rare.[26] If there is no multihoming by consumers this implies that there is no possibility of substitution between the two platforms.[27] There are some differences in demographics across users of Iphones (Apple) and Android phones (Google) with for instance Iphone owners tending to have higher incomes.[28] Thus, limited differences in the level of use across platforms may exist but the visual evidence in Figs. 1 and IA.5-IA.8 indicate that the same demand shocks are affecting users on both platforms. Arguably, when comparing a typical user on these markets we compare a user of a Samsung smart phone with the user of an Iphone and expect limited differences – something also consistent with some detailed questionnaire studies such as Götz et al. (2017) which points to very minor differences in personality traits between

[26] Given the cost of using two smartphones with different operating systems, and the limited benefit of doing so, a level of multihoming by consumers close to zero is intuitive. Competition & Markets Authority (2022, p. 41) cites evidence for the UK that supports this intuition. The level of multihoming that is relevant for a typical game user is further likely to be even lower than the share of consumers that have two smartphones with different operating systems – a user may for instance have an Android phone supplied by her employer and a private Apple phone. In such a case it is unlikely to be company policy to allow users to play games on their company phone.

[27] Clearly the decision of what smart phone to use depends on the overall level of prices in the “eco-system” of Android or Apple but we take that as exogenous here.

[28] See e.g. Competition & Markets Authority (2022) and Mobileapps.com (2020) for an overview and Accent (2022) for a detailed study based on a sample of UK consumers. MAG does not collect any demographic information on users.

users of Ios and Android smartphones in German data. Together these observations imply that usage of the same app on the other platform can serve as a counterfactual for what would have happened in the absence of a treatment in terms of a price change.

6. Results from estimation

6.1. Elasticity of in-app purchases with respect to price

Panel A of Table 4 reports the estimated effect of the 2021 Apple price decreases on conversion rate for the case where all games are pooled (Column 1) and then separately for each game. With *W3* as the only exception we estimate statistically significant effects of the price changes on the Apple platform on the conversion ratio of Apple users relative to Google users. This is evidence that in-app purchases indeed respond to price changes, despite being relatively small ticket items. The penultimate row of *Panel A* in Table 4 presents the average change in the weighted price. The weights are created by the share of sales in the 120 days prior to the price change that is in the respective tier for that game/market/platform. These weights are then kept constant to calculate the weighted price change. To exemplify, assume for simplicity that tier 1 has a share of sales of 0.5 prior to the price change and tier 2 likewise a share of 0.5. If tier 1 price changes by 0.08 and tier 2 by 0.12 the weighted price change is then 0.1 (.5×.08+.5×.12). We report the median price change across the respective national markets in *Panel A* and, as seen, the median price change is around 10% for all the games. All the Apple

Table 4
Difference-in-difference estimates, treatment effect of price changes on conversion rate.

	Panel A: 2021 Price decreases in Apple App store					
	(1) ALL	(2) *W1*	(3) *W2*	(4) *W3*	(5) *W4*	(6) *W5*
postxapple	0.158**	0.169***	0.161***	−0.073	0.381***	0.104***
	(0.067)	(0.034)	(0.046)	(0.048)	(0.026)	(0.028)
Country x Game FE	YES	-	-	-	-	-
Country FE	-	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Adj. R2	0.106	0.564	0.109	0.267	0.216	0.259
Observations	12,655	2771	2067	2060	2877	2860
Price change	−0.105	−0.114	−0.102	−0.126	−0.092	−0.097
Elasticity	−1.501	−1.483	−1.580	NS	−4.138	−1.072
	Panel B: 2019 Price increases in Apple App store					
		W1	*W2*	*W3*	*W4*	*W5*
postxapple		−0.255***	−0.184***	−0.095	−0.102	−0.292**
		(0.085)	(0.053)	(0.094)	(0.071)	(0.114)
Time FE		YES	YES	YES	YES	YES
Adj. R2		0.103	0.348	0.310	0.321	0.343
Observations		350	391	350	332	350
Price		0.148	0.138	0.138	0.125	0.143
Elasticity		−1.721	−1.330	NS	NS	−2.048
	Panel C: 2018 Idiosyncratic price changes (of tier 1 product in *W1*) in Google App store					
	Price Decreases				Price Increases	
	(1) DE	(2) FR	(3) NL	(4) IT	(5) GB	(6) SE
postxgoogle	0.372***	−0.107	−0.096	0.435***	−0.001	−0.078
	(0.110)	(0.126)	(0.176)	(0.146)	(0.041)	(0.125)
Time FE	YES	YES	YES	YES	YES	YES
Adj. R2	0.361	0.522	-0.057	0.357	0.656	0.512
Observations	284	264	200	238	216	272
Price	−0.101	−0.101	−0.101	−0.101	0.145	0.112
Elasticity	−3.685	NS	NS	−4.307	NS	NS

This table reports the findings from estimation of Eq. (1) using data from five word games provided by MAG Interactive for six European markets. Dependent variable is conversion *ln*(number of in-app purchases/users) per day. Elasticity is treatment effect/weighted change in price. Robust standard errors in parenthesis apart from Column (1) of *Panel A* which clusters standard error at the country× game level (30 clusters). *Panel A* reports the effect of price decreases in the Apple app store in 2021 for France, Germany, Great Britain, Italy and Netherlands (August 7–8, 2021) and Sweden (May 6, 2021). *Panel B* reports the effect of price increases in the Apple app store in Sweden (October 6, 2019). *Panel C* reports the effect of a idiosyncratic price changes of a tier 1 product in the Google app store (July 24, 2018).

tiers change at the same time but to slightly different degrees and countries and games differ by how large a share of sales that occur att different tiers. Across all games and countries the average change is a drop of around 10.5% and the implied elasticity (percentage change in conversion/percentage change in price) is -1.5. We only calculate elasticity for cases where the treatment effect is statistically significant at the 10% level of significance or higher.

Panel B of Table 4 reports the estimated effect of the 2019 Apple price increases in Sweden. Here we expect a decrease in conversion and for three of the games the effect is negative and statistically significant at conventional levels with elasticities ranging from -1.3 to -2.0.

At this point let us also comment on that the treatment effect for *W3* is not statistically significant in either *Panel A* or *Panel B*. Clearly, certain features of that game might make demand less price sensitive but it does not stand out in terms of descriptive statistics (e.g. in Table 1). An explanation for what characteristics of games that shape the elasticity of demand is clearly of great interest to the industry but will have to remain outside the scope of the present article.

A key insight of the present article is that users on the other platform can function as a control group to capture what developments would have been with an unchanged price - thereby acting as a control for demand shocks. We are thus able to estimate the effect of a price change on demand while controlling for demand shocks at a high level of precision. It should be pointed out however that the elasticity so calculated relies on that all other apps on the Apple platform also (exogenously) change their price whereas a standard own-price elasticity would keep all other prices constant. With a very large number of apps competing for attention we expect the cross-price effects relative to other individual apps to be low but we nevertheless expect positive cross-price effects to substitutes. For this reason we may view the elasticity of demand with respect to price that we estimate as a bound where the true own-price elasticity is more elastic. In other words, the absolute value of the own-price elasticity is expected to have a lower bound of around 1.

The same logic that we applied for price changes across all tiers on a platform can also be used to examine the effect of idiosyncratic price changes. While the pricing tiers are set by Apple a developer is free to change tiers for their product. On the Google app store developers are also free to change prices even if Apple's policy tends to spill over onto pricing structure on Google. Clearly a price change on Google or a change of tiers on Apple might come in reaction to a change in demand, but with unchanged price on the other platform we still have access to a set of consumers that act as a control group.

On August 24, of 2018 MAG implemented a set of price changes of a tier 1 product in *W1* - decreasing price by around 10% in the euro area countries and increasing by roughly the same amount in Great Britain and Sweden. We report the estimated effects in *Panel C* of Table 4 where the outcome variable and controls now are sales of this product/users. Effects are less precisely estimated but the two estimated coefficients that are statistically significant at conventional levels point to an elasticity of -3.7 to -4.3, thus more elastic than what we found for the Apple price changes in *Panels A* and *B*. We expect several potential reasons for differences between the results in *Panel C* and those in *Panels A* and *B*. Partly they refer to a different time period (2018 rather than mostly 2021) and to Google rather than Apple. More fundamentally however, the estimates in *Panel C* concern a case where prices of other apps on the same platform, as well as of other items in the same game, are kept unchanged and we would therefore expect to see more substitution which would explain the more elastic estimates. A very rough ballpark estimate of the own-price elasticity would thus note that in the case of these apps and markets it is broadly bounded by -1 and -4.

A lack of app-level data and limited price variation implies that there is little published work that reports demand elasticities for mobile apps.[29] We contribute both by highlighting how institutional features allow for estimation of price sensitivity of demand and by providing numbers that may be valuable as ballpark estimates for various applications. While clearly the results are likely to be specific to these games and markets it is notable that the results reflect a total of 30 different market/product combinations.

Let us also comment on that for two out of three games the demand for price decreases (Panel A) is less elastic than that for price increases (Panel B). Differences are minor but let us nevertheless note that a pattern where demand responds more to price increases than to price decreases has been documented across many types of products (e.g. branded food products in Kalyanaram and Winer (1995) and Biondi et al. (2020), public transport in Yaman and Offiaeli (2022) or energy in Gately and Huntington (2002)). If firms loose more customers when prices rise than they gain when prices fall back, this also serves as a motivation for stable prices. Different classes of models that feature such asymmetric demand responses have been used to motivate rigid prices – for instance models where a fraction of consumers are "searchers" and a price increase triggers them to search but a lowering of price doesn't necessarily attract these customers back (Blinder et al. (1998), Slade (1999)).[30] As discussed in Section 4, prices in the current study are indeed highly stable.

Finally, we argued in the introduction that the in-app purchases in these games are consumption rather than investment goods. The one exception to this is that in some of the games users can purchase freedom from advertising – this is a one time purchase and as such is an investment. Price changes by Apple are announced just a few days before they are implemented so there is little response time, but in principle forward-looking agents that want to buy such ad-free access would postpone their purchase if prices are to be lowered or accelarate them if prices are to be raised. As we show in

[29] One early exception is Ghose and Han (2014) that estimates a demand system in the tradition of Berry et al. (1995) and reports own-price elasticities in the -2 to -3.7 range.

[30] Models where consumers are loss averse with respect to a reference price (Heidhues and Kőszegi (2008)) have also been used to explain asymmetric price responsiveness.

Table 5
Difference-in-difference estimates, treatment effect of price changes on number of users.

	(1) ALL	(2) *W1*	(3) *W2*	(4) *W3*	(5) *W4*	(6) *W5*
postxapple	−0.015	−0.013	−0.040	−0.006	0.030	−0.046**
	(0.012)	(0.019)	(0.026)	(0.016)	(0.025)	(0.023)
Country x Game FE	YES	-	-	-	-	-
Country FE	-	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Adj. R2	0.902	0.853	0.941	0.900	0.807	0.909
Observations	14,400	2880	2880	2880	2880	2880

This table reports the findings from estimation of Eq. (1) using data from five word games provided by MAG Interactive for six European markets. Both panels reports the effect of price decreases in the Apple app store in 2021 for France, Germany, Great Britain, Italy and Netherlands (August 7–8, 2021) and Sweden (May 6, 2021). Dependent variable is number of users per day. Robust standard errors in parenthesis apart from Column (1) of each panel which clusters standard error at the country× game level (30 clusters).

Table 6
Difference-in-difference estimates, treatment effect of price changes on number of videos watched.

	ALL	*W1*	*W2*	*W3*	*W4*	*W5*
postxapple	−0.050*	−0.093***	0.080***	−0.014***	−0.184***	−0.037***
	(0.029)	(0.005)	(0.019)	(0.004)	(0.016)	(0.004)
Country x Game FE	YES	-	-	-	-	-
Country FE	-	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Adj. R2	0.739	0.953	0.518	0.943	0.981	0.956
Observations	14,400	2880	2880	2880	2880	2880
Price change	−0.105	−0.114	−0.102	−0.126	−0.092	−0.097
Elasticity	0.473	0.817	−0.789	0.109	2.001	0.385

This table reports the findings from estimation of Eq. (1) using data from five word games provided by MAG Interactive for six European markets. Both panels reports the effect of price decreases in the Apple app store in 2021 for France, Germany, Great Britain, Italy and Netherlands (August 7–8, 2021) and Sweden (May 6, 2021). Dependent variable is number of videos watched per day/number of users per day. Robust standard errors in parenthesis apart from Column (1) of each panel which clusters standard error at the country× game level (30 clusters).

Table IA.7 in the Online appendix however, the share of ad-free access purchases is very low and such dynamic concerns are not likely to affect the estimated elasticities for these apps. Note that the question of whether to purchase freedom from advertising or not is independent of the decision of whether to pay for hints via money or via watching of rewarded videos.

6.2. Elasticity of number of users with respect to price

Other questions regarding how demand is affected by changes in the price of in-app purchases beyond the effect on the number of purchases are also potentially interesting. In Table 5 we examine the effect of the 2021 price decreases in Apple on the number of users per day on the Apple platform. As seen, there is little evidence of an effect. This suggests that the decision of whether to play a freemium game is separate from the decision of whether, and if so how much, to purchase in-app. The evidence thus does not suggest that users to an important degree incorporate the price they would need to pay in the future if they were to decide to become one of the few who make in-app purchases.

A growing literature examines various aspects of the determinants of usage in freemium business models, frequently relying on questionnaires (see e.g. Hamari et al. (2020) for a recent study and overview of the literature) but we are not aware of any previous published work that addresses the question of how overall usage depends on price changes of in-app purchases. Somewhat related however is that counterfactual simulations in Ghose and Han (2014) indicate that demand for an app increases if it offers an in-app purchase option. Somewhat related is also Deng et al. (2021) who show that the introduction of a free version of an app increases demand for a paid version of the app – an effect that is consistent with consumers learning about the existence of, and becoming familiar with, a product when it is available in a free version. In our case we show that use is not significantly affected by changes in-app prices of around 10%. The adjusted R-squared is above 0.8 in all these regressions, implying that just the set of fixed effects account for much of the variation in the data also at a daily level, as would be expected from the patterns seen in Figures IA.5-IA.7 in the Online Appendix.

6.3. Elasticity of number of rewarded videos watched with respect to price

Table 6 presents the effect of the change in Apple prices on the number of rewarded videos watched in the game. As seen, and as expected from the model, the effects are mostly negative such that fewer videos are watched when a market and game is treated by a lower price. The bottom column also calculates the implied elasticity of the number of videos watched with respect to price. That the number of videos (with the exception of *W2*) moves in the same direction as price indicates that the two are substitutes as expected: users can pay with money or with time, as the price in money falls players pay less with time.

There is some dispersion in the elasticity across games, a potential interpretation being that the design of the game influences the willingness to substitute time for money. The pooled estimate for the elasticity is around 0.5, such that a price increase of 10% raises the number of videos watched by some 5%.

While a number of studies have examined the correlates of usage in mobile markets (see e.g. Rutz et al. (2019) or Tong et al. (2020)) we are not aware of previous published evidence on the elasticity of watching of rewarded videos with respect to price of in-app purchases.

We do note however that the literature on valuation of time in economics is large and let us briefly relate our results to the broader literature. One strand of research focuses on the substitutability between market work (with wages and prices in money) and work at home or other non-market work (where payment is with time), with important applications in macroeconomics and time use over the business cycle. See Becker (1965) for foundational work and e.g. Benhabib et al. (1991) for an analysis emphasizing the importance of the associated elasticity of substitution for business cycle development. Against this backdrop several papers estimate the associated elasticity of substitution between time and money (see e.g. Aguiar and Hurst (2007), Nevo and Wong (2019)) using household grocery purchases. Nevo and Wong (2019) for instance make use of that various grocery shopping practices (such as use of coupons) can be seen as paying with time to achieve a lower monetary price. Their point estimate of 1.7 for the elasticity of substitution between time and money in this context is broadly representative of this literature.

Another strand of research uses substitutability between costs of travel and travel duration to estimate a value of time (see McFadden (1974) for seminal work). Typical estimates of the elasticity in this context between time and money is in the range of 0.5 to 0.9 (Small (2012), Buchholz et al. (2020)).

Clearly the difference in settings imply that we need not expect the elasticity between time and money to be the same as in the literatures above. Two aspects might be especially noteworthy. First, while, in particular, the literature on substitutability of market and nonmarket work relies on a number of assumptions that translate actions (e.g. coupon use) into time, the current setting provides a setting with a very direct choice between time and money. Players can choose to purchase the same benefits in a game with money or via watching rewarded videos that last up to 30 seconds. Second, one might expect that the current setting, where "paying" with time imposes no additional costs or hazzles would point towards a high substitutability. In contrast, our estimates are on lower bound of those found in the literature. To understand the estimates however we note that previous research (e.g. Buchholz et al. (2020)) points to a high heterogeneity in the opportunity cost of time. Very few users pay in the mobile app markets which imply that the marginal consumer has a high opportunity cost of time and hence is relatively uninterested in substituting.

7. Concluding comments

Applying an off-the-shelf estimation of demand for in-app purchases in mobile apps faces several difficulties. Beyond the fact that much of the data is hidden behind the corporate veil the task is complicated by difficulties in finding proxy variables for demand shocks and valid instruments for price. This paper has shown how the institutional set-up of mobile app markets can be used to gauge the sensitivity of demand for mobile apps to price (finding elasticities in the -1 to -4 range), highlighting how we can use users in one eco-system (Apple or Google) as control group for the changes in the other ecosystem.

We have shown how the same identification strategy can be used to not only examine the effect of price on in-app purchases, but also the effect of price on other consumer choices such as the number of rewarded videos to watch within an app. The effects of price changes that we estimate rhyme well with the predictions from a simple model where different users have different opportunity costs of time. With mobile apps becoming evermore important we expect that these results are useful building blocks for future research. For instance a question that has been the topic of increased attention in the literature is how time use on mobile apps and on social media should be valued (see e.g. Brynjolfsson et al. (2019), Allcott et al. (2022)). With the value of time being context dependent direct measures of substitutability between time and money from mobile apps may be useful input into such research.

A final question is how representative we believe that these results are for other mobile apps. Given the paucity of published work this is somewhat speculative but we see little reason why these results for five games and six national markets should not be somewhat representative. One aspect to point out is that these intellectual word games are likely to attract a smaller share of children and teenage players than some other mobile app games.

Credit Author Statement

All three authors participated in conceptualization and writing; empirical analysis by Enache and Friberg.

Data availability

The normalized data series for the 2021 event windows that are used for the key regression analysis are available in a replication package, Enache et al. (2023). Additional data referred to in the article are sensitive for the firm to share and not publicly available.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.ijindorg.2023.102945

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