

Competition and Defaults in Online Search

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Online Appendix

B.1 Additional Information on the EEA Case

Play Choice Screen Before the “pay-to-play” choice screen was implemented, starting in April 2019, Google presented users with a choice screen for browsers and one for search engines. The two choice screens allowed the user to select and download additional search and browser apps to the ones that were pre-installed on the device. This preliminary choice screen was displayed the first time a user opened Google Play after receiving an update, hence we refer to it as the “Play Choice Screen”.⁹⁶ The two choice screens allowed users to install as many apps as they wanted from two lists composed by five search and browser apps. If an additional search or browser app was chosen, the user was then shown an additional screen with instructions on how to set up the new app (e.g., placing app icons and widgets or setting defaults). However, this initial choice screen attempt was short-lived and was replaced by the “pay-to-play” choice screen in March 2020. Due to the very brief period of experimentation with the “Play choice screen” and the lack of available related information, we do not study its effects in our main analysis. Our findings are robust to the exclusion of the period corresponding to the “Play choice screen” (April 2019 - March 2020), as shown in Table A.2.

Unbundling Android Apps In addition to the choice screen, the EC also required Google to modify its Android licensing terms in Europe. Prior to the Google Android case, Google licensed Chrome to device manufacturers free of charge as part of its Google Mobile Services (GMS).⁹⁷ This bundling made it impossible for a device manufacturer to access Google Play without pre-installing Chrome or Google Search. After October 2018, manufacturers can license Chrome and Search separately at no cost but must pay for GMS under the European Mobile Application Distribution Agreement (EMADA).⁹⁸ To offset EMADA costs, manufacturers can enter into Placement Agreements (PAs) or Revenue Share Agreements (RSAs) with Google. PAs provide payments for pre-installing Chrome with specific placement obligations, while RSAs share advertising revenue from Google Search and Assistant access points in exchange for promotional placement.⁹⁹ From the data pattern in Figure 9, we do not see any significant market share change in the EEA mobile search market. By comparison with the TCA intervention, we suspect that this lack of effect might be due to the RSAs and PAs providing sufficient incentives for OEMs to continue pre-installing Google Search and Chrome after the unbundling.

Pay-to-play versus Free-to-play To compare the impacts of EEA choice screen under different designs, we conducted three exercises to compare the effects of the “high powered” Free-to-Play

⁹⁶See <https://www.blog.google/around-the-globe/google-europe/presenting-search-app-and-browser-options-android-users-europe/> (accessed August 1st, 2024).

⁹⁷See <https://techcrunch.com/2018/10/16/google-tweaks-android-licensing-terms-in-europe-to-allow-google-app-unbundling-for-a-fee/> (accessed on August 3, 2024).

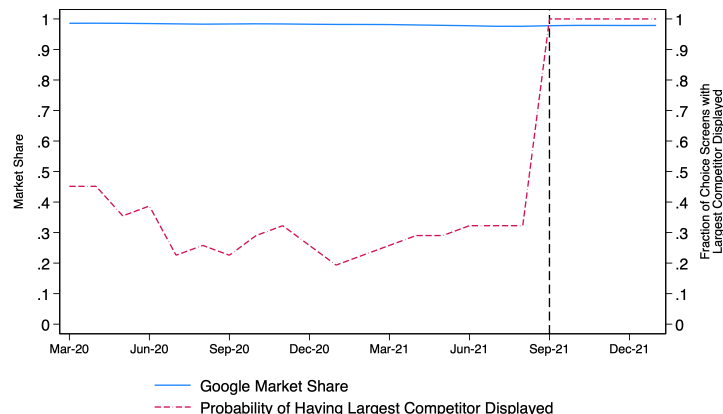
⁹⁸See <https://blog.google/around-the-globe/google-europe/complying-ecs-android-decision/> (accessed on August 3, 2024).

⁹⁹See <https://www.gov.uk/cma-cases/mobile-ecosystems-market-study> (accessed on August 3, 2024).

choice screen to the previous “low powered” Pay-to-Play design. In the first exercise, we evaluate whether the discrete change in the probability of having Google’s largest competitor displayed on the choice screen was matched by a change in Google’s market share. In the second exercise, we study the effect of appearing on the list of top 5 search engines on the choice screen. In the last exercise, we separately estimate the effect of the two remedies on Google’s competitors’ market shares. Based on our results it seems that changing from Pay-to-Play to Free-to-Play remedy design did not have a significant impact.

The Free-to-Play design always displays the top 5 most popular search engines. This was not the case with the Pay-to-Play design, where each search engine had to win a slot in the auction to appear on the choice screen. We study whether this discrete change in the probability of having Google’s largest competitor displayed on the choice screen in each country was accompanied by a change in Google’s market share. Figure B.1 shows that even though the probability of having the biggest competitor displayed on the choice screen increased with the Free-to-Play design, there was no corresponding decrease in Google’s market share. This suggests that the switch in remedy design did not have a significant impact on Google’s market share.

Figure B.1: Google Market Share vs. Largest Competitor Display Probability



Notes: The figure shows Google’s market share (solid blue line, left axis) alongside the probability of choice screens displaying its largest competitor (dashed red line, right axis) from March 2020 to December 2021. The vertical line corresponds to the change from the Pay-to-Play to the Free-to-Play choice screen.

Next, we investigated whether a search engine gained more market share during the Free-to-Play choice screen period when it appeared on the top-5 search engine list of the choice screen. To do this, we first constructed an indicator for whether the search engine was being displayed in the top-5 list of the choice screen and then estimated regressions. Precisely, our dependent variable is the difference between (i) the search engine’s monthly market share and (ii) the market share held before the Free-to-Play choice screen was implemented. The explanatory variable is the indicator for whether the search engine was appearing in the top-5 search engine list of the choice screen.

We only performed this exercise for Ecosia and Yandex. We did so because these were the only search engines that had some variation in whether they appeared on the top-5 search engine list across countries. Bing, DuckDuckGo and Yahoo almost always appeared on the top-5 list and Seznam and Qwant only did so in three countries. Table B.1 shows the results. Being on the top-5 search engine list is negatively correlated with the market share gain of Ecosia and Yandex. The takeaways from these results are twofold. First, we can infer that these competitor search engines grew more in countries where they were not as popular before the intervention. Second, we can conclude that appearing on the top-5 most popular search engine list did not provide a boost to

search engines appearing on the choice screen.

Table B.1: Effect of Top-5 Search Engine List (Free-to-Play Choice Screen)

Dependent variable: Mkt. Share Gain during Free-to-Play CS				
	(1) Ecosia	(2) Ecosia	(3) Yandex	(4) Yandex
Ecosia in Top-5 List	-0.032 (0.010)	-0.184 (0.028)		
Yandex in Top-5 List			-0.102 (0.029)	-0.046 (0.064)
Country FE		Yes		Yes
R-squared	0.060	0.596	0.075	0.749
Observations	155	155	155	155

Notes: The dependent variable is the difference between the search engine's current market share and the market share held before the Free-to-Play choice screen was implemented.

Finally, we estimated DD regressions to separately analyze the effects of the Pay-to-Play and Free-to-Play choice screens on Google's competitors. The results are shown in Table B.2. To separately estimate the effect of each remedy design, we removed the period where the other design appeared from the estimation sample. The findings are less intuitive than the ones we include in the paper, which show the effects of the overall EEA remedy on competitor market shares. Yandex's gain is no longer statistically significant (see columns 5-6), and DuckDuckGo experienced a loss from the remedy (see column 2). Yahoo did not win any auctions but still gained market share from the Pay-to-Play choice screen (see column 7).

Table B.2: Effect of Pay-to-Play and Free-to-Play Choice Screens on Competitors

	(1) DuckDuckGo	(2) DuckDuckGo	(3) Bing	(4) Bing	(5) Yandex	(6) Yandex	(7) Yahoo!	(8) Yahoo!
EEA $\times$ Post 03/2020	0.041 (0.024)		0.071 (0.046)		0.057 (0.232)		0.100 (0.043)	
Post 03/2020	0.144 (0.020)		0.075 (0.039)		0.021 (0.194)		-0.415 (0.036)	
EEA	0.074 (0.012)	0.074 (0.012)	-0.026 (0.024)	-0.026 (0.026)	-1.867 (0.122)	-1.867 (0.120)	-0.144 (0.022)	-0.144 (0.024)
EEA $\times$ Post 09/2021		-0.060 (0.037)		0.019 (0.084)		0.282 (0.385)		0.168 (0.077)
Post 09/2021		0.297 (0.031)		0.234 (0.070)		-0.134 (0.322)		-0.451 (0.064)
R-squared	0.103	0.106	0.013	0.018	0.102	0.105	0.113	0.054
Pre-remedy Share	0.19	0.19	0.27	0.27	0.11	0.11	0.59	0.59
Observations	2795	2236	2795	2236	2795	2236	2795	2236

Notes: Odd columns consider the pay-to-play choice screen and restrict the sample to before the free-to-play choice screen appeared (i.e. from April 2016 to August 2021). Even columns consider the free-to-play remedy and remove from the estimation sample the period where the pay-to-play choice screen appeared (i.e. from April 2016 and February 2020, and from September 2021 to January 2022). The control group for all regressions is composed of European countries.

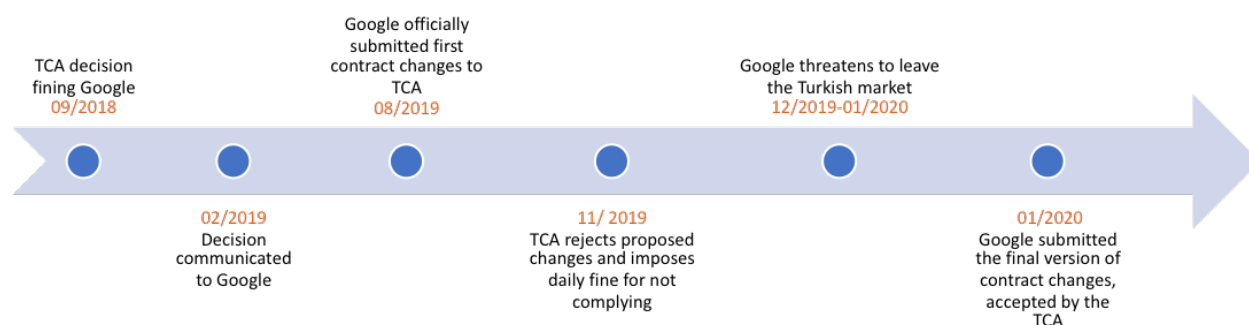
B.2 Additional Information on the Turkish Case

TCA Timeline and More Background Information The case started following a complaint launched by Yandex with the allegation that Google violated the Turkish Competition Law by forcing the original equipment manufacturers through agreements to pre-install certain Google apps on their mobile devices. The Turkish case is closely related to the European Commission’s Google-Android case, but there are some significant differences in terms of market definition, nature of the infringement, and remedy design.

The TCA did not consider Google liable for imposing anti-fragmentation obligations, which essentially prohibit Android “forks”. The TCA’s case was instead centered on the abusive tying of the Android OS. Through contractual arrangements with OEMs, Google provided Android OS forcing OEMs to have Google as the default search engine and to place the search widget on the device’s main screen. The remedies imposed by the TCA were meant to allow OEMs the freedom to choose alternative search providers, by removing restrictive clauses in their Android licensing contracts.

As shown in the main text, a timeline figure for the Turkish case could be summarized as follows

Figure B.2: Turkish Case Timeline



Shortly after Google submitted the final version of the contract with the OEM, Huawei, one of the largest OEMs, replaced Google with Yandex. In May 2020, Yandex Turkey General Manager, Onur Karahayıt, announced a deal, making Yandex the default search engine on Huawei phones. An industry journal article describes the agreement as follows: “Within the scope of the cooperation between Huawei and Yandex, Yandex has become the default search engine in the Huawei internet browser and the search bar on the home screen of devices with Huawei Mobile Services (HMS).”¹⁰⁰ Moreover, the same article reports official press releases from Yandex Turkey General Manager, who describes the growth of Yandex search in Turkey as a very successful experience with Yandex providing search services to more than 10 million unique users per month in the Turkish search engine market. The press release explains the breadth of the agreement with Huawei, involving not just search but the whole range of services offered by Yandex: “As a result of this experience (i.e., the growth of Yandex in Turkey), we are very happy to have signed this cooperation with one of the most important players in the world smartphone market, Huawei. As part of our collaboration, we have completed the necessary developments to be included in AppGallery, Huawei’s application store, with Yandex’s applications such as maps, navigation, e-mail, and translation, which have millions of users in Turkey.” In the subsequent years, there were further changes, and currently,

¹⁰⁰See <https://www-aa-com-tr.translate.google.tr/sirkethaberleri/bilisim/huawei-ve-yandexten-turkiye-de-is-birligi/657379?x.tr.sl=auto&x.tr.tl=en&x.tr.hl=en&x.tr.pto=wapp> (accessed August 1st, 2024).

Huawei has Petal Search as its default.¹⁰¹ Yandex, instead, is currently the default search engine for the Microsoft Edge browser (not only in Turkey but in various countries neighboring Russia).

TCA document Translation The following text is derived from our tentative translation of the related law document: <https://www.rekabet.gov.tr/Dosya/geneldosya/google.pdf>.

An investigation was carried out to determine whether the conduct of the business group, consisting of Google LLC, Google International LLC, and Google Advertising and Marketing Ltd, violates Law No. 4054 in its agreement signed with device manufacturers regarding the provision of mobile operating systems and mobile application services. After evaluating all the evidence, including information and documents collected, the report prepared, the written defenses, and the statements made at the oral defense meeting, the following final decision was taken at the Competition Board meeting held on 19.09.2018 with the number 18-33/555-273¹⁰²:

1. *Google LLC, Google International LLC, and Google Advertising and Marketing Ltd have a dominant position in the “licensable mobile operating systems” market,*
2. *Google business group violated Article 6 of Law No.4054 through its practices in Mobile Application Distribution Agreements signed with device manufacturers. This includes the assignment of Google search as the default at the points specified in the agreement, the positioning of the Google search widget on the home screen, the assignment of the Google Webview component as the default and only component for the relevant function, and the provisions in Revenue Sharing Agreements that ensure the exclusive installation of Google search on devices,*
3. *Therefore, according to the third paragraph of Article 16 of Law No. 4054, subparagraph (b) of the first paragraph, subparagraph (b) of the second paragraph, and subparagraph (b) of the third paragraph of Article 5 regarding the “Regulation on Fines to be imposed in the Event of Agreements, Concerted Practices, and Decisions Restricting Competition and Abuse of Dominant Position”, the following administrative fine is placed over the annual gross revenues generated at the end of the fiscal year 2017 and determined by the Board,*
 - *TL 93,083,422.30 severally to Google LLC, Google International LLC, and Google Advertising and Marketing Ltd.*
4. *Although the obligations regarding other Google applications included in the Mobile Application Distribution Agreements do not constitute a violation under Law No. 4054, it was unanimously voted to have the Presidency send an opinion letter to the aforementioned business group, ensuring publicity for contracting device manufacturers and to prevent future competitive concerns. The letter includes an explicit provision to all Mobile Application Distribution Agreements regarding the prevention of the preloading of competing applications on the device together with Google applications.*
5. *Google’s business group should end the infringement and ensure the restoration of effective competition in the market to fulfill their obligations:*
 - *In its contracts with device manufacturers who want to use the Commercial Android Operating System in their devices produced for sale in Turkey;*

¹⁰¹Initially, this was meant to be the Huawei competitor of Google, but it appears that in the fall 2023, Huawei switched to using Bing to power the Petal search results.

¹⁰²See <https://www.rekabet.gov.tr/en/Guncel/investigation-on-google-llc-google-inter-60928a8075bde81180e300505694b4c6> (accessed August 1st, 2024).

- *Removing contractual provisions that require or directly/indirectly imply the exclusive placement of the Google search widget on the home screen as a condition of licensing. Guarantee the right of device manufacturers to choose the provider of the search widget to be placed on the home screen from Google or its competitors, and establish the freedom of device manufacturers to place non-Google search widgets on the home screen on their own,*
 - *Removing the terms of the license that require Google search to be assigned by default to all search access points within the existing design structure, and not introducing new obligations to assign Google search by default to all search points that may arise as a result of design choices,*
 - *Removal of contractual provisions that require or directly/indirectly imply the installation of Google Webview as the default and exclusive in-app web browser as a condition of licensing,*
 - *not to provide incentives, financial or otherwise, in a manner that would have the consequences prohibited by the three obligations listed above,*
 - *Remove from all existing agreements, in particular Revenue Sharing Agreements with device manufacturers, the obligations that Google search competitors cannot be preloaded on devices and that device manufacturers cannot use Google search competitors on any of the search points on devices.*
6. *It was unanimously voted that the amendments required to be made in the agreements within the framework of the aforementioned obligations shall be submitted to the Competition Authority within 6 months following the notification of the reasoned decision,*

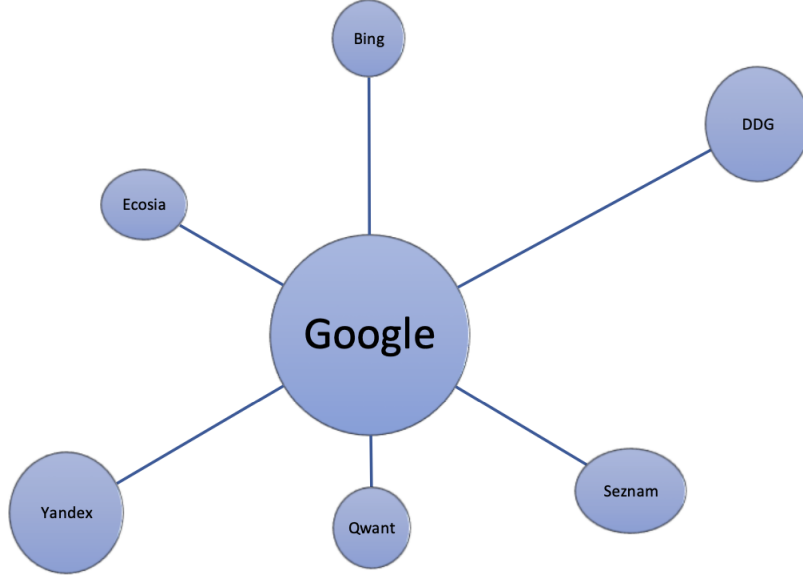
It has been decided that the judicial remedy in Ankara Administrative Courts shall be open within 60 days from the notification of the reasoned decision.

B.3 Basic Framework

Model Setup To understand how policy design affects market outcomes, we present a simple theoretical framework for the user’s choice of search engines. There are two types of firms and two types of users in the model. One firm is the incumbent, denoted by g , and the others are the competing firms accessible to users, denoted by $j \in \{1, 2, \dots, J\}$. Each firm owns and operates one search engine and each user has a unit demand. Without loss of generality, the user size is normalized to one. Among them, a portion $1 - N$ of users are captive to the incumbent firm g , meaning that they will always choose firm g . Others are shoppers who consider not only firm g but also alternatives. The model is a version of Hotelling lines, such that firm g is placed in the middle of the star, and competing companies $j \in \{1, 2, \dots, J\}$ accessible to users are located at the ends as shown in Figure B.3. Each link between firm g and a competing firm is a normalized hotelling line. A shopper can choose between companies only after they know their product and service values. However, it is costly to collect information. As a consequence, users make sequential rationalizable choices as Manzini and Mariotti (2007): they first determine the consideration set, i.e. the firms they collect information about, and then choose the best option in this consideration set. As discussed in Caplin et al. (2011), lack of information can discourage users from putting all firms in the consideration set. To simplify the model, we assume each user only has two firms in its consideration set. As users have no prior information about the firm’s service quality, their optimal strategy would be to save search costs and begin with firms they are more familiar with. Thus,

one search engine in the consideration set must be the incumbent firm g , and the other one is the competing search engine that the user is most familiar with.

Figure B.3: Remedy in the European Economic Area



Based on the consideration sets, users are placed on corresponding Hotelling lines. Precisely, a user is on the link L_j between firm g and firm j if its consideration set consists of these two companies. In the context of normalized user size, the density l_j of the link L_j equals the probability a user chooses firm j in its consideration set.

Market Equilibrium A user's familiarity with a specific firm is determined by her awareness of its product. Specifically, the awareness of user i of competing firm j equals:

$$W(i, j) = w_j + \epsilon_{ij}$$

where w_j is market awareness of firm j , and ϵ_{ij} is the idiosyncratic awareness for user i . We assume that each ϵ_{ij} is independently and identically distributed with the standardized Gumbel (Type I Extreme Value) distribution. As a consequence, firm j will be chosen in the user's consideration set only if $W(i, j) > W(i, j')$ for all competing firms accessible to the user such that $\forall j' \in \{1, 2, \dots, J\} \neq j$. In this context, the probability that user i chooses search engine j into its consideration set equals:

$$P_j = \text{Pro}\{\epsilon_{ij'} < \epsilon_{ij} + w_j - w_{j'}, \forall j' \neq j\} = \frac{e^{w_j}}{\sum_{j'=1}^J e^{w_{j'}}}$$

Users on link L_j then choose between firm g and firm j in their consideration set. We allow the competitors' service to be vertically differentiated from firm g , which may be due to technology, data access, and so on. Since the products (search engine services) are all free for the user, the utility on the user side is determined solely by the service quality and network effect. If user i on link L_j chooses product $k \in \{g, j\}$, she receives utility equal to:

$$U(i, k) = v_k + em_k - rd(i, k)$$

where v_k is the stand-alone utility from firm k 's product, m_k is the existing market share, $d(i, k)$ is the distance between user i 's location and firm k , r is the transportation cost, and e is the network

effect. Since users always prefer adopting a firm with a larger existing user size, we assume the network effect $e > 0$ throughout the paper. Within this setup, the indifferent user on link L_j must satisfy:

$$U(i, j) = U(i, g) \text{ and } d(i, j) + d(i, g) = 1$$

Solving the equations, we derive the demand for competing firm j :

$$q_j^t = N \frac{e^{w_j}}{\sum_{j'=1}^J e^{w_{j'}}} \left(\frac{1}{2} + \frac{v_j - v_g + em_j - em_g}{2r} \right)$$

where N is the proportion of shoppers, $e^{w_j} / \sum_{j'=1}^J e^{w_{j'}}$ is the probability a user has search engine j in its consideration set and $1/2 + (v_j - v_g + em_j - em_g)/2r$ is the probability of a user choosing search engine j given it is included in the user's consideration set. Correspondingly, the demand for firm g equals:

$$q_g^t = 1 - \sum_{j=1}^J q_j^t$$

Equilibrium Analysis The market equilibrium yields several interesting observations that can possibly shed light on the determinants of antitrust policy effectiveness. The initial observation is that the market share of firm g decreases with N , the proportion of users having access to the pro-competitive intervention, while the market share of a competing firm j increases with N . In other words, higher market visibility of competing search engines to users should reduce Google's market share while increasing competing search engines' market share. Without interventions, Google is always the default search engine on Android mobile devices and no user has access to any alternatives. As a consequence, the introduction of policy intervention, regardless of its format, always benefits the competing search engines if it increases their market visibility.

Furthermore, our model also illustrates that not every search engine always enjoys significant growth after the intervention. Indeed, there exists a service cutoff $v_j^* > v_g - t - em_j + em_g$, such that only when the service value of competing firm j is sufficiently high $v_j > v_j^*$ does the market share of the competing firm increases gradually after the intervention. Otherwise, this competing search engine still gains no market share even if it is made accessible to users. In other words, only search engines that have relatively good search service quality may benefit from the intervention.

The model further highlights the potential factors determining the efficacy of policy interventions. Given a search engine whose quality is sufficiently high as to be selected by users, its gain in market shares is increasing with its service quality and its market awareness, while it is decreasing with the number of other search engines accessible to users, their market awareness, and Google's service quality. Hence competing search engines that are more popular also have stronger incentives to compete with Google in the market for mobile search.

In summary, our model highlights several aspects that policy interventions may target to bolster competition in the search engine market. First, regulators should work on exposing more users to alternative search engines. An increase in the number of shoppers reduces a user's chance of being locked-in with Google. Also, it is critical for regulators to carefully design the mechanisms selecting which competing search engines are made accessible to users, as the number and characteristics of competitors shown to users affect their consideration sets and thus their choice of search engines. Furthermore, we show that the effectiveness of a remedy is also determined by the characteristics of competing search engines, including their service quality and market awareness. Precisely, we find that search engines with high popularity and quality are more likely to attract users and to diminish Google's market power.

B.4 Identification

Parameters Assume there are two groups $i \in \{e, c\}$ covered for T periods. Group e receives the choice screen treatment at period $t^* \in \{1, \dots, T\}$, while group c is the control group and is never treated. We introduce the following parameters: Let b_i be the initial stock of mobile devices; δ be the fraction of the initial stock that gets destroyed each period; $ship_i$ be the number of mobile devices shipped to group i in each period; γ_i be the fraction of shipped devices that become active in each period; λ_i be the fraction of Android mobile devices out of total devices; σ_i be the number of online searches made by each active device; μ_i be the baseline market share for Google in mobile search; and θ be the rate at which users select Google from the choice screen (“CS”).

Devices and Market Shares Total mobile devices in group i at period t are given by:

$$dev_{it} = \underbrace{b_i \times (1 - \delta_i)^t}_{\text{remaining stock}} + \underbrace{ship_i \times \gamma_i \times t}_{\text{shipments}} \quad (13)$$

Android devices are computed as:

$$Android_dev_{it} = \lambda_i \times dev_{it} \quad (14)$$

The number of devices that have access to the choice screen in the treatment group are given by:

$$cs_dev_{et} = \begin{cases} 0 & t < t^* \\ \underbrace{\lambda_e \times ship_e \times \gamma_e}_{\text{choice screen devices activated}} \times \underbrace{(t - t^* + 1)}_{\text{periods treated}} & t \geq t^* \end{cases} \quad (15)$$

No device ever gets access to the choice screen in the control group: $cs_dev_{ct} = 0 \forall t$.

Google market shares in mobile search in group i and period t are given by:

$$Google_{it} = \frac{\underbrace{[(dev_{it} - cs_dev_{it}) \times \mu_i \times \sigma_i] + [cs_dev_{it} \times \theta \times \sigma_i]}_{\text{Google searches}}}{\underbrace{[(dev_{it} - cs_dev_{it}) \times \mu_i \times \sigma_i] + [cs_dev_{it} \times \theta \times \sigma_i] + [(dev_{it} - cs_dev_{it}) \times (1 - \mu_i) \times \sigma_i] + [cs_dev_{it} \times (1 - \theta) \times \sigma_i]}_{\text{competitors' searches}}} \quad (16)$$

Similarly, Google market shares in Android mobile search in group i and period t are given by:

$$Google_Android_{it} = \frac{[(Android_dev_{it} - cs_dev_{it}) \times \mu_i \times \sigma_i] + [cs_dev_{it} \times \theta \times \sigma_i]}{\underbrace{Android_dev_{it} \times \sigma_i}_{\text{total Android searches}}} \quad (17)$$

Models To estimate the remedy effect we employ the following *binary treatment* model specification:

$$Google_{it} = \alpha + \beta_{\text{binary}}(Post_t \times Treat_i) + \psi Post_t + \phi Treat_i + \varepsilon_{it} \quad (18)$$

where $Post_t = \mathbb{1}(t \geq t^*)$ and $Treat_i = \mathbb{1}(i = e)$. Under the assumptions we made, it can be shown that the coefficient β_{binary} in regression (7) identifies the difference in the trend of Google market shares in overall mobile search in treated group vis-à-vis the same trend in the control group. Our

estimated coefficient $\hat{\beta}_{\text{binary}}$ captures the following difference-in-differences:

$$\hat{\beta}_{\text{binary}} = \underbrace{\left[\frac{1}{T - t^* + 1} \sum_{t=t^*}^T Google_{et} - \frac{1}{t^* - 1} \sum_{t=1}^{t^*-1} Google_{et} \right]}_{\text{treated group trend}} - \underbrace{\left[\frac{1}{T - t^* + 1} \sum_{t=t^*}^T Google_{ct} - \frac{1}{t^* - 1} \sum_{t=1}^{t^*-1} Google_{ct} \right]}_{\text{control group trend}}$$

To estimate the remedy effect we also employ the following *weighted treatment* model specification:

$$Google_{it} = \alpha + \beta_{\text{ship}}(Post_t \times Treat_i \times Android_ship_i) + \rho Android_ship_i + \psi Post_t + \phi Treat_i + \varepsilon_{it} \quad (19)$$

where $Android_ship_i$ is the fraction of Android devices out of total mobile shipments in each period. It can be shown that, under our assumed configuration, the coefficient β_{ship} in regression (11) identifies the difference in the trend of Google market shares in Android mobile search in the treated group vis-à-vis the same trend in the control group. Our estimated coefficient $\hat{\beta}_{\text{ship}}$ captures the following difference-in-differences:

$$\hat{\beta}_{\text{ship}} = \underbrace{\left[\frac{1}{T - t^* + 1} \sum_{t=t^*}^T Google_Android_{et} - \frac{1}{t^* - 1} \sum_{t=1}^{t^*-1} Google_Android_{et} \right]}_{\text{treated group trend}} - \underbrace{\left[\frac{1}{T - t^* + 1} \sum_{t=t^*}^T Google_Android_{ct} - \frac{1}{t^* - 1} \sum_{t=1}^{t^*-1} Google_Android_{ct} \right]}_{\text{control group trend}}$$

Implications The sign, size and similarity of our estimates are determined by the following effects:

- (i) The sign of both estimated coefficients $\hat{\beta}_{\text{binary}}$ and $\hat{\beta}_{\text{ship}}$ depends on the relation between Google's baseline market share in the treated group μ_e and Google's selection rate from the choice screen θ :

→ If users select Google from the choice screen at a lower rate than its baseline market share, the estimated treatment effect is negative: $\theta \leq \mu_e \implies \hat{\beta}_{\text{binary}} \leq 0$ and $\hat{\beta}_{\text{ship}} \leq 0$.

- (ii) The size of both estimated coefficients $\hat{\beta}_{\text{binary}}$ and $\hat{\beta}_{\text{ship}}$ is determined by:

→ The users' propensity to select Google from the choice screen (θ) relative to its baseline market share (μ_e). If users select Google at a rate that is very close to its baseline share, the effect of the remedy is small. Moreover, note that the absolute value of both estimates is always smaller than the absolute value of the difference $|\theta - \mu_e|$. Intuitively, the two would coincide only if all mobile users were shown the choice screen. Since only a subset of users actually have access to the remedy, the effect $|\theta - \mu_e|$ is attenuated when measured on the broader population of Android users and even more so when measured in the population of overall mobile users.

- The timing of the remedy: the effect of the remedy builds over time as more devices are exposed to the choice screen, hence if the treatment occurs at the end period ($t^* \rightarrow T$), the effect is smaller. If the number of treated periods grows, the effect is larger.
- The existing stock of devices (b_e), the rate of destruction (δ), the per-period shipments ($ship_e$) and the activation rate (γ_e). Intuitively, these four parameters determine the mobile device accumulation pattern and the weight that devices with the choice screen have in the overall population of mobile devices. The smaller is the fraction of devices treated by the choice screen compared to the ones already circulating before the remedy, the smaller is the estimated effect.

(iii) The difference between the two coefficients $\hat{\beta}_{\text{binary}}$ and $\hat{\beta}_{\text{ship}}$ is driven by the fraction of Android devices out of total mobile devices λ_e :

- As the fraction of Android devices falls, the two estimates will diverge more. Indeed, given our setting, λ_e measures the share of Android devices in mobile search. Intuitively, if all devices were Android $\lambda_e = 1$, then the two estimates would coincide $\hat{\beta}_{\text{binary}} = \hat{\beta}_{\text{ship}}$ as the effect on Android mobile search and on overall mobile search would be trivially the same. However, as the share of Android falls ($\lambda_e \rightarrow 0$), choice screen devices are very few among overall devices, hence the effect of the remedy on overall mobile search becomes negligible, $\hat{\beta}_{\text{binary}} \rightarrow 0$. However, the few choice screen devices still matter in the same proportion in the small number of Android mobile searches, hence the effect of the remedy on Android mobile search $\hat{\beta}_{\text{ship}}$ is unchanged. The following relation holds:

$$\hat{\beta}_{\text{ship}} = \frac{1}{\lambda_e} \times \hat{\beta}_{\text{binary}} \implies |\hat{\beta}_{\text{ship}}| > |\hat{\beta}_{\text{binary}}| \quad (20)$$

Therefore, our two estimates capture different effects, with distinct policy relevance. The estimate from the binary treatment model ($\hat{\beta}_{\text{binary}}$) captures the effect of the remedy on overall mobile search, while the estimate from the weighted treatment model ($\hat{\beta}_{\text{ship}}$) captures the effect of the remedy on Android mobile search. In the language of causal identification, the former effect resembles an Average Treatment Effect (ATE) while the latter is more closely related to an Average Treatment Effect on the Treated (ATT). However, the actual population of treated units is even more restricted in the case of the EEA remedy, which is only targeted towards new Android users. To measure the effectiveness of the antitrust choice screen remedy in leveling the playing field for competing search engines, the ATT is arguably more informative as it captures the effect on the sub-population affected by the remedy. We attempt to get an informative estimate of the effect of the choice screen remedy on treated consumers in the next section.

Inversion Given the data at our disposal, we can perform a back-of-the-envelope calculation of θ : the parameter that describes users' propensity to select Google as their preferred search engine from the choice screen.

Inverting equation (16), which determines Google's market share in overall mobile search, we can construct an estimate for θ as follows:

$$\hat{\theta} = \frac{(\overline{Google_e} \times \overline{dev_e}) - (\overline{dev_e} - \overline{cs_dev_e}) \times \mu_e}{\overline{cs_dev_e}} \quad (21)$$

where, on the right-hand-side, we have Google's baseline market share in the treatment group (μ_e) and averages over the post-treatment period for the treated group of Google's mobile market share

$(\overline{Google_e})$, of the number of total devices ($\overline{dev_e}$) and of the number of choice screen devices ($\overline{cs_dev_e}$) respectively.

From market size data (Newzoo), shipments data (Gartner) and market share data (StatCounter) at our disposal, we can compute the implied value $\hat{\theta}$ as in equation (21). We consider the 22 quarters between April 2016 and October 2021, with treatment occurring in March 2020. We focus on the 2016Q2-2021Q3 time-window since the three datasets overlap only from 2016 onwards, while the quarterly frequency is chosen since shipments are measured on per-quarter basis. Throughout, we consider only the countries covered by the shipments data, as seen in Table B.3. We exclude Russia and Turkey from the analysis as they are subject to their own interventions, and, following the discussion in Appendix A.4, we also remove Czechia. Therefore, seventeen EEA countries form the treated group, while the control group consists of eleven OECD and European countries.

To calculate $\hat{\theta}$ we need to assign values to the following model parameters: The initial stock of devices in each group (b_i); the device destruction rate (δ); the number of mobile devices shipped to each group in every quarter ($ship_i$); the fraction of shipped devices that become active in each group in every quarter (γ_i); the share of Android devices in each group (λ_i); and Google’s baseline market share in mobile search in each group (μ_i).

First, we assign values to the parameters that govern the mobile device accumulation pattern. From our market size data, we compute the total number of active smartphones as of 2016 in the EEA and in the control group and we assign the resulting values to the parameter b_i . We obtain a smartphone device stock equal to about 552 million for the control group and to roughly 373 million devices for the treated group. These figures appear reasonable when compared to the corresponding population of the two groups, which we can also compute from our Newzoo data. In 2016, the control group had a population of 765 million while the EEA counted 457 million, suggesting that the EEA had slightly higher smartphone penetration. The number of devices shipped and the activation rate determine the inflow of devices that each group adds in each period, while the destruction rate determines the outflow of devices that each group loses in every period. Given the short time frame we consider (2016Q2-2021Q3), we assume that only the initial stock of devices gets destroyed at the constant rate, while the newly added shipped devices do not. We assume that the initial pool of mobile devices gets destroyed at a constant rate of 2.5% each quarter. Increasing this value would make the incoming shipped devices relatively more prevalent as the initial stock would diminish faster, while reducing the destruction rate would have the opposite effect. Importantly, these changes in the relative prevalence of new devices, would affect the relative prevalence of Android devices with access to the choice screen in the EEA following the remedy. Turning our attention to inflows, from our shipments data, we can compute the average number of devices shipped in the EEA and in the control group, in each quarter over the 2016Q2-2021Q3 period. On average, about 35 million devices are shipped in each quarter in the EEA and about 29 million to the control group. We assume that in both the treated and control group, 36% of shipped devices become active in each group.¹⁰³ The assumed destruction rate essentially sets the control group to an equilibrium number of mobile devices, whereby the inflow of shipped devices essentially compensates for the destruction of the initial stock. Since the EEA receives a greater inflow of devices in every period and starts from a lower initial stock, the accumulation pattern in the treated group is instead slightly upward-sloped. Indeed, in each quarter the EEA receives shipments worth 10% of its initial stock of active devices and 36% of these shipped devices become active. This results in a gross increase in active devices that is worth roughly 3.6% of the initial stock in each period. With a quarterly destruction rate of 2.5% for the existing stock, we estimate

¹⁰³The value we assume was reported by Tim Cook to investors in 2019, for more information, please visit <https://www.ft.com/content/2b382af0-23ff-11e9-8ce6-5db4543da632> (accessed August 1st, 2024).

that the the EC’s intervention affects about one-third of the total Android devices by the end of the six quarters we use in our estimation.

Finally, we consider the parameters related to the mobile search market. In our setting, an important parameter is the share of Android in mobile search, captured by λ_i . From our shipment data, we compute the average fraction of Android devices out of total mobile shipments in the EEA and in the control group over the whole period. In the EEA, on average, 70.3% of shipped devices where Android, while in the control group this figure rises to 75.4%. By construction, as seen in equation (14), these same figures constitute the Android shares in the stock of active phones in the two groups. We therefore assign these two values to the corresponding parameters governing the share of Android in mobile search in the two groups. Lastly, we deal with the parameter related to Google’s baseline market share in mobile search, captured by μ_i . From our search engine market share data, we compute the pre-treatment average market share of Google in mobile search both in the EEA and in the control group. From April 2016 to February 2020, Google had an average market share of 98.67% and 92.99% in the EEA and in the control group respectively.

Given these assumed parameter values, we can compute the implied value of $\hat{\theta}$, which measures the users’ propensity to select Google as their preferred search engine from the choice screen. To do this, we compute the post-treatment average of the total number of mobile devices in each group and of the number of choice screen devices. Finally, we compute the post-remedy average Google mobile market share from our StatCounter data. Given all these quantities, we compute our implied value $\hat{\theta}$ as in equation (21).

Our estimate for Google’s selection rate from the choice screen is equal to 95.21%. This value is smaller than the baseline market share of Google in mobile search in the EEA, which is equal to 98.67%. Our estimated difference between Google’s baseline market share in mobile search and the frequency with which users select it as their preferred search engine from the choice screen is consistent with the small yet negative treatment effect that we estimate in both the binary and weighted model specifications. Moreover, as seen in Table 11 the weighted and binary specifications yield very close estimates for the effect of the EEA remedy. This is likely due to the fact that θ is close to Google’s baseline market share in the EEA. From equation (20), we see that while the absolute difference in the coefficients may be small, the ratio of the two estimates is driven by Android’s share of mobile search. If users selected Google very rarely from the choice screen ($\theta \rightarrow 0$), then both coefficients would be larger in absolute value, while their ratio would remain constant. Therefore, the two estimates would no longer be as close. Finally, note that the difference between our estimate for Google’s selection rate from the choice screen and Google’s baseline market share in the EEA ($|\hat{\theta} - \mu_e|$) is slightly greater than 3 percentage points. This difference is considerably larger than our estimates for the effect of the EEA remedy in both the binary and weighted specifications. Indeed, the difference between our estimate for users’ propensity to select Google and its baseline market share is about three times larger than our remedy effect estimate from the weighted model specification and more than four times larger than our estimate from the binary model specification, as seen in the first two columns of Table 11. Intuitively, since only new Android users had access to the choice screen, the effect is attenuated when measured on the broader population of Android users and it decreases even more when measured in the population of overall mobile users. The difference between our counterfactual estimate and our regression estimates is consistent with the fact that we estimate that about one-third of the Android devices actually accessed the choice screen.¹⁰⁴

¹⁰⁴The calculations underpinning our counterfactual estimate rely on several assumptions that can significantly influence the final estimate (e.g. the device accumulation pattern). In contrast, the analysis presented in the main text is conducted without the need to rely on such assumptions.

B.5 Additional Tables

This section reports the remaining tables that complement the main text and appendix.

Table B.3: Countries Included in Alternative Samples

Country	European Treated	European Sample	European & OECD Sample	European & OECD (population $\geq$ 10M)	Shipment Data
Albania		X	X		
Andorra		X	X		
Australia			X	X	X
Austria	X	X	X		X
Belarus		X	X		
Belgium	X	X	X	X	X
Bosnia		X	X		
Bulgaria	X	X	X		
Canada			X	X	X
Chile			X	X	X
Colombia			X	X	X
Costa Rica			X		
Croatia	X	X	X		
Cyprus	X	X	X		
Czechia	X	X	X	X	X
Denmark	X	X	X		X
Estonia	X	X	X		
Finland	X	X	X		X
France	X	X	X	X	X
Georgia		X	X		
Germany	X	X	X	X	X
Greece	X	X	X	X	X
Holy See		X	X		
Hungary	X	X	X		X
Iceland	X	X	X		
Ireland	X	X	X		X
Israel			X		X
Italy	X	X	X	X	X
Japan			X	X	X
Korea, Rep.			X	X	X
Latvia	X	X	X		
Liechtenstein	X	X	X		
Lithuania	X	X	X		
Luxembourg	X	X	X		
Malta	X	X	X		
Mexico			X	X	X
Moldova		X	X		
Monaco		X	X		
Montenegro		X	X		
Netherlands	X	X	X	X	X
New Zealand			X		X
North Macedonia		X	X		
Norway	X	X	X		X
Poland	X	X	X	X	X
Portugal	X	X	X	X	X
Romania	X	X	X	X	
San Marino		X	X		
Serbia		X	X		
Slovak Republic	X	X	X		
Slovenia	X	X	X		
Spain	X	X	X	X	X
Sweden	X	X	X	X	X
Switzerland					
Ukraine		X	X	X	
United Kingdom	X	X	X	X	X
United States			X	X	X

Notes: we remove Czechia from the treatment group in the intervention effect analysis of the EEA remedy, as explained in detail in the main text.

Table B.4: Testing for Parallel Trends

	(1)
	Google
Post 03/2020	0.077 (0.180)
EEA	2.107 (0.297)
EEA*2016 Quarter2	-0.551 (0.393)
EEA*2016 Quarter3	-0.394 (0.393)
EEA*2016 Quarter4	-0.101 (0.393)
EEA*2017 Quarter1	-0.065 (0.393)
EEA*2017 Quarter2	-0.102 (0.393)
EEA*2017 Quarter3	-0.127 (0.393)
EEA*2017 Quarter4	0.254 (0.393)
EEA*2018 Quarter1	0.052 (0.393)
EEA*2018 Quarter2	-0.080 (0.393)
EEA*2018 Quarter3	-0.022 (0.393)
EEA*2018 Quarter4	0.000 (.)
EEA*2019 Quarter1	0.104 (0.393)
EEA*2019 Quarter2	0.074 (0.393)
EEA*2019 Quarter3	-0.497 (0.393)
EEA*2019 Quarter4	-0.021 (0.393)
EEA*2020 Quarter1 (Treatment)	0.010 (0.397)
EEA*2020 Quarter2	-0.053 (0.432)
EEA*2020 Quarter3	-0.286 (0.432)
EEA*2020 Quarter4	-0.308 (0.432)
EEA*2021 Quarter1	-0.456 (0.432)
EEA*2021 Quarter2	-0.718 (0.432)
EEA*2021 Quarter3	-0.887 (0.432)
EEA*2021 Quarter4	-0.747 (0.432)
Observations	2967

Notes: The model includes all European countries, besides Turkey, Russia, Switzerland, and Czechia. The time frame of the model is between April 2016 and December 2021.

Table B.5: Google EEA Remedy Estimates (Pay-to-play & Free-to-Play)

	(1) Google	(2) Google	(3) Google
EEA $\times$ Post 03/2020	-0.346 (0.088)		-0.346 (0.087)
EEA $\times$ Post 09/2021		-0.486 (0.155)	-0.139 (0.158)
Month FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
R-squared	0.888	0.876	0.888
Observations	2795	2236	3010

Notes: All models include European countries, except Turkey, Russia, Switzerland, and Czechia. The time frame of the first model is between April 2016 and August 2021, the time frame of the second model is between April 2016 to January 2022 but with the pay-to-play period (March 2020-August 2021) removed, and the time frame of the third model is between April 2016 to January 2022.

Table B.6: Google Turkish Intervention Estimates with Alternative Time Cutoff

	(1) Google	(2) Google	(3) Google	(4) Google	(5) Google	(6) Google	(7) Google	(8) Google	(9) Google
Turkey $\times$ Post	-6.551 (1.987)	-6.551 (0.458)	-7.788 (1.834)	-7.781 (0.716)	-6.766 (2.285)	-6.766 (0.527)	-7.763 (2.003)	-7.753 (0.867)	-6.887 (0.789)
Post 09/2018	-0.036 (0.290)		0.479 (0.268)		0.178 (0.300)		0.454 (0.263)		
Turkey	1.226 (1.229)		2.463 (0.672)		1.987 (1.414)		2.984 (0.734)		
Month FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
R-squared	0.006	0.949	0.004	0.852	0.003	0.949	0.003	0.818	0.948
Observations	2209	2209	6273	6273	2726	2726	7747	7747	1095

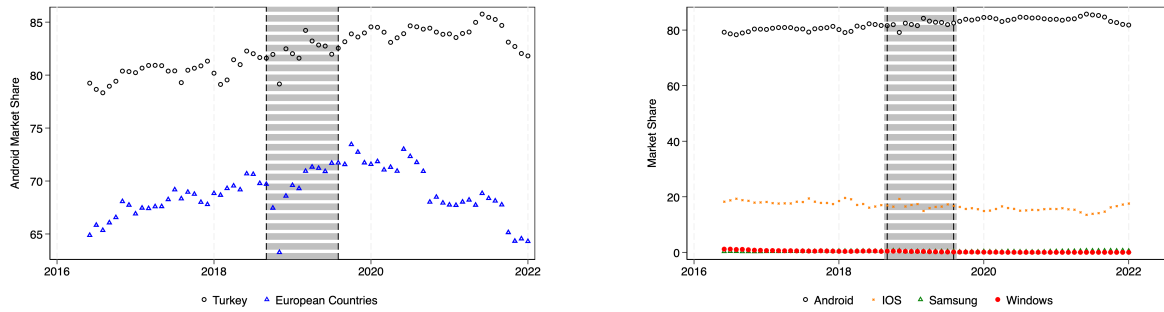
Notes: The first four models include all European countries. The time frame of the first two models is between April 2016 and February 2020, and between January 2009 and February 2020 for the third and fourth models. All other models add OECD countries, with the last one selecting as control group only countries whose population exceeds 10 million. Among the last five models, the time frame of the first two and the last models is between April 2016 and February 2020, and is between January 2009 and February 2020 for the rest. All models set September 2018 as the beginning month of the treatment.

B.6 Mobile Operating Systems in Turkey

Differently from the EEA and Russian remedies, the remedy in Turkey mainly focused on the contracts between Google and Android mobile device manufacturers. The goal was to ensure that manufacturers could freely choose between Google and any of its rivals for the default position on their devices. Consequently, Google had to remove the terms in its previous revenue-sharing agreements with manufacturers that forbid competitors to be preloaded or set as default on any search access point on Android mobile devices in Turkey. Considering Google's search quality and users' preference for Google, Google remained able to generate more queries and revenues than its rivals when occupying search access points. Therefore, it is no surprise that manufacturers continue to find Google the optimal solution even under the new contractual terms. However, the revenue sharing agreements might have completely changed for OEMs as Google was given precise conditions to which it had to abide in its contracts with manufacturers.

It is thus uncertain whether and how manufacturers in Turkey responded to the contractual changes by adjusting their device prices. To investigate this, we employ our StatCounter data to study the evolution of operating system market shares in Turkey before and after the remedy. If the manufacturers were to raise the prices for their Android mobile devices substantially, we would expect to observe the mobile market share of Android operating systems in Turkey move in the opposite direction.

Figure B.4: Mobile Operating System in Turkey



(a) Android Mobile Market Share

(b) Turkish OS Market Share

Notes: The vertical lines correspond to the TCA decision and to Google's officially accepted contractual changes in Turkey.

In Figure B.4a and Figure B.4b, we plot the evolution of the mobile market share in operating systems in Turkey and in European control countries. Comparing the two groups, we did not find significant changes. We further applied the same difference-in-differences model to study the evolution of OS market shares: $Android_{ct} = \alpha + \beta(Turkey_c \times Post_t) + \lambda_c + \gamma_t + \varepsilon_{ct}$, where $Android_{ct}$ is the mobile market share of the Android system in country c in period t . Our results in Table B.7 show no evidence of any significant change in the percentage of mobile devices adopting the Android operating system after the remedy. Therefore, we doubt the remedy generated any substantial change in the Android device price in Turkey.

Table B.7: Mobile Operating System Market Share

	(1) Turkish Mobile OS	(2) Turkish Mobile OS	(3) Turkish Mobile OS	(4) Turkish Mobile OS
Turkey $\times$ Post	-0.763 (6.003)	-0.763 (1.167)	-0.538 (6.520)	-0.538 (1.158)
Post 08/2019	3.633 (0.876)		3.407 (0.856)	
Turkey	12.420 (2.368)		13.457 (2.571)	
Month FE	No	Yes	No	Yes
Country FE	No	Yes	No	Yes
R-squared	0.023	0.965	0.018	0.970
Observations	2115	2115	2610	2610

Notes: The first two models include all European countries and the last two models add OECD countries. The time frame is between June 2016 and February 2020.

B.7 Tablet and Desktop Analysis

Since the choice screen applies to both mobile and tablet devices in the EEA and Russia, we also examine the impact of the choice screen on tablet devices. As depicted in Table B.8, the impact of the EEA remedy on tablet devices aligns qualitatively with that on mobile devices. We observed a small but overall significant reduction in Google's market share in the tablet search market, accompanied by a significant increase in market share for both Bing and Yandex.

Table B.8: EEA Remedy Estimates on Tablet

	(1) Google	(2) Google	(3) Google	(4) Google	(5) Google	(6) DuckDuckGo	(7) Bing	(8) Yandex
EEA $\times$ Post	-0.390 (0.161)	-0.705 (0.185)	-0.007 (0.132)	-0.402 (0.152)	0.099 (0.166)	-0.013 (0.075)	0.131 (0.045)	0.238 (0.051)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.713	0.627	0.893	0.857	0.967	0.227	0.798	0.949
Pre-remedy Share	96.53	96.53	96.53	96.53	96.53	0.43	1.14	0.17
Observations	3010	4899	3780	6153	1416	3010	3010	3010

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The first two models and the last three models include all European countries, besides Turkey, Russia, Czechia, and Switzerland. The time frame of the first model is between April 2016 and January 2022, and between August 2012 and January 2022 for the second model. The third and fourth models add OECD countries. The time frame of the third model is between April 2016 and January 2022 and the time frame of the fourth model is between August 2012 and January 2022. The fifth model selects as control group only countries whose population exceeds 10 million and the time frame is between April 2016 and January 2022. The time frame of the last three models is between April 2016 and January 2022.

As for the impact of the Russian remedy, it is documented in Table B.9. Precisely, we find a reduction of more than 6 percentage points in Google's market share in tablet search. Similarly to what discussed in the main text about mobile, the intervention effect is notably larger for Russia than in the EEA.¹⁰⁵

Table B.9: Russian Remedy Estimates on Tablet

	(1) Google	(2) Google	(3) Google	(4) Google	(5) Google	(6) Google	(7) Google	(8) Google	(9) Google
Russia $\times$ Post	-6.491 (1.079)	-6.491 (0.319)	-10.616 (1.056)	-10.617 (0.540)	-6.542 (1.654)	-6.542 (0.361)	-10.710 (1.538)	-10.709 (0.532)	-6.125 (0.467)
Post 04/2017	0.552 (0.157)		0.462 (0.154)		0.604 (0.217)		0.556 (0.202)		
Russia	-38.604 (0.763)		-34.479 (0.602)		-37.538 (1.170)		-33.371 (0.877)		
Month FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
R-squared	0.705	0.975	0.606	0.900	0.440	0.974	0.357	0.925	0.986
Observations	2538	2538	3898	3898	3132	3132	4811	4811	972

Standard errors in parentheses

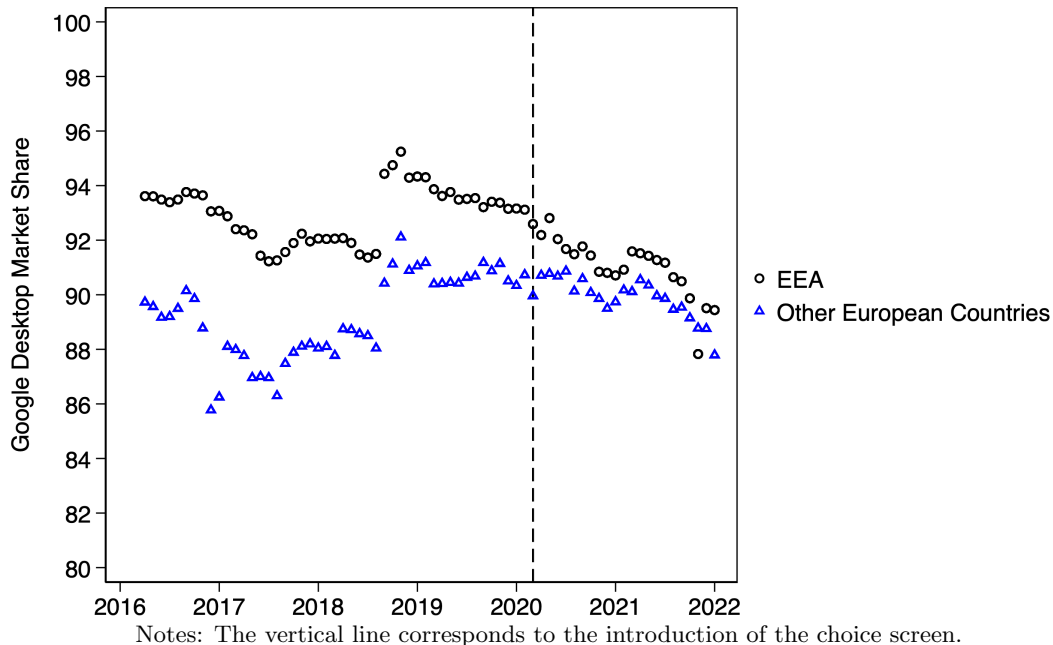
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The first four models include all European countries. Among them, the time frame of the first two models is between January 2015 and June 2019, and between August 2012 and June 2019 for the third and fourth models. The last five models add OECD countries, with the last model selecting as control group only countries whose population exceeds 10 million. The time frame of the fifth, sixth, and last models is January 2015 and June 2019, and is between August 2012 and June 2019 for the rest.

¹⁰⁵The time frame of the baseline estimates is set between January 2015 and July 2019, which is different from that used for Russian mobile estimates in the main text, to ensure the respect of the parallel trend assumption.

Regarding the desktop market shares, we report them in Figure B.5. Although desktop devices were not directly affected by the treatment and might, in principle, have been used as a control group for the analysis, its pre-treatment evolution in the EEA is substantially different from both that in the mobile market and that from the desktop market in the control countries used in our baseline analysis. We do not seek to analyze the desktop market in our study, but we would like to hint at possible spillover effects from the EEA choice screen intervention to the desktop market that might rationalize the steeper drop in the desktop market share post-intervention. This would be consistent with our understanding of how the desktop and mobile markets are interlinked.

Figure B.5: EEA Remedy



B.8 Alternative Data Source

To ensure the robustness of our results, we conducted additional investigations into the impact of the remedy in Russia and Turkey using an alternative data source: Yandex Radar.¹⁰⁶ Introduced by Yandex in 2017, Yandex Radar is a new analytics tool that provides search engine usage data in Russia, Belarus, Kazakhstan, and Turkey since 2015. For each country, we collected market share information for both Google and Yandex on Android mobile devices.

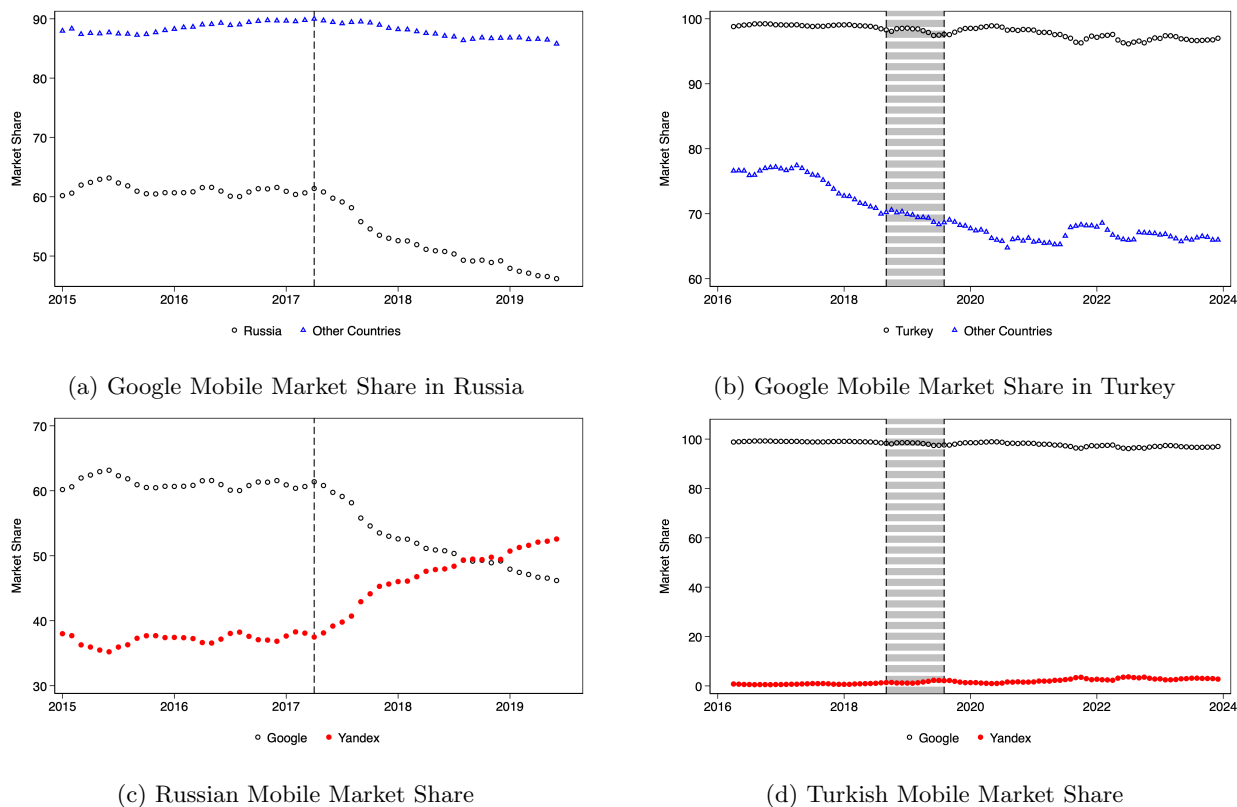
Following the same estimation strategy adopted in the main text, we first generate plots depicting Google's market share in Russia and Turkey, comparing them with other countries based on the Yandex Radar dataset. As depicted in Figure B.6, for Russia, we observed patterns similar to those discussed in the main text. However, in Turkey, distinct patterns emerge: there seems to be no clear reduction in Google's market share following the Turkish remedy. According to Yandex, its coverage of Russia is particularly accurate with 78.88% of traffic in the .ru domain zone.¹⁰⁷

¹⁰⁶See <https://radar.yandex.ru/search?period=all&group=month&country=983&device-category=5&platform=2> (accessed August 1st, 2024).

¹⁰⁷See <https://yandex.com/blog/yacompany-com/new-search-traffic-and-browser-usage-analytics-tool-yandex-radar> (accessed August 1st, 2024).

We then apply the DD model to the Yandex Radar data. The results in Table B.10 reveal even more pronounced impacts in Russia compared to our main analysis using Statcounter data. However, we observed no significant impact in Turkey.

Figure B.6: Russian and Turkish Remedies



Notes: In Russia, the vertical line corresponds to the introduction of the choice screen. In Turkey, the vertical lines correspond to September 2018 when the TCA decision, and August 2019 when Google adjusted its contracts.

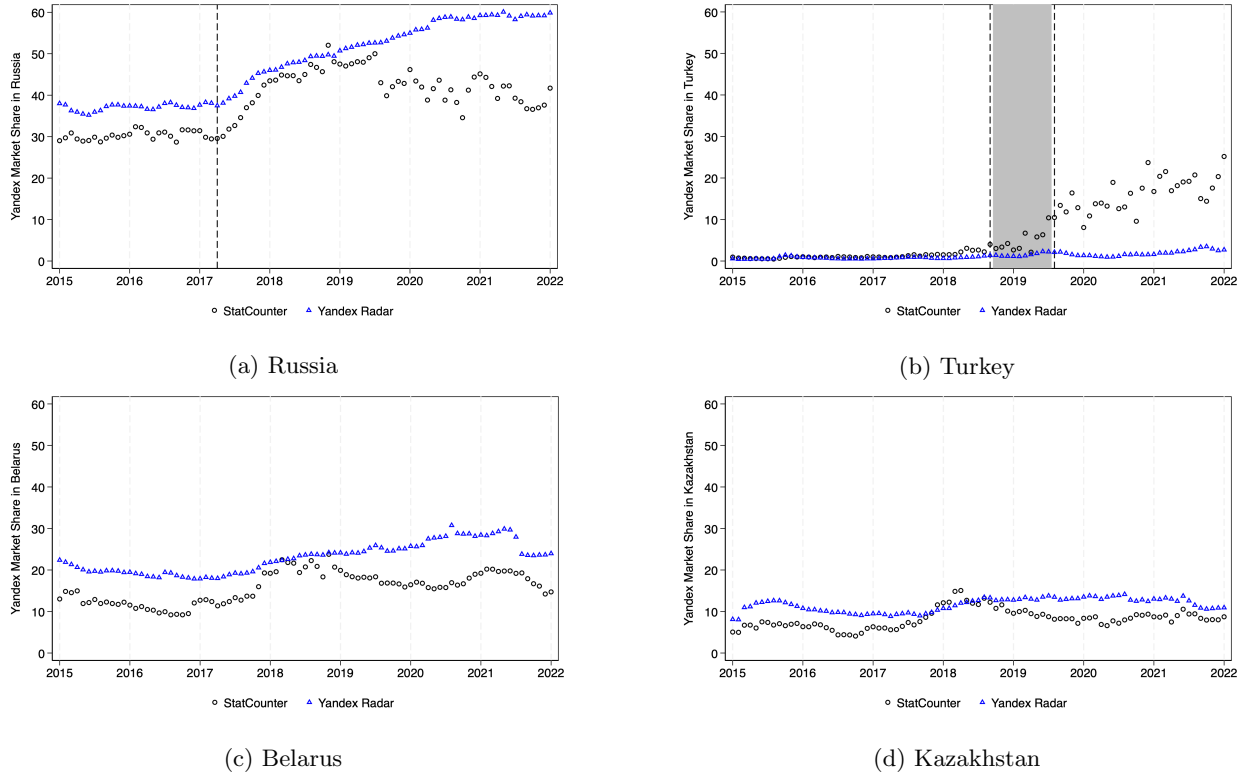
Table B.10: Remedy Estimates in Russia and Turkey

	(1) Google	(2) Yandex	(3) Google	(4) Yandex
Russia $\times$ Post	-15.195 (1.684)	14.621 (1.704)		
Post 04/2017	-2.280 (0.972)	3.551 (0.984)		
Russia	-22.175 (1.459)	22.217 (1.476)		
Turkey $\times$ Post			1.200 (1.367)	-1.764 (1.372)
Post 08/2019			-2.483 (0.789)	3.168 (0.792)
Turkey			15.829 (1.032)	-15.116 (1.035)
Constant	83.339 (0.842)	14.900 (0.852)	82.926 (0.596)	16.070 (0.598)
R-squared	0.877	0.873	0.688	0.679
Observations	324	324	279	279

Notes: The time frame is between January 2015 and December 2023 for the first two models, and between April 2016 and December 2023 for the last two.

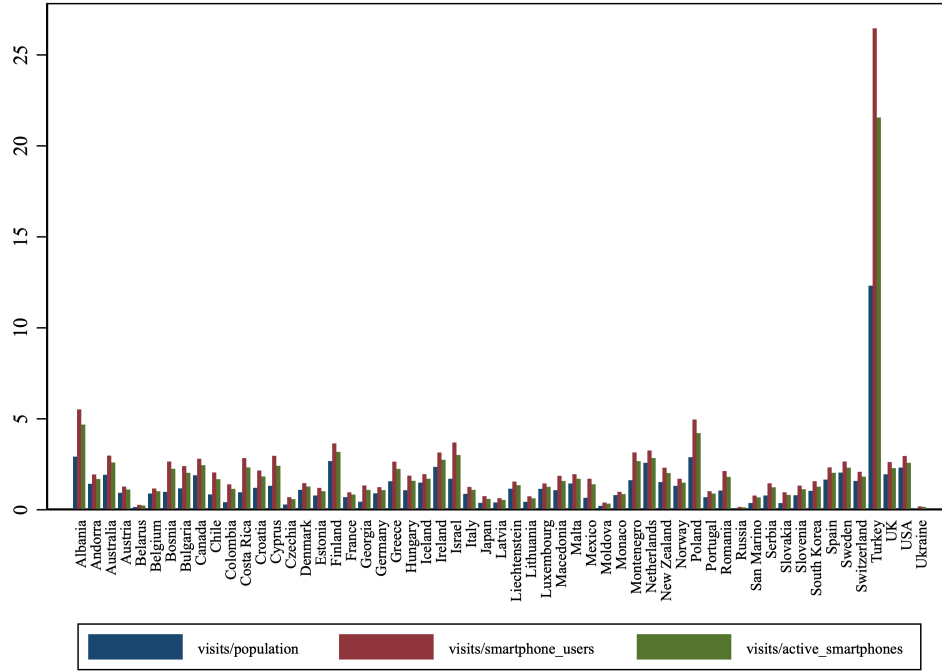
To investigate the underlying mechanisms generating different patterns in Turkey, we compare Yandex’s market share using Statcounter and Yandex.Radar data across all four countries: Russia, Belarus, Kazakhstan, and Turkey.

Figure B.7: Yandex Search Market Share on Mobile: Statcounter vs. Yandex Radar



As depicted in Figure B.7, the patterns for Russia are strikingly similar until the end of 2019, particularly following the Russian choice screen intervention. Subsequently, they diverge in the years after 2019. In the case of Turkey, the patterns closely align until the TCA intervention. However, Statcounter records substantial market share increases thereafter that are not mirrored in the Yandex Radar data. Belarus and Kazakhstan are not part of our analysis, but, similarly to what we observe for Russia, they indicate patterns that are similar, but not identical, in terms of both levels and dynamics across the two data sources.

Figure B.8: Statcounter: Penetration by Country



Notes: We construct three measures of “coverage” from the monthly country-specific Statcounter page visits and market size data from Newzoo. For each country in our sample, we compute the ratio of Statcounter monthly page visits to population, smartphone users and active smartphones respectively. The three measures of market size we employ are from 2016, as that is the earliest year covered by the Newzoo data. The figure compares the three measures of coverage across the countries in our sample. We observe that the number of page visits in Turkey is relatively high, while the number of page visits in Russia is instead low compared to the other countries in our sample.

Upon assessing multiple sources of evidence, we consider Statcounter to be a more reliable data source for the following reasons. First, the Yandex market share provided by Statcounter aligns well with the number of users claimed by the Yandex Turkey General Manager in May 2020, but is inconsistent with Yandex Radar data. As outlined in Appendix B.2, there are more than 10 million unique Yandex users per month. Considering Turkey’s population (80 million), the market share of Yandex closely corresponds to Statcounter’s estimate (12.82% in May 2020). Second, we observed that the market share of Huawei in Turkey in 2020 is approximately 13%¹⁰⁸. Given that Yandex is the default search engine for Huawei, we anticipate this search engine to capture a similar market share, which is significantly higher than the 3% estimated by Yandex Radar. Third, Statcounter has particularly good coverage of Turkey, as indicated by our breakdown of the Statcounter data by county in Figure B.8. This coverage surpasses that of most EU countries, where the EC relies on Statcounter data for implementing the choice screen.¹⁰⁹

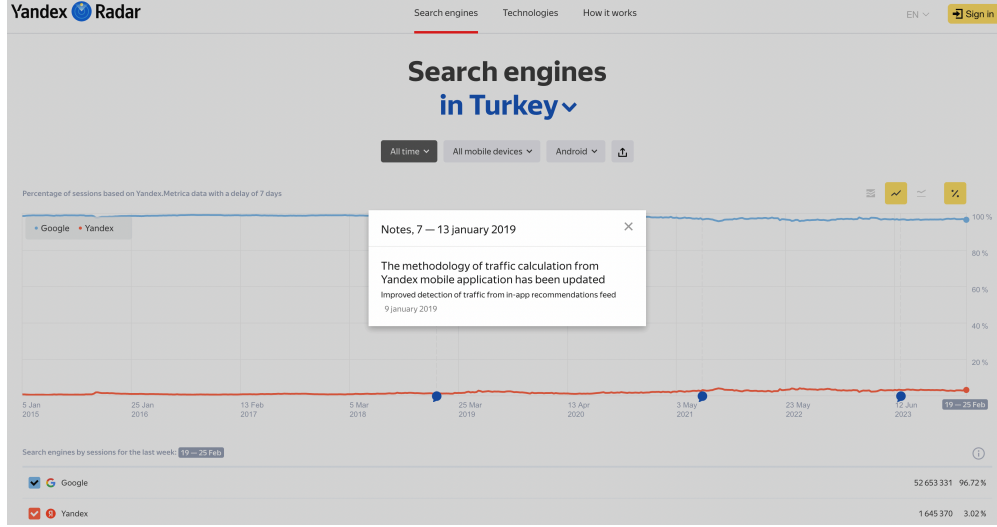
Finally, the recording of Yandex data over time might not be fully consistent. For instance, as we observe in the snapshot of Yandex Radar for Turkey mobile on Android phones reported below (Figure B.9), on at least three occasions changes to the data recording system occurred (the small

¹⁰⁸See: <https://gs.Statcounter.com/vendor-market-share/mobile/turkey/#monthly-200901-202401> (accessed August 1st, 2024).

¹⁰⁹The global number of websites with the Statcounter tracking code installed exceeds 2 million. By tracking these websites, Statcounter compiles a sample of over 10 billion monthly page visits, with approximately half originating from mobile devices. Statcounter’s website provides a breakdown of the number of page visits from mobile devices recorded in each country in September 2015.

blue clouds in the figure) and one of them (the 13th January 2019 change) happened right after the TCA intervention and involved changes to the methodology of traffic calculation from Yandex mobile application. Based on all these elements and considering that Statcounter should have no motive to provide an inaccurate representation of the Yandex market share in Turkey, and since Statcounter did not implement any change to its measurement system of mobile traffic in Turkey around the TCA remedy, we consider the Statcounter data as the most reliable for our research.

Figure B.9: Google and Yandex Android Market Shares - Yandex Radar (Turkey)



Notes: Screenshot taken on March 5th, 2024 from: <https://radar.yandex.ru/search?period=all&country=983&device-category=5&platform=2>.

B.9 App Downloads Analysis

In this subsection we use the app downloads data to compare the evolution of download shares of competitor search engine apps. We compute the search engine app a 's download share (s_{act}) in country c at time t as:

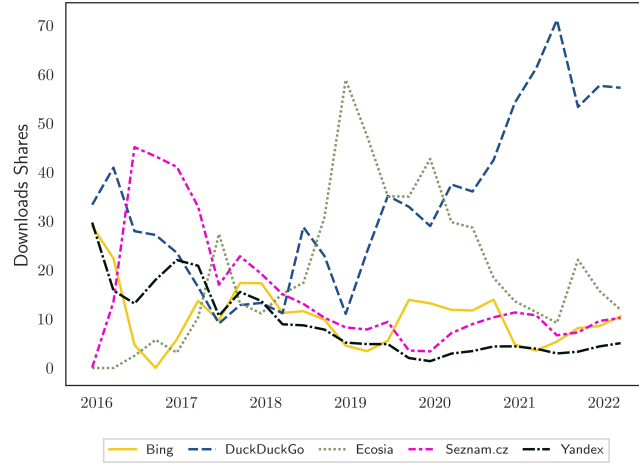
$$s_{act} = \frac{q_{act}}{\sum_{i \in M} q_{ict}},$$

where q_{act} is the number of downloads of search engine app a in country c at time t and M is the set of all the remaining search engine apps present in our data.

Crucially, we remove Google from the analysis to better investigate the competitive environment among the smaller competitor search engines. Figure B.10 plots the evolution of the download shares of the top 5 competitor search engine apps in the EEA on Google Play Store.¹¹⁰ From Figure B.10 we observe that DuckDuckGo gained the most among competitor search engines following the remedy, while Ecosia suffered. Clearly, these data only reflect app downloads rather than actual usage. Users may have downloaded competitor search engine apps without switching to them as

¹¹⁰We restrict our attention to downloads of search engine apps and do not consider downloads of launcher apps.

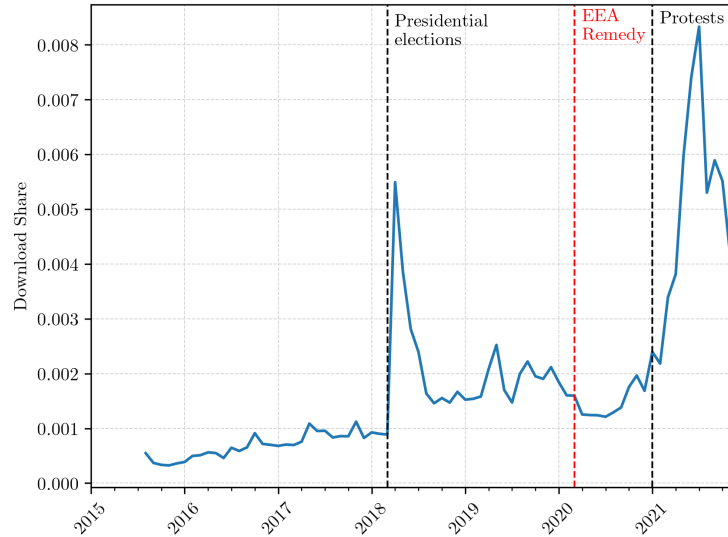
Figure B.10: EEA Competing Search Engines Download Shares



Notes: Play Store downloads for search engine apps aggregated at the quarterly level.

their preferred search engine following the remedy. This is behind the choice of usage-related market share measures upon which our main analysis is founded.

Figure B.11: Evolution of VPN App Downloads in Russia



Notes: The three vertical lines from left to right correspond to (i) the presidential elections in March 2018, (ii) the EEA remedy in March 2020, and (iii) the protests in early to mid-2021.

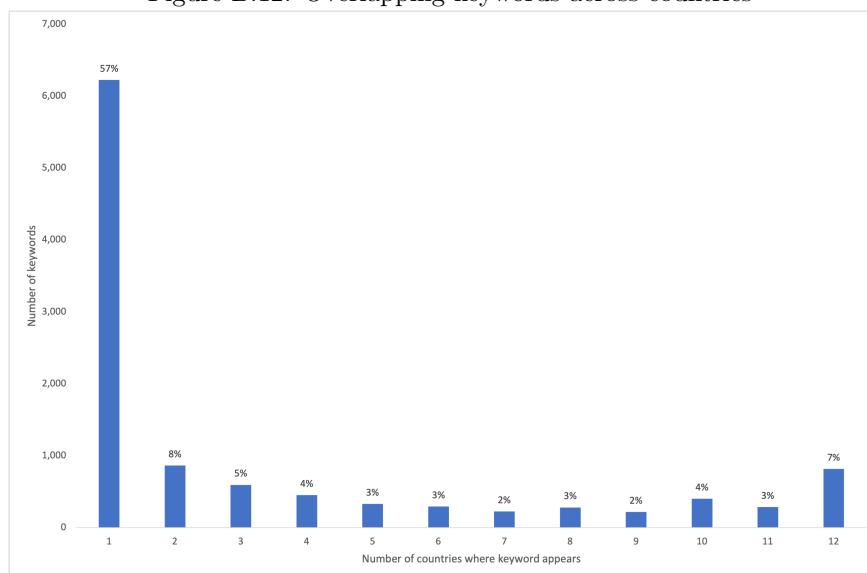
We also employ the Apptweak data on app downloads to study the adoption of VPN apps in Russia in the relevant time frame of our analysis. Specifically, we focus on the share of VPN app downloads relative to the total number of app downloads in Russia during the 2015Q3-2021Q4 period. Figure B.11 shows the evolution of the VPN app download share. Although we see an increase in the VPN app download share over our period of analysis with also two noticeable peaks around politically tense periods in Russia, no spike is recorded around the EEA remedy. This suggests that our findings are unlikely to be biased by an differential access to the web of Russian users via VPN

around the period of the EEA remedy implementation.

B.10 Keyword Popularity Across Countries

We collect data from SEMrush on the outcomes of Google’s sponsored search auctions for mobile search. Our data covers the most searched keywords in twelve different countries, with each country having its own list of popular keywords. Four of these countries are English-speaking (Australia, Canada, the USA, and the UK), while the remaining eight countries speak different languages (Brazil, France, Germany, Italy, the Netherlands, Russia, Spain and Turkey). Clearly, the list of most popular keywords in each country reflects the language spoken in that country.¹¹¹

Figure B.12: Overlapping keywords across countries



In Figure B.12 we plot the number of keywords overlapping across the twelve country-specific lists of keywords. The majority of the keywords in our sample are idiosyncratic to one country, with few keywords being popular in all twelve countries.¹¹² The fact that we observe little overlap in the most popular keywords across countries suggests that our approach of collecting country-specific keyword lists is appropriate. Indeed, selecting a fixed keyword list for all twelve countries would lead to a sample selection issues.

¹¹¹For instance, users looking to find weather forecasts in the USA search for “weather”, while users in Italy search for “meteo”.

¹¹²The keywords overlapping across many countries are often ones referring to websites, such as “facebook”.