# Competition and Defaults in Online Search*

Francesco Decarolis [†] Muxin Li [‡] Filippo Paternollo [§]

**Abstract**

This paper offers the first systematic quantitative assessment of default-option interventions designed to mitigate Google's search dominance. By analyzing interventions in the European Economic Area, Russia, and Turkey, we find that, across all three cases, changes to default settings effectively reduced Google's market share. The causal impact amounts to less than 1 percentage point in the EEA and over 10 percentage points in Russia and Turkey. Differences arise from intervention nuances, including the size of the targeted users' group, local market characteristics, and remedy designs. We discuss the complexity of assessing the interventions' impact on welfare deriving from quality responses.

**Keywords**: Online Advertising, Antitrust, Platform Competition
**JEL Codes**: C45, D44, G34, L13, L81, M37.

*We are grateful for the comments received from Joshua Angrist, Özlem Bedre Defolie, Dirk Bergemann, Alessandro Bonatti, Emilio Calvano, Chiara Farronato, Joshua Gans, Megan Gray, Recep Gündüz, Michael Ostrovsky, Patrick Rey, Fiona Scott Morton, Marc Rysman, Joan Calzada, and the seminar participants at the Barcelona Summer Forum, EARIE, Lisbon Meeting, NBER Digitization, NBER Regulation, OECD meeting on Competition and Regulation, Yale-TSE Digital Economy conferences, and the Bocconi University, European Competition Network Annual Meeting, Paris School of Economics, Institute Mines Telecom Business School seminars where preliminary versions of this study have been presented. We are also grateful for comments from the Competition and Markets Authority UK and the Turkish Competition Authority International Team. We acknowledge the financial support of ERC Consolidator Grant "CoDiM" (GA No: 101002867).

†IGIER, Bocconi University, via Roentgen 1, Milan, 20122, Italy. Email: francesco.decarolis@unibocconi.it
‡IGIER, Bocconi University, via Roentgen 1, Milan, 20122, Italy. Email: muxin.li@unibocconi.it
§Columbia University, 420 West 118th Street, New York, NY 10027. Email: f.paternollo@columbia.edu

# Contents

*"For a general search engine, by far the most effective means of distribution is to be the preset default general search engine for mobile and computer search access points. Even where users can change the default, they rarely do. (...) As Google itself has recognized, this is particularly true on mobile devices, where defaults are especially sticky."*

— US Department of Justice, *DOJ Complaint Against Google, United States v. Google LLC, 1:20-cv-03010 (D.D.C. 2020)*

## 1 Introduction

In recent years, several influential policy reports have argued for the introduction of new regulations to address antitrust concerns in digital markets.[1] Proponents claim that it is not sufficient to verify ex post whether digital platforms have illegally altered competition according to antitrust laws; instead, an ex ante regulatory approach is urgently needed to determine which practices should be forbidden. Several countries are already moving rapidly in this direction (Decarolis and Li, 2023). For instance, new regulations for digital platforms are in place in Europe starting in 2024 under the Digital Markets Act ("DMA") and Digital Sevices Act ("DSA"). At the same time, various antitrust investigations are currently ongoing, including the case of *U.S. vs. Google* referenced in the opening quote. The ruling in this case determined that Google acted illegally by exploiting its default status to maintain a monopoly in online search.[2]

Despite the heated debate and enormous efforts by regulators, there is surprisingly little evidence on whether the proposed regulatory approaches will be effective and even less on what types of behaviors these regulations should either prevent or promote. To understand the potential impact of such regulations, it is useful to consider two dimensions that characterize the markets in which digital platforms operate: first, whether the market is a natural monopoly, and second, whether the users served by the platform have behavioral biases. If the market is a natural monopoly and the users are rational, then a long and revered literature (Viscusi et al., 2018; Laffont and Tirole, 1993) in industrial organization offers insights on how optimal regulation should be designed. More interesting, however, is the situation in which the market is not a natural monopoly. In this case, the right tools to bolster competition will crucially depend on whether the platform's users have behavioral biases. To illustrate this, consider online search: if users are rational, they will cluster on the dominant search engine, Google, because of its superior quality relative to the other search engines. In this setting, a regulation mandating Google to share its extensive click-and-query data with other search engines would allow these rivals to improve their services and compete more effectively. However, if users are locked in with Google due to a default effect – meaning that they use whatever search engine is pre-installed on their device – mandating that Google shares its data with competing search engines would be ineffective in fostering competition. Instead, regulatory interventions should account for users' behavioral biases to effectively promote competition.

This study presents the first systematic quantitative assessment of the impact of preset defaults on competition in the online search market. We focus on mobile search, the main market for online

[1] These include the US Stigler Committee Report, the Furman Review for the UK government, the Competition Policy for the Digital Era report by the European Commission, and the UK Competition and Markets Authority ("CMA") Report on Online Platforms and Digital Advertising.

[2] See `https://www.justice.gov/opa/pr/justice-department-sues-google-monopolizing-digital-advertising-technologies` (accessed August 5th, 2024).

advertising worth €31 billion in Europe and $78 billion in the United States in 2021 (Statista, 2022). The market for mobile search is highly concentrated, with Google accounting for up to 95% of market share globally (Statcounter, 2021). Google operates as the default search engine for most search access points on mobile devices sold to consumers.[3] As documented in a report by the Competition and Markets Authority (CMA, 2020), Google was set as the default search engine on over 99% of mobile devices in the UK in February 2020. Google pays substantial amounts to device manufacturers to secure the default position on their devices. In the *U.S. vs. Google* case, it was documented that, in 2022, Google's revenue share payment to Apple was an estimated $20 billion, which accounted for approximately 17.5 percent of Apple's operating profit. Additionally, in 2021, Google spent $26.3 billion on traffic acquisition costs—the revenue share paid to its partners-four times more than the company's other search-related costs combined, including research and development.[4]

We study various interventions aimed at removing restrictive terms imposed by Google to restrict the pre-installation of competing search engines as defaults on Android mobile devices. Scholars, including Morton and Dinielli (2022), have argued that Google's role as the preset default is a key pillar of its strategy to maintain dominance in search – a view that was also central to the recent DOJ case against Google. However, no prior study has quantified the impacts of existing regulatory interventions aimed at opening up competition for the preset search default on mobile devices. We study three different but related policies implemented in the European Economic Area (EEA), Russia, and Turkey. In Russia, a choice screen is provided to all Android users to choose between Google, Mail.ru, and Yandex as their default search engine. In the EEA, a similar choice screen has been introduced, but it is only accessible during the initial setup of new Android devices and features a regularly changing list of search engines for users to choose from.[5] In Turkey, a different approach has been taken to target Google's default role: the Turkish Competition Authority mandated changes to the contracts between Google and mobile device manufacturers to ensure the manufacturers' freedom in negotiating the default search engine.

Through the evaluation and comparison of these three interventions, we analyze the effect of the default option on competition and investigate the potential determinants of the effectiveness of the interventions. We leverage data from multiple sources, covering search engine market shares, mobile device shipments, the number of actively used mobile devices, app downloads, and sponsored search auctions. This enables us to quantify the effect of the three policy interventions on search engine market shares and Google's advertising revenues via a difference-in-differences strategy. We find that, in all three cases, the interventions were effective in reducing Google's market share and advertising revenues, allowing competitors to gain a larger share of the market. The extent of this reduction, however, varies drastically. The decrease in Google's mobile market share amounts to less than 1 percentage point in the EEA, and about 10 percentage points in Russia and Turkey. Similarly, the effects on Google's advertising revenues are negligible in the EEA but are negative and significant in Turkey and Russia. We also analyze the market share gains enjoyed by Google's competitors following the interventions. Our results indicate that search engines with higher brand

[3] Consumers search the web through various access points on their mobile and desktop devices. The main search access points available to users include browsers, search widgets, and voice assistants. We refer to the search engine initially associated with these access points on devices sold to consumers as the "default" search engine.

[4] See `https://www.justice.gov/opa/press-release/file/1328941/download` (accessed February 25, 2024), pp. 228 and 241.

[5] Although this policy was the outcome of an agreement between Google and the European Commission, without any formal remedy being imposed on Google, we refer to it as the "EEA remedy" throughout our paper.

awareness and local popularity have a greater chance of gaining market share when made available to users via a choice screen. Furthermore, within the EEA, we find that these search engines also have a stronger incentive to secure a slot on the choice screen.

We also analyze two counterfactual designs of the EEA remedy to examine how different remedy design choices may have impacted competition. First, we simulate what would have happened if the choice screen had been made accessible to all Android mobile devices rather than new devices only. Exploiting our data on mobile device shipments to estimate a weighted-treatment model, we assess the effect of the policy on Google's market share in Android mobile search. Under reasonable assumptions, we then quantify the difference between Google's selection rate from the choice screen and Google's baseline market share in the EEA. This estimate, which amounts to 3 percentage points, represents the effect that the EEA remedy would have achieved had it been implemented on all Android devices rather than on new devices only. Second, we estimate how much Google's market share would have declined if the top rival had always been displayed on the EEA choice screen. For this scenario, our model predicts that Google's market share would decline by a value of also approximately 3 percentage points. Both counterfactual analyses thus point to how different remedy design choices would have impacted competition.

We conclude by discussing improvements in quality implemented by search engines in response to the interventions. Internal documents revealed during the court debate of the *U.S. vs. Google* case show that Google responded to the EEA intervention by implementing significant quality-enhancing investments. At the same time, testimonies from top executives at competing search engines revealed their reluctance to invest in the quality of their own products. Thus, while EEA users might have benefited from both free choice and higher quality, users in Turkey, where OEMs like Huawei switched to Yandex as the preset default search engine, might have found themselves with a default not of their choosing and, possibly, of inferior quality. This disparity underscores the complexity of assessing the impact of the interventions on welfare and the need to go beyond changes in the dominant firm's market share to measure the efficacy, not only the effectiveness of this type of market intervention.

Our findings represent a threefold contribution. First, they offer comprehensive evidence of how the default effect influences competition in the online search market. Numerous papers have emphasized the importance of default options, but most focus on traditional markets such as health insurance. By analyzing three distinct interventions, we show the existence of the default effect in the online search market and provide useful evidence for future regulations. Moreover, while the majority of studies on internet search focus on search advertising design and how users respond *within* a given search engine (Athey and Ellison (2011); Blake et al. (2015); Motta and Penta (2022)), our paper offers new insights into users' choice *across* heterogeneous search engines, making it more relevant for emerging antitrust and privacy concerns in digital markets. In this respect, Farronato et al. (2024) and Rosaia (2023) are related and consider the issue of users choosing between rival digital platforms.

Second, this study demonstrates that apparently similar remedies may have highly differentiated impacts on local online search markets, and show that the determinants of this varied effectiveness. The effect of a specific remedy depends on its design, on the preferences of local users, and on the characteristics of local rivals. Complementary to a small number of recent studies that have also looked at online search regulation but focused mostly on the EEA choice screen mechanism design (Ostrovsky, 2023), our study provides new insights into how and why users and competing search engines respond to interventions in the online search market.

Our third contribution concerns the policy lessons that can be learned from the three remedies. Interventions involving consumer choice via a choice screen can hardly have impacts on online search market competition unless there is a qualified challenger that can compete with Google on quality (like Yandex in Russia) or a rival that has the means and motivation to replace Google by investing in the local market (like Yandex in Turkey). To effectively restore competition, regulators need to invest in careful remedy design and tailor their interventions to the presence of "viable" competitors to the gatekeeper. Indeed, we explore two instances of remedy design choices with our counterfactual analyses quantifying how the EEA remedy could have been made more effective. However, we also discuss how responses in quality can significantly alter the interpretation of changes (or lack of changes) in market share following the intervention.

**Literature** Our study is related to several branches of the literature. First, we contribute to the rapidly evolving literature on the economics of digital markets. The industrial organization literature has stressed that network externalities, paired with dynamic scale economies, significantly raise the entry barriers in digital markets and create a tendency for competition to assume a winner-takes-all form (see, among others, Dubé et al., 2010; Belleflamme and Peitz, 2018; Calvano and Polo, 2021). Specifically for internet search, Klein et al. (2023) analyze the role of differential data access in search engine quality through an experimental design. Furthermore, law and economics scholars have studied the abusive strategies that dominant platforms adopt to foreclose horizontal and vertical competitors, providing guidelines for competition authorities to approach such cases (see Fumagalli et al., 2018 for an overview). In our work, we focus on antitrust remedies imposed following pre-installation practices that effectively resulted in the abusive tying of Google's mobile search engine to its Android operating system. As pointed out by Gans (2011), pre-installation is a special form of tying that affects user willingness to pay for the rival's complementary goods and transfers profits from the rival to the monopolist. Choi and Jeon (2021) develop a theory of tying in two-sided markets, showing how tying provides a mechanism for a monopolist to leverage its power to monopolize another market where it faces competition.

Our work is directly related to studies that examine the choice screens imposed in antitrust cases. One well-known case is that of Microsoft in the EEA in 2010, which centered on its abusive tying of Internet Explorer to Windows. Economides and Lianos (2010) discuss the remedy implemented by the European Commission and compare it to a remedy previously imposed on Microsoft following the case of abusive tying of Windows Media Player with Windows. Vásquez Duque (2022) performs an exploratory analysis of the choice screen applied in the Microsoft case on browser market shares and finds a small decline in Microsoft's browser market share of between 1.4 and 2 percent. While this is similar to the decline in Google's market share that we report for the EEA, the interpretation needs to consider product differences as, relative to browsers, search engines are more differentiated in terms of the quality of service. For the same Google remedy that we study, Ostrovsky (2023) conducts a theoretical analysis of the auction mechanism characterizing the initial implementation of the choice screen. He shows that the "pay-per-install" auction favors search engines that maximize their surplus from each user, possibly offering low-quality services, and considers an alternative based on a "pay-per-click" auction.

The second branch of the literature to which we contribute is that on behavioral economics. Choice screens might be interpreted as a tool to make certain choices more salient in the sense of Bordalo et al. (2022). Among the studies concerning behavioral consumers, the ones most closely related to our work are those investigating the impact of default options on consumer choices (see Jachimowicz et al., 2019). Beshears et al. (2018) define status quo bias (or default bias) as a behavioral bias that occurs whenever there is a preference for the current state of affairs and list several mechanisms that make default options powerful. Spiegler (2011) defines an additional bias that makes default options overly influential: inertia. Inertia occurs at an earlier stage of the decision process, meaning the consumer fails to get to the stage where she applies a preference ranking to the available alternatives.

Numerous empirical studies have attempted to quantify the market effects of defaults. Most of these contributions focus on health insurance markets, showing that inertia creates differences in the health insurance plans that individuals hold depending upon what plans were offered when they joined their current company (Madrian and Shea, 2001; Handel, 2013; Chetty et al., 2014; Chetty, 2015; Ho et al., 2017). Marzilli Ericson (2014) shows that firms respond to inertia by raising prices for existing enrollees while introducing cheaper alternative plans. Similarly, Ho et al. (2017) find that consumers switch plans infrequently and search imperfectly. As pointed out by Grubb (2015), behavioral IO insights allow for the identification of more market failures or inefficiencies—and the corresponding need for intervention—than would arise in standard models and suggest novel policy tools with which to intervene.

A recent body of work has focused on the competitive effect of defaults in mobile search. Hovenkamp (2023) develops a model to examine the competitive dynamics between two-sided search platforms, considering the network effects that enhance a platform's quality and the consumer costs of switching from the default platform. Hovenkamp finds that consumer welfare is maximized when no default is set and a choice screen is provided, highlighting how default agreements can lead to allocative inefficiency and dampen competition and investment. Vásquez Duque (2024) argues that Google's agreements with Apple to be the default search engine on its devices not only block competitors from a significant distribution channel but also deter Apple – a potential competitor – from entering the search market due to the high costs and loss of payments from Google. Based on a visual inspection of mobile market share trends in Europe, Vásquez Duque suggests that there was no change in Google's market share after the intervention and points out that the EEA choice screen has been ineffective in leveling the playing field among competitors. Beyond academic research, industry studies have evaluated the role of choice screens in the search market. For instance, DuckDuckGo has published a series of articles discussing the potential competitive impacts of choice screens,while other commentaries have highlighted the notable success of Russia's choice screen in altering market shares.[6] Complementary to these findings, our paper, as far as we know, is the first comprehensive assessment of defaults in mobile search.

# 2 Institutional Background

## 2.1 Search Engines

Internet search is a typical multi-sided market, connecting users surfing the web with advertisers wishing to attract eyeballs. Search engines supply links to content on the internet to users in response to their search queries. To do this, they index data from the public web and proprietary sources and return relevant content - ranked by an algorithm. In exchange for their services, search

[6]See https://spreadprivacy.com/tag/preference/ (accessed February 24, 2024) and https://www.searchenginejournal.com/yandex-seo-interview-yandex-search-team/315787/ (accessed February 24, 2024).

engines extract data and attention from users. Advertisers seeking to target consumers then pay search providers to display their ads, allowing search engines to offer their services free of charge to users. The mobile search market has experienced tremendous growth over recent decades due to the rapid adoption of smartphones. In 2021, mobile advertisement revenues accounted for over $135 billion, more than double the revenues earned from advertisements on desktop devices.[7] Google virtually monopolizes the search market, holding almost the entirety of the market. However, Google is not the only search engine available to consumers. Competitor search engines differ along many dimensions. Some pursue social causes (e.g., Ecosia and Panda Search), while others pride themselves on their strong protection of user privacy (e.g., DuckDuckGo). Some search engines focus on their local market (e.g., Qwant in France and Seznam.cz in Czechia), while others have global reach but differ in their geographical presence. Google, Bing, and DuckDuckGo are all based in the U.S., while Yandex is based in Russia. Among these, Bing seems to be the most viable competitor to Google in the U.S. and much of Europe. Indeed, several search engines, including DuckDuckGo, Ecosia, and Qwant, rely on Bing to provide search results.

Mobile devices often come with several search access points pre-installed, each associated with a default search engine. Since mobile users suffer from inertia and status quo bias, being the default search engine is extremely valuable for search providers. To become the default search engine, search providers can either develop their own search access points or enter into contractual arrangements with device manufacturers (or other "access point owners") to set their search engine as the default. Google adopts both strategies to ensure that its search engine is the default on most access points available to consumers, including all of those on both Apple and Android mobile devices. According to a CMA Report (CMA, 2020), other search engines are likely to have to offer at least as much financial compensation as Google does in order to win a default contract. Given Google's high popularity among users, it is extremely challenging for a rival to match Google's financial compensation and secure the default position. The report concludes that the positive feedback loop between Google's position as the largest and highest revenue-generating search engine and its ability to acquire default positions generates entry barriers that other search engines struggle to overcome. This perspective was also highlighted in the ruling of the *U.S. vs. Google* case. Even before these recent testimonies, this phenomenon -—where Google's market dominance is perpetuated by its ability to outbid competitors for default positions – had already raised significant global regulatory concerns over the apparent lack of a level playing field. Since 2017, Google has been accused by the competition authorities in the European Union, Russia, and Turkey, of imposing illegal contractual restrictions on Android device manufacturers and mobile network operators.

### 2.2 Remedy in the European Economic Area

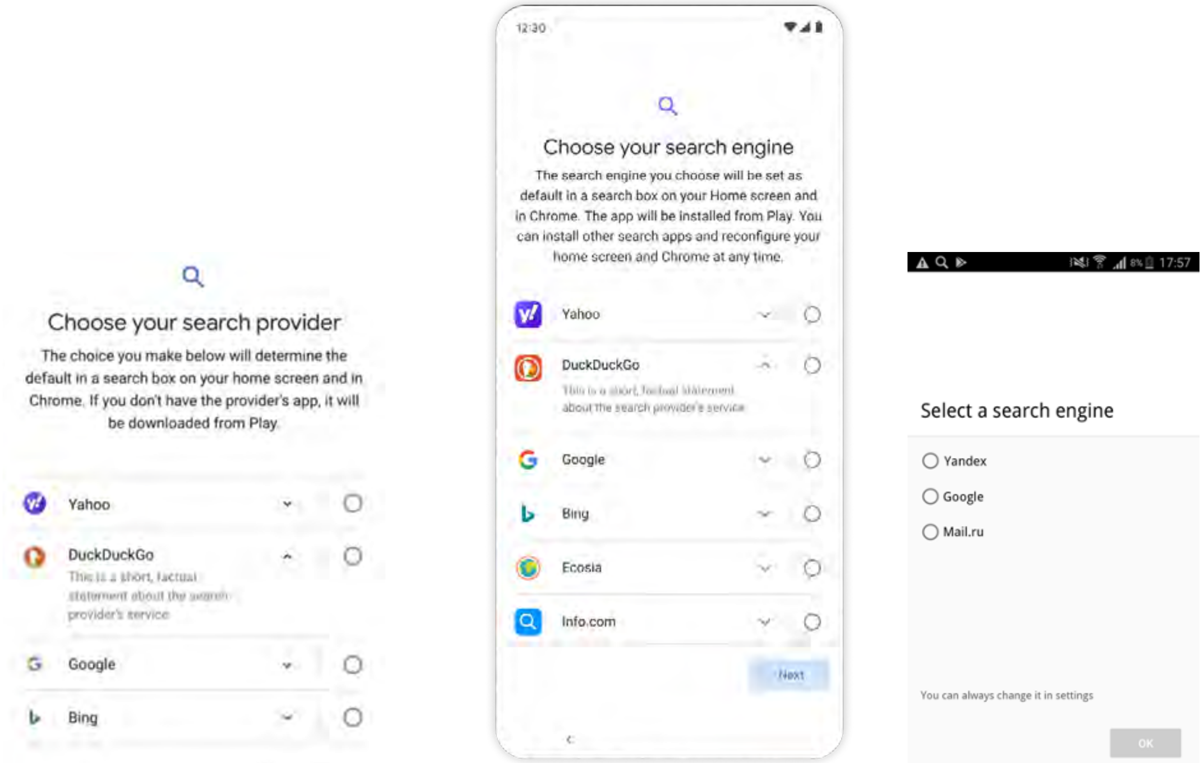
In July 2018, the European Commission ("EC") fined Google €4.34 billion for offering the Play Store, the Search app, and the Chrome browser as a bundle (known as Google Mobile Services) to mobile manufacturers in the European Economic Area.[8] The tying between the Play Store and the Search app essentially gave manufacturers no choice but to pre-install Google as the default search engine. This enabled Google to occupy critical entry channels for search queries on mobile devices and not only reduced the incentive for users to download competing search apps, but also discouraged manufacturers from pre-installing such apps. The EC concluded that Google's conduct

[7] See `https://www.iab.com/wp-content/uploads/2022/04/IAB_Internet_Advertising_Revenue_Report_Full_Year_2021.pdf` (accessed February 25, 2024).

[8] See `https://ec.europa.eu/commission/presscorner/detail/en/IP_18_4581` (accessed February 25, 2024).

had distorted market competition and negotiated with the company to implement a reform to address these competition concerns.

Figure 1: Choice Screen Comparison




(a) EEA Pay-to-Play (b) EEA Free-to-Play (c) Russian Choice Screen

Following the EC decision, Google implemented a choice screen for general search providers on all new Android phones and tablets sold in the EEA and in the UK after March 2020. During the device setup, new Android users could select their preferred search provider on a screen offering a choice among four different providers. Choosing the provider (i) sets the search provider in a home screen search box; (ii) if Google Chrome is installed, makes the selected search provider Chrome's default search engine; and (iii) prompts the downloading of the app of the selected provider. To appear on the choice screen (alongside Google), search providers have to participate in auctions, conducted quarterly and separately for each EEA member state, during which they bid the amount they are willing to pay Google each time a user selects them from the choice screen. The three highest bidders win the auction and appear on the choice screen for that country (together with Google, all in random order) as shown in Figure 1. Each time a user chooses a search provider, the selected search engine has to pay Google an amount equal to the fourth-highest bid received in the auction. We refer to this as the "pay-to-play" choice screen.

The "pay-to-play" remedy attracted considerable questions and complaints after its implementation. Search providers and researchers (Ostrovsky, 2023; Kwoka and Valletti, 2021) expressed concerns that the auction mechanism favored search engines that extracted high value from customer data while pricing out alternatives whose business models address social, ethical, or ideological problems. On October 27, 2020, competitor search engines DuckDuckGo, Lilo, Seznam, Ecosia, and Qwant filed an open letter to Google and to the EC, expressing their dissatisfaction with the "pay-to-play" auction model in the choice screen.[9]

In response, Google and the EC made further adjustments, changing the "pay-to-play" choice screen to a "free-to-play" choice screen. From September 1, 2021, participation in the choice screen became free, meaning all eligible search providers could appear and be selected on the choice screen without having to pay Google. Additionally, twelve search providers, instead of four, could appear on the new choice screen. Among these, the five most popular eligible general search engines in each country (including Google, all in random order) are always displayed at the top of the customer's scrollable list, as shown in Figure 1. Below these, up to seven additional search engines can appear on each country's choice screen. These additional search providers are chosen randomly and are also listed in random order.[10]

### 2.3 Remedy in Russia

A similar antitrust investigation in Russia also resulted in a choice screen for mobile search providers. In April 2017, Russia's Federal Antimonopoly Service ("FAS") fined Google 438 million roubles[11] for violating the antimonopoly legislation. The abuse revolved around Google prohibiting the pre-installation of competing mobile applications of other developers.[12] The FAS determined that Google's conduct constituted an abuse of dominance that distorted market competition. To restore competition, the FAS requested that Google (i) remove the exclusivity of Google applications on Android-based devices in Russia; (ii) stop restricting the pre-installation of competing search engines and applications; (iii) refrain from promoting pre-installation of Google as the only general search engine; (iv) stop enforcing the clauses in its previously signed settlement contract with the FAS; and (v) ensure the rights of third party search engines to be included in the choice window.

Yandex and Mail.ru were the only two search engines that appeared on the choice screen alongside Google, as shown in Figure 1. For mobile and tablet devices that were already circulating before April 2017, users had the chance to choose their default search engine in the "choice window" that appeared upon the first system update, which took place on April 17th, 2017.[13] For new devices sold in Russia after August 2017, a widget was developed that allowed users to select their preferred search engine from a new choice screen at first launch.

[9]See https://ddg-staticcdn.s3.amazonaws.com/press/2110_Search_coalition_letter_calling_on_a_default_ban_in_DMA.pdf (accessed February 25, 2024). DuckDuckGo produced seven articles between October 2019 and May 2021 on the limitations of the "pay-to-play" choice screen. The series of posts is available at https://spreadprivacy.com/tag/preference/ (accessed February 25, 2024).

[10]The top five search providers are determined each year by their market shares, estimated with the same StatCounter data we rely on. Across EEA countries, a total of 25 search providers have appeared on the choice screen shown to new Android users wishing to select their default search engine. The search engines that appeared on the choice screen are DuckDuckGo, Qwant, Ecosia, Lilo, MetaGer, Info.com, Yahoo!, Bing, Presearch, Seznam.cz, Google, Mojeek, Panda Search, Fairsearch, Quendu.com, Gigablast, Norton Safe Search, Ask.com, GMX, Mail.ru, Nona, Yandex, OceanHero, PrivacyWall, Givero. As of November 1, 2021, this revised choice screen also started appearing on new devices distributed in Switzerland. We remove Switzerland from our sample in the following analysis of the EEA remedy.

[11]Amounting to just over €7.2 million at the April 2017 exchange rate; see European Central Bank (2024a).

[12]As in the EEA, device manufacturers in Russia were also required to fulfill several conditions, including mandatory pre-installation of Google applications, their preferential placement on devices' home screen, and mandatory installing Google as the default. See http://en.fas.gov.ru/press-center/news/detail.html?id=49774 (accessed February 25, 2024).

[13]See https://en.wikipedia.org/wiki/Google_Chrome_version_history (accessed February 25, 2024).

## 2.4 Remedy in Turkey

Following an investigation dating back to 2015, when the Russian search engine Yandex first initiated a complaint, the Turkish Competition Authority investigated and ultimately sanctioned Google for its restrictive terms imposed on original equipment manufacturers. In September 2018, the TCA imposed a fine of TRY 93 million[14] on Google for forcing manufacturers to pre-install Google apps on their mobile devices through agreements. The TCA declared that Google held a dominant position in the market for licensable mobile operating systems and that it provided the Android OS with the conditions of having the manufacturers pre-installing Google as the default search engine and placing the search widget on the device's main screen. The TCA concluded that the tying of Google's mobile search services to its operating system constituted abusive behavior.[15]

Instead of introducing a choice screen to restore competition as in the EEA and Russia, the TCA required Google to modify its contracts with device manufacturers wishing to adopt the Commercial Android Operating System on their devices produced for sale in Turkey, to satisfy the following conditions:[16] (i) removal of 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, thereby guaranteeing the right of device manufacturers to choose the search provider; (ii) removal of the licence terms that require Google search to be assigned by default to all search access points within the existing design structure and included in the agreements, and not introducing new obligations to assign Google search by default to all search points that may arise as a result of design choices; (iii) removal of contractual provisions that require or directly/indirectly imply the installation of Google Webview[17] as the default and exclusive in-app web browser as a condition of licensing; (iv) prohibition to provide incentives, financial or otherwise, in a manner that results in the conditions banned by the three obligations listed above. Furthermore, Google was also requested to remove from all existing agreements with device manufacturers (including Revenue Sharing Agreements) any obligation precluding competitor search engines from being preloaded on devices or set as default on any of the device's search access points.

Google modified its contracts with mobile manufacturers in August 2019, but these efforts were considered unsatisfactory as they continued to prohibit changes to the devices' default search engine.[18] In November 2019, the TCA imposed a daily fine on Google at a rate of five per ten

[14] Amounting to just over 12.5 million euros at the September 2018 exchange rate, see European Central Bank (2024b).

[15] See `http://competitionlawblog.kluwercompetitionlaw.com/2018/11/05/google-fined-this-time-by-the-turkish-competition-watchdog/` (accessed February 25, 2024).

[16] See `https://www.rekabet.gov.tr/en/Guncel/investigation-on-google-llc-google-inter-60928a8075bde81180e300505694b4c6` (accessed February 25, 2024).

[17] A system component that lets Android apps display web content inside them without opening a dedicated browser. In other words, Android System WebView is a web browser engine or an embedded web browser dedicated solely to apps to show web content.

[18] See `https://www.theverge.com/2019/12/16/21024311/google-android-phone-turkey-antitrust-default-search` (accessed February 25, 2024).

thousand of its turnover generated in Turkey until it addressed the outstanding issues.[19] On January 9, 2020, Google submitted the final version of its revised contracts with device manufacturers to the TCA, which were deemed satisfactory by the competition agency. Device manufacturers were now free to negotiate with Google and any other competing search providers for access to the valuable search access points on mobile devices. In 2020, Yandex was chosen as the preset default search engine in Turkey by Huawei - among the largest OEMs in the country.[20]

# 3 Data

The combination of multiple datasets lies at the core of our analysis. To investigate the impact of the three remedies, we combine data from various sources, allowing us to measure search engine market shares, device shipments, the total number of smartphone users, search engine app downloads, and the outcomes from Google's sponsored search auctions in each country during a given period.

## 3.1 Data Description

The data on search engine market shares come from StatCounter, a web analytics service that records more than 10 billion page views each month and is used to determine the list of most popular search engines on the EEA "free-to-play" choice screen. The data cover monthly market shares of over 70 search engines, including Google, Baidu, Bing, DuckDuckGo, Ecosia, Seznam, Yahoo! and Yandex in more than 200 countries from January 2009 onwards.[21] We collect data up to January 2022, resulting in over 100,000 observations. Based on the StatCounter dataset, we can observe the usage of search engines in each country on three platforms: desktops, mobile devices, and tablets. We are particularly interested in mobile devices as these are the main targets of the three interventions.

We also employ data from Gartner and Newzoo to measure the number of new and existing mobile phones. Gartner's quarterly data cover device shipments in the largest 50 countries between the first quarter of 2016 and the third quarter of 2021. Shipments are recorded in each country by vendor, OS, customer type, and device type. Newzoo's data consist of annual measures of population, smartphone users, and active smartphones in 194 countries from 2016 to 2021. Together, these two data sources endow us with detailed information on the evolution of the stock of active mobile devices in each country. We also investigate app downloads based on data from AppTweak, an app store optimization tool that estimates the number of daily downloads of any app in over 70

[19] See `https://www.actecon.com/en/news-articles/p/the-turkish-competition-authority-imposes-a-daily-fine-on-a-big-tech-company-for-not-complying-with-obligations-previously-imposed-google-134` (accessed February 25, 2024). As a consequence, reports circulated indicating that Google would stop issuing licenses for new Android phones sold in Turkey after December 2019, meaning new users would no longer have access to Google services such as the Play Store, Gmail, YouTube, and other apps. See, e.g., `https://www.reuters.com/article/us-turkey-google/google-warns-turkish-partners-over-new-android-phones-amid-dispute-idUSKBN1YK0QR?feedType=RSS&feedName=technologyNews` and `https://www.haberturk.com/google-den-yaptirim-tehdidi-turkiye-de-android-pazari-patlayabilir-2549571` (accessed February 25, 2024).

[20] Further information about the different choice screen designs in the EEA and the Turkish remedy is provided in the Online Appendix. We also present a simple theoretical model that illustrates the main incentives of the players and assesses how they interact with different remedy designs.

[21] From each recorded page visit, StatCounter records the browser, operating system and, screen resolution, and obtains information, such as referral search engines and user devices. More than 2 million websites covering various activities and geographic locations use the StatCounter tracker. This widespread penetration has made its data a reference point in the industry. The minimum positive market share recorded by StatCounter is 0.01%. We treat the missing market shares as zero correspondingly.

countries. Further information and analyses based on these ancillary datasets can be found in the Online Appendix.

Lastly, we collect data from SEMrush on the outcomes of Google's sponsored search auctions for mobile search. For each keyword searched on Google, SEMrush collects information on the average cost-per-click ("CPC") and search volume in a given country at a given time. Since the product of CPC and volume provides a proxy for the revenue earned by Google from a given keyword, these data endow us with information on the evolution of advertising revenues earned by Google in each country over time. Our data cover the most searched keywords in twelve countries, each with its own list of popular keywords. Details on our sampling strategy can be found in the Online Appendix. Six of the countries we consider are in the EEA (Germany, Spain, France, Italy, the Netherlands, and the UK), four are control countries (Australia, Brazil, Canada, and the USA), and the remaining two are Russia and Turkey. The period we consider allows us to observe at least two years of data before and after each remedy, and its exact length was chosen to better satisfy the parallel trend assumption required by our estimation. In the baseline sample, we consider 2016-2022 for the EEA, 2015-2019 for Russia, and 2017-2021 for Turkey, resulting in a final sample of just under 70,000 observations.

### 3.2 Data Patterns

Based on the data at our disposal, we can investigate the effects of the antitrust interventions in the EEA, Russia, and Turkey. We begin by comparing changes in average market shares in the treated countries to those in the control countries. The control group consists of all European and OECD countries besides the treated ones.[22] As displayed in Table 1, the reductions in Google's average market share in the EEA, Russia, and Turkey following the respective remedies exceed the reductions observed in the control group. However, the magnitudes of these reductions vary, with the Russian and Turkish remedies being associated with larger drops in Google's market share than the EEA remedy. We also find that each remedy has differentiated effects on competing search engines, with Yandex being the biggest winner.

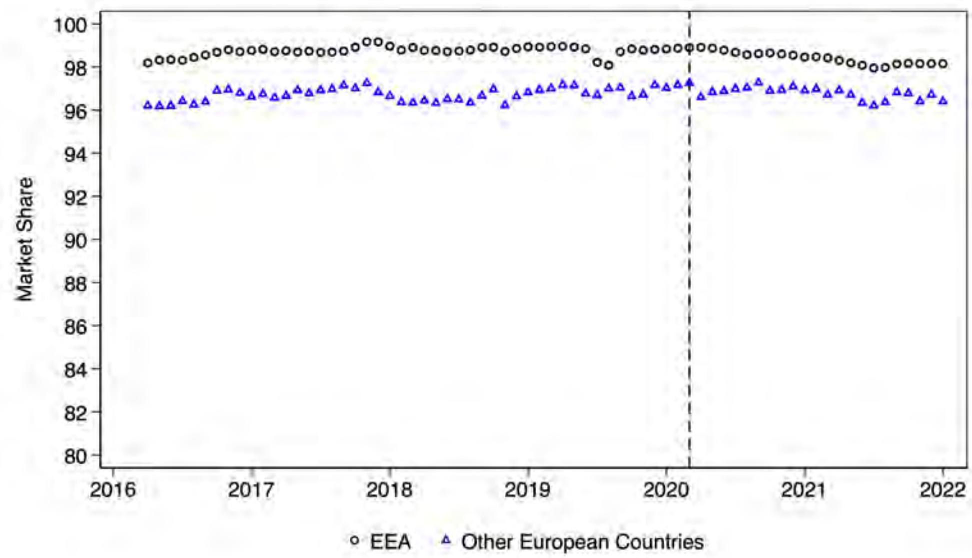
Table 1: Market Share Changes Following the EEA, Russian and Turkish Remedies

| | | EEA | | Russia | | Turkey | |
|---|---|---|---|---|---|---|---|
| | | Treatment | Control | Treatment | Control | Treatment | Control |
| Google | Before | 98.50 | 95.65 | 67.07 | 94.54 | 96.82 | 95.38 |
| | After | 98.19 | 95.52 | 57.99 | 95.23 | 86.54 | 95.79 |
| Bing | Before | 0.30 | 0.34 | 0.44 | 0.46 | 0.13 | 0.30 |
| | After | 0.41 | 0.40 | 0.29 | 0.29 | 0.47 | 0.34 |
| DDG | Before | 0.28 | 0.24 | 0.06 | 0.06 | 0.02 | 0.16 |
| | After | 0.37 | 0.37 | 0.11 | 0.13 | 0.09 | 0.30 |
| Yandex | Before | 0.13 | 1.12 | 30.68 | 1.02 | 2.80 | 1.07 |
| | After | 0.20 | 1.11 | 40.31 | 1.06 | 12.21 | 1.02 |

Notes: Mobile market share averages over the 18 months before and after each remedy. The control group consists of all European and OECD countries besides the treated ones.

[22]The complete list of treated and control group countries is provided in the Online Appendix.

Figure 2: Google Mobile Market Share




Notes: The vertical line corresponds to the introduction of the choice screen. We remove Russia and Turkey from the control group.

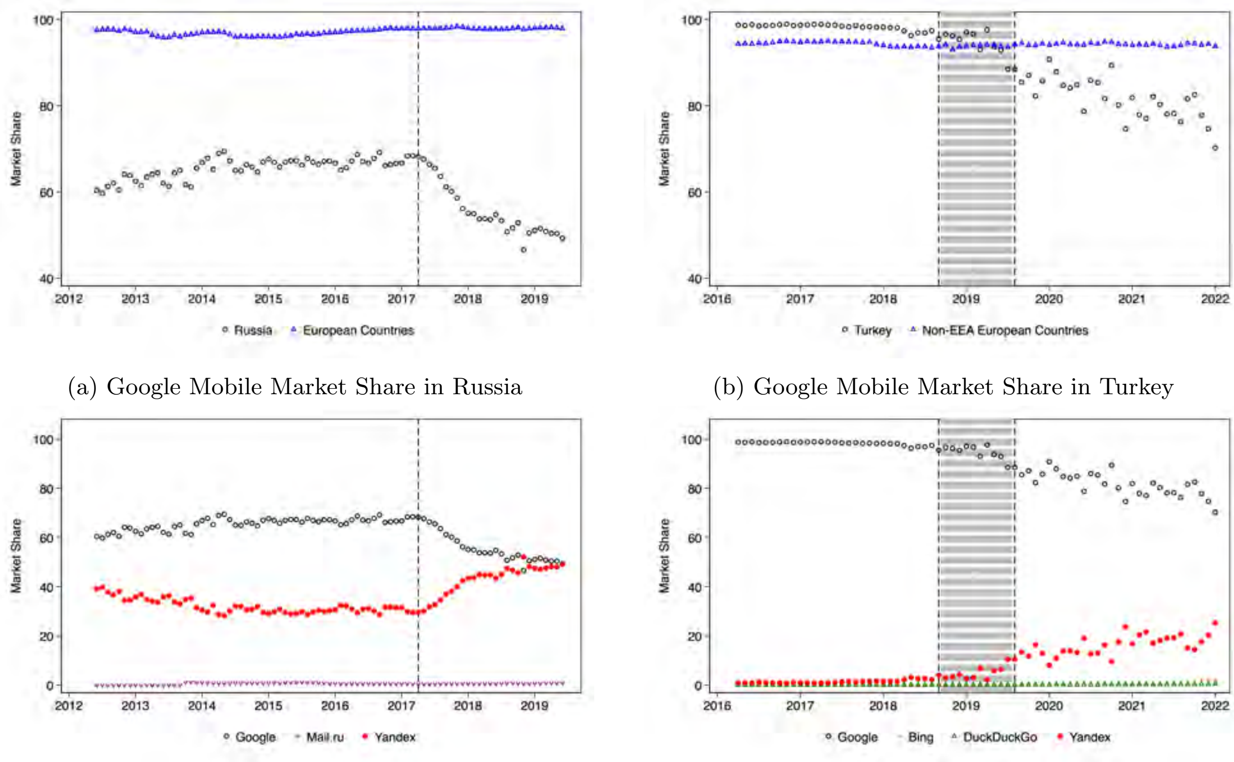
We now move to a visual inspection of search engine market share trends. In Figure 2, we plot Google's average market shares in the EEA and the rest of the European countries. The dashed line corresponds to March 2020, when the "pay-to-play" remedy was first introduced. From a visual inspection of the graph, there appears to be a decline in Google's market share in the EEA, which is slightly more pronounced than that in the control group countries. Still, the difference appears relatively small, in the order of 1 percentage point.[23]

In Figure 3, we plot Google's market share for Russia and Turkey compared to the European control countries and the evolution of the market shares for all of the main alternative search engines. In both cases, the trends appear to move in parallel before the interventions, but then diverge after the corresponding policies are implemented. We restrict our data to the time frame between June 2012 and July 2019 for the analysis of the Russian remedy (i.e., before the Russian government drafted the foreign ownership law in July 2019);[24] for Turkey, we consider the same period as the EEA (i.e., from April 2016 to January 2022). We observe that Google's market share in Russia started to decrease in April 2017, when the choice screen was first shown to users, while Yandex's market share increased. In April 2017, Google accounted for more than 60% of mobile searches and Yandex's market share was around 30%. However, in July 2019, Yandex and Google shared almost

[23]Interestingly, we observe a drop in the EEA market shares from April 2019 to August 2019, corresponding to the implementation of the temporary "Play choice screen" in the EEA.

[24]See `https://www.themoscowtimes.com/2019/07/29/yandex-shares-drop-on-draft-foreign-ownership-law-a66606` (accessed February 25, 2024).

Figure 3: Russian and Turkish Remedies




(a) Google Mobile Market Share in Russia

(b) Google Mobile Market Share in Turkey

(c) Russian Mobile Market Share

(d) Turkish Mobile Market Share

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.

the market equally.[25] Similar patterns are also observed for Turkey in Figure 3. Google's market share began to decrease soon after September 2018, when the TCA asked Google to start working on its contracts with mobile manufacturers. This pattern persisted after August 2019, when Google finished adjusting its contracts and officially submitted the compliance package to the TCA. After reviewing the main competing search engines in Turkey, we found that Yandex benefited the most from the TCA's remedy on Google, as its market share kept increasing after this intervention.

# 4 Empirical Strategy and Results

## 4.1 Intervention Effect Analysis

In this section, we employ a difference-in-differences identification strategy to study how different policy interventions affect the search engine market. We begin our analysis by investigating how Google's market share changed after the introduction of the choice screen in the EEA. We then

[25]An episode worth noting occurred in May 2017 when all Yandex services were banned in Ukraine. According to StatCounter data, after this ban, there was an immediate drop in Yandex's Ukraine market share, equal to 3.37 percentage points. Some Ukraine-based users might have responded by using a VPN to connect to Yandex and pretending to be in Russia. This type of behavior might distort our estimates of the Russian remedy upward, but only to a modest extent. Indeed, the Russian population is more than three times that of Ukraine, and hence, even if all pre-ban Yandex users from Ukraine became Yandex users in Russia (via VPN), this would account for less than a 1.03 percentage point change in the Russian market share of Yandex. Therefore, the ban in Ukraine is unlikely to be the main driver of the increase in the Yandex market share that we estimate for Russian intervention.

investigate the interventions in Russia and Turkey, respectively.

**European Remedy** To estimate the effects of the remedy that was implemented in the EEA, we adopt the following difference-in-differences (DiD) model as our baseline specification:

$$Google_{ct} = \alpha + \beta(EEA_c \times Post_t) + \lambda_c + \gamma_t + \varepsilon_{ct} \tag{1}$$

where $Google_{ct}$ is Google's market share in country $c$ in month $t$, $\lambda_c$ is a country fixed effect, $\gamma_t$ is a month fixed effect, and $EEA_c \times Post_t$ is the treatment variable and is an indicator that turns from zero to one for EEA countries after the policy is implemented (March 2020).

We apply the difference-in-differences model to a wide range of alternative sample choices, control groups, and regression specifications. Our first control group consists of all European countries not participating in the EEA remedy, and the baseline time frame is set between April 2016 and January 2022. Our second control group further adds all other OECD countries. For some analyses, we also consider an alternative, longer time frame between January 2009 and January 2022. We also consider a control group consisting of only European and OECD countries whose population exceeds ten million.

Exploring different control groups and time frames introduces some variability in the estimates. We use as our baseline sample one that includes all European countries, except Turkey, Russia, Czechia, and Switzerland, with a time frame spanning from April 2016 to January 2022. For this sample, the data indicate that the parallel trend assumption between treatment and control groups is likely respected.[26] Moreover, the greater similarity among countries within this sample – compared to those including also non-European countries – enhances the credibility of our DiD strategy. As the results below will show, this choice leads to the most conservative estimates of the choice screen effect. In any case, the variability across estimates is moderate, and the qualitative results remain consistent across estimation samples and model specifications.

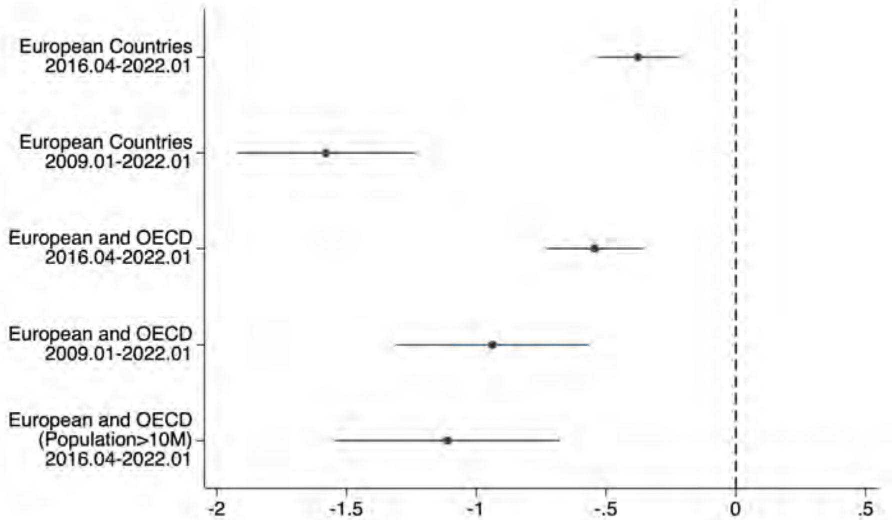
We remove Czechia from the treatment group since it represents an outlier. Google faces significantly stronger competition in the market for online search there compared to any other European country. The domestic search engine, Seznam.cz, has a double-digit market share for the majority of the period that we analyze and, as a consequence, the evolution of market shares in Czechia is different from those in other European countries, both in terms of the magnitude and the specific trends. Indeed, the latter entailed a sharp increase right before the EEA intervention and a drop right after.

As shown in Figure 4, the estimates across all control groups and time windows indicate a negative and significant effect, ranging from a low point estimate of around half of a percentage point to a high point estimate of more than one and a half percentage points.[27] This result indicates that the choice screen remedy effectively reduced Google's market share, as intended by the European Commission, although the magnitude of the reduction is clearly small relative to the goal of inducing a less concentrated market for search engines on mobile devices. Nevertheless, the change in Google's market share induced by the choice screen remedy is not negligible: the drop of 1.5

[26] We provide the results of a pre-intervention parallel trends test in the Online Appendix.

[27] To ease the exposition, we summarize the main insights from the difference-in-differences estimates through figures (displaying the point estimate and its 95% confidence interval) and simplified tables (reporting exclusively the more relevant estimated coefficients). Readers can find in Appendix A.1 the complete set of results. The appendix also contains an extensive list of additional results that will be briefly described below.

Figure 4: Impact of the EEA remedy on Google's market shares with alternative samples




Notes: on each row, we report the point estimate of the treatment effect and its 95% confidence interval. The horizontal axis denotes the estimate of mobile market share change by the choice screen in percentage points.

percentage points is more than two-thirds of a standard deviation of Google's pre-remedy mobile market share.

Following the same methodology, we also analyze whether competitor search engines that won at least one "pay-to-play" auction gained from the remedy. These search engines include DuckDuckGo, GMX, Info.com, PrivacyWall, Bing, Qwant, Yandex, Seznam, Givero, and Ecosia. Among them, PrivacyWall, Info.com, GMX, and Givero have extremely low market shares and thus are not recorded by StatCounter. The market shares of Seznam, Qwant, and Ecosia are highly localized; thus, there are few observations in the European control group. We therefore focus on how the market shares of Bing, DuckDuckGo, and Yandex responded to the EEA remedy and compare these effects to the one suffered by Google in Table 2.[28] We find that Yandex, in particular, gained from the intervention, increasing its market share by over 1 percentage point. In terms of the magnitudes of the effects of the choice screen on competitor search engines, it is useful to consider the average market share of these search engines before the remedy was implemented. Indeed, the small increases in market shares we estimate are large compared to the tiny initial market shares of these search providers in EEA countries. The estimated effect of the choice screen for Yandex is about 0.106 percentage points, which is almost the same as its pre-treatment average market share in EEA countries of 0.11%.

The baseline estimates for the EEA presented in this section quantify the effect on Google's overall mobile search market share of an intervention that was targeted to a limited group of users, namely, those purchasing new Android devices from March 2020. In the next section, we complement this analysis with a counterfactual assessment of what would have happened had the EEA remedy been applied to the whole population of Android users.

[28]It's important to note that the market share of rivals is significantly smaller compared to that of Google. As a result, we expect greater fluctuations and reduced precision in the market share measurement and corresponding analysis of competing search engines.

Table 2: Google and Competing Search Engines EEA Remedy Estimates

| | (1) Google | (2) Google | (3) Google | (4) Google | (5) Google | (6) DuckDuckGo | (7) Bing | (8) Yandex |
|---|---|---|---|---|---|---|---|---|
| EEA × Post | -0.377 | -1.580 | -0.545 | -0.938 | -1.113 | 0.019 | 0.060 | 0.106 |
| | (0.080) | (0.175) | (0.095) | (0.189) | (0.221) | (0.018) | (0.040) | (0.059) |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| R-squared | 0.888 | 0.725 | 0.939 | 0.756 | 0.943 | 0.494 | 0.134 | 0.933 |
| Pre-remedy Share | 98.40 | 98.40 | 98.40 | 98.40 | 98.40 | 0.19 | 0.27 | 0.11 |
| Observations | 3010 | 6726 | 3780 | 8453 | 1416 | 3010 | 3010 | 3010 |

Notes: The first two and the last three models include all European countries besides Turkey, Russia, Czechia, and Switzerland. The time frame of the first and the last three models is between April 2016 and January 2022 and between January 2009 and January 2022 for the second model. The third and fourth models further include 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 January 2009 and January 2022. The fifth model restricts the sample to European or OECD countries whose population exceeds 10 million and considers months between April 2016 and January 2022. All models include month and country fixed effects. In Table A.2, we further extend the analysis to investigate the role of VPN adoption on the Yandex estimates and the interaction between the browsers (Chrome and Yandex browser) and the EEA remedy.

**Russian Remedy** To investigate the effect of the choice screen in Russia, we apply the following difference-in-differences model:

$$Google_{ct} = \alpha + \beta(Russia_c \times Post_t) + \lambda_c + \gamma_t + \varepsilon_{ct}, \tag{2}$$

where $(Russia_c \times Post_t)$ is a binary treatment variable that turns from zero to one for observations for Russia after April 2017. The countries used as controls include EEA countries and OECD countries.[29] In Figure 5, we report the estimate of the treatment effect for both the baseline case (a time frame between June 2012 and July 2019 and a control group of European countries) and alternative time frames and control groups. The complete regression results are listed in Table A.3. The estimates show a significant reduction in Google's market share in the Russian mobile market of between 7.37 and 12.25 percentage points following the intervention, which amounts to between 11% and 19% of Google's pre-treatment average market share of 65.49%.[30] For the Russian remedy, we also present estimates based on a measure of search engine market share data obtained from Yandex Radar, a Yandex-owned competitor to StatCounter, which covers four countries (Belarus, Kazakhstan, Russia, and Turkey) and has a broad penetration in Russia (see details in the Online Appendix). The results are qualitatively very close to the baseline estimates.

**Turkish Remedy** To estimate the effect of the remedy that was implemented in Turkey, we estimate the same difference-in-differences model:

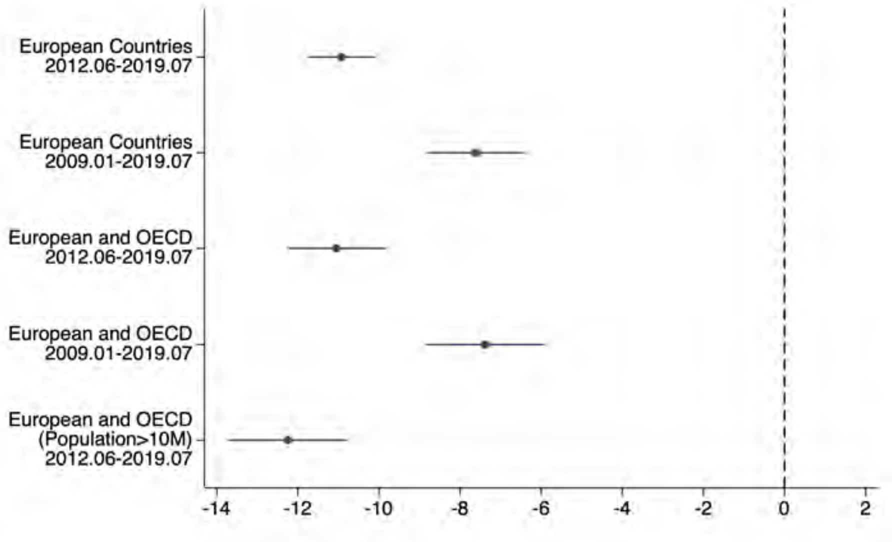
$$Google_{ct} = \alpha + \beta(Turkey_c \times Post_t) + \lambda_c + \gamma_t + \varepsilon_{ct}, \tag{3}$$

where $Turkey_c \times Post_t$ is a dummy variable that turns from zero to one for observations for Turkey after August 2019. The set of control countries is as described in the Russian case. To avoid having treated EEA countries in the control group, we restrict the sample to observations up to February 2020. In Figure 6, we report the estimated treatment for both the baseline case (a time

[29] The use of EEA countries in the control group is justified by the fact that we restrict our sample to before the EEA choice screen was implemented, as we only keep observations from before August 2019 in our sample.

[30] For remedies applicable to both mobile devices and tablets (i.e., the EEA and Russian cases), we investigate their impact on tablet devices and discuss potential spillover effects to desktops in the Online Appendix.

Figure 5: Impact of Russian remedy on Google market shares with alternative samples




Notes: on each row, we report the point estimate of the treatment effect and its 95% confidence interval. The horizontal axis denotes the estimate of mobile market share change by the choice screen in percentage points.

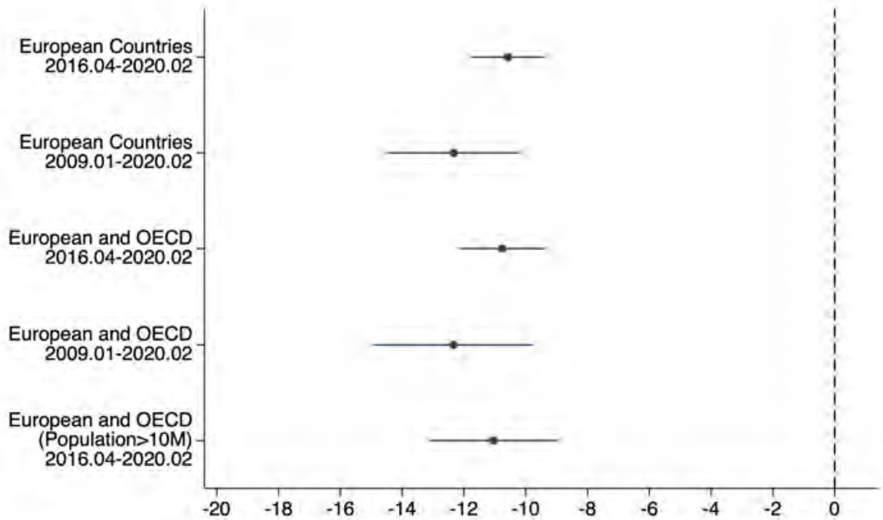
frame between June 2006 and September 2019 and a control group of European countries) and alternative time frames and control groups. The complete set of estimates is reported in Table A.4. The estimates show a drop in Google's market share of about 11 percentage points, which is equal to about five standard deviations of its pre-treatment mobile market share.[31]

We conclude by briefly exploring one extension that plays a critical role in understanding the broader implication of our findings, namely the pass-through to consumers. Local manufacturers may experience conflicting effects from the TCA intervention: on the one hand, they attain the freedom to negotiate and choose alternative search engines, but on the other hand, they cannot receive payments from Google in exchange for setting its search engine as the default. Whether these changes affect manufacturers' pricing strategies and, thus, consumer welfare is not directly observable in our data. However, since demand is negatively related to price, we can investigate changes in Android device prices by studying the mobile market share distributions across operating systems (OS) in Turkey before and after the remedy. Our analysis (in the Online Appendix) indicates no significant changes in the OS mobile market shares after the remedy, suggesting that consumers were unlikely to incur welfare losses due to price changes for Android mobile devices.

**Robustness** We conduct multiple robustness checks to ensure the validity of our baseline findings. Our first set of checks focuses on the standard errors used to conduct inference for the remedy impacts. In particular, we take into account the potential issues of heteroskedasticity and error autocorrelation noted by Bertrand et al. (2004), as well as the challenge posed by having a small number of treated group units following Conley and Taber (2011). To account for these issues, we re-evaluate our baseline estimates through a battery of alternative methods described in Appendix A.2 along with the associated results. These results broadly confirm the baseline findings.

[31] We set August 2019, when Google officially submitted contract changes to the TCA, as the beginning of the treatment. The results remain robust if we set alternatively September 2018, when the TCA placed a fine on Google and announced its decision. See estimates in the Online Appendix.

Figure 6: Impact of Turkish intervention on Google market shares with alternative samples




Notes: on each row, we report the point estimate of the treatment effect and its 95% confidence interval. The horizontal axis denotes the estimate of mobile market share change by the Turkish remedy in percentage points.

Our second set of robustness checks deals with the chosen estimators. In Appendix A.3, we relax the assumptions of static treatment effects and employ modern identification strategies developed by De Chaisemartin and d'Haultfoeuille (2024). We also explore the implications of relaxing the assumptions of homogeneous and static treatment effects in the Appendix A.4. Regarding the temporal dynamics of the treatment, we find that the effects tend to grow over time throughout the whole post-treatment sample period that we observe. In Appendix A.5, we estimate the impact of three remedies using the alternative synthetic control method of Abadie et al. (2010).

A third type of robustness check that we consider is one targeted to the Russian and Turkish cases and accounts for the dynamic of anti-Americanism (i.e., anti-US sentiment). Specifically, we check whether the drop in Google's market share associated with the regulatory interventions occurs simultaneously with local spikes in anti-Americanism. Based on the anti-Americanism data and analysis described in Appendix A.6, we find no evidence of an association between anti-Americanism dynamics, the antitrust remedies, and the changes in Google's market share. Indeed, our findings remain qualitatively unchanged even after incorporating anti-Americanism measures as a control in our baseline model. The main insight from these three sets of robustness checks is that the baseline findings are qualitatively robust.

**Intervention Comparison** According to the baseline estimates in the previous section, Google's market share in EEA countries decreased by less than 1 percentage point, while in Russia and Turkey, it fell by more than 10 percentage points. Variations in both the remedy design and the pre-existing conditions contribute to explaining these differences in remedy effectiveness. In terms of pre-existing conditions, the most visible element is the size of Google's market share: 60 percent in Russia compared to nearly 100 percent in both Turkey and the EEA. The post-intervention evolution of this market share across the three cases has two implications. First, the large effect observed for Turkey implies that antitrust remedies can be effective in reducing Google's market share despite the initial lack of a strong competitor. Second, the smaller effect observed in the EEA relative to Russia may be driven, at least in part, by the initially larger market share of Google in the EEA.

To properly assess the latter feature, however, the differences in design between the remedies in the EEA and Russia need to be accounted for. The two main differences are the extent of the population involved in the treatment and the set of Google's rivals displayed in the choice screen.[32] In the next two sections, we explore in more detail the mechanisms driving the baseline estimates presented above and explore some counterfactual analyses aimed at evaluating the relative importance of the two differences in remedy design between the EEA and Russia.

## 4.2 Mechanisms

To understand the mechanisms at play, several forces on the side of users, competing search engines, and advertisers need to be considered simultaneously, including (a) the population of users exposed to the interventions, (b) users' awareness of alternative search engines, and (c) the quality of the alternatives. In this section, we explore these forces to the extent that they are observable within our data.

**User Choices** First, we investigate whether search engines experienced heterogeneous market gains based on their brand awareness and quality. We calculate the market share change of competing search engines during the treated period and employ the following model:

$$MobileChange_{ck} = \alpha + \beta desktop_{ck} + \delta Y_{ck} + \varepsilon_{ck}, \tag{4}$$

where $MobileChange_{ck}$ is the mobile market share change by search engine $k$ in country $c$;[33] $desktop_{ck}$ is the desktop market share of search engine $k$ before the treatment; and, finally, $Y_{ck}$ collects a dummy for whether search engine $k$ is founded domestically in country $c$. The desktop share is a reasonable proxy for awareness because, as argued in the CMA report mentioned in the introduction, users tend to make more active choices of their search engine on desktops, meaning the share in the desktop search market is a good indicator of how aware users are of the different search engines available. Moreover, the desktop market share, to some extent, also reflects the quality of search engines in the local market: intuitively, desktop users should prefer to use search engines with accurate search results.

The estimates reported in Table A.5 and Table A.6 reveal a positive and significant relationship between the mobile market share gain and the pre-remedy desktop share for most search engines, while there is no significant effect of the dummy for the domestic nature of the search engine. Interestingly, there is also a difference among competing search engines, with Bing being the only

[32]Recall that the list of search engines in the Russian choice screen is fixed, meaning that only Yandex and Mail.ru always appear on choice screens. In contrast, the list of search engines in the EEA countries during the "pay-to-play" period was determined by the auction outcomes, meaning that the search engines listed on the choice screen could change for each country in each quarter.

[33]For the EEA, we calculate the market changes of Bing, DuckDuckGo, Ecosia, Qwant, Seznam, or Yandex during the whole "pay-to-play" period in the treated countries where they won at least once. For Turkey, our sample also includes market share changes of the same list of search engines between July 2019 and January 2022. For Russia, we only include the Yandex and mail.ru market change between March 2017 and July 2019, as it is the only search engine that appeared on the choice screen.

Table 3: Bidding Strategy Estimates

| | (1) Slots Won | (2) Slots Won | (3) Slots Won | (4) Slots Won |
|---|---|---|---|---|
| Desktop Share 2020 Feb | 0.092 | 0.294 | 0.131 | 0.379 |
| | (0.028) | (0.039) | (0.028) | (0.041) |
| Mobile Share 2020 Feb | 2.410 | 0.257 | 3.085 | 0.427 |
| | (0.311) | (0.232) | (0.347) | (0.226) |
| Domestic Search Engine | | | -0.287 | 0.661 |
| | | | (0.570) | (0.477) |
| Search Engine FE | No | Yes | No | Yes |
| Country Controls | No | No | Yes | Yes |
| Pseudo R-squared | 0.046 | 0.196 | 0.065 | 0.214 |
| Observations | 870 | 870 | 870 | 870 |

Notes: The dependent variable is the number of auctions won by Bing, DuckDuckGo, Ecosia, Qwant, Seznam, or Yandex in all the treated countries of the EEA remedy. The last models control for country characteristics, including GDP, population, the ratio of males in the population, the working age ratio, and the percentage of young people between 20 and 29. The data is from the World Bank. The estimates in the table are obtained through a negative binomial model. The corresponding OLS estimates are reported in Table A.7.

search engine whose interaction with the desktop share is negative and significant. This might be explained by desktop users of Bing not being keen to switch to it on their mobile phones.

**Search Engine Bidding Strategy** A controversial element of the EEA remedy is whether and to what extent the auction mechanism distorts the options available on the choice screen. As discussed earlier, Ostrovsky (2023) convincingly explains why a pay-per-view system would likely have induced a better selection of winners than the pay-per-click model adopted. However, the previous estimates indicate that the usage of alternative search engines increased in the EEA and that this increase is associated with awareness of the search engines among users and their quality. It is thus worth exploring the bidding strategies of the search engines in pay-to-play auctions. Since the only available data are on the identity of the winners in each auction, we estimate a negative binomial model to assess how the number of auctions won by search engine $k$ in country $c$ depends on its pre-intervention desktop market share in country $c$ and on its pre-intervention mobile market share in country $c$, as well as on other country-specific and search-engine specific control variables.

The estimates are listed in Table 3. Across all of the models estimated, we find that a search engine is more likely to win an auction if it has a larger pre-remedy share in the desktop market in that country. Similarly, the pre-remedy mobile market share also has a positive effect, although the magnitude and significance vary across models. The controls for domestic search engines, as well as those for the country characteristics included in the models of columns (3) and (4), are never significant, but they alter the size and significance of the two pre-remedy market share variables. Interestingly, in column (4), where we add search engine fixed effects, the magnitude of the desktop share effect grows relative to the other specification, which is explained by Bing behaving differently than the other search engines. Similar to the finding above on user choice, Bing's desktop share is not predictive of winning auctions. Hence, it appears overall that search engines in the EEA auctions display a behavior that is coherent with user choices.

**Advertisers' Response** Our analysis indicates that the three remedies caused increased usage of alternative search engines. It is natural to believe that online advertisers may have responded to this reallocation of traffic among search engines. We exploit our data on Google's mobile search advertisement auction outcomes from SEMrush to evaluate the effect of the three remedies on the dominant search engine's revenues. Our data cover the most searched keywords on Google in twelve countries. In addition to Russia and Turkey, we include in our analysis the six largest EEA markets (Germany, Spain, France, Italy, the Netherlands, and the UK), while our control group always consists of Australia, Brazil, Canada, and the USA.

Due to the limited number of countries observed and the selected set of keywords, the analysis that follows should be interpreted as mostly descriptive. We do not aim to identify a precisely estimated causal effect but to illustrate whether the advertising channel responded. For each intervention, we consider three outcomes: the keyword level cost-per-click (CPC), volume, and revenue. We construct keyword-level revenue as the product of CPC and volume, following Decarolis and Rovigatti (2021). We estimate the following difference-in-differences model:

$$Outcome_{ctk} = \alpha + \beta(Treat_c \times Post_t) + \lambda_c + \gamma_t + \varepsilon_{ctk}$$

where $Outcome_{ctk}$ is the CPC, volume, or revenue of keyword $k$ in country $c$ and year $t$, $\lambda_c$ is a country fixed effect, $\gamma_t$ is a year fixed effect and $Treat_c \times Post_t$ is a binary variable that indicates treated countries (depending on the regression, this can either indicate EEA countries, Russia or Turkey) in the years following the corresponding remedy.

Table 4: Advertisers' response to the EEA, Russian and Turkish Remedies

| | (1)<br>CPC | (2)<br>Volume | (3)<br>Revenue | (4)<br>CPC | (5)<br>Volume | (6)<br>Revenue | (7)<br>CPC | (8)<br>Volume | (9)<br>Revenue |
|---|---|---|---|---|---|---|---|---|---|
| EEA×Post | -0.018<br>(0.015) | 29.042<br>(29.458) | -43.194<br>(17.096) | | | | | | |
| Russia×Post | | | | -0.036<br>(0.048) | -182.951<br>(82.235) | -117.318<br>(51.288) | | | |
| Turkey×Post | | | | | | | -0.163<br>(0.043) | -53.794<br>(76.252) | -148.774<br>(46.194) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| R-squared | 0.092 | 0.085 | 0.168 | 0.126 | 0.153 | 0.257 | 0.132 | 0.139 | 0.256 |
| Pre-remedy Mean | 0.58 | 804.94 | 397.47 | 0.28 | 271.35 | 49.97 | 0.18 | 628.93 | 73.11 |
| Observations | 64539 | 64539 | 64539 | 27700 | 27700 | 27700 | 27869 | 27869 | 27869 |

Notes: The time frames considered in these regressions span from 2016 to 2022 for EEA countries, from 2015 to 2019 for Russia, and from 2017 to 2021 for Turkey. The control group consistently includes Australia, Brazil, Canada, and the USA. Volume and revenue are recorded in thousands. Table A.8 and Table A.9 expand on the estimates in this table.

The results are displayed in Table 4. The estimates are negative, with mostly statistically insignificant effects for the EEA but significant effects for Russia and Turkey on ad revenues. The fact that CPC decreased under the Turkish remedy possibly shows that the policy hurt the ecosystem of Google more broadly, perhaps by also changing the ability of Google to target users.

### 4.3 Counterfactual Analysis

We conclude our analysis with two counterfactual exercises, both of which evaluate a feature of the EEA remedy that differs from the Russian remedy and that represents a design choice under the control of the regulator. The first exercise involves the population exposed to the remedy: we estimate what the effect of the intervention would have been had the choice screen been imposed on all Android devices in the EEA. The second exercise involves the alternative search engines shown on the choice screen: we compute the effect of always including the top rival to Google on the choice screen.

**EEA Remedy Exposing a Larger Population to the Intervention** We proceed in two steps: first, we quantify the remedy effect on the population of Android users, and second, we estimate the counterfactual effect on the Google market share of an EEA remedy applied to the whole population of Android users (rather than limited to new devices). It is particularly useful in the evaluation of the EEA remedy to analyze how the number of new and old Android devices in a given country altered the effectiveness of the EEA intervention. In fact, imagine an extreme case where new Android users can select alternative search engines from the choice screen (i.e. the country is being treated with the remedy), but where no Android phones are purchased. Then, the remedy would have no effect, regardless of its actual design and potential for leveling the playing field. Indeed, the effect of the choice screen on mobile search depends on two factors. First, the impact on the market for mobile search depends on the number of users who access the choice screen. If very few users have access to the choice screen, the effect of the remedy is bound to be negligible. Second, the effect on Google's mobile market share depends on the propensity of users to select Google from the choice screen relative to Google's baseline market share. If users, when confronted with the choice screen, often choose a competitor search engine as their default, the choice screen remedy will negatively impact Google's market share. The larger the divergence between the rate at which users select Google from the choice screen and Google's baseline market share, the greater the effect of the remedy on Google's mobile market share.

We employ data on device shipments and smartphone users by country. The sample covers European and OECD countries between April 2016 and January 2022, for which we have data on device shipments, as shown in Table B.3. We begin by estimating the remedy effect on Android mobile search via the following weighted difference-in-differences model:

$$Google_{ct} = \alpha + \beta(EEA_c \times Post_t \times ship_{cq(t)}) + \psi ship_{cq(t)} + \gamma_c + \lambda_t + \varepsilon_{ct} \tag{5}$$

where $ship_{cq(t)}$ measures the fraction of Android shipments over total phone shipments in country $c$ in quarter $q$ corresponding to period $t$. The regression estimates are listed in Table 5, where we observe stronger effects by weighting the treatment by the number of new Android users relative to our baseline estimates. These findings remain valid also when we restrict our sample to countries whose populations are higher than 10 million, as shown in the last column of Table 5.

The estimates from the binary treatment model in Table 2 and from the weighted treatment model in Table 5 capture different effects with distinct policy relevance. The estimate from the binary treatment model captures the effect of the remedy on overall mobile search, while the estimate from the weighted treatment model captures the effect of the remedy on Android mobile search. The latter is arguably more informative as it captures the effect on the population of Android users. We discuss the identification of these effects in greater detail in the Online Appendix.

Table 5: Google EEA Remedy Weighted Treatment Estimates

| | (1) Google | (2) Google | (3) Google | (4) Google | (5) Google | (6) Google |
|---|---|---|---|---|---|---|
| EEA × Post | -0.701 | -0.701 | | | -0.880 | |
| | (0.693) | (0.179) | | | (0.254) | |
| EEA × Post × % Android | | | -0.831 | -0.903 | | -1.134 |
| | | | (0.921) | (0.241) | | (0.322) |
| % Android in shipments | | | 0.405 | 1.055 | | 0.854 |
| | | | (1.106) | (0.672) | | (0.945) |
| Month FE | No | Yes | No | Yes | Yes | Yes |
| Country FE | No | Yes | No | Yes | Yes | Yes |
| R-squared | 0.147 | 0.946 | 0.147 | 0.946 | 0.945 | 0.945 |
| Observations | 1782 | 1782 | 1782 | 1782 | 1221 | 1221 |

Notes: All models exclude countries where shipment data is unavailable, and the time frame is from April 2016 to January 2022. The first four models include all the European and OECD countries, except Turkey, Russia, Switzerland, and Czechia. The last two models only consider countries with populations greater than 10 million.

The second step entails assessing what the effect would be if the European Commission imposed the search engine choice screen on all Android phones. We leave the exact steps for Appendix B.4 and here offer a simplified overview of our approach. From our data on market sizes and device shipments, assuming plausible activation and destruction rates for mobile devices, we can estimate the Android mobile device accumulation patterns in EEA countries. Then, we isolate the devices that actually accessed the choice screen from all other Android devices that never received the treatment. Finally, from our data on search engine market shares, we back out the rate at which users select Google from the choice screen, given that we can identify the contribution of treated devices to the market for mobile search.

In this way, we determine that, under a reasonable device depreciation rate, EEA users choose Google from the choice screen at a rate approximately 3 percentage points lower than Google's baseline market share. Stated differently, if about 99 out of 100 users use Google as their search engine in EEA countries, then we should expect about 96 out of 100 users to select Google from a choice screen implemented for all Android phones. Thus, in a counterfactual scenario where the EEA choice screen is made available to all Android users, we would estimate an effect that would be of the order of 3 percentage points for the treated population of Android users, which is higher than the estimates from all our specifications.

**EEA Remedy Enhancing Visibility of the Top Competitor** To evaluate this counterfactual, we exploit the differences across the EEA countries in the frequency with which the top competitor wins a pay-to-play remedy auction to estimate what would have happened to Google's market share had the EEA choice screen always displayed this top rival.

We begin our analysis by re-evaluating the heterogeneous treatment effects discussed earlier by estimating model (5) separately for each treated EEA country. The results indicate a range of estimates from -2 for Austria and Denmark to -0.09 for Hungary. We then use these coefficients as dependent variables in the following OLS model:

$$DiD_c = \alpha + \beta CompetitorFreq_c + \delta X_c + \gamma Y_c + \varepsilon_c \tag{6}$$

where $DiD_c$ is the absolute value of the difference-in-differences coefficient estimated in country $c$, $CompetitorFreq_c$ is the number of choice screen auctions won by the search engine with the largest market share in mobile search besides Google before the choice screen, $X_c$ collects characteristics of country $c$, and $Y_c$ records characteristics of the largest competitor to Google. We do not include Czechia in this analysis due to its role as an outlier, as previously discussed.

The estimates in Table A.11 indicate a positive and significant relationship between the impact of the EEA remedy on Android mobile devices and the number of auctions won by Google's largest competitor in the local market. While the results are not significant in the baseline difference-in-difference coefficient due to the smaller impact of the remedy on all mobile devices, the overall effects remain positive. This implies that a search engine with a larger existing user base before the remedy is more likely to benefit from the choice screen and gain market share. These results are also consistent with those in Table A.5, where we find a positive relationship between the market share gain and pre-intervention market share for search engines that appeared in the EEA choice screen.

Lastly, we can use the estimates in Table A.11 to assess how much the market share of Google would have declined in response to a remedy in which the top rival was always displayed on the choice screen. We first find that the biggest competitor in each EEA country won 0.53 auctions on average among the 17 countries in models (1)-(3), and 1.34 auctions among the 29 countries in models (4)-(6). We then predict the value of beta if the biggest competitor in each country had won all 5 auctions during the pay-to-play period and thus was always shown on the choice screen. The predicted values for the six regression models reach up to 3.17. Hence, the counterfactual estimates suggest that the impact of an EEA remedy designed such that the leading competitor always appears can achieve up to a 3 percentage point reduction in Google's market share. This is higher than our baseline and, interestingly, is a similar magnitude to that obtained through the first counterfactual exercise above. Thus, we can conclude that modifications of the EEA remedy design to make it closer to the one adopted in Russia would have likely enhanced its effectiveness, although only to a small extent. The large effect achieved by the Russian intervention is likely to be linked more to the greater pre-intervention awareness of Yandex than to the two features of the remedy design explored in this section.

### 4.4 Quality Improvements and Search Defaults

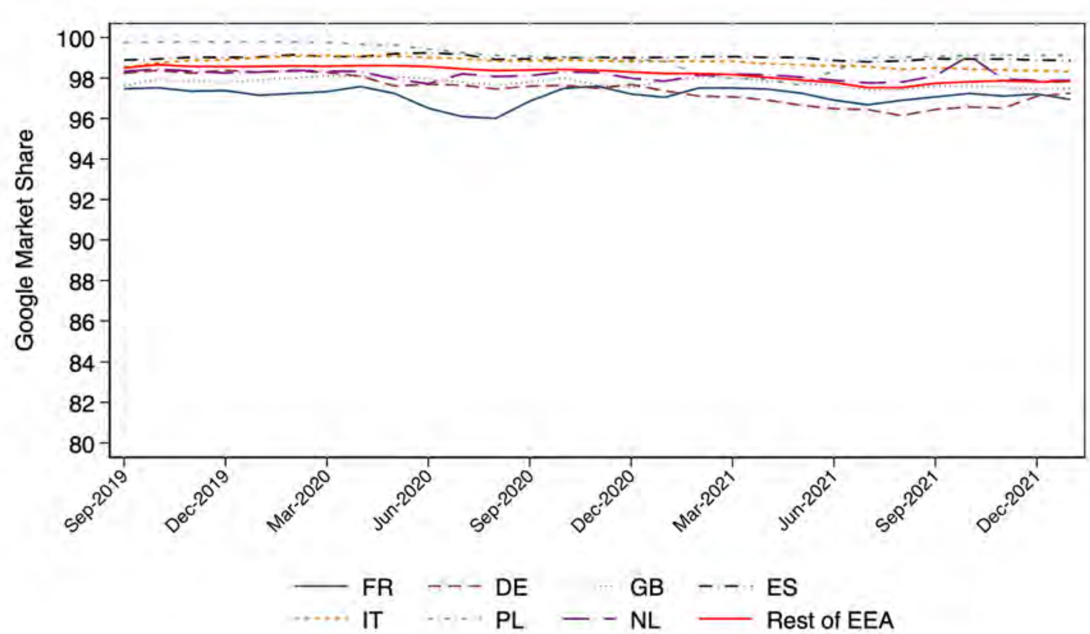
The recent *U.S. vs. Google* case referenced in the opening quote uncovered important information on the interplay between mobile search quality and the role of defaults. First, internal documents revealed that Google responded to the EEA intervention by implementing major, cross-country quality-enhancing investments. Second, testimonies from top executives of competing search engines highlighted how Google's default position renders investment in their own product quality less appealing.

In 2019, Google anticipated revenue losses due to the EEA choice screen. In response, it launched a plan called "Go Big In Europe" aimed at enhancing the quality of its services for EEA users and increasing its chances of being selected as the preferred option in the choice screen.[34] Initially focusing on France and Germany in 2019 and 2020, Google aimed to improve its search services

[34] See `https://www.justice.gov/d9/2023-11/417573.pdf`, (accessed February 25, 2024).

by adding post-game soccer video highlights, more local content and news, pronunciation practice for different languages, and more information on local television options available for streaming. According to the documents presented by the DOJ in court, Google intended to hire more than 80 new employees and spend more than $200 million on the initiative. The updates were planned to be rolled out successively in the UK, Spain, Italy, Poland, and the Netherlands.

Figure 7: Go Big in Europe and Google Market Shares




*Notes*: evolution of Google's mobile market shares in the seven EEA countries who received the "Go big in Europe" plan (FR, DE, GB, ES, IT, PL, NL) compared to the average Google market share in the rest of the EEA.

Despite the limited information revealed in the ongoing court case, we attempt to assess the effect of Google's Go Big in Europe plan by comparing how its market share changed in the seven EEA countries where the plan was implemented with the remaining EEA countries in Figure 7. Google's market share did not seem to change drastically in the targeted countries, even compared to the rest of the EEA. Finally, in Table 6, we present regression estimates that dissect the impact of the EEA remedy on countries affected by Google's Go Big in Europe plan. We estimate our baseline regression (1) distinguishing between the seven countries that were part of the plan and those that were not. We find that the effect of the remedy was remarkably consistent across both sets of countries, suggesting that the Go Big in Europe plan did not differentially alter the efficacy of the remedy within the targeted countries compared to non-targeted countries. However, it is important to note that the absence of an observable differential effect does not necessarily imply that the plan was ineffective: the remedy might have led to more pronounced market share losses in the targeted countries if Google had not implemented its Go Big in Europe plan. Indeed, by forcing Google to make quality-enhancing investments, the EEA remedy may have greatly befitted EEA users, despite the small effect on Google's market shares.

Table 6: Effect of Go Big in Europe on EEA Remedy

| | (1) Google | (2) Google | (3) Google | (4) Google | (5) Google | (6) Google | (7) Google | (8) Google |
|---|---|---|---|---|---|---|---|---|
| EEA × Post | -0.376 | -0.380 | -0.376 | -0.380 | -0.544 | -0.547 | -0.544 | -0.547 |
| | (0.248) | (0.452) | (0.081) | (0.160) | (0.411) | (0.746) | (0.104) | (0.194) |
| Post 03/2020 | 0.063 | 0.063 | | | 0.231 | 0.231 | | |
| | (0.198) | (0.267) | | | (0.288) | (0.354) | | |
| EEA | 2.108 | 1.706 | | | 3.568 | 3.166 | | |
| | (0.142) | (0.259) | | | (0.236) | (0.428) | | |
| Month FE | No | No | Yes | Yes | No | No | Yes | Yes |
| Country FE | No | No | Yes | Yes | No | No | Yes | Yes |
| R-squared | 0.105 | 0.039 | 0.909 | 0.887 | 0.086 | 0.033 | 0.943 | 0.937 |
| Observations | 2520 | 1400 | 2520 | 1400 | 3290 | 2170 | 3290 | 2170 |

Notes: Odd columns remove countries treated by Go Big in Europe (FR, DE, GB, ES, IT, PL, NL) from the treatment group, while even columns only consider countries treated by Go Big in Europe in the treatment group. Columns (1)-(4) only include European countries in the control group, while columns (5)-(8) add OECD countries to the control group. The time frame for all regressions is between April 2016 and December 2021.

Given that Google attempted to increase its quality to maintain its dominant position in the EEA, it is fair to ask whether competitors would be able to erode Google's dominance by improving their own service quality. Ideally, we would measure the extent to which consumers value quality in their search engine with methodologies similar to those employed by Bronnenberg et al. (2012). Unfortunately, this exercise is unfeasible without extensive data that only the search engines themselves have. For instance, Klein et al. (2023) are able to assess the relative quality of the search outcomes of Google and a small rival by partnering with the latter and conducting a series of controlled experiments. However, the testimonies from Bing executives in the court case help to shed some light on these issues. Mikhail Parakhin, Microsoft's CEO of Advertising and Web Services, testified that Microsoft's mobile search is not as good as Google's mobile search and that it would be "uneconomical" for Microsoft to invest more in mobile search because the company would not be able to distribute it at scale. The testimonies also highlighted some of Google's less obvious advantages over its rivals, such as the fact that the quality gap between Google and its rivals is amplified on mobiles by the geolocational element of mobile searches, which tend to seek uncommon, granular, location-based information, making them akin to searches for tail keywords (i.e., queries that occur rarely on general search engines). Google's scale is crucial to its ability to provide adequate responses to such queries. Other sources of advantage are even more peculiar, for instance, it was reported in court that businesses are more likely to update their opening hours on Google due to its higher user traffic, thus contributing to the higher quality of Google.[35]

Overall, the evidence arising from the US vs Google case indicates that regulatory interventions can have a broader impact than simply helping competitors to gain market share. Indeed, the reduction of the dominant firm's market share should not be the sole indicator in welfare analysis. Although the impact of EEA remedy on Google's market share might be small, such measures can encourage dominant companies to invest in improving their service quality. Also, the testimonies by Bing executives highlight the difficulties competitors face in matching Google's level of quality, given that Google remains the default search engine on most devices. In fact, recent literature

[35]For more details, please see `https://searchengineland.com/google-search-antirust-trial-hearing-updates-431977`, (accessed February 24, 2024).

(Hovenkamp, 2023) suggests that policymakers should remove the entrenched default positions held by dominant firms to ensure a competitive playing field and promote welfare.

## 5 Conclusions

This paper contributes to filling the gaps in the literature on competition in digital markets by studying the role of preset default on internet search competition. Understanding the role played by default options is essential to our understanding of the digital economy, and it is important to guide policymakers in designing interventions that consider the behavioral biases displayed by consumers. Indeed, the Digital Markets Act in Europe introduced the requirement of a search choice screen, starting in March 2024, for platforms like Google that are designated gatekeepers.

The paper offers the first systematic evaluation of the policy interventions observed in this area thus far. It quantitatively evaluates three antitrust remedies in the EEA, Russia, and Turkey, all aimed at removing Google's default position on Android mobile devices, but each with a different remedy design and under different market characteristics. The remedy implemented in the EEA introduced a choice screen for new Android users, allowing them to choose their preferred default search engine. The list of search engines on the choice screen changed regularly and was initially determined by an auction mechanism.

In Russia, a similar choice screen was implemented, but it was made accessible to all Android devices circulating in the country. In addition, the list of search engines appearing on the choice screen was fixed from the beginning and included Yandex, Google's largest competitor in the local market. Crucially, the difference in market share between Google and Yandex in Russia before the remedy was around 20 percentage points, while the distance between Google and its closest competitors in the EEA exceeded 90 percentage points. Therefore, network effects, scale advantages, and users' preferences for Google's rival were much stronger in Russia than in EEA countries and contributed to its greater effectiveness.

In Turkey, no choice screen was implemented. Instead, the authority intervened by regulating contracts between Google and device manufacturers. Pre-installation of Google as default search engine in exchange for licensing the Android OS or any form of remuneration of the OEMs was forbidden. We observe significant reductions in Google's market shares in the EEA, Russia and Turkey after the policy interventions. However, there is a wide variation in the magnitude of the estimated reduction, which exceeds 10 percentage points in Russia and Turkey but is less than 1 percentage point in the EEA. This latter result may be partially driven by unprecedented efforts by Google to bolster the quality of its service.

We find that the effectiveness of a remedy is determined by multiple factors, including nuances in intervention designs, user preferences, and characteristics of the local market. Investigating the potential factors determining the heterogeneous gains in market share across different search engines, we show that competing search engines with higher pre-remedy popularity are more likely to be chosen by users in local markets. Further analyzing the EEA remedy during the pay-to-play period, we also observe consistent results showing that search engines with a larger existing user base and high popularity in the local market have strong incentives to participate in the remedy and to be visible to users.

We also examine the extent to which the limited effectiveness of the EEA remedy is caused by lower choice screen visibility or by a lack of strong competitors: we estimate how much Google's market share would have declined if the choice screen had been shown to every Android user or if Google's top rival were always displayed in the choice screen. The estimates from both counterfactual scenarios are higher than the baseline estimates but in the same order of magnitude. Combining these findings, we argue that simply implementing a choice screen is unlikely to have a satisfying impact on competition in the online search market unless there exists a rival with sufficient quality and popularity, or one with a strong incentive to invest in the local market to replace Google.

Overall, these results underscore the crucial role of preset default in mobile internet search. They indicate a path for competition policies intended to foster a more balanced market among search engines through interventions aimed at the preset default. These interventions are likely more effective than fines in restoring competition because, compared to the economic value at stake, antitrust fines appear negligible. However, in all of the cases that we have analyzed, the success of the intervention rested to some extent on the presence of a viable competitor.

Our paper focuses on a quantitative analysis of three remedies; future investigations and experiments are needed to confirm the underlying mechanisms causing the patterns we uncovered. For instance, researchers might study which users are most affected by these policies, whether users try alternative search engines through the choice screen but then switch back to the incumbent, and in particular, whether changing the relative market shares has an impact on the quality of the search options available to consumers. These are fundamental questions that researchers and authorities need to address in the coming years to design effective regulations.

# References


Abadie, A., A. Diamond, and J. Hainmueller (2010). Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of the American Statistical Association 105*(490), 493–505.

Athey, S. and G. Ellison (2011). Position Auctions with Consumer Search. *The Quarterly Journal of Economics 126*(3), 1213–1270.

Belleflamme, P. and M. Peitz (2018). Platforms and Network Effects. *Handbook of Game Theory and Industrial Organization, Volume II*.

Bertrand, M., E. Duflo, and S. Mullainathan (2004). How Much Should We Trust Difference-in-Difference Estimates? *The Quarterly Journal of Economics 119*(1), 249–275.

Beshears, J., J. J. Choi, D. Laibson, and B. C. Madrian (2018). Behavioral Household Finance. In *Handbook of Behavioral Economics: Applications and Foundations 1*, Volume 1, pp. 177–276. Elsevier.

Blake, T., C. Nosko, and S. Tadelis (2015). Consumer Heterogeneity and Paid Search Effectiveness: A Large-Scale Field Experiment. *Econometrica 83*(1), 155–174.

Bordalo, P., N. Gennaioli, and A. Shleifer (2022). Salience. *Annual Review of Economics 14*, 521–544.

Bronnenberg, B. J., J.-P. H. Dubé, and M. Gentzkow (2012). The Evolution of Brand Preferences: Evidence from Consumer Migration. *American Economic Review 102*(6), 2472–2508.

Calvano, E. and M. Polo (2021). Market Power, Competition and Innovation in Digital Markets: A Survey. *Information Economics and Policy 54*, 100853.

Caplin, A., M. Dean, and D. Martin (2011). Search and Satisficing. *American Economic Review 101*(7), 2899–2922.

Chetty, R. (2015). Behavioral Economics and Public Policy: A Pragmatic Perspective. *American Economic Review 105*(5), 1–33.

Chetty, R., J. N. Friedman, S. Leth-Petersen, T. H. Nielsen, and T. Olsen (2014, 05). Active vs. Passive Decisions and Crowd-Out in Retirement Savings Accounts: Evidence from Denmark. *The Quarterly Journal of Economics 129*(3), 1141–1219.

Choi, J. P. and D.-S. Jeon (2021). A Leverage Theory of Tying in Two-Sided Markets with Nonnegative Price Constraints. *American Economic Journal: Microeconomics 13*(1), 283–337.

CMA (2020). Online platforms and digital advertising market study. Accessed: August 18, 2024.

Conley, T. G. and C. R. Taber (2011). Inference with "Difference in Differences" with A Small Number of Policy Changes. *The Review of Economics and Statistics 93*(1), 113–125.

De Chaisemartin, C. and X. d'Haultfoeuille (2024). Difference-in-Differences Estimators of Intertemporal Treatment Effects. *Review of Economics and Statistics*, 1–45.

Decarolis, F. and M. Li (2023). Regulating Online Search in the EU: From the Android Case to the Digital Markets Act and Digital Services Act. *International Journal of Industrial Organization 90*, 102983.

Decarolis, F. and G. Rovigatti (2021, October). From Mad Men to Maths Men: Concentration and Buyer Power in Online Advertising. *American Economic Review 111*(10), 3299–3327.

Dubé, J.-P. H., G. J. Hitsch, and P. K. Chintagunta (2010). Tipping and Concentration in Markets with Indirect Network Effects. *Marketing Science 29*(2), 216–249.

Economides, N. and I. Lianos (2010). A critical appraisal of remedies in the EU microsoft cases. *ColuM. Bus. l. rev.*, 346.

European Central Bank (2024a). Euro Foreign Exchange Reference Rates. `https://www.ecb.europa.eu/stats/policy_and_exchange_rates/euro_reference_exchange_rates/html/eurofxref-graph-rub.en.html` (accessed February 25, 2024).

European Central Bank (2024b). Euro Foreign Exchange Reference Rates. `https://www.ecb.europa.eu/stats/policy_and_exchange_rates/euro_reference_exchange_rates/html/eurofxref-graph-try.en.html` (accessed February 25, 2024).

Farronato, C., J. Fong, and A. Fradkin (2024). Dog Eat Dog: Balancing Network Effects and Differentiation in A Digital Platform Merger. *Management Science 70*(1), 464–483.

Fumagalli, C., M. Motta, and C. Calcagno (2018). *Exclusionary Practices: The Economics of Monopolisation and Abuse of Dominance*. Cambridge University Press.

Gans, J. S. (2011). Remedies for Tying in Computer Applications. *International Journal of Industrial Organization 29*(5), 505–512.

Grubb, M. D. (2015). Failing to Choose the Best Price: Theory, Evidence, and Policy. *Review of Industrial Organization 47*, 303–340.

Handel, B. R. (2013, December). Adverse Selection and Inertia in Health Insurance Markets: When Nudging Hurts. *American Economic Review 103*(7), 2643–82.

Ho, K., J. Hogan, and F. Scott Morton (2017). The Impact of Consumer Inattention on Insurer Pricing in the Medicare Part D Program. *The RAND Journal of Economics 48*(4), 877–905.

Hovenkamp, E. (2023). The Competitive Effects of Search Engine Defaults. *USC CLASS Research Paper No. 24-10*.

Jachimowicz, J. M., S. Duncan, E. U. Weber, and E. J. Johnson (2019). When and Why Defaults Influence Decisions: A Meta-Analysis of Default Effects. *Behavioural Public Policy 3*(2), 159–186.

Klein, T., M. Kurmangaliyeva, J. Prüfer, P. Prüfer, and N. Park (2023). How Important Are User-Generated Data for Search Result Quality? Experimental Evidence.

Kwoka, J. and T. Valletti (2021). Unscrambling the Eggs: Breaking Up Consummated Mergers and Dominant Firms. *Industrial and Corporate Change 30*(5), 1286–1306.

Laffont, J.-J. and J. Tirole (1993). *A Theory of Incentives in Procurement and Regulation*. MIT press.

Madrian, B. C. and D. F. Shea (2001). The Power of Suggestion: Inertia in 401 (k) Participation and Savings Behavior. *The Quarterly Journal of Economics 116*(4), 1149–1187.

Manzini, P. and M. Mariotti (2007). Sequentially Rationalizable Choice. *American Economic Review 97*(5), 1824–1839.

Marzilli Ericson, K. M. (2014). Consumer Inertia and Firm Pricing in the Medicare Part D Prescription Drug Insurance Exchange. *American Economic Journal: Economic Policy 6*(1), 38–64.

Morton, F. M. S. and D. C. Dinielli (2022). Roadmap for An Antitrust Case against Facebook. *Stanford Journal of Law, Business Finance 27*, 268.

Motta, M. and A. Penta (2022). Market Effects of Sponsored Search Auctions. *CEPR Discussion Paper No. DP17401*.

Ostrovsky, M. (2023). Choice Screen Auctions. *American Economic Review 113*(9), 2486–2505.

Rosaia, N. (2023). Competing Platforms and Transport Equilibrium. *Working Paper*.

Spiegler, R. (2011). *Bounded Rationality and Industrial Organization.* Oxford University Press.

Statcounter (2021). Mobile Search Engine Market Share Worldwide. `https://gs.statcounter.com/search-engine-market-share/mobile/worldwide/2021` (accessed February 25, 2024).

Statista (2022). Mobile Search - Statistics & Facts. `https://www.statista.com/topics/2479/mobile-search/#topicHeader__wrapper` (accessed February 25, 2024).

Vásquez Duque, O. (2022). Active Choice vs. Inertia? An Exploratory Analysis of Choice Screens Applied in the European Microsoft Antitrust Case. *Journal of Competition Law & Economics*.

Vásquez Duque, O. (2024). Monopolization by Exploiting People's Inertia? On the DOJ's 2020 Complaint Against Google and Revenue Sharing Agreements as Non-Compete Arrangements. *UC Law San Francisco, Vol 75(4) (formerly Hastings Law Review).*

Viscusi, W. K., J. E. Harrington Jr, and D. E. Sappington (2018). *Economics of Regulation and Antitrust.* MIT press.

# A Appendix

## A.1 Reduced-Form Analysis Tables

Table A.1: Google EEA Remedy Estimates

| | (1) Google | (2) Google | (3) Google | (4) Google | (5) Google | (6) Google | (7) Google | (8) Google |
|---|---|---|---|---|---|---|---|---|
| EEA × Post | -0.377 | -0.377 | -1.614 | -1.580 | -0.545 | -0.545 | -0.968 | -0.938 |
| | (0.222) | (0.080) | (0.311) | (0.175) | (0.362) | (0.095) | (0.359) | (0.189) |
| Post 03/2020 | 0.063 | | 1.479 | | 0.231 | | 0.833 | |
| | (0.185) | | (0.260) | | (0.269) | | (0.268) | |
| EEA | 2.015 | | 3.251 | | 3.474 | | 3.897 | |
| | (0.127) | | (0.120) | | (0.207) | | (0.138) | |
| Month FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Country FE | No | Yes | No | Yes | No | Yes | No | Yes |
| R-squared | 0.100 | 0.888 | 0.104 | 0.725 | 0.091 | 0.939 | 0.094 | 0.756 |
| Observations | 3010 | 3010 | 6726 | 6726 | 3780 | 3780 | 8453 | 8453 |

Notes: The first four models include all European countries, besides Turkey, Russia, Switzerland, and Czechia. The time frame of the first two models is between April 2016 and January 2022, and is between January 2009 and January 2022 for the third and fourth models. The last four models add OECD countries. Among them, the time frame for the first two models is between April 2016 and January 2022, and for the last two models, it is between January 2009 and January 2022.

Table A.2: Google EEA Remedy Estimates (Alternative Samples & Periods)

| | (1) Google | (2) Google | (3) Google | (4) Google | (5) Google | (6) Yandex | (7) Google | (8) Google |
|---|---|---|---|---|---|---|---|---|
| EEA × Post (DD) | -1.142 | -1.113 | -0.701 | -0.701 | -0.098 | 0.137 | -0.223 | -0.775 |
| | (0.808) | (0.221) | (0.385) | (0.099) | (0.116) | (0.030) | (0.105) | (0.246) |
| Post 03/2020 | 0.862 | | 0.380 | | | | | |
| | (0.608) | | (0.287) | | | | | |
| EEA | 6.989 | | 3.631 | | | | | |
| | (0.460) | | (0.241) | | | | | |
| Yandex Pre Mkt Share | | | | | | | 18.357 | |
| | | | | | | | (16.576) | |
| DD × Yandex Pre Mkt | | | | | | | -5.446 | |
| | | | | | | | (1.706) | |
| Chrome Pre Mkt Share | | | | | | | | 0.017 |
| | | | | | | | | (0.015) |
| DD × Chrome Pre Mkt | | | | | | | | 0.006 |
| | | | | | | | | (0.004) |
| Constant | 91.742 | 96.928 | 95.113 | 97.368 | 98.279 | 0.147 | 97.384 | 96.544 |
| | (0.343) | (0.488) | (0.179) | (0.256) | (0.219) | (0.057) | (0.196) | (0.861) |
| Month FE | No | Yes | No | Yes | Yes | Yes | Yes | Yes |
| Country FE | No | Yes | No | Yes | Yes | Yes | Yes | Yes |
| R-squared | 0.179 | 0.943 | 0.092 | 0.942 | 0.912 | 0.993 | 0.889 | 0.889 |
| Observations | 1416 | 1416 | 3186 | 3186 | 1075 | 1075 | 2730 | 2730 |

Notes: The first two models include countries whose population exceeds 10 million and the time frame is between April 2016 and January 2022. All other models consider only European countries, except Turkey, Russia, Switzerland, and Czechia. The third and fourth models exclude the period corresponding to the "play choice screen" (April 2019 - March 2020). The fifth and sixth models restrict the time frame to January 2019 and January 2021, when the downloads of VPN in Russia are quite stable as shown in Appendix B.9. In the last two models, the time frame is between April 2016 and January 2022.

Table A.3: Google Russian Remedy Estimates

| | (1) Google | (2) Google | (3) Google | (4) Google | (5) Google | (6) Google | (7) Google | (8) Google | (9) Google |
|---|---|---|---|---|---|---|---|---|---|
| Russia × Post | -10.924 | -10.923 | -7.611 | -7.606 | -11.046 | -11.045 | -7.382 | -7.373 | -12.246 |
| | (0.876) | (0.423) | (1.066) | (0.610) | (1.480) | (0.624) | (1.388) | (0.750) | (0.745) |
| Post 04/2017 | 1.083 | | 0.716 | | 1.205 | | 0.487 | | |
| | (0.128) | | (0.156) | | (0.194) | | (0.182) | | |
| Russia | -31.407 | | -34.719 | | -30.420 | | -34.084 | | |
| | (0.494) | | (0.494) | | (0.834) | | (0.643) | | |
| Month FE | No | Yes | No | Yes | No | Yes | No | Yes | Yes |
| Country FE | No | Yes | No | Yes | No | Yes | No | Yes | Yes |
| R-squared | 0.653 | 0.922 | 0.542 | 0.854 | 0.337 | 0.885 | 0.352 | 0.816 | 0.961 |
| Observations | 3994 | 3994 | 5897 | 5897 | 4929 | 4929 | 7283 | 7283 | 972 |

Notes: The first four models include all European countries. The time frame of the first two models is between June 2012 and July 2019, and between January 2009 and July 2019 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 June 2012 and July 2019, and is between January 2009 and July 2019 for the rest.

Table A.4: Google Turkish Intervention Estimates

| | (1) Google | (2) Google | (3) Google | (4) Google | (5) Google | (6) Google | (7) Google | (8) Google | (9) Google |
|---|---|---|---|---|---|---|---|---|---|
| Turkey × Post | -10.574 | -10.574 | -12.343 | -12.336 | -10.761 | -10.761 | -12.349 | -12.340 | -11.049 |
| | (2.710) | (0.613) | (2.810) | (1.097) | (3.118) | (0.711) | (3.070) | (1.328) | (1.061) |
| Post 08/2019 | 0.038 | | 0.494 | | 0.225 | | 0.500 | | |
| | (0.395) | | (0.410) | | (0.409) | | (0.403) | | |
| Turkey | 0.292 | | 2.061 | | 0.998 | | 2.586 | | |
| | (1.046) | | (0.642) | | (1.203) | | (0.702) | | |
| Month FE | No | Yes | No | Yes | No | Yes | No | Yes | Yes |
| Country FE | No | Yes | No | Yes | No | Yes | No | Yes | Yes |
| R-squared | 0.008 | 0.951 | 0.004 | 0.853 | 0.004 | 0.950 | 0.003 | 0.818 | 0.949 |
| 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 August 2019 as the beginning month of the treatment.

Table A.5: Search Engine Market Share Gains

| | (1)<br>Market Share Change | (2)<br>Market Share Change | (3)<br>Market Share Change | (4)<br>Market Share Change |
|---|---|---|---|---|
| Desktop | 0.381 | 0.377 | 0.415 | 0.302 |
| | (0.026) | (0.035) | (0.023) | (0.124) |
| Domestic Search Engine | | 0.270 | | |
| | | (1.389) | | |
| Bing | | | 0.493 | 0.890 |
| | | | (0.848) | (0.166) |
| DDG | | | -0.397 | |
| | | | (0.496) | |
| Others | | | -0.408 | -0.010 |
| | | | (0.467) | (0.101) |
| Bing $\times$ Desktop | | | -0.531 | -0.418 |
| | | | (0.150) | (0.127) |
| DDG $\times$ Desktop | | | -0.113 | |
| | | | (0.669) | |
| Others $\times$ Desktop | | | -0.235 | -0.122 |
| | | | (0.779) | (0.190) |
| Constant | -0.216 | -0.213 | 0.422 | 0.025 |
| | (0.175) | (0.176) | (0.288) | (0.075) |
| R-squared | 0.732 | 0.733 | 0.835 | 0.411 |
| Observations | 79 | 79 | 79 | 60 |

Notes: Yandex is the base category in the first three models. We remove Yandex in the last model and use DuckDuckGo as the base category.

Table A.6: EEA Search Engine Market Gains

| | (1) Market Share Change | (2) Market Share Change | (3) Market Share Change |
|---|---|---|---|
| Desktop | 0.022 | 0.022 | 0.035 |
| | (0.013) | (0.013) | (0.117) |
| Consecutive | 0.023 | 0.025 | 0.027 |
| | (0.023) | (0.023) | (0.024) |
| Domestic Search Engine | | 0.184 | |
| | | (0.246) | |
| Bing | | | 0.421 |
| | | | (0.190) |
| DDG | | | -0.168 |
| | | | (0.107) |
| Others | | | -0.082 |
| | | | (0.098) |
| Bing × Desktop | | | -0.087 |
| | | | (0.121) |
| DDG × Desktop | | | 0.363 |
| | | | (0.176) |
| Others × Desktop | | | 0.150 |
| | | | (0.189) |
| Constant | 0.087 | 0.081 | 0.068 |
| | (0.050) | (0.051) | (0.069) |
| R-squared | 0.049 | 0.057 | 0.237 |
| Observations | 74 | 74 | 74 |

Notes: The dependent variable is the mobile market share change of Bing, DuckDuckGo, Ecosia, Qwant, Seznam, or Yandex in the treated countries of the EEA remedy, where the search engine won at least once in the choice screen auction. Particularly, "consecutive" is a discrete variable that measures the number of consecutive slots won during the pay-to-play period. It equals zero if there were no consecutive wins and equals the number of consecutive wins otherwise. The last column uses Yandex as the base category.

Table A.7: Number of Auctions Won OLS Estimates

| | (1) Slots Won | (2) Slots Won | (3) Slots Won | (4) Slots Won |
|---|---|---|---|---|
| Desktop Share 2020 Feb | 0.132 | 0.497 | 0.138 | 0.580 |
| | (0.026) | (0.049) | (0.026) | (0.049) |
| Mobile Share 2020 Feb | 2.608 | 0.169 | 3.046 | 0.479 |
| | (0.259) | (0.282) | (0.265) | (0.287) |
| Domestic Search Engine | | | -0.721 | 0.063 |
| | | | (0.393) | (0.328) |
| Search Engine FE | No | Yes | No | Yes |
| Country Controls | No | No | Yes | Yes |
| R-squared | 0.190 | 0.450 | 0.223 | 0.479 |
| Observations | 870 | 870 | 870 | 870 |

Notes: The dependent variable is the number of auctions won by Bing, DuckDuckGo, Ecosia, Qwant, Seznam, or Yandex in all of the treated countries of the EEA remedy. The country controls include GDP, population, the ratio of males in the population, the working age ratio, and the percentage of young people between 20 and 29 provided by the World Bank.

Table A.8: Advertisers' Response to the EEA remedy

| | (1) CPC | (2) CPC | (3) Volume | (4) Volume | (5) Revenue | (6) Revenue |
|---|---|---|---|---|---|---|
| EEA×Post | -0.010 | -0.018 | 46.844 | 29.042 | -23.062 | -43.194 |
| | (0.016) | (0.015) | (30.720) | (29.458) | (18.623) | (17.096) |
| EEA | -0.200 | | -246.200 | | -213.749 | |
| | (0.008) | | (16.370) | | (9.924) | |
| Post 2020 | 0.048 | | -2.787 | | 95.194 | |
| | (0.012) | | (23.950) | | (14.520) | |
| Year FE | No | Yes | No | Yes | No | Yes |
| Country FE | No | Yes | No | Yes | No | Yes |
| R-squared | 0.013 | 0.092 | 0.004 | 0.085 | 0.012 | 0.168 |
| Observations | 64539 | 64539 | 64539 | 64539 | 64539 | 64539 |

Notes: The time frame is between 2016 and 2022 and the control group consists of Australia, Brazil, Canada, and USA.

Table A.9: Advertisers' Response to the Russian remedy

| | (1) CPC | (2) CPC | (3) Volume | (4) Volume | (5) Revenue | (6) Revenue |
|---|---|---|---|---|---|---|
| Russia×Post | -0.129 | -0.036 | -94.406 | -182.951 | -169.241 | -117.318 |
| | (0.046) | (0.048) | (80.954) | (82.235) | (53.708) | (51.288) |
| Russia | -0.501 | | -662.725 | | -473.453 | |
| | (0.031) | | (55.422) | | (36.770) | |
| Post 2017 | 0.020 | | 162.090 | | 159.793 | |
| | (0.014) | | (25.062) | | (16.627) | |
| Year FE | No | Yes | No | Yes | No | Yes |
| Country FE | No | Yes | No | Yes | No | Yes |
| R-squared | 0.022 | 0.126 | 0.014 | 0.153 | 0.021 | 0.257 |
| Observations | 27700 | 27700 | 27700 | 27700 | 27700 | 27700 |

Notes: The time frame is between 2015 and 2019 and the control group consists of Australia, Brazil, Canada, and USA.

Table A.10: Advertisers' Response to the Turkish remedy

| | (1) CPC | (2) CPC | (3) Volume | (4) Volume | (5) Revenue | (6) Revenue |
|---|---|---|---|---|---|---|
| Turkey×Post | -0.121 | -0.163 | -88.491 | -53.794 | -136.790 | -148.774 |
| | (0.044) | (0.043) | (80.524) | (76.252) | (52.059) | (46.194) |
| Turkey | -0.569 | | -430.354 | | -504.555 | |
| | (0.028) | | (51.056) | | (33.008) | |
| Post 2019 | 0.112 | | -21.152 | | 143.080 | |
| | (0.013) | | (23.403) | | (15.130) | |
| Year FE | No | Yes | No | Yes | No | Yes |
| Country FE | No | Yes | No | Yes | No | Yes |
| R-squared | 0.031 | 0.132 | 0.005 | 0.139 | 0.020 | 0.256 |
| Observations | 27869 | 27869 | 27869 | 27869 | 27869 | 27869 |

Notes: The time frame is between 2017 and 2021 and the control group consists of Australia, Brazil, Canada, and USA.

Table A.11: Heterogeneous Effects across EEA Countries

| | (1) DiD Weighted | (2) DiD Weighted | (3) DiD Weighted | (4) DiD Baseline | (5) DiD Baseline | (6) DiD Baseline |
|---|---|---|---|---|---|---|
| Competitor Won Freq | 0.510 | 0.499 | 0.492 | 0.107 | 0.083 | 0.084 |
| | (0.139) | (0.147) | (0.148) | (0.114) | (0.118) | (0.121) |
| Mobile Share 2020 Feb | -0.236 | -0.023 | -0.491 | -1.107 | -0.840 | -0.879 |
| | (0.492) | (0.486) | (0.683) | (0.617) | (0.605) | (0.678) |
| GDP 2020 | 0.203 | | | 0.360 | | |
| | (0.119) | | | (0.188) | | |
| Population 2020 | | 0.006 | 0.009 | | 0.011 | 0.011 |
| | | (0.005) | (0.006) | | (0.008) | (0.008) |
| Young Ratio | | | 0.083 | | | 0.009 |
| | | | (0.085) | | | (0.063) |
| Constant | 0.593 | 0.557 | -1.260 | 0.441 | 0.403 | 0.201 |
| | (0.261) | (0.291) | (1.884) | (0.334) | (0.367) | (1.488) |
| R-squared | 0.525 | 0.475 | 0.514 | 0.169 | 0.116 | 0.117 |
| Observations | 17 | 17 | 17 | 29 | 29 | 29 |

Notes: The dependent variable of the first three models is the weighted DD coefficients listed in Figure A.3. The dependent variable of the last three models is the heterogeneous coefficients across countries in the baseline DD model of Equation 1.

## A.2 Inference

In this section, we focus on the standard errors used to conduct inferences about the effect of remedies. Our baseline results in Figures 4-6 report standard errors not clustered. Clustering in DD settings received criticism from Bertrand et al. (2004) due to error autocorrelation, but a host of other problems might exist. For instance, particularly relevant for our analysis of the Russian and Turkish cases is the presence of a small number of treated units which is the sort of concern addressed by the method proposed by Conley and Taber (2011).

In Table A.12, we report the results obtained by calculating the standard errors of the DD estimate under alternative methodologies. In particular, the entries in the table report the 95 percent confidence intervals (CI) obtained by replicating our baseline model with different sets of standard errors. The first row displays the CI in our baseline model, while the second row allows standard errors to be heteroskedastic. Beginning from the third row, we show the CIs when the standard errors are clustered at different levels. In the last row, we address the issues induced by the small number of the treated group as suggested by Conley and Taber (2011).

Table A.12: Standard errors

| | EEA | | Russia | | Turkey | |
|---|---|---|---|---|---|---|
| | Lower bound | Upper bound | Lower bound | Upper bound | Lower bound | Upper bound |
| Baseline | -.5330476 | -.2203131 | -11.75317 | -10.09341 | -11.77562 | -9.371411 |
| Heteroskedastic | -.5681598 | -.185201 | -13.25936 | -8.587221 | -12.55773 | -8.589304 |
| Country Clusters | -.9481051 | .1947444 | -11.33009 | -10.51649 | -10.8893 | -10.25773 |
| Country-Quarter Clusters | -.6848362 | -.0685245 | -12.84832 | -8.998261 | -12.72567 | -8.421358 |
| Country-Year Clusters | -.8481417 | .0947809 | -16.92419 | -4.922392 | -12.26222 | -8.884807 |
| Country-Year-Quarter Clusters | -.6727041 | -.0806567 | -14.85484 | -6.991744 | -12.83927 | -8.307756 |
| Year-Quarter Clusters | -.5697346 | -.1836262 | -15.18709 | -6.659495 | -13.15692 | -7.990107 |
| Conley & Taber | -.0991264 | .02879188 | -13.209387 | -8.0567951 | -13.78968 | -6.7579999 |

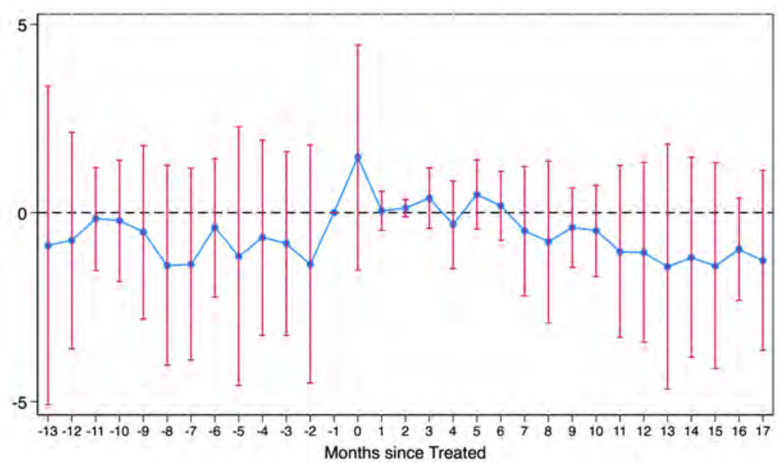
Notes: Confidence intervals (95% level) for the estimates from the regression specification of baseline models in Figures 4-6.

The results are broadly in line with those in our baseline in the main text. In particular, for the

Russian and Turkish remedies, it is always the case that the treatment effect estimated by the DD is negative ad statistically significant. For the EEA remedy, most results confirm the same evidence of the baseline estimates. In two cases ("Country Clusters" and "Conley & Taber"), the upper bound of the confidence interval is positive but very close to zero. Moreover, the interval is the EEA case is rather narrow and close to a small, negative value. Hence, the qualitative indication is the same as in our baseline of a small, negative effect of the EEA treatment.

## A.3 Heterogenous and Dynamic Treatment Effects

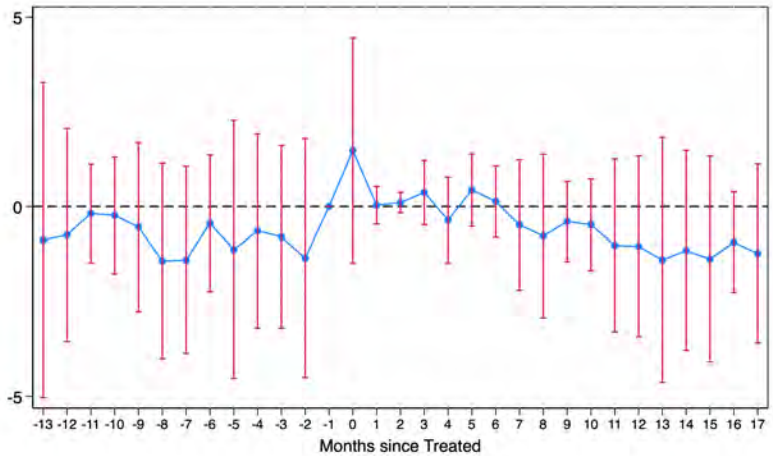
Figure A.1: Heterogenous and Dynamic Effect of the EEA Remedy (Binary Specification)




Notes: Each estimate, with its 95% CI, is the average cumulative effect of having been treated X periods ago. To the left of zero are placebo estimates testing the common trends assumption. We remove Russia, Turkey, Czechia, and Switzerland from the sample.

We estimate the effect of the EEA remedy using the methodology proposed by De Chaisemartin and d'Haultfoeuille (2024). This strategy allows us to identify the treatment effect, allowing it to be heterogeneous across countries and allowing the current outcome in each country to depend also on the past values of the treatment. The only identification assumption required is the classic common trends assumption. Our estimates from the binary treatment specification in equation (1) and from the weighted treatment specification in equation (5) are shown in Figure A.1 and Figure A.2 respectively. According to the point estimates, there are negative cumulative effects of the remedy, as do all our previous results, but they lack statistical significance. The reason for this is probably that the estimation procedure clusters standard errors at the country-period level, since data is aggregated at that level before running the bootstrap. The two models yield very close estimates of the treatment effect, with the point estimates from the weighted treatment specification being slightly more negative than those from the binary treatment specification, and with both specifications pointing to effects that build over time. The average effect across all the instantaneous and dynamic effects estimated is equal to -.4455 (SE: .6209) for the binary treatment specification and to -.6461 (SE: .8774) for the weighted treatment specification. The estimation is performed with the `did_multiplegt` package.

Figure A.2: Heterogenous and Dynamic Effect of the EEA Remedy (Weighted Specification)

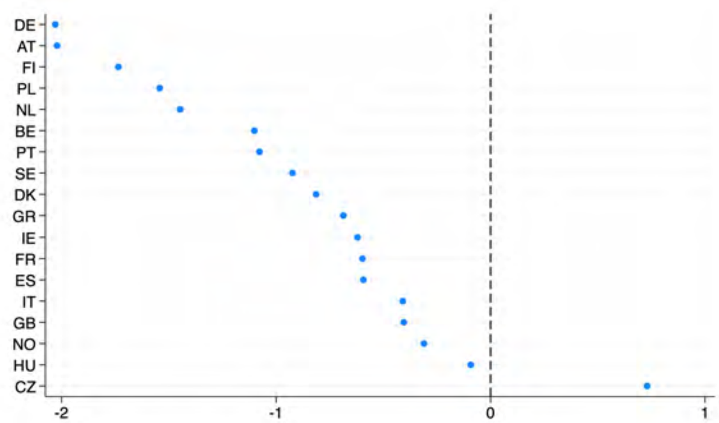



Notes: Each estimate, with its 95% CI, is the average cumulative effect of having been treated X periods ago. To the left of zero are placebo estimates testing the common trends assumption.

## A.4 Heterogeneous Effects of the EEA Remedy by Country

We estimate the weighted difference-in-differences model in equation (5) separately for each country to investigate whether the countries in our EEA treatment group show signs of heterogeneous treatment effects. The results are shown in Figure A.3.

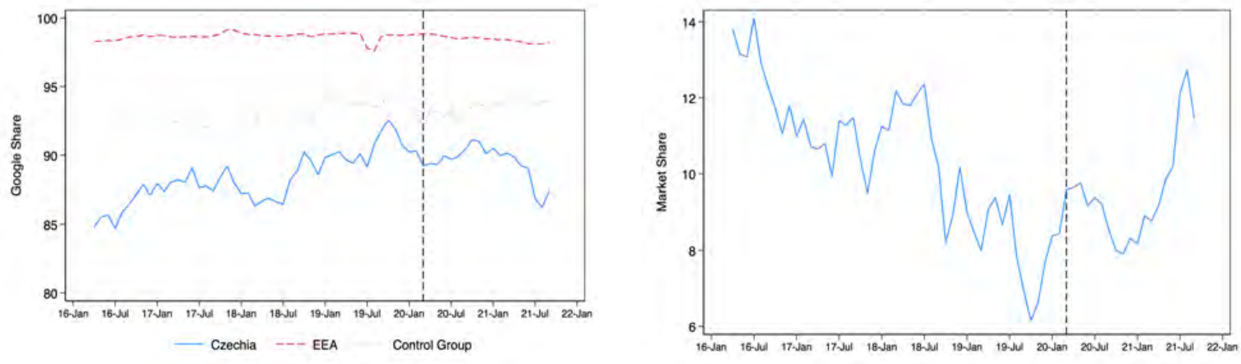
Figure A.3: Difference-in-Differences Estimates by Country




Notes: the sample used in the weighted difference-in-difference models includes Czechia, which is removed in all other analyses of the EEA remedy.

All treated countries exhibit a negative point estimate of the treatment effect, with the exception of Czechia, which seems to be an outlier. Czechia is unique compared to the other treated countries since Google is not as dominant there as it is in all other treated countries and faces competition from the domestic incumbent search engine, Seznam. As shown in Panel (a) of Figure A.4, Czechia is the only treated European country where Google's market share is lower than its average market share in the control group consisting of other European and OECD countries. As Panel (b) shows, losses in Google market shares correspond to gains for Seznam. Throughout the whole period, the market share of Google has an upward trend until the fall 2019, after which it begins declining in favor of Seznam. This reflects long-run competition between these two players in ways that we have no evidence to directly link to the EEA remedy.

Figure A.4: Mobile Market Share Trends in Czechia




(a) Google

(b) Seznam

Indeed, Seznam was established in Czechia in 1996, before Google was even founded. In addition to being a search provider, Seznam also offered products targeted specifically to the domestic Czech market. For instance, it ties a daily newspaper to its services "Seznam Zpravy", which is one of the most visited news sources in the country.[36] Among its additional services, Seznam's map program was considered very effective as it was updated daily, faster than Google's maps services in the country. Its ability to cater to a specific domestic market initially advantaged Seznam over the globally established Google.[37]

According to Seznam, around 2010 Google was able to rapidly gain market shares in Czechia because it provided unfair advantages to its own services—specifically, pre-installing its search engines on mobile devices..[38] According to Michal Feix, former chief executive of Seznam, the biggest drops in Seznam market shares came every Christmas, as users "unwrapped new smartphones with Google apps installed". In response, Seznam has made heavy investments in its products and technology since 2012, resulting in substantial innovations and market share improvements throughout 2013 and 2014. For instance, the company introduced several important additions to its services, such as Stream.cz, Lide.cz, and Email.cz, all of which contributed to an enhanced overall user experience. During this period, Seznam also innovated the presentation of search results by introducing a new interface and launched its own mobile application, enabling users to access all Seznam.cz services with just one click on the application icon.[39] The strong innovation motivation of Seznam also makes Czechia a unique case different from other countries. According to SatCounter data, the years 2014 and 2015 have seen the peak period for Seznam with a 20 percent market share on mobile search.

[36]See `https://www.digitalnewsreport.org/survey/2017/czech-republic-2017/` (accessed August 1st, 2024).

[37]See `https://www.economist.com/babbage/2014/02/24/searching-for-answers` (accessed August 1st, 2024).

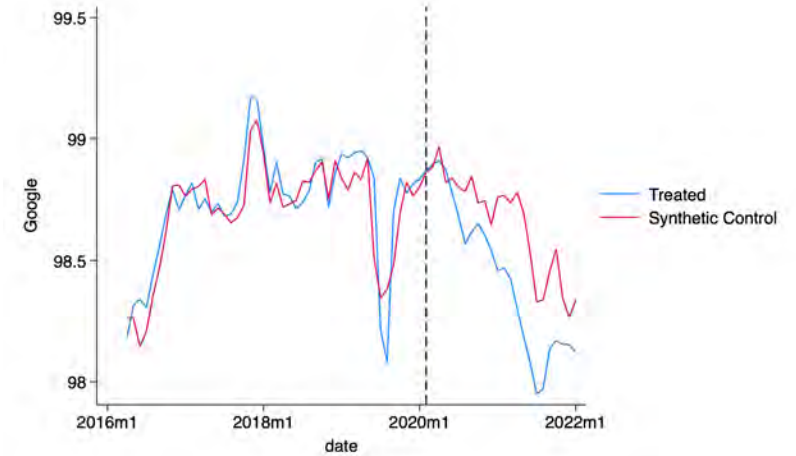
[38]See `https://www.nytimes.com/2022/02/02/technology/google-seznam-antitrust-czech-republic.html` (accessed August 1st, 2024).

[39]See `https://blog.seznam.cz/en/2013/10/seznamcz-introduces-a-new-way-of-presenting-full/` (accessed August 1st, 2024).

## A.5 Alternative Estimator: Synthetic Control

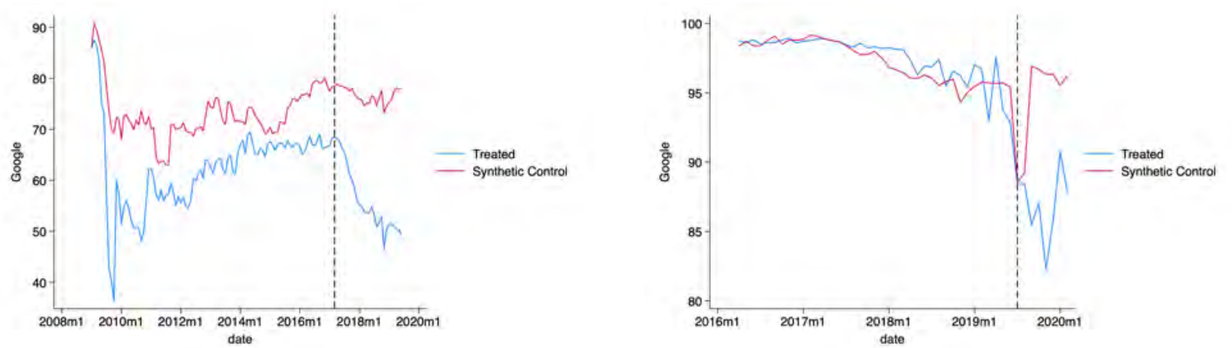
We employ the synthetic control technique proposed in Abadie et al. (2010) to identify and quantify the causal effect of the three interventions. For each one of the three antitrust remedies, we construct the synthetic group consisting of the European and OECD countries that most closely resemble the treatment group in terms of Google's pre-treatment market shares.[40] The findings are best illustrated through the following three graphs reporting the actual and synthetic treatment groups.

Figure A.5: Synethetic Control Estimator of the EEA Remedy




In particular, in Figure A.5, Figure A.6a, and Figure A.6b, we display Google's average mobile market share in the treatment group and its synthetic counterpart for the remedies in the EEA, Russia, and Turkey respectively. As clearly illustrated by these figures, the evidence obtained through the synthetic control approach is qualitatively similar to that based on the DD discussed in the main text: there is a very minor effect in the EEA (blue line falling slightly below the red line for most of the post-remedy period), and a more visible effect in both Russia and Turkey.

Figure A.6: Synethetic Control Estimator of the Russian and Turkish Remedy




(a) Russia

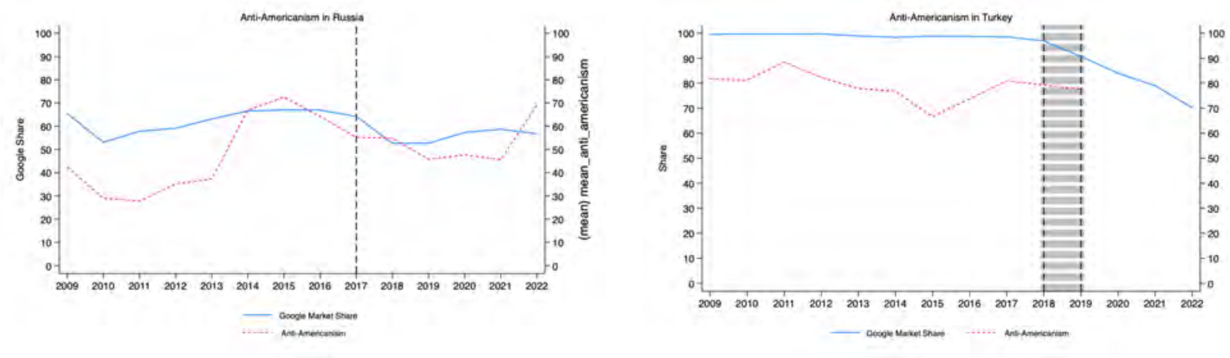
(b) Turkey

[40]We drop Vatican City and San Marino from the synthetic control analysis as there are missing observations in these countries. We also drop Czechia from the EEA analysis due to its specialty as illustrated in Appendix A.3.

## A.6 Anti-Americanism

Anti-American sentiment characterizes a nontrivial share of the population of Russia and Turkey. Changes in its intensity might partially drive changes in the Google market share if people were to associate Google and the US. To estimate whether anti-Americanism has any relevance to explain our findings, we employ survey data from the Pew Research Center (Pew) and Levada Analytical Center (Levada). Since its inception, the Global Attitudes Project conducted by Pew has interviewed over $600,000$ people across 69 countries, recording their opinions of the United States between 2009 and 2019.[41] We use the percentage of respondents who have somewhat unfavorable or very unfavorable opinions against the United States as a measure of anti-Americanism in each country. Levada, on the other hand, solely focuses on Russia, and its surveys cover a wide range of urban and rural populations across 50 regions in Russia between 1990 and 2022.[42]

Figure A.7: Anti-American Sentiment and Google Mobile Market Share




(a) Russia (b) Turkey

In Figure A.7a and Figure A.7b, we plot Google's mobile market share and the anti-Americanism measurement in Russia and Turkey respectively. In Turkey, we utilized data from Pew's Global Attitudes Project to gauge local anti-Americanism.[43] Since there are missing entries in Pew's Global Globel Attitudes Project around the introduction of the Russian choice screen, we employ the percentage of Russian respondents in the Levada survey holding negative attitudes toward the United States to measure the Russian anti-American sentiment. In both countries, the Google market share is substantially more stable than the anti-American sentiment and there is no significant correlation observed.

To investigate this relationship further, we incorporate anti-Americanism into our baseline model for Russian intervention.[44] Specifically, we utilized Pew's data to measure the degree of anti-Americanism in European and OECD countries. To account for missing values in Russia, we apply a linear regression to predict Pew's anti-Americanism value based on Levada's data and interpolate missing values accordingly. As shown in Table A.13, we find that anti-Americanism has negligible effects on the intervention's impact. As in our baseline estimates, all estimates in Table A.13 indicate a

[41] See `https://www.pewresearch.org/global/database/indicator/1` (accessed August 1st, 2024).

[42] See `https://www.levada.ru/en/about-us/` (accessed August 1st, 2024).

[43] Note that the list of countries participating in Pew's Globel Attitudes Project varies each year and is based on budget and research considerations. There are missing entries in Turkey in 2016 and 2018. In Russia, the entry in 2016 is missing.

[44] For Turkey, instead, the available data do not cover a time horizon that allows estimating a DD model.

causal decline in Google's market share induced by the Russian choice screen.[45]

Table A.13: Google Russian Remedy Estimates Controlling Anti-American Sentiment

| | (1) Google | (2) Google | (3) Google | (4) Google | (5) Google |
|---|---|---|---|---|---|
| Russia × Post | -11.595 | -11.441 | -9.024 | -12.988 | -13.338 |
| | (0.685) | (0.428) | (2.646) | (0.759) | (0.837) |
| Post 04/2017 | 1.252 | | -1.580 | | |
| | (0.208) | | (0.652) | | |
| Russia | -31.314 | | -33.995 | | |
| | (0.439) | | (2.206) | | |
| Anti-Americanism | 0.007 | -0.007 | 0.151 | -0.055 | -0.068 |
| | (0.006) | (0.007) | (0.017) | (0.013) | (0.016) |
| Month FE | No | Yes | No | Yes | Yes |
| Country FE | No | Yes | No | Yes | Yes |
| R-squared | 0.934 | 0.979 | 0.535 | 0.968 | 0.967 |
| Observations | 858 | 858 | 792 | 792 | 666 |

Notes: The time frame is between January 2013 and July 2019, during Vladimir Putin's presidency. The first two models include all European countries, the last three models add OECD countries with the last model selecting as control countries only ones whose population exceeds 10 million.

[45] Since we have very limited observations in Pew's data after the Turkish remedy, we won't be able to incorporate anti-Americanism into the Turkish baseline model due to data restrictions.

# B 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".[46] 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 the last two columns of 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).[47] 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).[48] 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.[49] From the data pattern in Figure 2, 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 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

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

[47] See `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).

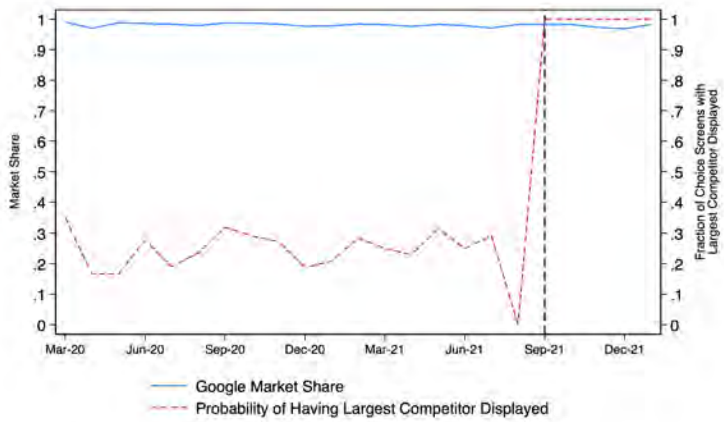
[48] See `https://blog.google/around-the-globe/google-europe/complying-ecs-android-decision/` (accessed on August 3, 2024).

[49] See `https://www.gov.uk/cma-cases/mobile-ecosystems-market-study` (accessed on August 3, 2024).

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 | -0.184 | | |
| | (0.010) | (0.028) | | |
| Yandex in Top-5 List | | | -0.102 | -0.046 |
| | | | (0.029) | (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 × Post 03/2020 | 0.041 | | 0.071 | | 0.057 | | 0.100 | |
| | (0.024) | | (0.046) | | (0.232) | | (0.043) | |
| Post 03/2020 | 0.144 | | 0.075 | | 0.021 | | -0.415 | |
| | (0.020) | | (0.039) | | (0.194) | | (0.036) | |
| EEA | 0.074 | 0.074 | -0.026 | -0.026 | -1.867 | -1.867 | -0.144 | -0.144 |
| | (0.012) | (0.012) | (0.024) | (0.026) | (0.122) | (0.120) | (0.022) | (0.024) |
| EEA × Post 09/2021 | | -0.060 | | 0.019 | | 0.282 | | 0.168 |
| | | (0.037) | | (0.084) | | (0.385) | | (0.077) |
| Post 09/2021 | | 0.297 | | 0.234 | | -0.134 | | -0.451 |
| | | (0.031) | | (0.070) | | (0.322) | | (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 January 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 January 2016 and February 2020, and from September 2021 to January 2022). The control group for all regressions is composed of European countries.

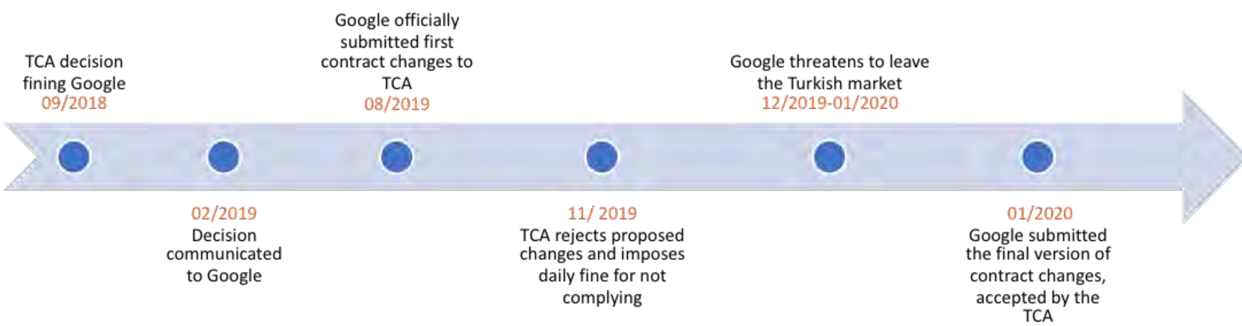
## B.2 Additional Information on the Turkish Case

**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)."[50] 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,

[50]See `https://www-aa-com-tr.translate.goog/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.[51] 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 18-33/555-273*[52]*:*

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;*

[51] Initally, 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.

[52] See `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.*

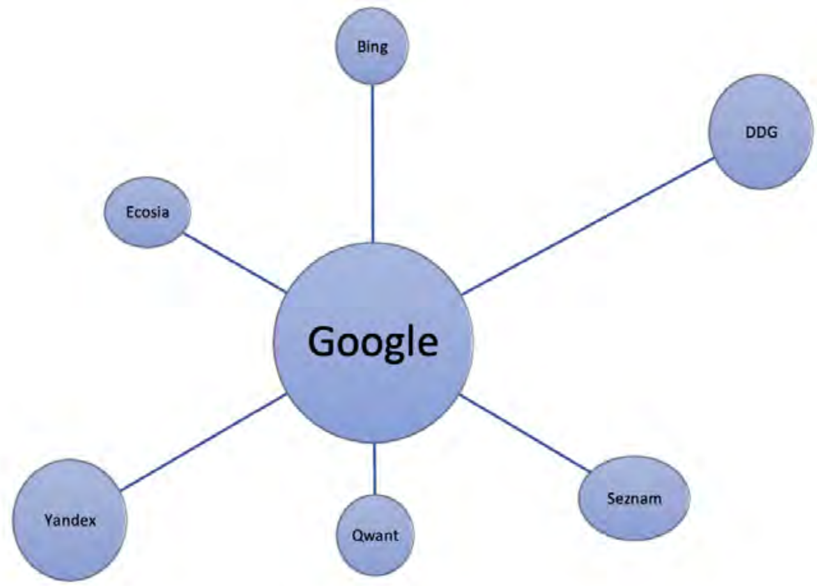
6. *It was unanimously voted that the amendments required to be made in the agreements within the framework of the aforementioned obligations shall be submitted to the Competition Authority within 6 months following the notification of the reasoned decision,*

*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 $j \in \{1, 2, ...J\}$. 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 $j \in \{1, 2, ...J\}$ 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 hoteling 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,

Figure B.3: Remedy in the European Economic Area




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.

Based on the consideration sets, users are placed on corresponding Hoteling 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 $\epsilon_{ij}$ is the idiosyncratic awareness for user $i$. We assume that each $\epsilon_{ij}$ 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 $\forall j' \in \{1, 2, ...J\} \neq j$. In this context, the probability that user $i$ chooses search engine $j$ into its consideration set equals:

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

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 $t^* \in \{1, ..., T\}$, 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; $\delta$ 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; $\gamma_i$ be the fraction of shipped devices that become active in each period; $\lambda_i$ be the fraction of Android mobile devices out of total devices; $\sigma_i$ be the number of online searches made by each active device; $\mu_i$ be the baseline market share for Google in mobile search; and $\theta$ 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:

$$dev_{it} = \underbrace{b_i \times (1 - \delta_i)^t}_{\text{remaining stock}} + \underbrace{ship_i \times \gamma_i \times t}_{\text{shipments}} \tag{7}$$

Android devices are computed as:

$$Android\_dev_{it} = \lambda_i \times dev_{it} \tag{8}$$

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

$$cs\_dev_{et} = \begin{cases} 0 & t < t^* \quad \underbrace{\lambda_e \times ship_e \times \gamma_e}_{\text{choice screendevices activated}} \times \underbrace{(t - t^* + 1)}_{\text{periodstreated}} \\ t \geq t^* & \end{cases} \tag{9}$$

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:

$$Google_{it} = \frac{[(dev_{it} - cs\_dev_{it}) \times \mu_i \times \sigma_i] + [cs\_dev_{it} \times \theta \times \sigma_i]}{\underbrace{\underbrace{[(dev_{it} - cs\_dev_{it}) \times \mu_i \times \sigma_i]}_{\text{non CS device searches}} + \underbrace{[cs\_dev_{it} \times \theta \times \sigma_i]}_{\text{CS device searches}}}_{\text{Google searches}} + \underbrace{\underbrace{[(dev_{it} - cs\_dev_{it}) \times (1 - \mu_i) \times \sigma_i]}_{\text{non CS device searches}} + \underbrace{[cs\_dev_{it} \times (1 - \theta) \times \sigma_i]}_{\text{CS device searches}}}_{\text{competitors' searches}}} \tag{10}$$

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

$$Google\_Android_{it} = \frac{[(Android\_dev_{it} - cs\_dev_{it}) \times \mu_i \times \sigma_i] + [cs\_dev_{it} \times \theta \times \sigma_i]}{\underbrace{Android\_dev_{it} \times \sigma_i}_{\text{total Android searches}}} \tag{11}$$

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

$$Google_{it} = \alpha + \beta_{\text{binary}}(Post_t \times Treat_i) + \psi Post_t + \phi Treat_i + \varepsilon_{it} \tag{12}$$

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 $\beta_{\text{binary}}$ in regression (1) 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:

$$Google_{it} = \alpha + \beta_{\text{ship}}(Post_t \times Treat_i \times Android\_ship_i) + \rho Android\_ship_i + \psi Post_t + \phi Treat_i + \varepsilon_{it} \quad (13)$$

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 $\beta_{\text{ship}}$ in regression (5) 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 $\mu_e$ and Google's selection rate from the choice screen $\theta$:

→ If users select Google from the choice screen at a lower rate than its baseline market share, the estimated treatment effect is negative: $\theta \leq \mu_e \Longrightarrow \hat{\beta}_{\text{binary}} \leq 0$ 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 ($\theta$) relative to its baseline market share ($\mu_e$). 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 ($t^* \to T$), 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 ($\delta$), the per-period shipments ($ship_e$) and the activation rate ($\gamma_e$). 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 $\lambda_e$:

→ As the fraction of Android devices falls, the two estimates will diverge more. Indeed, given our setting, $\lambda_e$ 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 ($\lambda_e \to 0$), choice screen devices are very few among overall devices, hence the effect of the remedy on overall mobile search becomes negligible, $\hat{\beta}_{\text{binary}} \to 0$. 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:

$$\hat{\beta}_{\text{ship}} = \frac{1}{\lambda_e} \times \hat{\beta}_{\text{binary}} \Longrightarrow |\hat{\beta}_{\text{ship}}| > |\hat{\beta}_{\text{binary}}| \tag{14}$$

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 $\theta$: the parameter that describes users' propensity to select Google as their preferred search engine from the choice screen.
Inverting equation (10), which determines Google's market share in overall mobile search, we can construct an estimate for $\theta$ as follows:

$$\hat{\theta} = \frac{(\overline{Google_e} \times \overline{dev_e}) - (\overline{dev_e} - \overline{cs\_dev_e}) \times \mu_e}{\overline{cs\_dev_e}} \tag{15}$$

where, on the right-hand-side, we have Google's baseline market share in the treatment group ($\mu_e$) 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 (15). 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 ($\delta$); 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 ($\gamma_i$); the share of Android devices in each group ($\lambda_i$); and Google's baseline market share in mobile search in each group ($\mu_i$).

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.[53] 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

[53]The 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 $\lambda_i$. 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 (8), 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 $\mu_i$. 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 (15).

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 5 the weighted and binary specifications yield very close estimates for the effect of the EEA remedy. This is likely due to the fact that $\theta$ is close to Google's baseline market share in the EEA. From equation (14), 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 ($\theta \to 0$), 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 5. 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.[54]

[54]The 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 Kindom | X | X | X | X | X |
| United States | | | X | X | X |

Table B.4: Testing for Parallel Trends

| | (1)<br>Google |
|---|---|
| Post 03/2020 | 0.077<br>(0.180) |
| EEA | 2.085<br>(0.297) |
| EEA*2016 Quarter2 | -0.529<br>(0.393) |
| EEA*2016 Quarter3 | -0.372<br>(0.393) |
| EEA*2016 Quarter4 | -0.079<br>(0.393) |
| EEA*2017 Quarter1 | -0.043<br>(0.393) |
| EEA*2017 Quarter2 | -0.080<br>(0.393) |
| EEA*2017 Quarter3 | -0.105<br>(0.393) |
| EEA*2017 Quarter4 | 0.276<br>(0.393) |
| EEA*2018 Quarter1 | 0.074<br>(0.393) |
| EEA*2018 Quarter2 | -0.058<br>(0.393) |
| EEA*2018 Quarter3 | 0.000<br>(0.000) |
| EEA*2018 Quarter4 | 0.022<br>(0.393) |
| EEA*2019 Quarter1 | 0.126<br>(0.393) |
| EEA*2019 Quarter2 | 0.096<br>(0.393) |
| EEA*2019 Quarter3 | -0.475<br>(0.393) |
| EEA*2019 Quarter4 | 0.001<br>(0.393) |
| **EEA*2020 Quarter1 (Treatment)** | 0.032<br>(0.397) |
| EEA*2020 Quarter2 | -0.031<br>(0.432) |
| EEA*2020 Quarter3 | -0.264<br>(0.432) |
| EEA*2020 Quarter4 | -0.286<br>(0.432) |
| EEA*2021 Quarter1 | -0.434<br>(0.432) |
| EEA*2021 Quarter2 | -0.696<br>(0.432) |
| EEA*2021 Quarter3 | -0.865<br>(0.432) |
| EEA*2021 Quarter4 | -0.725<br>(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 × Post 03/2020 | -0.346 | | -0.346 |
| | (0.088) | | (0.087) |
| EEA × Post 09/2021 | | -0.486 | -0.139 |
| | | (0.155) | (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 × Post | -6.551 | -6.551 | -7.788 | -7.781 | -6.766 | -6.766 | -7.763 | -7.753 | -6.887 |
| | (1.987) | (0.458) | (1.834) | (0.716) | (2.285) | (0.527) | (2.003) | (0.867) | (0.789) |
| Post 09/2018 | -0.036 | | 0.479 | | 0.178 | | 0.454 | | |
| | (0.290) | | (0.268) | | (0.300) | | (0.263) | | |
| Turkey | 1.226 | | 2.463 | | 1.987 | | 2.984 | | |
| | (1.229) | | (0.672) | | (1.414) | | (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 |

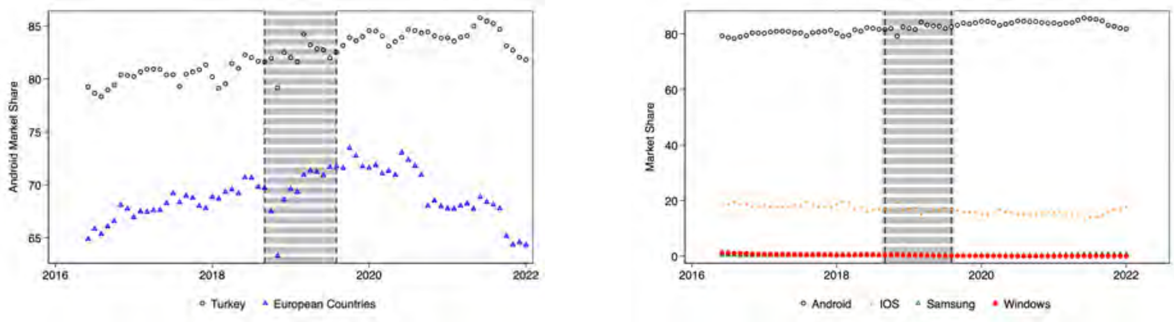
Notes: The first four models include all European countries. The time frame of the first two models is between April 2016 and February 2020, and between January 2009 and February 2020 for the third and fourth models. All other models add OECD countries, with the last one selecting as control group only 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)<br>Turkish Mobile OS | (2)<br>Turkish Mobile OS | (3)<br>Turkish Mobile OS | (4)<br>Turkish Mobile OS |
|---|---|---|---|---|
| Turkey × Post | -0.763<br>(6.003) | -0.763<br>(1.167) | -0.538<br>(6.520) | -0.538<br>(1.158) |
| Post 08/2019 | 3.633<br>(0.876) | | 3.407<br>(0.856) | |
| Turkey | 12.420<br>(2.368) | | 13.457<br>(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 April 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 × Post | -0.390 | -0.705 | -0.007 | -0.402 | 0.099 | -0.013 | 0.131 | 0.238 |
| | (0.161) | (0.185) | (0.132) | (0.152) | (0.166) | (0.075) | (0.045) | (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 January 2009 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 January 2009 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.[55]

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 × Post | -6.491*** | -6.491*** | -10.616*** | -10.617*** | -6.542*** | -6.542*** | -10.710*** | -10.709*** | -6.125*** |
| | (1.079) | (0.319) | (1.056) | (0.540) | (1.654) | (0.361) | (1.538) | (0.532) | (0.467) |
| Post 04/2017 | 0.552*** | | 0.462*** | | 0.604*** | | 0.556*** | | |
| | (0.157) | | (0.154) | | (0.217) | | (0.202) | | |
| Russia | -38.604*** | | -34.479*** | | -37.538*** | | -33.371*** | | |
| | (0.763) | | (0.602) | | (1.170) | | (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
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

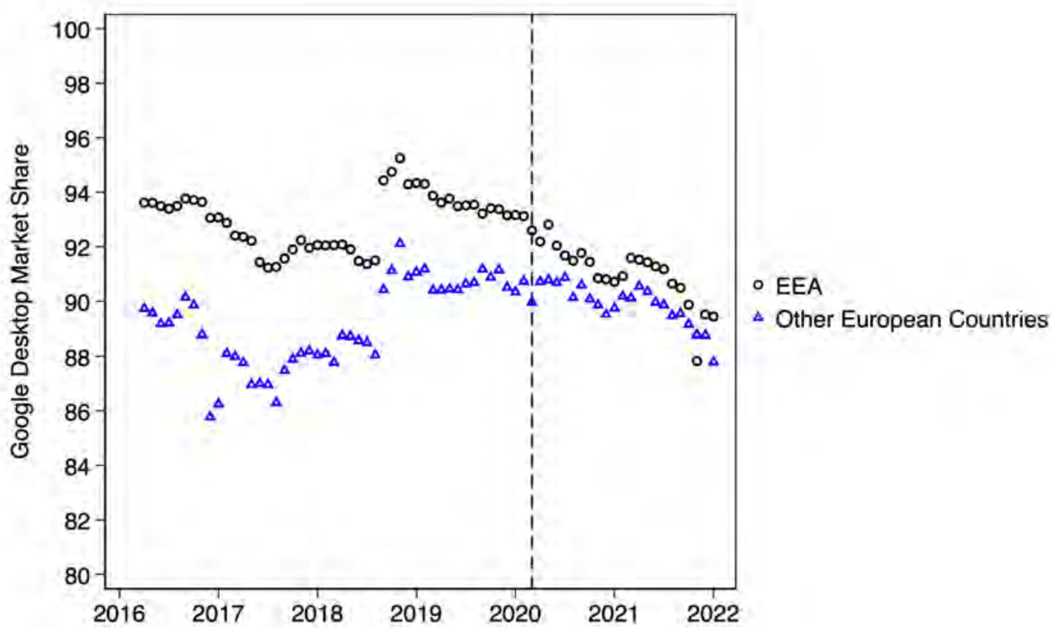
Notes: The first four models include all European countries. Among them, the time frame of the first two models is between January 2015 and July 2019, and between January 2009 and July 2019 for the third and fourth models. The last five models add OECD countries, with the last model selecting as control group only countries whose population exceeds 10 million. The time frame of the fifth, sixth, and last models is between January 2015 and July 2019, and is between January 2009 and July 2019 for the rest.

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

[55]The 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.

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




Notes: The vertical line corresponds to the introduction of the choice screen.

## 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.[56] 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.

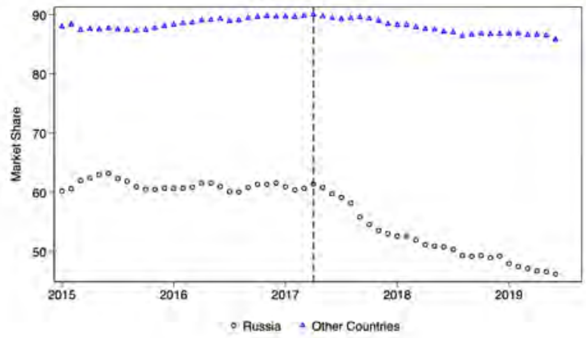
Following the same estimation strategy adopted in the main text, we first generate plots depicting Google's market share in Russia and Turkey, comparing them with other countries based on the Yandex Radar dataset. As depicted in Figure B.6, for Russia, we observed patterns similar to those discussed 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.[57]

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.

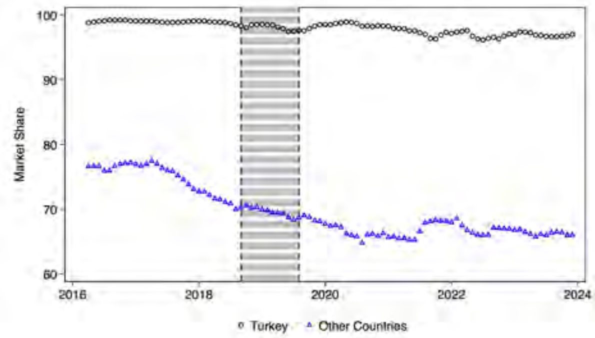
[56]See `https://radar.yandex.ru/search?period=all&group=month&country=983&device-category=5&platform=2` (accessed August 1st, 2024).

[57]See `https://yandex.com/blog/yacompany-com/new-search-traffic-and-browser-usage-analytics-tool-yandex-radar` (accessed August 1st, 2024).

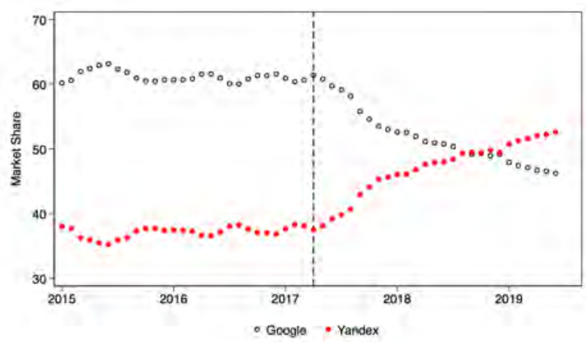
Figure B.6: Russian and Turkish Remedies



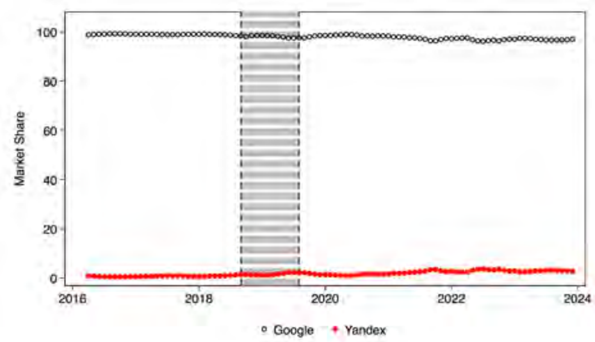

(a) Google Mobile Market Share in Russia




(b) Google Mobile Market Share in Turkey




(c) Russian Mobile Market Share




(d) Turkish Mobile Market Share

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.

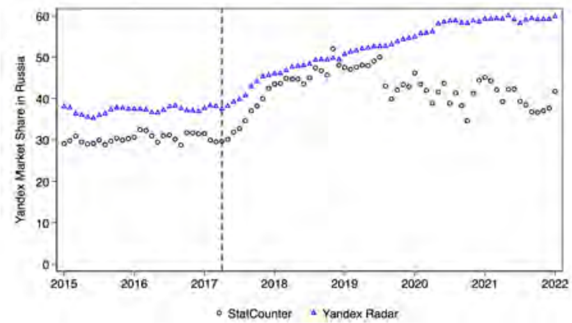
Table B.10: Remedy Estimates in Russia and Turkey

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

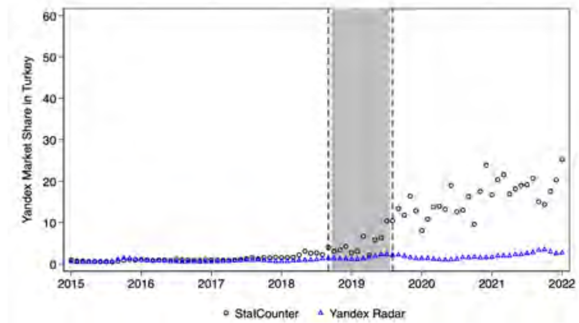
Notes: The time frame is between June 2012 and December 2023 for the first two models, and between April 2016 and December 2023 for the last two.

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.

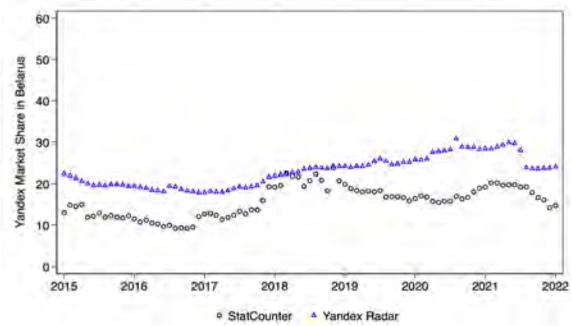
Figure B.7: Yandex Search Market Share on Mobile: Statcounter vs. Yandex Radar



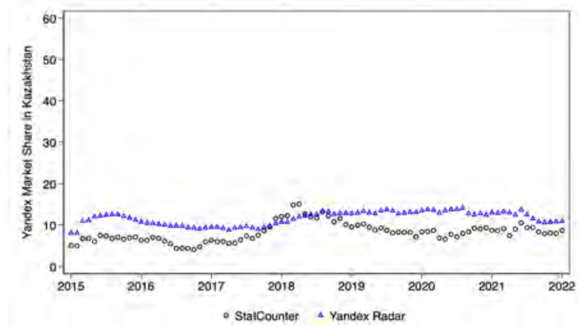

(a) Russia




(b) Turkey



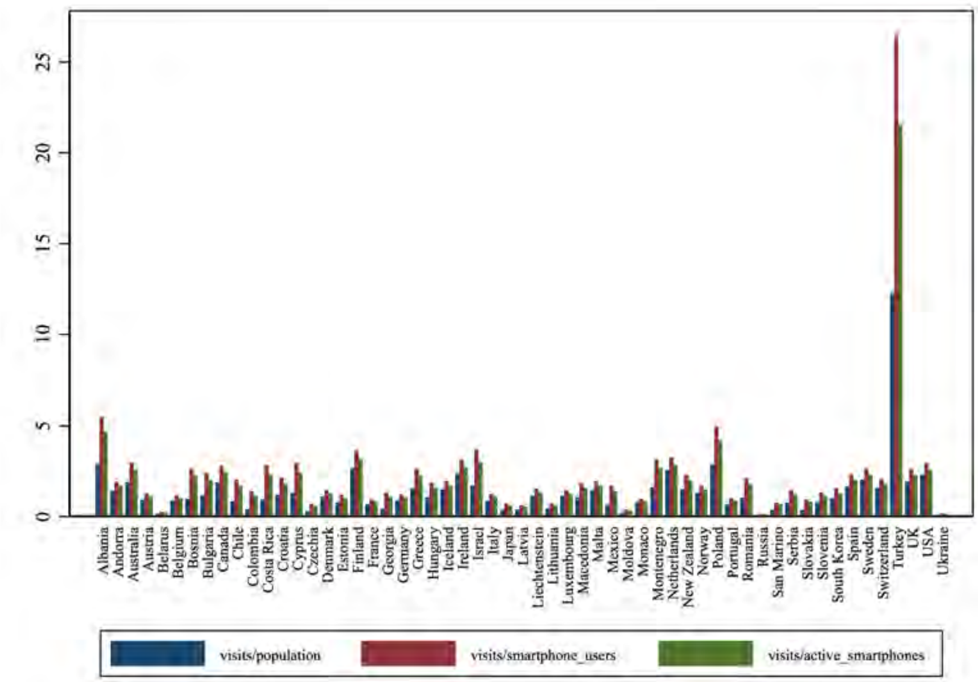

(c) Belarus




(d) Kazakhstan

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%[58]. 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.[59]

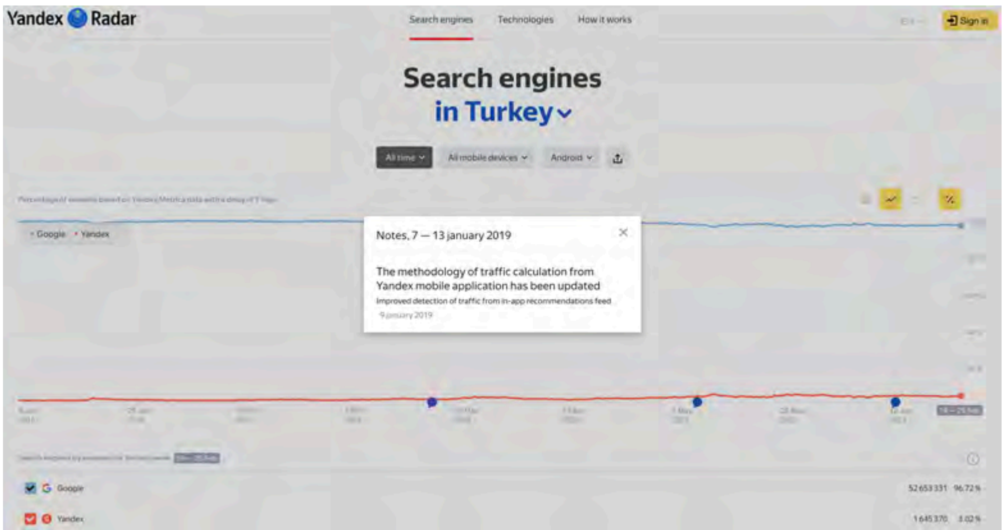
Finally, the recording of Yandex data over time might not be fully consistent. For instance, as we observe in the snapshot of Yandex Radar for Turkey mobile on Android phones reported below (Figure B.9), on at least three occasions changes to the data recording system occurred (the small

[58]See: `https://gs.Statcounter.com/vendor-market-share/mobile/turkey/#monthly-200901-202401` (accessed August 1st, 2024).

[59]The 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:

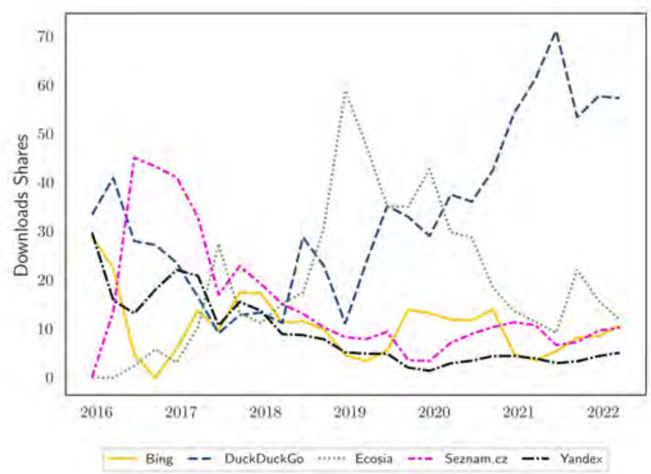
$$s_{act} = \frac{q_{act}}{\sum\limits_{i \in M} q_{ict}},$$

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.[60] 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

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

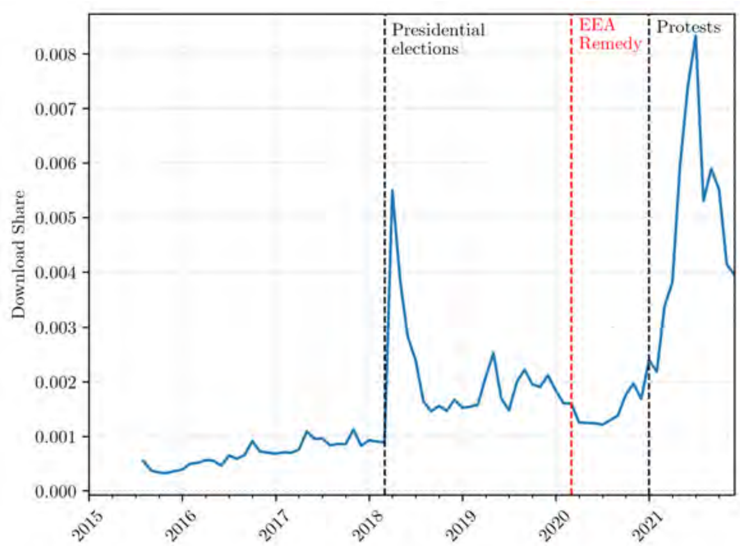
Figure B.10: EEA Competing Search Engines Download Shares




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



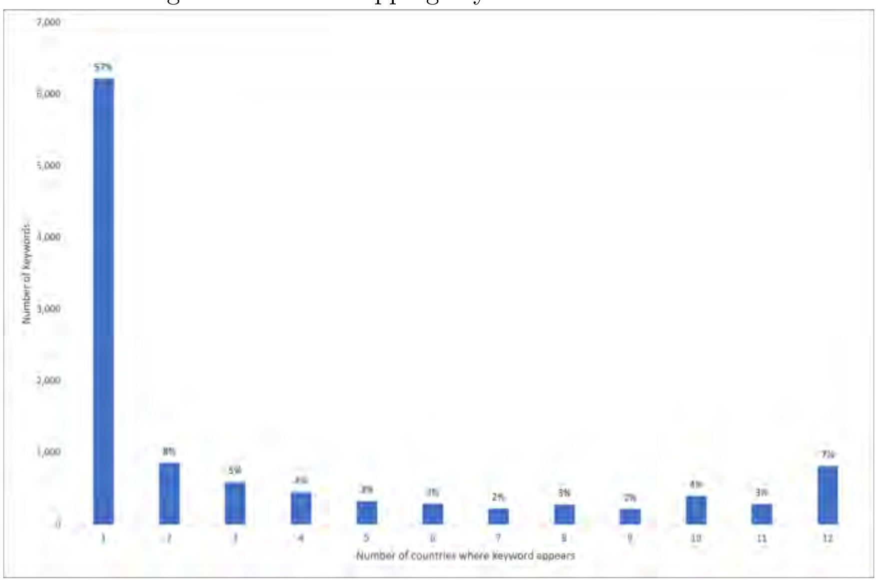

Notes: The three vertical lines from left to right correspond to (i) the presidential elections in March 2018, (ii) the EEA remedy in March 2020, and (iii) the protests in early to mid-2021.

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.[61]

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.[62] 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.

[61] For instance, users looking to find weather forecasts in the USA search for "weather", while users in Italy search for "meteo".

[62] The keywords overlapping across many countries are often ones referring to websites, such as "facebook".