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Abstract

Promoting and maintaining competition in the online markets dominated by few, large platforms has been an elusive quest for governments and their competition authorities. In this study, we offer the first systematic assessment of the quantitative effects of a series of interventions taken across countries to curb Google's dominance in search by limiting its use as the default option. By exploiting the timing with which such interventions occurred in the European Economic Area, Russia, and Turkey relative to control group countries, we study how changes to the default settings on mobile devices impacted the penetration of different search engines. Our findings show that in all of these three cases, the interventions were effective in reducing the market share of Google. The causal impact of the public intervention amounts to less than 2 percentage points in the European Economic Area, 7 percentage points in Russia, and 12 percentage points in Turkey. These differences are driven by the nuances of the specific interventions such as the size of the targeted group of users, local market characteristics, and remedy designs.

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Competition and Defaults in Online Search*

Francesco Decarolis †   Muxin Li ‡   Filippo Paternollo §

Abstract

Promoting and maintaining competition in the online markets dominated by few, large platforms has been an elusive quest for governments and their competition authorities. In this study, we offer the first systematic assessment of the quantitative effects of a series of interventions taken across countries to curb Google's dominance in search by limiting its use as the default option. By exploiting the timing with which such interventions occurred in the European Economic Area, Russia, and Turkey relative to control group countries, we study how changes to the default settings on mobile devices impacted the penetration of different search engines. Our findings show that in all of these three cases, the interventions were effective in reducing the market share of Google. The causal impact of the public intervention amounts to less than 2 percentage points in the European Economic Area, 7 percentage points in Russia, and 12 percentage points in Turkey. These differences are driven by the nuances of the specific interventions such as the size of the targeted group of users, local market characteristics, and remedy designs.

Keywords: Online Advertising, Antitrust, Platform Competition
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"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 to Restore Competition in Search and Search Advertising Markets*

1 Introduction

The advent of digital platforms is dramatically affecting the functioning of our societies. From how consumers discover and purchase products to how firms connect to consumers and other businesses, from the way workers and companies learn about each other to the way labor itself is organized. Under the new opportunities and enormous profits created by these digital platforms, there are new risks and challenges emerging for individuals, businesses, and governments. Distinguished from conventional markets, digital platforms have network effects, making dominant firms even more attractive among users. One illustrating example is the online search market, where search engines rely heavily on users' data to train algorithms and improve search quality. Consequently, search engines that already have a large number of users, like Google, carry significant comparative advantages in market competition and further accumulate a larger market share. This gives rise to the tendency for digital platforms to assume a winner-takes-all phenomenon, where the market tips to a situation of highly concentrated oligopoly or even monopoly.

In recent years, several influential policy reports have argued for the introduction of new regulations specifically conceived to address antitrust concerns in digital markets.[1] The proponents of this approach claim that for digital platforms it is inadequate to verify ex post whether they illegally altered competition according to antitrust laws. Hence, an ex ante regulatory approach is urgently needed to determine which types of practices should be forbidden. Several countries are already moving rapidly in this direction. For instance, new regulations for digital platforms will be in place in Europe starting in 2024 under the Digital Markets Act ("DMA") and Digital Sevices Act ("DSA"). At the same time, various antitrust investigation are currently ongoing, like the case *U.S. vs Google* referenced in the opening quote.[2]

Despite the heated debate and enormous efforts by regulators, there is surprisingly little evidence available on whether the proposed regulatory approach might work, and even less on what types of behaviors these regulations should either prevent or promote. To understand the potential impact of these regulations, it is useful to think about two dimensions characterizing the markets where digital platforms operate. The first is whether the market is a natural monopoly or not, while the second is 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 and 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

[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] https://www.justice.gov/opa/pr/justice-department-sues-monopolist-google-violating-antitrust-laws.

monopoly. In this case, the right tools to bolster competition will then crucially dependent on whether the platform's users have behavioral biases. To illustrate this, consider online search: if users are rational, then they cluster on the dominant search engine, Google, because of the superior quality relative to the other search engines. In this setting, regulation mandating Google to share its extensive click-and-query data with other search engines would allow these rivals to improve their own services and compete more effectively. However, if users are just locked in with Google due to a default effect, meaning that they only use whatever search engine is pre-installed on their device, then for the sake of fostering competition it would be ineffective to mandate that Google shares its data with competing search engines. What is needed, instead, is a regulatory intervention that accounts for users' behavioral biases.

This study presents the first empirical assessment of how preset default impacts competition in the market for online search. We focus on mobile search, the main market for online advertising worth €31 billion in Europe and $78 billion in the United States in 2021.[3] The market for mobile search is highly concentrated, as Google takes up to 95% of market share globally.[4] Google operates as the default search engine for most search access points on mobile devices sold to consumers:[5] as reported by the CMA, the proportion of mobile device manufacturers having Google as the default search engine was over 99% in the UK in February 2020.[6] Google is willing to pay large amounts to device manufactures to occupy the default position on their devices. The DOJ antitrust complaint against Google showed that in exchange for being the default search engine on Apple products, Google pays Apple around 8–12 billion dollars each year, a figure that makes up approximately 15–20 percent of Apple's worldwide net income.[7] In 2019, Google paid Apple and other device manufacturers around £1.2 billion in the UK alone for being the preset default.[8]

We study multiple interventions whose goal is to remove restrictive terms put in place by Google to limit the pre-installment of competing search engines as default on Android mobile devices. Scholars like Scott Morton and Dinielli (2020) have already argued that its role as the preset default is a key pillar of Google strategy to maintain dominance in search, and the ongoing DoJ investigation on Google is founded upon the same view. But no previous study has quantified the impacts of the existing regulatory interventions on mobile devices to open competition for being the preset search default. We study three related but different policies implemented in Russia, the European Economic Area (EEA) and Turkey. In Russia, a choice screen is provided to all Android users so that they can choose their default search engine between Google, Mail.ru, and Yandex. In the EEA[9], a similar choice screen is introduced, but it is accessible only during the initial setup of

[3]See the mobile advertising 2021 key figures here: https://www.statista.com/topics/2479/mobile-search/#topicHeader__wrapper.

[4]See https://gs.statcounter.com/search-engine-market-share/mobile/worldwide/2021.

[5]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 that is initially associated with these access points on devices sold to consumers as the "default" search engine.

[6]The remaining 1% involves devices that for which the CMA was unable to determine the default search engine. See https://www.gov.uk/cma-cases/online-platforms-and-digital-advertising-market-study.

[7]As pointed out by the Digital Regulation Project of the Tobin Center for Economic Policy, Google can leverage its market power into a monopoly position in mobile search through several approaches, including occupying exclusive default positions on mobile devices, controlling home screen design through pre-installation of a series of Google apps, restricting "forked" Android versions, or bundling its critical apps. See https://www.justice.gov/opa/press-release/file/1328941/download.

[8]See https://www.gov.uk/cma-cases/online-platforms-and-digital-advertising-market-study.

[9]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.

new Android devices and features a regularly changing list of search engines for users to choose from. In Turkey, a different approach has been implemented to alter the default role of Google: the Turkish Competition Authority mandated changes to the contracts between Google and mobile phone manufacturers to ensure their freedom in negotiating the default search engine.

Through the evaluation and comparison of these three highly related but distinct interventions, our paper empirically analyzes the effect of the default option on competition and investigates potential determinants of regulation effectiveness in the online search market. We exploit 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. Based on these data, we 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 the market share and advertising revenues of Google, allowing competitors to gain a larger share of the market. The extent of this reduction, however, varies drastically across policies. The decrease in Google's mobile market shares amounts to less than 2 percentage points in the EEA, about 7 percentage points in Russia, and about 12 percentage points in 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 remedies. Our results indicate that search engines with higher brand awareness and popularity in the local market have higher chances of gaining market shares when made available to users via a choice screen. Furthermore, within the EEA, we find that these search engines also have stronger motivation to gain a slot in the choice screen.

We conclude the study by analyzing two counterfactual designs of the EEA remedy. First, we simulate what the EEA would have experienced if the choice screen had been made accessible to all Android mobile devices. 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 estimates 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 the market share of Google would have declined if the top rival had always been displayed in the EEA choice screen. Assuming the top rival in each country always got a slot in the choice screen, our model predicts that the market share of Google 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.

Our findings represent a threefold contribution. First, they offer systematic evidence of how the default effect influences competition in the online search market. Numerous papers have emphasized the importance of default options, but most of them focus on traditional markets, such as that for health insurance. By analyzing three distinct interventions that aim at removing Google's pre-installation as the default search engine on Android mobile devices, 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), and Motta and Penta (2022)), our paper offers new insights into users' choice *across* heterogeneous search engines, making it more relevant for recent antitrust and privacy concerns emerged in digital markets. In this respect, Farronato et al. (2020) and Rosaia (2020) are related to use in that they consider the problem 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. We also show the determinants of this varied effectiveness. The effect of a specific remedy depends on its design, on the preferences of local users, and on local rivals' characteristics. More specifically, factors such as whether the policy focuses more on the user side or the device manufacturer side, the difference in market shares and popularity between Google and its rivals in the local market, and whether there exist challengers who are motivated to replace Google as the default, all affect the outcome of a policy intervention aimed at bolstering competition in the market. Complementary to a small number of recent studies that have also looked at online search regulation but mostly focused on the EEA choice screen mechanism design (Ostrovsky, 2020), our study provides new insights into how and why users and competing search engines respond to interventions in the online search market. Indeed, Ostrovsky (2020) provides a model of the auction format used to allocate slots in the choice screen adopted in the EEA. Our analysis is different both for its empirical focus and because it looks at the usage of search engines rather than the outcomes of the EEA choice screen auctions. As it will be discussed below, this is important to understand why, despite the pitfalls in the auction design highlighted by Ostrovsky (2020), the increase in usage of search engines other than Google that we measure benefited viable competitors and not merely search engines that exploited weaknesses in the design of the auction.

The third contribution regards the policy lessons that can be learned from the three remedies. Interventions involving consumer choices via a choice screen can hardly have impacts on online search market competition, unless there is a qualified challenger who can compete with Google in quality (like Yandex in Russia) or a rival who 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 against 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.

Literature This study is related to several branches of the literature. First of all, we contribute to the rapidly evolving literature on the economics of digital markets. The industrial organization literature has stressed that the presence of network externalities, paired with dynamic scale economies, significantly raises the entry barriers in digital markets and creates a tendency for competition to assume a winner-takes-all form, where the market tips to a situation of highly concentrated oligopoly or even monopoly (see, among others, Dubé et al., 2010; Belleflamme and Peitz, 2018; Calvano and Polo, 2021). 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 this work, we focus on antitrust remedies imposed following pre-installation practices that effectively resulted in the abusive tying of Google's mobile search engine with its Android operating system. In fact, 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. In a recent contribution to this field, Choi and Jeon (2021) develop a theory of tying in two-sided markets. The authors show how tying provides a mechanism for a monopolist to leverage its monopoly power to monopolize another market where it faces competition. They show Google has strong incentives to tie as by doing so it denies scale to rival search engines, possibly leading to the exclusion of (more efficient) competitors.

Competition authorities worldwide have brought antitrust investigations against Microsoft and, more recently, against Apple, Amazon, and Google, inducing further research and discussions by scholars. Our work is particularly related to the studies that examine the choice screen imposed on Microsoft in 2010 in the EEA, following a case of abusive tying of Internet Explorer with Windows. Economides and Lianos (2010) discuss the remedy implemented by the European Commission and compare it to the remedy that had been previously imposed on Microsoft following the case of abusive tying of Windows Media Player with Windows, while Vásquez Duque (2021) performs an exploratory analysis to quantify the effects of the choice screen on browser market shares. Instead of the browser market, our paper focuses on the choice screen in online search, a complicated, essential, and economically relevant market for antitrust analysis.[10] A recent paper by Ostrovsky (2020) conducts a theoretical analysis of the auction mechanism characterizing the initial implementation of the choice screen adopted by Google in the EEA. It shows that the "pay-per-install" auction design favored search engines that rather than focusing on their product's quality, maximize their surplus from each user. Therefore, the auction design in the EEA remedy would allow low-quality search engines to win frequently at the expense of higher-quality rivals, who do not monetize their users as aggressively.

The second branch of the literature to which we contribute is that on behavioral economics. Indeed, 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 related to our work are the ones investigating the impact of default options on consumer choices (see Jachimowicz et al., 2019). Beshears et al. (2018) define the status quo bias (or default bias) as a behavioral bias that occurs whenever there is a preference for the current state of affairs and lists several mechanisms that make default options powerful.[11] Spiegler (2011) defines an additional bias that makes default options overly influential: inertia. Inertia occurs at an earlier stage of the decision process, such that the consumer fails to get to the stage where she actually applies a preference ranking to the available alternatives.

Numerous empirical studies have attempted to quantify the market effects of defaults. Most of these contributions focused on health insurance markets, showing that inertia creates differences in the health insurance plans that individuals have depending upon what plans were offered when they joined their current company (See Madrian and Shea (2001), Handel (2013), Chetty et al. (2014), Chetty (2015), and Ho et al. (2017)) Marzilli Ericson (2014) shows that firms respond to inertia by raising prices on 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 to identify 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.

[10]The existing studies on online search have mostly focused on online advertising selling mechanism (See Edelman et al. (2007), Varian (2007), Athey and Nekipelov (2010), Börgers et al. (2013), and Celis et al. (2014)), and their effectiveness (See Goldfarb (2014), Johnson et al. (2017), Simonov et al. (2018) and Golden and Horton (2021)).

[11]Among the mechanisms they list there are other known behavioral biases such as loss aversion and cognitive dissonance.

2 Institutional Background

2.1 Search Engines

The market for online search is a typical multi-sided market, connecting users wishing to surf the web and advertisers wishing to attract eyeballs. Search engines supply links to content from the internet to users in response to their search queries. To do this, search engines index data from the public web and proprietary sources and return relevant content - ranked by an algorithm - to the user who is searching for information. In exchange for their services, search engines extract data and attention from users. Advertisers seeking to target consumers then pay search providers to display their ads, allowing search engines to provide their services without financial compensation from users. In past decades, the mobile search market has experienced tremendous growth due to the rapid adoption of smartphones. In 2021, mobile advertisement revenues accounted for over 135 billion dollars, a figure that is more than double the revenues earned by desktop advertisements.[12] Google virtually monopolizes the search market, holding almost the entirety of the market. But Google is not the only search engine available to consumers. Competitor search engines differ along many dimensions: some pursue social causes, such as Ecosia and Panda Search, while others pride themselves on their strong protection of user privacy, such as DuckDuckGo. Some search engines focus on the local market, such as the French search engine Qwant and the Czech search engine Seznam.cz, while others with global reach are also different in their geographical presence. Google, Bing, and DuckDuckGo are all based in the USA, while Yandex[13] is instead based in Russia. Among them, 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 is 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 those on both Apple and Android mobile devices. According to a CMA Report[14], other search engines are likely to have to offer at least as much financial compensation as Google in order to win a default contract, while Google, given its high popularity among users, can always generate more queries than the other search engines. Therefore, it becomes extremely difficult for a search engine to offer as much financial compensation as Google can and win the default position. The report concludes that the positive feedback loop between Google's position as the largest and most revenue-generating search engine and its ability to acquire default positions generates entry barriers other search engines can hardly conquer. This phenomenon has raised regulatory concerns, arising from the apparent lack of a level playing field. Since 2017, the company has been accused respectively by the competition authorities in Russia and Turkey, and by the European Commission, of imposing illegal contractual restrictions on Android device manufacturers and mobile network operators.

[12]See `https://www.iab.com/wp-content/uploads/2022/04/IAB_Internet_Advertising_Revenue_Report_Full_Year_2021.pdf`.

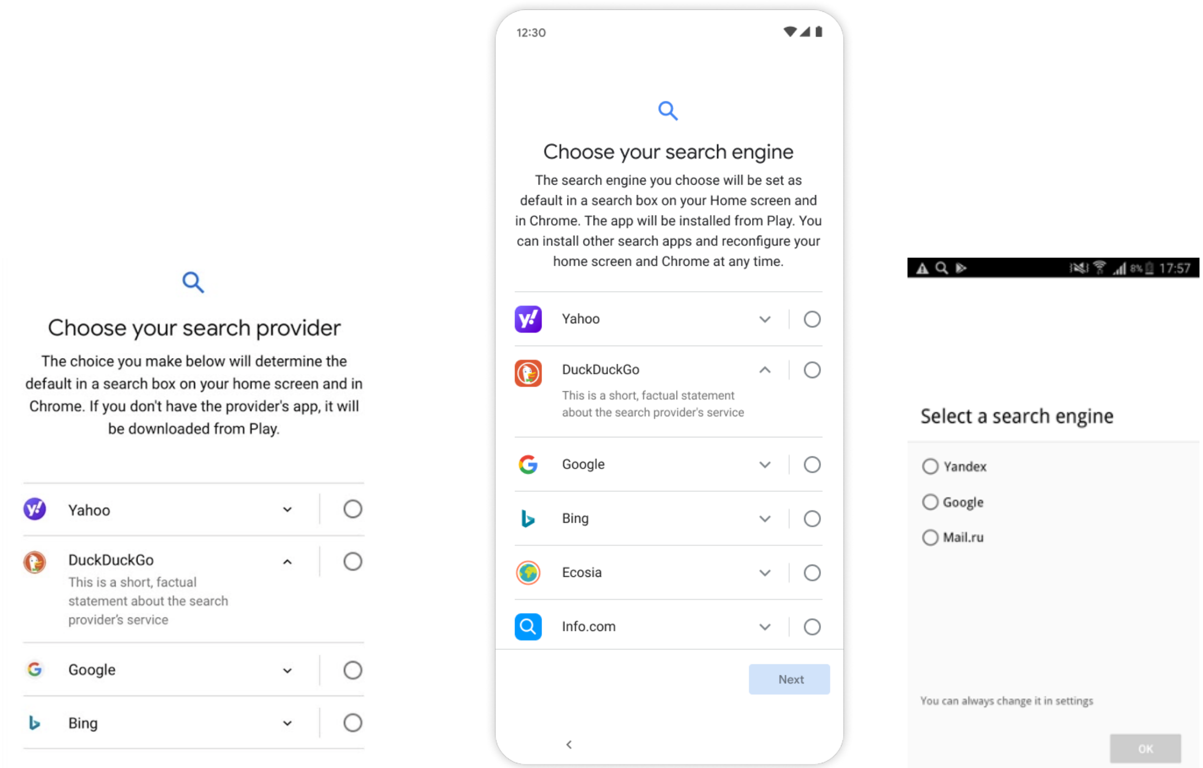
[13]Yandex has two separate domains: `https://yandex.ru/` and `https://yandex.com/`. Throughout the paper, we consider these two domains to form a single search engine.

[14]See `https://www.gov.uk/cma-cases/online-platforms-and-digital-advertising-market-study`.

2.2 Remedy in the European Economic Area

In July 2017, the European Commission ("EC") fined Google 4.34 billion euros for offering the Play Store, the Search app, and the Chrome browser as a bundle (Google Mobile Services) to mobile manufacturers in the European Economic Area.[15] The tying between Play Store and Search app basically 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 reduced not only the incentive for users to download competing search apps, but also discouraged manufacturers from pre-installing such apps. Thus, the EC concluded that Google's conduct had distorted market competition and negotiated with Google to implement a reform to address these competitive 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 European Economic Area 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 of four different providers. Choosing a search 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 an auction, conducted quarterly and separately for each EEA member state. During

[15] See `https://ec.europa.eu/commission/presscorner/detail/en/IP_18_4581`.

the auction, search providers 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 auction-based choice screen implemented in the EEA as the "pay-to-play" choice screen.

The "pay-to-play" remedy received considerable questions and complaints after its implementation. Search providers[16] and researchers (Ostrovsky, 2020 and Kwoka and Valletti, 2021) also expressed concerns that the auction mechanism favored search engines that exacted high value from customer data while pricing out alternatives whose business models address broader 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.[17]

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 from the choice screen without having to pay Google. Additionally, twelve search providers, instead of four, could appear on the new choice screen. Among them, the five most popular eligible general search engines[18] 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 the most popular five search providers, up to seven additional search engines can appear on each country's choice screen. These last seven search providers are chosen randomly and are listed in random order.[19]

2.3 Remedy in Russia

A similar antitrust investigation resulting in a choice screen for mobile search providers occurred in Russia. In April 2017, Russia's Federal Antimonopoly Service ("FAS") agency fined Google 438 million roubles[20] for violating the antimonopoly legislation. The abuse revolved around Google prohibiting the pre-installation of the competing mobile applications of other developers.[21] The FAS determined that Google's conduct constituted an abuse of dominance that distorted market competition. To restore competition, the FAS requested Google to (i) remove the exclusivity of Google applications on Android-based devices in Russia; (ii) stop restricting the pre-installation of

[16] 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/`.

[17] See `https://ddg-staticcdn.s3.amazonaws.com/press/2110_Search_coalition_letter_calling_on_a_default_ban_in_DMA.pdf`.

[18] The top five search providers are determined each year by their market shares, estimated with StatCounter data.

[19] 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.

[20] Amounting to just over 7.2 million euros at the April 2017 exchange rate, available at `https://www.ecb.europa.eu/stats/policy_and_exchange_rates/euro_reference_exchange_rates/html/eurofxref-graph-rub.en.html`.

[21] 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`.

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 into 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 devices that had been 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.[22] For new devices sold in Russia after August 2017, a new widget was developed where users could select their preferred search engine from a new choice screen at the first launch.

2.4 Remedy in Turkey

In Turkey, no choice screen appeared on mobile devices as in the EEA or Russia. However, the Turkish Competition Authority also investigated and ultimately sanctioned Google for its restrictive terms imposed on original equipment manufacturers. The investigation in Turkey dates back to 2015 when Russian search engine Yandex first initiated a complaint. In September 2018, the TCA imposed a fine of TRY 93 million[23] 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 at the conditions of having the manufacturers pre-install Google as the default search engine and place 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.[24]

To restore competition, the TCA required Google to modify its contracts with device manufacturers wishing to adopt the Commercial Android Operating System in their devices produced for sale in Turkey, to satisfy the following conditions[25]: (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 provider of the search widget to be placed on the home screen from Google or its competitors, and establishing the freedom of device manufacturers to place non-Google search widgets on the home screen on their own; (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[26] 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

[22] See `https://en.wikipedia.org/wiki/Google_Chrome_version_history`.

[23] Amounting to just over 12.5 million euros at the September 2018 exchange rate, see `https://www.ecb.europa.eu/stats/policy_and_exchange_rates/euro_reference_exchange_rates/html/eurofxref-graph-try.en.html`.

[24] See `http://competitionlawblog.kluwercompetitionlaw.com/2018/11/05/google-fined-this-time-by-the-turkish-competition-watchdog/`.

[25] See `https://www.rekabet.gov.tr/en/Guncel/investigation-on-google-llc-google-inter-60928a8075bde81180e300505694b4c6`.

[26] 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 for apps to show web content.

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. Additional information of the TCA case are provided in Appendix A.1

In August 2019, Google modified its contracts with mobile manufacturers. However, these efforts were considered unsatisfactory as they continued to prohibit changes to the devices' default search engine.[27] In November 2019, the TCA imposed a daily fine on Google at a rate of five per ten thousand of its turnover generated in Turkey until the search engine addressed the outstanding issues.[28] 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.[29] On January 9, 2020, Google ultimately 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 both Google and any other competing search providers for access to the valuable search access points on mobile devices.[30] Parallel to the Google Android case, the TCA also went through an investigation against Google's illegal practice in Shopping comparison service during the same period.[31] To respond to the TCA's decision about Google shopping made on February 13, 2020, Google removed its own online shopping comparator, a critical service on Google search.

3 Data

To investigate the impact of the three remedies, we combine data from various sources, allowing us to measure in each country in a given period search engine market shares, the number of shipped devices, the total number of smartphone users, search engine app downloads, and outcomes from Google's sponsored search auctions.

3.1 Data Description

The data on search engine market shares come from StatCounter, a traffic analysis service that records more than 10 billion page views each month.[32] On the "free-to-play" choice screen, the list of most popular search engines is determined by their estimated market shares on StatCounter. To the best of our knowledge, there is no other publicly available service providing market share stats that have a bigger sample size than StatCounter. The data covers monthly market shares of

[27]See https://www.theverge.com/2019/12/16/21024311/google-android-phone-turkey-antitrust-default-search.

[28]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.

[29]See https://www.haberturk.com/google-den-yaptirim-tehdidi-turkiye-de-android-pazari-patlayabilir-2549571.

[30]See https://www.lexology.com/library/detail.aspx?g=45dff3f3-e408-4634-8b19-4ed74d23236c.

[31]See http://competitionlawblog.kluwercompetitionlaw.com/2020/09/17/google-removes-display-of-its-shopping-unit-in-turkey-after-the-remedy-phase-of-the-turkish-competition-authoritys-tca-google-shopping-decision-gets-stuck/.

[32]From each of these page visits, StatCounter records the browser, operating system, 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 and this widespread penetration has made its data a point of reference in the industry. The EEA "free-to-play" remedy uses StatCounter data to determine search engine market shares and, accordingly, to decide which search engine will be part of the choice screen.

76 search engines over 238 countries from January 2009 onwards. We collect data up to January 2022, resulting in $101,826$ observations. StatCounter collects data on all the main search engines, including Google, Yahoo!, Bing, Baidu, Yandex, Ecosia, Seznam, DuckDuckGo, and so on.[33] Based on the StatCounter dataset, we are able to observe the usage of search engines in each country on three platforms: desktop, mobile devices[34], and tablets. We are particularly interested in mobile devices as these are the main targets of the three interventions.

Besides market shares, we also employ Gartner's data and Newzoo's data to measure the number of new and existing mobile phones. In particular, 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.[35] Precisely, Newzoo's data consist of annual measures of population, smartphone users, and active smartphones in 194 countries from 2016 to 2021. Newzoo collects global monthly device usage data from strategic partners and provides figures for the number of total smartphones and tablets actively used in each country. Taken together, these two data sources endow us with detailed information on the evolution of the stock of active mobile devices in each country. In addition, 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 countries.[36]

Further, we compute a measure for search engine consumer protection based on the amount of privacy protection that the search engine guarantees to its users: the more the search engine protects its users the higher its consumer protection score. Scores are computed from inspection of the official websites and privacy policies of each search engine and are estimated as of July 2020, at the time of the second EEA choice screen auction. The scoring adopted are in line with the RDR Corporate Accountability Index, where we include the sub-indicators that relate to user information (P3-P9). Major search engines, like Google, Yandex, and Bing, are included in the RDR Corporate Accountability Index. We estimate the scores according to the same methodology for the remaining search engines.[37]

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 volume of searches in a given country at a given point in time. Since the product of CPC and volume provides a proxy for the revenue earned by Google on 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 covers the most searched keywords in twelve different countries, with each country having its own list of popular keywords.[38] Six of the countries we consider are EEA countries (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. Given that the three remedies we study occur at different times, to guarantee that at least

[33]StatCounter does not collect the market share of search engines whose market share is extremely small, thus we treat the missing market shares as zero correspondingly.

[34]Precisely, StatCounter has all pocket-sized competing devices included in mobile devices.

[35]Devices are distinguished into eight categories: basic phone, premium phone, desk-based, notebook, ultramobile basic, ultramobile premium, ultramobile utility, and utility phone. The dataset also has a less granular variable that splits devices into three broader categories: phone, UMT, and PC.

[36]Apptweak implements a machine learning model where the app's daily downloads are estimated from information on the app's category rank and date.

[37]See `https://rankingdigitalrights.org`.

[38]See Appendix A.2 for more details on the keywords forming our sample.

two years of data are present before and after each remedy, we collect data for the 2016-2022 period for EEA and control countries, for the 2015-2019 period for Russia and the 2017-2021 period for Turkey, resulting in a final sample of $69,148$ 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 the change in average market shares in the treated countries compared to control countries corresponding to the three policies we wish to study. The control group consists of all European countries besides the treated ones, that is, all European countries that are not members of the European Economic Area (excluding the UK).[39] 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 are heterogeneous, with the Russian and Turkish remedies being associated with larger drops in Google's market share than the EEA. Moreover, we also find that each remedy has quite differentiated effects on competing search engines, with Yandex seeming to be the biggest winner. Based on the Apptweak data, we also investigate the download dynamics for competitor search engines in the EEA in Appendix A.3 and find similar patterns.

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

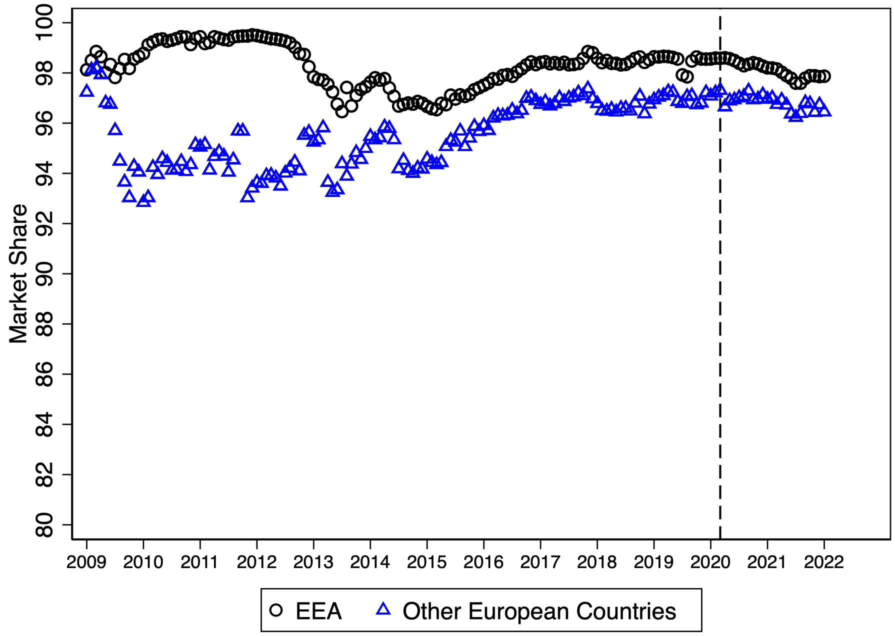
		EEA		Russia		Turkey	
		Treatment	Control	Treatment	Control	Treatment	Control
Google	Before	98.50	95.75	67.07	94.54	96.82	95.38
	After	98.19	95.59	57.99	95.23	86.54	95.79
Bing	Before	0.30	0.34	0.44	0.46	0.13	0.30
	After	0.41	0.40	0.29	0.29	0.47	0.34
DDG	Before	0.28	0.25	0.06	0.06	0.02	0.16
	After	0.37	0.39	0.11	0.13	0.09	0.30
Yandex	Before	0.13	1.08	30.68	1.02	2.80	1.07
	After	0.20	1.07	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 countries besides the treated ones.

We move to a visual inspection of search engine market share trends. In Figure 2, we plot Google's average market shares in both the EEA and the rest of the European countries (except Russia and Turkey). The dashed line corresponds to March 2020, when the "pay-to-play" remedy first started. From visual inspection of the graph, there appears to be a decline in Google's market share in the EEA that is slightly more pronounced than that in the control group countries, but this difference appears rather small, of the order of 1 percentage point. Interestingly, we observe a drop in the EEA market shares from April 2019 to August 2019 corresponding to the implementation of the "Play choice screen" which is discussed in Appendix A.4.

[39]See the list of treated and control group countries in Table A.1 of Appendix A.5.

Figure 2: Google Mobile Market Share



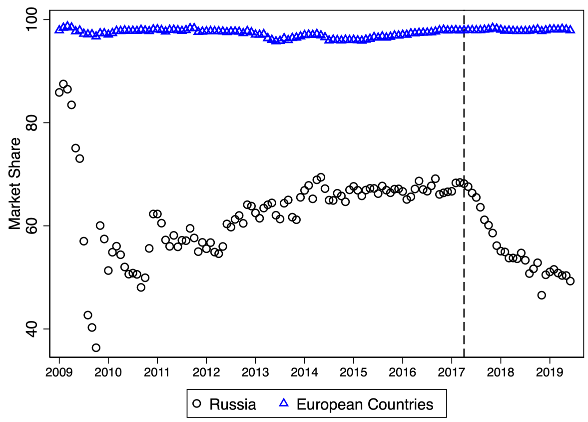
Notes: The vertical line corresponds to the introduction of the choice screen.

We plot Google's market share for Russia and Turkey compared to European control countries and the evolution of the market shares for all of the main alternative search engines in Figure 3. The trends in Google market shares appear to move in parallel directions before the interventions in both cases, only to then diverge after the corresponding policies are implemented. We restrict our data to the time frame between January 2009 and July 2019 for the Russian remedy analysis (i.e., before the Russian government drafted the foreign ownership law in July 2019[40]). For Turkey, instead, we consider the whole period from January 2009 to January 2022. We observe that Google's market shares 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 took more than 60% of mobile searches and Yandex's market share was around 30%. But in July 2019, Yandex and Google almost shared the market equally.[41] In Turkey, similar patterns are also observed in Figure 3. Google's market share began to decrease soon after September 2018, when Google was requested by the TCA 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. Reviewing the main competing search engines in Turkey, we find that Yandex benefited the most from the TCA's remedy on Google, as its market share kept increasing after

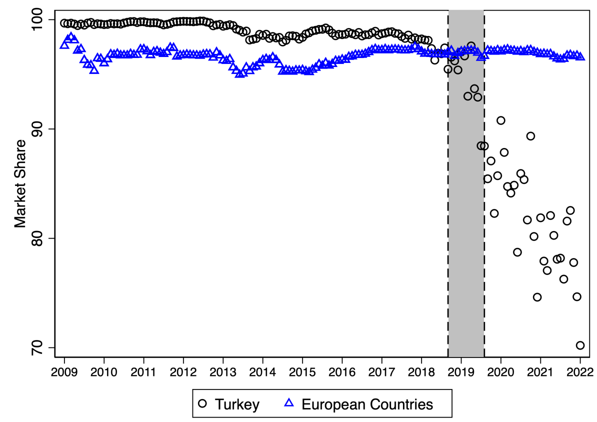
[40]See `https://www.themoscowtimes.com/2019/07/29/yandex-shares-drop-on-draft-foreign-ownership-law-a66606`

[41]An episode worth noticing occurred in May 2017 when all Yandex services were banned in Ukraine. According to Statcounter data, there was an immediate drop in Yandex's Ukraine market share after this ban, equalling 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 upward our estimates of the Russian remedy, 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 a main driver of the increase in the Yandex market share that we estimate for Russian intervention.

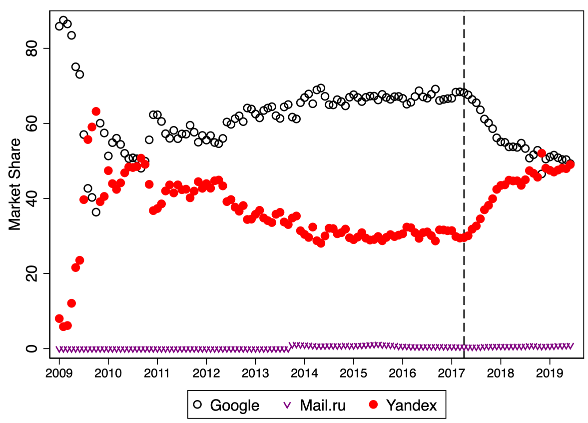
Figure 3: Russian and Turkish Remedies



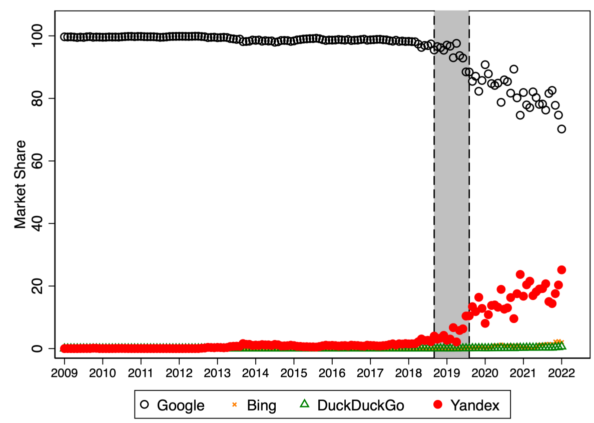
(a) Google Mobile Market Share in Russia



(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 the TCA decision and to Google's officially accepted contractual changes.

this intervention.

4 Reduced Form Evidence

4.1 Intervention Effect Analysis

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

Remedy in the European Economic Area To estimate the EEA remedy's effects, we adopt the following Two-Way-Fixed-Effects 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 and month t, λ_c is a country fixed effect, γ_t is a month fixed effect and $EEA_c \times Post_t$ is the treatment variable and is an indicator that turns on 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. As there exist other policies in those European control countries that may affect market shares before 2013, our alternative time frame is set between January 2013 and January 2022.[42] Our second control group further adds all other OECD countries. Once again, we also restrict the time frame to ensure that observations, where the market share may be affected by other policies, are excluded, focusing on the period between January 2016 and January 2022.[43] Finally, we consider in the control group only European and OECD countries whose population exceeds ten million. A detailed report of the countries included in the relevant control groups can be found in Table A.1.

As for the treatment group, we remove Czechia since it represents an outlier. In Czechia, Google faces significantly stronger competition in the market for online search compared to any other European country: the domestic search engine, Seznam.cz, has double digit market shares for the majority of the period that we analyze. As a consequence, the evolution of market shares in Czechia is unique and different from those in other European countries, both in terms of the magnitudes involved and the specific trends. Indeed, the latter entailed a sharp increase right before the EEA intervention and a drop right after. Czechia's situation and the reasons for its removal from the analysis are discussed in greater depth in Appendix A.9.

The complete regression estimates are reported in Table A.2 and Table A.3, where we observe a small but significant reduction in Google's market share[44]. As shown in Figure 4, across different control groups and time windows, all estimates indicate a negative and significant effect ranging from a low point estimate of half of a percentage point to a high point estimate of one and a half percentage points. This result indicates that the choice screen remedy effectively reduced Google's market share, as intended by the EU competition authority. However, the magnitude of the reduction is clearly small relative to the goal of inducing a more competitive market for search engines on mobile devices. Nevertheless, the change in Google's market share induced by the choice screen remedy is still not negligible: the drop of 1.4 percentage points in our first specification is about two-thirds of a standard deviation in Google's pre-remedy mobile market share.

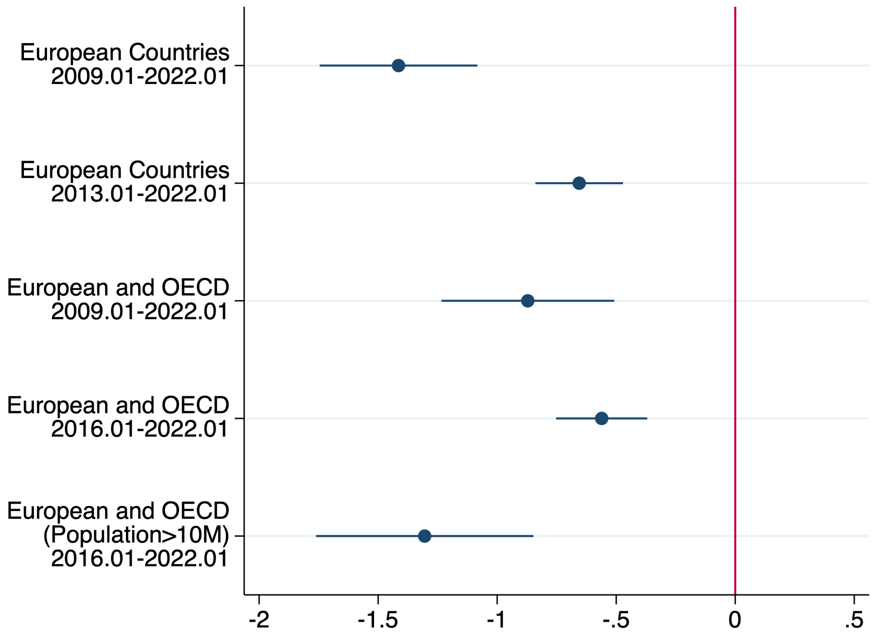
Following the same methodology, we also analyze whether competitor search engines that won at least once during the "pay-to-play" auctions, gained from the remedy. These search engines include

[42] See the Swiss Supreme Court case against Google `https://www.edoeb.admin.ch/edoeb/en/home/data-protection/Internet_und_Computer/online-services/google-street-view.html`.

[43] In 2015, the Japanese government passed the first amendment of the Japanese Protection of Personal Information Act such that anonymized personal data may be transferred to third parties. This affected the search engine market shares in Japan, for more information, please visit `https://www.ppc.go.jp/files/pdf/280222_amendedlaw.pdf`.

[44] Our paper focuses on the overall effect of the EEA remedy, but similar patterns can be obtained if we distinguish the pay-to-play and free-to-play remedy as shown in Table A.4.

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



Notes: the horizontal axis denotes the estimate of mobile market share change by the choice screen in percentage points.

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	-1.414***	-0.655***	-0.872***	-0.561***	-1.305***	0.026**	0.083***	1.202***
	(0.169)	(0.094)	(0.185)	(0.098)	(0.233)	(0.012)	(0.031)	(0.154)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.724	0.835	0.756	0.934	0.938	0.493	0.224	0.752
Pre-remedy Share	98.27	98.27	98.27	98.27	98.27	0.08	0.30	0.09
Observations	6883	4796	8610	4015	1476	6883	6883	6883

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is the market share of Google in the first five models and is the market share of a corresponding competing search engine in the last three models. The first two models include all European countries, besides Turkey, Russia, and Czechia. For these two models, the time frame of the first model is between January 2009 and January 2022, and is between January 2013 and January 2022 for the second model. Model three and model four add OECD countries. The time frame of the third model is between January 2009 and January 2022 and the time frame of the fourth model is between January 2016 and January 2022. Model five selects as control countries only ones whose population exceeds 10 million and considers months between January 2016 and January 2022. The last three models are all based on European countries between January 2009 and January 2022, except Turkey, Russia, and Czechia. All models include month and country fixed effects.

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. Therefore, we 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. We find that DuckDuckGo, Bing, and Yandex all increased their market shares after the policy intervention. Yandex particularly 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 convenient 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 market shares that these search providers initially possessed in EEA countries. The estimated effect of the choice screen for Yandex is equal to 1.2 percentage points, which seems small but is more than ten times larger than its pre-treatment average market share in EEA countries, which was equal to 0.09%. Bing and DuckDuckGo also gained as a consequence of the remedy. The estimated effects of the choice screen for Bing and DuckDuckGo are equal to 27% and 33% of their pre-treatment average market shares, indicating that the effect of the remedy was important for these competitors. We also apply the same model to investigate how the mobile market share sum of all other search engines, besides Google, Bing, DuckDuckGo, and Yandex, are affected by the remedy and we do not find any significant changes.

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

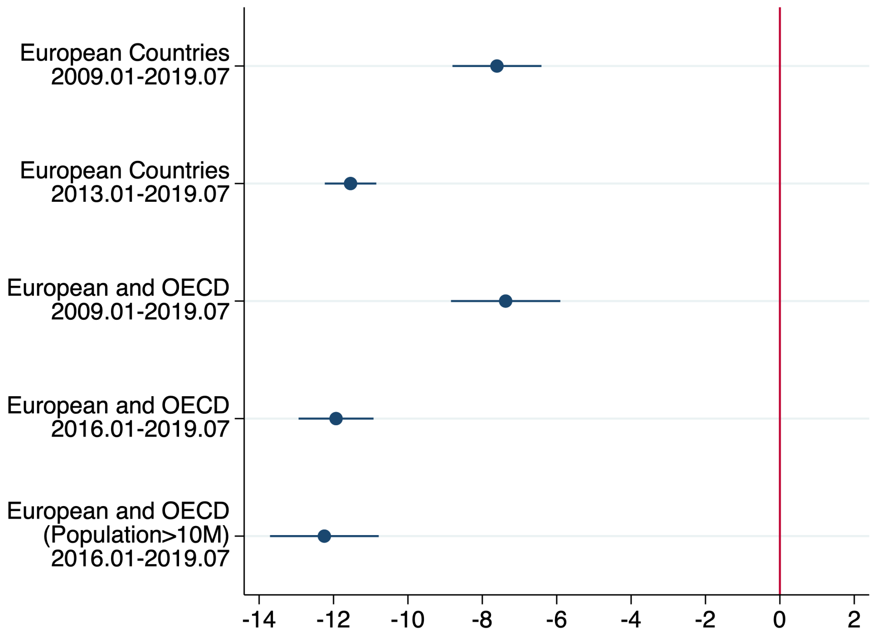
Remedy in Russia Only Yandex and Mail.ru appeared on the Russian choice screen and they did so uninterruptedly. To investigate the effect of choice screen in Russia, we apply the following difference-in-differences model:

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

where $(Russia_c \times Post_t)$ is a binary treatment variable that turns on for observations for Russia after April 2017. Our regression results are listed in Table A.5. The countries used as controls are European countries – including EEA countries – and OECD countries.[45] Our estimates show a reduction in Google's market share in the Russian mobile market caused by the policy. The finding remains robust over alternative samples and time frames as shown in Figure 5. The size of the effect is substantial: the drop in Google's market shares caused by the choice screen is estimated to be between 7.6 and 12.2 percentage points, which amount to about 12% and 20% of Google's pre-treatment average market share. These results indicate the Russian choice screen effectively lessened Google's dominant position and enhanced competition in the market for mobile search.

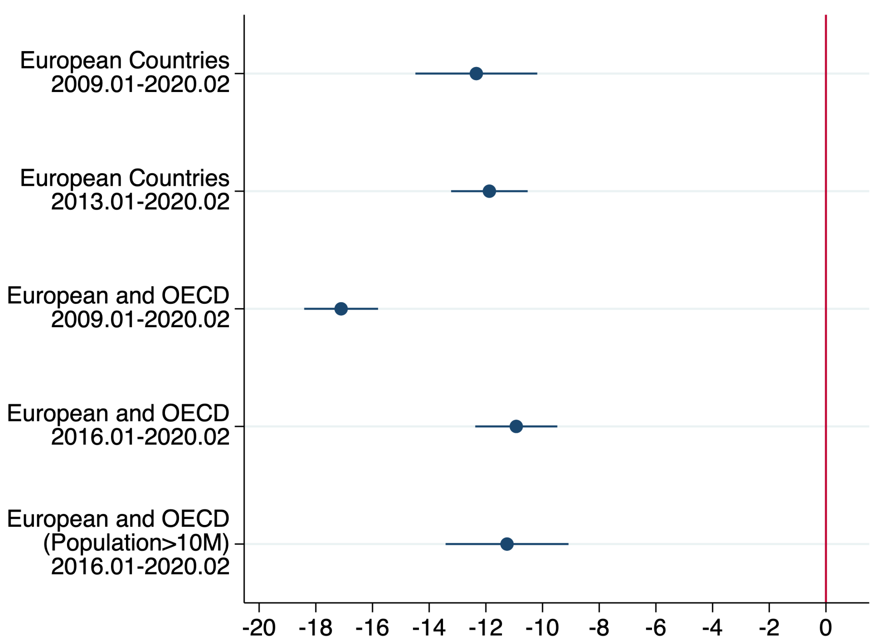
[45]The use of EEA countries in the control group is justified by the fact that we restrict our sample to before the EEA choice screen was implemented, as we only keep observations from before August 2019 in our sample.

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



Notes: the horizontal axis denotes the estimate of mobile market share change by the choice screen in percentage points.

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



Notes: the horizontal axis denotes the estimate of mobile market share change by the Turkish remedy in percentage points.

Intervention in Turkey The intervention in Turkey is different from the EEA and Russian instances since no choice screen appeared on mobile devices. The main focus was on freeing original device manufacturers from restricted terms imposed by Google that ensure a privileged position for its search engine. To estimate the effect of the Turkish remedy, 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 choose to restrict the sample to observations up to February 2020. We find the intervention effectively lowered Google's market share in the Turkish mobile market as shown in Table A.6. This conclusion remains robust over alternative samples and time frames as shown in Figure 6. Our estimates show that the Turkish remedy led to a drop in Google's market shares of about 11 percentage points, which is equal to about seven standard deviations of its pre-treatment mobile market shares.[46]

Robustness We conducted multiple robustness checks to ensure the validity of our baseline findings. Our first set of robustness checks focuses on the standard errors used to conduct inference for the remedy impacts. Particularly, 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 a small number of treated groups following Conley and Taber (2011). The results, in Appendix A.6 broadly confirm our baseline findings.

Our second set of robustness checks deals with the chosen estimators. First, we consider we relax the assumptions of static treatment effects in Appendix A.7 and employ modern identification strategies developed by de Chaisemartin and D'Haultfoeuille (2022). Next, in Appendix A.8, we estimate the impact of three remedies using the alternative synthetic control method suggested by Abadie et al. (2010). Finally, the third set of robustness checks handles the assumption that the treatment effect is homogeneous and static. We explore what happens if we relax the homogeneous and static treatment effects assumptions in Appendix A.9. We thus investigate whether treated countries show signs of heterogeneous effects of the remedy, by estimating model (6) separately for each treated EEA country. The main insights from these three sets of robustness checks is that the baseline findings are qualitatively robust to the alternative estimators used. Among these additional results, we also find particularly interesting that, in terms of the heterogeneity by EEA country, the estimated effects are fairly similar across all of the EEA countries: they range from a drop slightly above 2 percentage points in Austria and Germany to a drop of 0.5 percentage points in Hungary, Italy, and the UK. 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.

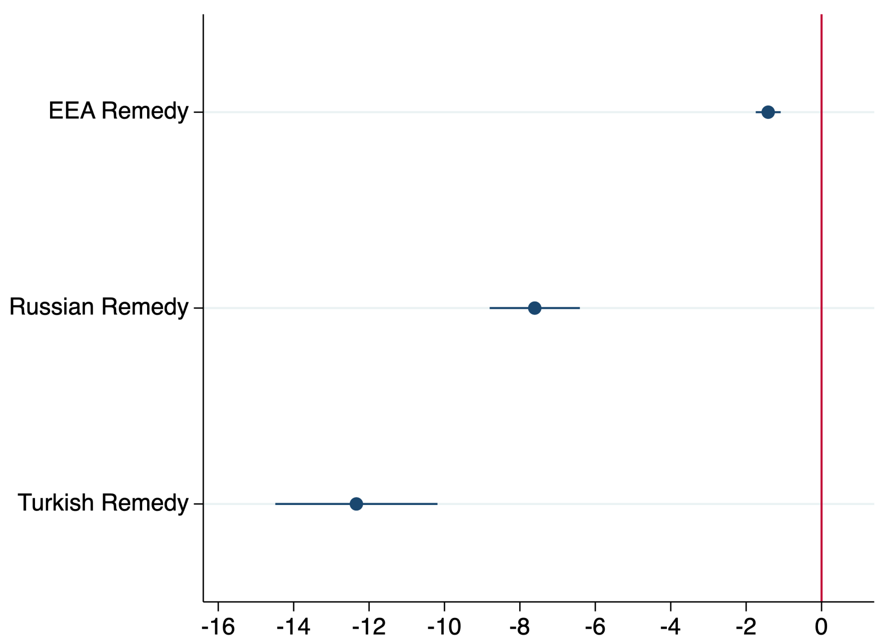
A third type of robustness check that we consider is one targeted to the Russian and Turkish cases and entails accounting for the dynamic of anti-Americanism (i.e., anti-US sentiment). It would be problematic for the interpretation of our estimates if the drop in the Google market share

[46] In our paper, we set August 2019, when Google officially submitted contract changes to the TCA, as the treatment beginning month. However, the results remain robust if we set September 2018, when the TCA placed a fine on Google and announced its decision, as the treatment beginning month as shown in Table A.7.

that we find associated with the antitrust intervention would occur at the same time of spikes in anti-Americanism in the local populations. The evidence that we collected, however, indicates that this is not the case: anti-Americanism data from various sources is described and analyzed in Appendix A.10. As shown in that section, there is no evident association between the dynamics of anti-Americanism, the antitrust remedies and the changes in Google market shares. Indeed, our findings remains qualitatively unchanged even after incorporating an anti-Americanism measures as a control into our baseline model.

Intervention Comparison As illustrated in the previous sections, the antitrust policies in the EEA, Russia, and Turkey all effectively lowered Google's market share in mobile search, but the magnitudes of these reductions are very different. In Figure 7, we display the effect baseline estimates of the three remedies: Google's market share in EEA countries decreased by less than 2 percentage points, while it did so by more than 5 percentage points in Russia and by over 10 percentage points in Turkey.

Figure 7: Effects of intervention on Google market shares in EEA, Russia, and Turkey



Notes: the horizontal axis denotes the estimate of mobile market share change by interventions in percentage points.

Variations in both the remedy design and the pre-existing conditions contribute to explaining these differences between the three cases. In terms of pre-existing conditions, the most visible element regards the size of Google's market share: 60 percent in Russia compared to nearly 100 percent in both Turkey and the EEA. The evolution of this market share post intervention across the three cases has two implications. First, the large effect observed for Turkey implies that antitrust remedies can be effective despite the initial lack of a strong competitor. Second, the smaller effect observed in the EEA relative to Russia might be driven, at least in part, by the initially larger market share of Google in the EEA.

To properly assess the latter feature, however, also the differences in remedy design between the remedy in the EEA and Russia need to be accounted for. The two main differences are the extent of the population involved by the treatment, which was the whole set of Android users in Russia, while only buyers of new Android devices in the EEA, and the set of Google rivals displayed in the choice screen, which always involved Google top rival in Russia, Yandex, while it did not always include the top rivals in the EEA choice screen available in the pay-to-play period.[47]

Furthermore, we find that the relative quality of Google's service changed in Turkey, but not in EEA or Russia during the intervention. The Turkish antitrust investigations led Google to remove some of its services from the country, including Google shopping. Meanwhile, Yandex expanded its services in digital marketplaces and actively negotiated with device manufacturers to improve its presence in the country. These changes increased the relative value to users of adopting Yandex as their search engine over Google. Consequently, Google's mobile market shares dropped to the benefit of Yandex after the antitrust intervention in Turkey.

In the next two sections, we explore more in detail the mechanisms driving the baseline estimates presented above and we explore some counterfactual analyses aimed at evaluating the relative importance of the two differences in remedy design between the EEA and Russia mentioned above.

4.2 Mechanisms

To understand the mechanisms at play, several forces on the sides of users, competing search engines, and advertisers need to be simultaneously considered. In Appendix A.11, we present a simple theoretical model that streamlines the main incentives of the main players and how they interact with different remedy designs. This model delivers the intuitive result that a remedy intended to enhance competition in search tends to have stronger effects on the market the greater it is: (a) the population of users exposed to the interventions, (b) the user's awareness of alternative search engines, (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 the privacy protection they offer to their users and their brand awareness. Thus, 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,[48]. $desktop_{ck}$ is the desktop market share of search engine k before the treatment. The desktop share is a reasonable proxy for awareness[49] because, as argued in the CMA report mentioned in the

[47] Recall that the list of search engines in the Russian choice screen is fixed, meaning that only Yandex and Mail.ru always appear on Russian choice screens. Instead, 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 changed for each country in each quarter.

[48] 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 market change between March 2017 and July 2019, as it is the only search engine that appeared on the choice screen and has complete information about consumer protection.

[49] A formal analysis about how past memory shapes users' choices is proposed in Bordalo et al. (2017).

introduction, users tend to make more active choices of their search engine on desktops, making the market share in that market a good indicator of how much users are aware of the different search engine available. Finally, Y_{ck} collects two characteristics of search engine k: a dummy for whether search engine k is founded domestically in country c, and a measure of privacy protection derived from the Ranking Digital Rights (RDR).

Table 3: Search Engine Market Share Gains

	(1) Market Share Change	(2) Market Share Change	(3) Market Share Change	(4) Market Share Change
Desktop	0.381***	0.377***	0.377***	0.415***
	(0.026)	(0.027)	(0.035)	(0.023)
Consumer Protection		-0.013		
		(0.018)		
Domestic Search Engine			0.270	
			(1.389)	
Bing				0.493
				(0.848)
DDG				-0.397
				(0.496)
Others				-0.408
				(0.467)
Bing × Desktop				-0.531***
				(0.150)
DDG × Desktop				-0.113
				(0.669)
Others × Desktop				-0.235
				(0.779)
Constant	-0.216	0.458	-0.213	0.422
	(0.175)	(0.982)	(0.176)	(0.288)
R-squared	0.732	0.734	0.733	0.835
Observations	79	79	79	79

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS estimates for the mobile market share change during the treatment periods in the EEA, Russia, and Turkey, with Yandex to be the base category.

The estimates in Table 3 show a positive and significant relationship between the mobile market share gain and market awareness for most search engines, while there is no significant effect of the consumer protection measure and 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 search engine whose interaction with the desktop share is negative and significant. This might be rationalized by users of Bing on desktops not being keen on switching to it for their mobile phones. All of the estimates in Table 3 pool together data from the whole set of countries affected by the EEA, Russian and Turkish remedies. However, the variability across EEA countries allows repeating the analysis within this more restricted, but also more homogeneous set of countries. These estimates, shown in Table A.8, are qualitatively the same: when a search engine appears on the choice screen, its probability of being chosen as the default search engine increases with its market awareness.

Table 4: Number of Auctions Won Negative Binomial Estimates

	(1) Slots Won	(2) Slots Won	(3) Slots Won	(4) Slots Won	(5) Slots Won
Slots Won					
Desktop Share 2020 Feb	0.092***	0.294***	0.093***	0.131***	0.379***
	(0.028)	(0.039)	(0.027)	(0.028)	(0.041)
Mobile Share 2020 Feb	2.410***	0.257	2.453***	3.085***	0.427*
	(0.311)	(0.232)	(0.309)	(0.347)	(0.226)
Consumer Protection			0.003		
			(0.005)		
Domestic Search Engine			-1.011*	-0.287	0.661
			(0.554)	(0.570)	(0.477)
Search Engine FE	No	Yes	No	No	Yes
Country Controls	No	No	No	Yes	Yes
Pseudo R-squared	0.046	0.196	0.047	0.065	0.214
Observations	870	870	870	870	870

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Estimates from the negative binomial model for 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, and the working age ratio, the percentage of young people between 20 and 29. The data is based on the latest data published by the World Bank.

Search Engine Bidding Strategy A element of the EEA remedy is whether and to what extent the auction mechanism distorted the options available on the choice screen. As discussed earlier, Ostrovsky (2020) convincingly explains why a pay-per-view system would have likely induced a better selection of winners than that produced by the pay-per-click model adopted. However, the previous estimates indicate that the usage of alternative search engines increased in the EEA and that such an increase is associated with their awareness among users. It is thus worth exploring the bidding strategies of the search engines in pay-to-play auctions. Since the only available data is that on the identity of the winners in each auction (i.e., country/trimester pair), we estimate the following negative binomial model for the number of auctions won:

$$log(SlotsWon_{ck}) = \alpha + \beta desktop_{ck} + \gamma mobile_{ck} + \eta X_c + \delta Y_k + \varepsilon_{ck} \tag{5}$$

where $SlotsWon_{ck}$ is the number of auctions won by search engine k in country c during the EEA choice screen auction between March 2020 and August 2021, $desktop_{ck}$ is the desktop market share of search engine k in country c in February 2020, $mobile_{ck}$ is search engine k's mobile market share in country c in February 2020, X_c collects country-specific control variables, and Y_k collects characteristics of search engine k which are, as in the previous analysis, a dummy for local search engine and a measure of the privacy protection.

The estimates are listed in Table 4. In moving from left to right in this column, the model is gradually more saturated. Across all models, we find that a search engine is more likely to win auctions if it has a larger pre-remedy share in the desktop market in that country.[50] Similarly, the

[50] These findings remain robust when using an OLS methodology, as shown in Table A.9.

market share in mobile pre-remedy also has positive effects, although its magnitude and significance vary across models. The controls for consumer protection, for domestic search engines, as well as those for the country characteristics included in the models of columns (4) and (5) are never significant, but they alter the size and significance of the two pre-remedy market share variables. Interestingly, in column (5) where we add search engine fixed effects the magnitude of the desktop shares grows relative to the other specification, which is explained by Bing behaving differently than the other search engines: similar to what was discussed above about user choices, its desktop share is not predictive of winning auctions. Hence, overall it appears that search engines in the EEA auctions display a behavior that is coherent with user choices and awareness, more than consumer protection, appears to be a key driver of winning a slot in the choice screen auction.

Advertisers' Response The analysis so far indicates that the remedies did trigger some increased usage of alternative search engines. Online advertisers might thus 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 covers 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 shall 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, volume, and revenue. We construct keyword-level revenue as the product of CPC and volume, following Decarolis and Rovigatti (2021). To analyze whether Google suffered any losses following the three antitrust interventions, we employ the following difference-in-differences methodology:

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

where $Outcome_{ctk}$ is the CPC, volume, or revenue of keyword k in country c and year t, λ_c is a country fixed effect, γ_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 years following the corresponding remedy.

The results are displayed in Table 5. The estimates are negative with mostly statistically insignificant effects for the EEA remedy but with significant effects for the Russian and Turkish remedies on CPC, volume and revenues. Furthermore, the fact that CPC decreased under the Turkish remedy possibly shows that the policy hurt the ecosystem of Google more broadly, perhaps also by changing the ability of Google to target users. These results are displayed in more detail in the Appendix in Table A.10, Table A.11 and Table A.12, where we present a richer set of models with differet sets of covariates and where we find similar qualitative results relative to those of Table 5.

4.3 Counterfactual Analysis

We conclude our analysis with two counterfactual exercises. Both of them evaluate a feature of the EEA remedy that differs from the Russian remedy and that represents a design choice under the

Table 5: Advertisers' response to the EEA, Russian and Turkish Remedies

	(1) CPC	(2) Volume	(3) Revenue	(4) CPC	(5) Volume	(6) Revenue	(7) CPC	(8) Volume	(9) Revenue
EEA×Post	-0.018	29.042	-43.194**						
	(0.015)	(29.458)	(17.096)						
Russia×Post				-0.036	-182.951**	-117.318**			
				(0.048)	(82.235)	(51.288)			
Turkey×Post							-0.163***	-53.794	-148.774***
							(0.043)	(76.252)	(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
Observations	64539	64539	64539	27700	27700	27700	27869	27869	27869

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: the time-frames considered in these regressions are the 2016-2022 period for EEA countries, the 2015-2019 period for Russia and the 2017-2021 period for Turkey. The control group always consists of Australia, Brazil, Canada and the USA.

control of the regulator. The first involves the population exposed to the remedy: we compute what would have been the effect of the intervention had the choice screen been imposed on all Android devices in the EEA. The second involves the alternative search engines shown in the choice screen: we compute the effect of always including the top rival of Google among the alternatives in 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 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. 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 of the choice screen 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 of the remedy on Google's mobile market shares depends on the propensity with which users 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 rather than Google to be their default search engine, the choice screen remedy negatively impacts Google's market share. The larger the divergence between the rate at which users select Google from the choice screen compared to Google's baseline market share, the larger the effect of the remedy on Google's mobile market shares.

Our analysis employs data on device shipments and smartphone users by country. The sample covers European Countries and OECD countries between January 2016 and January 2022, for which we have data on device shipments, as shown in Table A.1. We begin our assessment by estimating the remedy effect on Android mobile search via the following weighted difference-in-differences model:

Table 6: Google EEA Remedy Weighted Treatment Estimates

	(1) Google	(2) Google	(3) Google	(4) Google	(5) Google	(6) Google
EEA $\times$ Post	-0.706	-0.706***			-1.053***	
	(0.675)	(0.181)			(0.267)	
EEA $\times$ Post $\times$ % Android			-0.672	-0.904***		-1.331***
			(0.898)	(0.243)		(0.338)
% Android in shipments			-0.924	0.501		0.338
			(1.058)	(0.663)		(0.984)
Month FE	No	Yes	No	Yes	Yes	Yes
Country FE	No	Yes	No	Yes	Yes	Yes
R-squared	0.132	0.941	0.132	0.941	0.940	0.940
Observations	1932	1932	1932	1932	1275	1275

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: All models exclude countries where shipment data is not available. The first four models include all European and OECD countries between January 2016 and January 2022, except Turkey, Russia, and Czechia. The last two models only consider countries with populations greater than 10 million.

$$Google_{ct} = \alpha + \beta(EEA_c \times Post_t \times ship_{cq(t)}) + \psi ship_{cq(t)} + \gamma_c + \lambda_t + \varepsilon_{ct} \tag{6}$$

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 6, where we observe stronger effects of the remedy by weighting the treatment by the number of new Android users relative to our baseline estimates.[51]

The estimates from the binary treatment model in Table 2 and from the weighted treatment model in Table 6 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. In order to measure the effectiveness of the antitrust choice screen remedy in leveling the playing field for competing search engines, the estimate from the weighted model is arguably more informative as it captures the effect on the population of Android mobile users. In Appendix A.12 we discuss identification in both our econometric specifications in greater depth.

The second step entails assessing what would be the effect if the European Commission imposed on all Android phones the search engine choice screen. We leave the exact steps in Appendix A.12 and offer here a simplified overview of the approach followed. 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, from the device accumulation patterns, we can 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 are able to back out the rate at which users select Google from the choice screen,

[51] Furthermore, our conclusions 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 6.

given that we can identify the contribution of treated devices to the market for mobile search. Following these steps, which we outline in greater detail in Appendix A.12, we find that EEA users select Google from the choice screen at a rate that is about 3 percentage points lower than Google's baseline market share in the EEA. Put differently, while about 98 users out of 100 use Google as their search engine in EEA countries, if every Android user had access to the choice screen, only about 95 out of 100 would select Google as their search engine. Therefore, in a counterfactual scenario where the EEA choice screen was 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, a value that exceeds the estimates from all our specifications.

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

We begin our analysis by re-evaluating the heterogeneous treatment effects discussed earlier. As mentioned before, we obtained such estimates by estimating model (6) separately for each treated EEA country via the method proposed by de Chaisemartin and D'Haultfoeuille (2022). The results in Appendix A.9 indicate a range of estimates that goes from -2 for Austria and Denmark to -0.2 in Hungary. We then use these coefficients as dependent variables in the following OLS model:

$$DiD_c = \alpha + \beta CompetitorFreq_c + \delta X_c + \gamma Y_c + \varepsilon_c \tag{7}$$

where DiD_c is the heterogeneous Difference-in-Difference coefficients across EEA countries (excluding Czechia), $CompetitorFreq_c$ is the number of choice screen auctions won by the search engine that has 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. The estimates in Table 7 show a positive and significant relationship between the EEA remedy's impact and the number of auctions won by Google's largest competitor in the local market. Although the magnitudes are not identical across the baseline difference-in-difference coefficient and the Weighted difference-in-difference coefficient, the overall effects are similar. 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. The results are also consistent with our previous analysis list in Table 3, where we find a positive relationship between the market share gain and local popularity for search engines that appeared in the EEA choice screen.

Finally, we can use the estimates in Table 7 to assess how much the market share of Google would have declined in response to a remedy where the top rival was always displayed on the choice screen. In the sample, the average number of auctions won by the biggest competitor is 1.43 across all 30 countries, while it is 0.53 in the sample of 17 countries used in models (1)-(3) and it is 1.34 in the sample of 17 countries used in models (4)-(6). If we predict the value of beta when the number of auctions won by the largest competitor in all countries is set at the largest value 5, then the predicted value for the six regressions models are respectively 3.25, 3.20, 3.17, 2.10, 2.05 and 2.07. Hence, across all models we obtain a counterfactual estimate for the effect of an EEA remedy designed in a way such that the top rival wins such that the market share of Google would decline by a value of nearly 3 percent. This value is larger than that of our baseline and, interestingly, it is

Table 7: 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	0.518^{***}	0.504^{***}	0.498^{***}	0.192^{**}	0.182^{**}	0.186^{**}
	(0.145)	(0.152)	(0.153)	(0.071)	(0.074)	(0.075)
Mobile Share	-0.133	0.058	-0.394	-0.453	-0.227	-0.362
	(0.513)	(0.503)	(0.710)	(0.383)	(0.378)	(0.418)
GDP 2020	0.174			0.337^{***}		
	(0.125)			(0.117)		
Population 2020		0.004	0.008		0.011^{**}	0.013^{**}
		(0.005)	(0.006)		(0.005)	(0.005)
Young Ratio			0.080			0.031
			(0.088)			(0.039)
Constant	0.602^{**}	0.581^{*}	-1.176	1.115^{***}	1.043^{***}	0.347
	(0.273)	(0.301)	(1.960)	(0.207)	(0.230)	(0.918)
R-squared	0.503	0.461	0.496	0.300	0.246	0.265
Observations	17	17	17	29	29	29

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: the first three models use the weighted DiD coefficients listed in Figure A.8 and the last three models use baseline DiD coefficients in equation 1 separately for each country, having European countries as the control group.

similar in magnitude to that obtained through the first counterfactual experiment above involving expanding the population exposed to the treatment. 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 the effectiveness of the intervention, although only to a small extent. Hence, most likely the large effect achieved by the Russian intervention is more linked to the higher pre-intervention awareness of Yandex relative to two features of the remedy design explored in this section.

5 Conclusions

This paper contributes to fill the gaps in the literature on competition on 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 take into account the behavioral biases displayed by consumers.

This paper offers the first, systematic evaluation of what are the policy interventions in this area observed thus far. It quantitatively evaluates three antitrust remedies in the EEA, Russia, and Turkey respectively, all aiming at removing Google's default position on Android mobile devices, but doing so with varied market characteristics and remedy designs. 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 appearing on the choice screen changed regularly, and was initially determined by an auction mechanism, and only later by popularity of the search engines. Although the EEA remedy effectively reduced Google's market share, following the European Commission's expectations, we estimate the magnitude of the effect to be less than

2 percentage points.

In Russia, a similar choice screen was implemented. However, the Russian choice screen was made accessible to all Android devices circulating in the country, and the list of search engines appearing on the Russian choice screen was fixed from the start and included Yandex, Google's largest competitor in the local market. Crucially, the existing market share difference before the remedy in Russia between Google and Yandex 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 in Russia were much stronger than in EEA countries.All these factors are responsible for the greater effectiveness of the Russian intervention

In Turkey, no choice screen was ever implemented. However, the Turkish intervention removed all incentives for original equipment manufacturers to have Google as the default search engine for the mobile devices' search access points. In the EEA, Russia, and Turkey, we always observe significant reductions in Google's market shares after the policy interventions. But the magnitude of the reduction exceeds 7 percentage points in Russia and 12 percentage points in Turkey, with both policies proving considerably more effective than the EEA remedy.

Comparing the three interventions, we find that a remedy's effectiveness is jointly 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 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 larger existing user sizes and high popularity in the local market have strong motivations to participate in the remedy and to be shown 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 decline if the choice screen was 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 but in the same order of magnitude as the baseline estimates. Combing these findings, we argue that implementing choice screens alone can hardly have satisfying impacts on restoring competition in the online search market unless there exists a rival with sufficient quality and popularity, or one with strong motivation to invest in the local market to replace Google. Thus, successful regulations are expected to positively impact the market in multiple aspects simultaneously, including not only opening more potential markets for competitors but also fostering better rivals against the gatekeeper.

Overall, these results underscore the crucial role of preset default in mobile internet search. They, therefore, indicate a viable path for competition policies intended at fostering a more balanced market power among search engines that passes through interventions aimed at the preset default. These interventions are likely substantially more effective than fines to restore 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. This squares well with the usual practice of antitrust authorities that, when imposing remedies in the form of selling off some assets that raise competitive concerns, typically require them to be sold to the most effective competitor rather than diluting them to one or more smaller competitors.

Nevertheless, several questions remain open for future research. We conclude by briefly exploring one that plays a critical role in comprehending the broader impacts of our findings. The question is about whether and how device manufacturers respond to their contract changes with Google and the extent to which they pass these changes on to consumers. In Turkey, the remedy works by modifying the contracts between Google and Android device manufacturers to remove all terms granting Google the privilege to be pre-installed on mobile devices. Consequently, local manufacturers may experience conflicting effects. On the one hand, when the restrictive terms imposed by Google are removed, they have absolute freedom to negotiate and choose alternative search engines. On the other hand, the amended contracts provided by Google in response to the remedies might leave device manufacturers worse off, as Google may be prohibited to offer them rich monetary payments in exchange for default positions on their devices. What is more critical to consider is whether these changes affect manufacturers' pricing strategies and correspondingly affect consumer welfare. Although our data do not allow an exhaustive analysis of this issue, we can draw the following conclusions. Since demand is generally 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, reported in Appendix A.13, indicates no significant changes in the OS mobile market shares after the Turkish remedy. Consequently, we doubt consumers incur welfare losses due to price changes in Android mobile devices.

In addition to our findings, more future work is required to fully assess whether more search engine competition is necessarily welfare-increasing. Clearly, the Turkish remedy may have reduced the market share of Google, yet the removal of critical services, as threatened by Google (following its removal of Google Shopping from the country) could be a net negative for consumers. Even more generally, complaints, similar to the ones behind the policy interventions in this study, were made about the very large market share of Internet Explorer (IE), Myspace, and (perhaps today) Facebook. But today IE has been discontinued, Myspace is for the history books and few young people seem to use Facebook, switching to alternatives like TikTok. Our understanding of the digital economy is certainly still incomplete and the potential damages of ill conceived regulatory interventions might turn out to be harmful for society.

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

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A Appendix

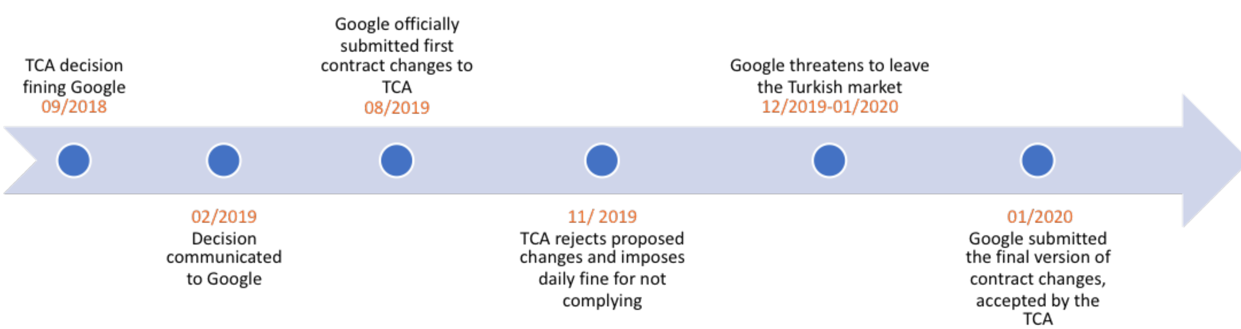
A.1 Additional Information on the Turkish Remedy

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 A.1: Turkish Case Timeline



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,*

[52]See `https://www.rekabet.gov.tr/en/Guncel/investigation-on-google-llc-google-inter-60928a8075bde81180e300505694b4c6`

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;*
        - *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.

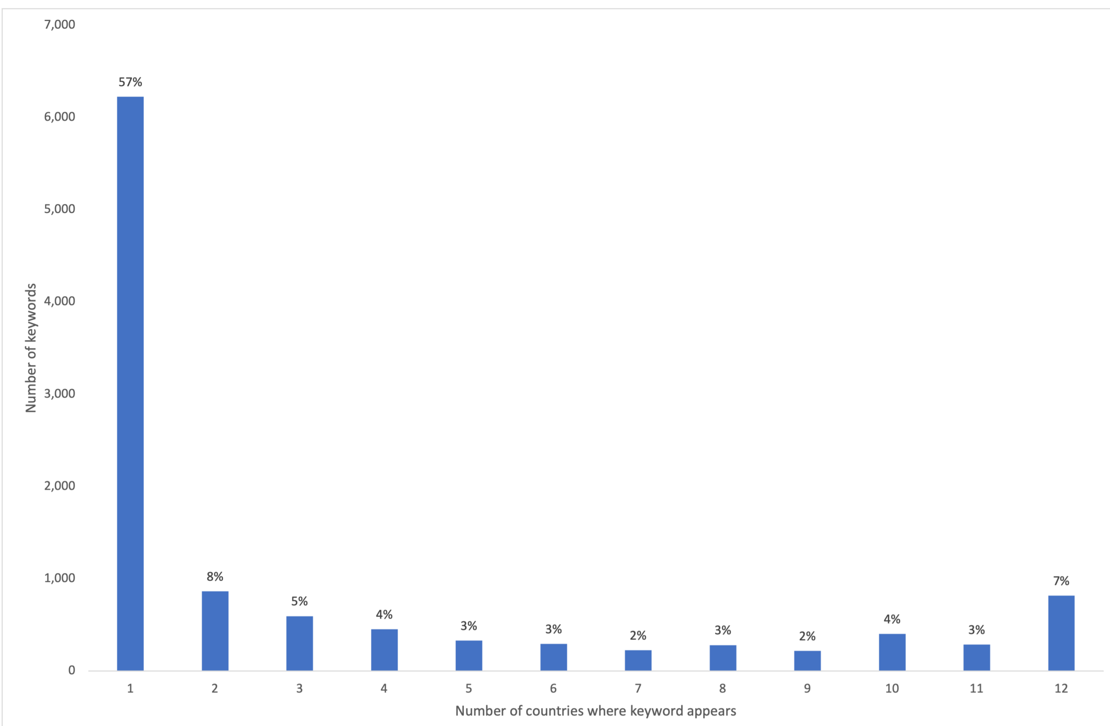
6. *It was unanimously voted that the amendments required to be made in the agreements within the framework of the aforementioned obligations shall be submitted to the Competition Authority within 6 months following the notification of the reasoned decision,*

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.

A.2 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.[53]

Figure A.2: Overlapping keywords across countries



In Figure A.2 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.[54] The fact that we observe little overlap in the most popular keywords across countries suggests that our approach of collecting country-specific

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

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

keyword lists is appropriate. Indeed, selecting a fixed keyword list for all twelve countries would lead to a sample selection issues.

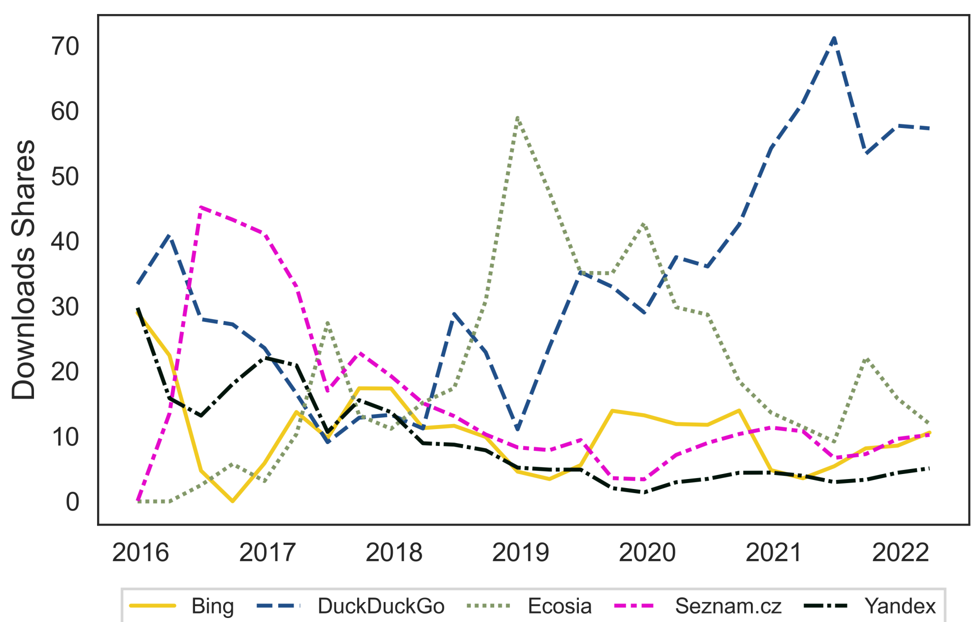
A.3 Search Engine App Downloads Analysis

We compare the evolution of downloads shares of competitor search engine apps, where search engine app a's download share (s_{act}) in country c at time t is computed as:

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

where q_{act} is the number of downloads of search engine app a in country c at time t and M is the set of all the remaining search engine apps present in our data. Crucially, we remove Google from the analysis to better investigate the competitive environment among the smaller competitor search engines. Figure A.3 plots the evolution of the download shares of the top 5 competitor search engine apps in the EEA on Google Play Store.[55]

Figure A.3: EEA Competing Search Engines Download Shares



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

From Figure A.3 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 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.

[55] We restrict our attention to downloads of search engine apps and do not consider downloads of launcher apps, as these are not appearing on the choice screen.

A.4 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".[56] 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.3.

[56] See https://www.blog.google/around-the-globe/google-europe/presenting-search-app-and-browser-options-android-users-europe/.

A.5 Reduced-Form Analysis Tables

Table A.1: 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		X	X		X
Ukraine		X	X	X	
United Kindom	X	X	X	X	X
United States			X	X	X

Table A.2: Google EEA Remedy Estimates

	(1) Google	(2) Google	(3) Google	(4) Google	(5) Google	(6) Google	(7) Google	(8) Google
EEA × Post	-1.444***	-1.414***	-0.655***	-0.655***	-0.899**	-0.872***	-0.561	-0.561***
	(0.301)	(0.169)	(0.214)	(0.094)	(0.353)	(0.185)	(0.357)	(0.098)
Post 03/2020	1.309***		0.863***		0.764***		0.285	
	(0.249)		(0.177)		(0.261)		(0.264)	
EEA	3.052***		2.263***		3.760***		3.422***	
	(0.116)		(0.098)		(0.135)		(0.200)	
Month FE	No	Yes	No	Yes	No	Yes	No	Yes
Country FE	No	Yes	No	Yes	No	Yes	No	Yes
R-squared	0.096	0.724	0.114	0.835	0.090	0.756	0.088	0.934
Observations	6883	6883	4796	4796	8610	8610	4015	4015

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The first four models include all European countries, besides Turkey, Russia and Czechia. The time frame of the first two models is between January 2009 and January 2022, and is between January 2013 and January 2022 for the third and fourth models. The latter four models add OECD countries. For the last four models, the time frame of the first two models is between January 2009 and January 2022, and is between January 2016 and January 2022 for the last two models.

Table A.3: Google EEA Remedy Estimates (Alternative Samples & Periods)

	(1) Google	(2) Google	(3) Google	(4) Google
EEA × Post	-1.338	-1.305***	-0.979***	-0.948***
	(0.817)	(0.233)	(0.360)	(0.191)
Post 03/2020	1.083*		0.859***	
	(0.615)		(0.266)	
EEA	7.186***		3.841***	
	(0.456)		(0.143)	
Month FE	No	Yes	No	Yes
Country FE	No	Yes	No	Yes
R-squared	0.180	0.938	0.091	0.750
Observations	1476	1476	8005	8005

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The first two columns select as control countries only ones whose population exceeds 10 million and consider months between January 2016 and January 2022. The last two models instead consider only European countries and exclude the period corresponding to the "Play choice screen" (April 2019 - March 2020).

Table A.4: Google EEA Remedy Estimates (Pay-to-play & Free-to-Play)

	(1) Google	(2) Google	(3) Google
EEA × Post 03/2020	-1.417***		-1.417***
	(0.339)		(0.335)
Post 03/2020	1.357***		1.357***
	(0.280)		(0.277)
EEA	3.052***	3.052***	3.052***
	(0.117)	(0.120)	(0.116)
EEA × Post 09/2021		-1.541**	-0.124
		(0.630)	(0.674)
Post 09/2021		1.137**	-0.220
		(0.520)	(0.557)
R-squared	0.097	0.097	0.096
Observations	6663	6091	6883

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: These three models include all European countries, besides Turkey, Russia, and Czechia. The time frame of the first model is between January 2009 and August 2021, the time frame of the second model is between January 2009 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 January 2009 to January 2022.

Table A.5: Google Russian Remedy Estimates

	(1) Google	(2) Google	(3) Google	(4) Google	(5) Google	(6) Google	(7) Google	(8) Google	(9) Google
Russia × Post	-7.611***	-7.606***	-11.543***	-11.543***	-7.382***	-7.373***	-11.932***	-11.932***	-12.246***
	(1.066)	(0.610)	(0.829)	(0.353)	(1.388)	(0.750)	(1.897)	(0.514)	(0.745)
Post 04/2017	0.716***		1.180***		0.487***		0.477*		
	(0.156)		(0.121)		(0.182)		(0.249)		
Russia	-34.719***		-30.788***		-34.084***		-29.534***		
	(0.494)		(0.488)		(0.643)		(1.521)		
Month FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
R-squared	0.542	0.854	0.687	0.945	0.352	0.816	0.414	0.959	0.961
Observations	5897	5897	3666	3666	7283	7283	2436	2436	972

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The first four models include all European countries. The time frame of the first two models is between January 2009 and July 2019, and is between January 2013 and July 2019 for the third and fourth models. The latter five models add OECD countries and the last model selects as control countries only ones whose population exceeds 10 million. The time frame of the first two models is between January 2009 and July 2019, and is between January 2016 and July 2019 for the last three models.

Table A.6: Google Turkish Intervention Estimates

	(1) Google	(2) Google	(3) Google	(4) Google	(5) Google	(6) Google	(7) Google	(8) Google	(9) Google
Turkey × Post	-12.343***	-12.336***	-11.875***	-11.875***	-17.511***	-17.107***	-10.927***	-10.927***	-11.252***
	(2.810)	(1.097)	(2.487)	(0.689)	(1.575)	(0.665)	(3.118)	(0.739)	(1.105)
Post 08/2019	0.494		0.657*		0.719***		0.295		
	(0.410)		(0.363)		(0.221)		(0.409)		
Turkey	2.061***		1.594**		2.586***		1.164		
	(0.642)		(0.709)		(0.687)		(1.167)		
Month FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
R-squared	0.004	0.853	0.006	0.926	0.014	0.829	0.004	0.946	0.945
Observations	6273	6273	4042	4042	8828	8828	2900	2900	1164

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The first four models include all European and EEA countries. The time frame of the first two models is between January 2009 and February 2020, and is between January 2013 and February 2020 for the third and fourth models. The next five models add OECD countries and the last model selects as control countries only those with populations exceeding 10 million. The time frame of the first two models is between January 2009 and February 2020, and is between January 2016 and February 2020 for the last three models. All models set August 2019 as the beginning month of the treatment.

Table A.7: 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	-7.788***	-7.781***	-7.528***	-7.528***	-14.324***	-14.027***	-6.895***	-6.895***	-7.067***
	(1.834)	(0.716)	(1.671)	(0.465)	(1.410)	(0.598)	(2.255)	(0.539)	(0.809)
Post 09/2018	0.479*		0.695***		0.648***		0.269		
	(0.268)		(0.244)		(0.193)		(0.296)		
Turkey	2.463***		2.203***		2.984***		2.116		
	(0.672)		(0.765)		(0.720)		(1.353)		
Month FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
R-squared	0.004	0.852	0.006	0.925	0.012	0.826	0.003	0.945	0.944
Observations	6273	6273	4042	4042	8828	8828	2900	2900	1164

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The first four models include all European and EEA countries. The time frame of the first two models is between January 2009 and February 2020, and is between January 2013 and February 2020 for the third and fourth models. The next five models add OECD countries and the last model selects as control countries only those with populations exceeding 10 million. The time frame of the first two models is between January 2009 and February 2020, and is between January 2016 and February 2020 for the last three models.All models set September 2018 as the beginning month of the treatment.

Table A.8: EEA Search Engine Market Gains

	(1) Market Share Change	(2) Market Share Change	(3) Market Share Change	(4) Market Share Change
Desktop	0.022*	0.022*	0.022*	0.035
	(0.013)	(0.013)	(0.013)	(0.117)
Consecutive	0.023	0.022	0.025	0.027
	(0.023)	(0.023)	(0.023)	(0.024)
Consumer Protection		0.000		
		(0.003)		
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*	0.063	0.081	0.068
	(0.050)	(0.166)	(0.051)	(0.069)
R-squared	0.049	0.049	0.057	0.237
Observations	74	74	74	74

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS estimates for 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.9: Number of Auctions Won OLS Estimates

	(1) Slots Won	(2) Slots Won	(3) Slots Won	(4) Slots Won	(5) Slots Won
Desktop Share 2020 Feb	0.132***	0.497***	0.132***	0.138***	0.580***
	(0.026)	(0.049)	(0.026)	(0.026)	(0.049)
Mobile Share 2020 Feb	2.608***	0.169	2.807***	3.046***	0.479*
	(0.259)	(0.282)	(0.263)	(0.265)	(0.287)
Consumer Protection			0.009**		
			(0.004)		
Domestic Search Engine			-1.117***	-0.721*	0.063
			(0.380)	(0.393)	(0.328)
Search Engine FE	No	Yes	No	No	Yes
Country Controls	No	No	No	Yes	Yes
R-squared	0.190	0.450	0.202	0.223	0.479
Observations	870	870	870	870	870

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS estimates for the number of auctions won by Bing, DuckDuckGo, Ecosia, Qwant, Seznam, or Yandex in all of the treated countries of the EEA remedy. The last models control for country characteristics, including GDP, population, the ratio of male in the population, the working age ratio, and the percentage of young people between 20 and 29. The data is based on the latest data published by the World Bank.

Table A.10: 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

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: the time-frames included in these regressions is the 2016-2022 period. The control group always consists of Australia, Brazil, Canada and USA.

Table A.11: 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

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: the time-frames included in these regressions is the 2015-2019 period. The control group always consists of Australia, Brazil, Canada and USA.

Table A.12: 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

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: the time-frames included in these regressions is the 2017-2021 period. The control group always consists of Australia, Brazil, Canada and USA.

A.6 Inference

In this section, we focus on the standard errors used to conduct inferences about the effect of remedies. Our baseline results in Figure 7 report standard errors clustered at the country-month level, as in the conventional DD studies. However, this methodology has received criticism from Bertrand et al. (2004), who contend that DD estimation may suffer from error autocorrelation difficulties. Another problem rearding inference with the DD model that is particularly relevant for our analysis of the Russian and Turkish cases is the presence of a small number of treated units, discussed in Conley and Taber (2011).

In Table A.13, we report the results obtained by calculating the standard errors of the DD estimate under alternative metodologies. 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.13: Standard errors

	EEA		Russia		Turkey	
	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
Baseline	-1.745579	-1.083293	-8.80242	-6.409818	-14.48695	-10.18566
Heteroskedastic	-1.744757	-1.084115	-10.37774	-4.834495	-14.23534	-10.43726
Country Clusters	-2.870134	.0412616	-8.137724	-7.074514	-12.93621	-11.73639
Country-Quarter Clusters	-2.136687	-.6921848	-10.9279	-4.284341	-14.47421	-10.19839
Country-Year Clusters	-2.400879	-.4279933	-14.23968	-.9725576	-14.09825	-10.57435
Country-Year-Quarter Clusters	-1.955564	-.8733084	-12.24756	-2.964674	-14.47504	-10.19756
Year-Quarter Clusters	-1.859136	-.9697365	-12.54371	-2.668527	-14.57596	-10.09665
Conley & Taber	-.27274731	.02793225	-13.784243	-4.7582159	-18.924194	-6.1077161

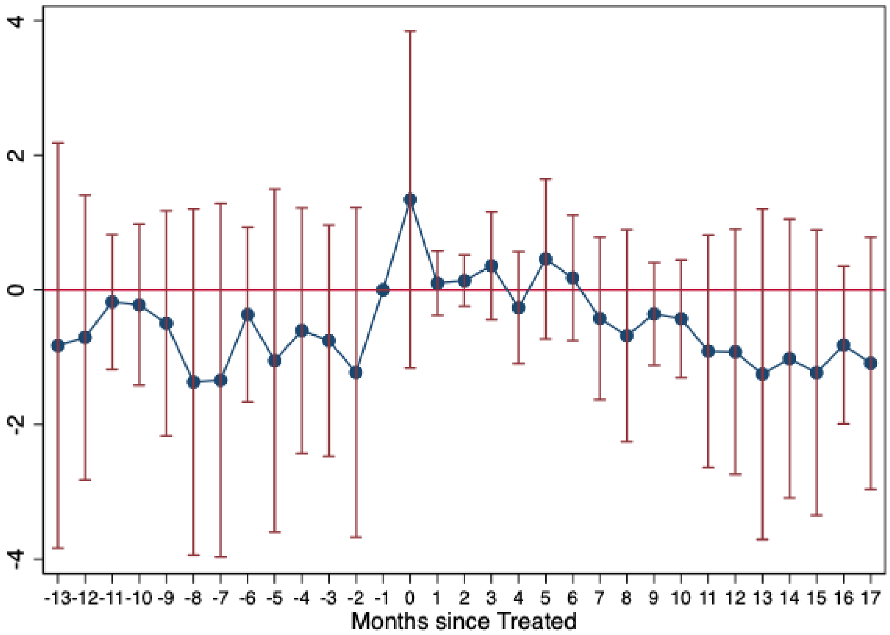
Notes: Confidence intervals (95% level) for the estimates from the regression specification of baseline mode in Figure 7.

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 a 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.7 Heterogenous and Dynamic Treatment Effects

We estimate the effect of the EEA remedy using the methodology proposed by de Chaisemartin and D’Haultfoeuille (2022). 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.

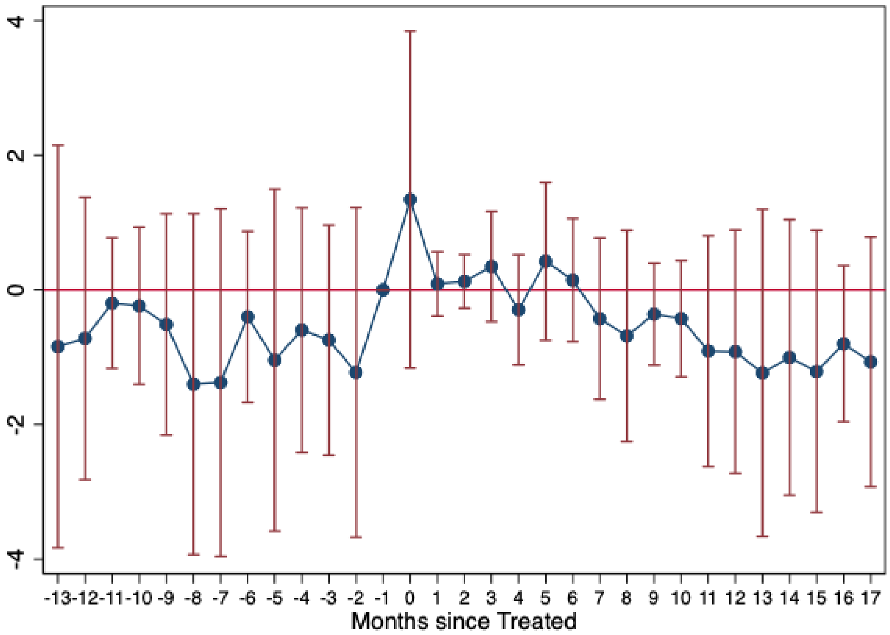
Figure A.4: Heterogenous and Dynamic Effect of the EEA Remedy (Binary Specification)



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.

Given its role as outlier, we remove Czechia from this analysis. Our estimates from the binary treatment specification in equation (1) and from the weighted treatment specification in equation (6) are shown in Figure A.4 and Figure A.5 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 -.3793 (SE: .5793) for the binary treatment specification and to -.5460 (SE: .8529) for the weighted treatment specification. The estimation is performed with the `did_multiplegt` package.

Figure A.5: Heterogenous and Dynamic Effect of the EEA Remedy (Weighted Specification)

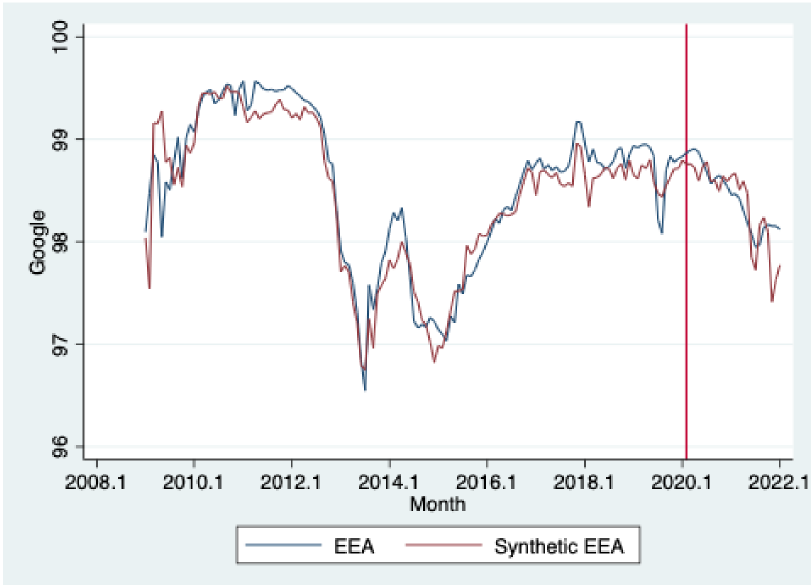


Notes: Each estimate, with its 95% CI, is the average cumulative effect of having been treated X periods ago. To the left of zero are placebo estimates testing the common trends assumption.

A.8 Alternative Estimator: Synthetic Control

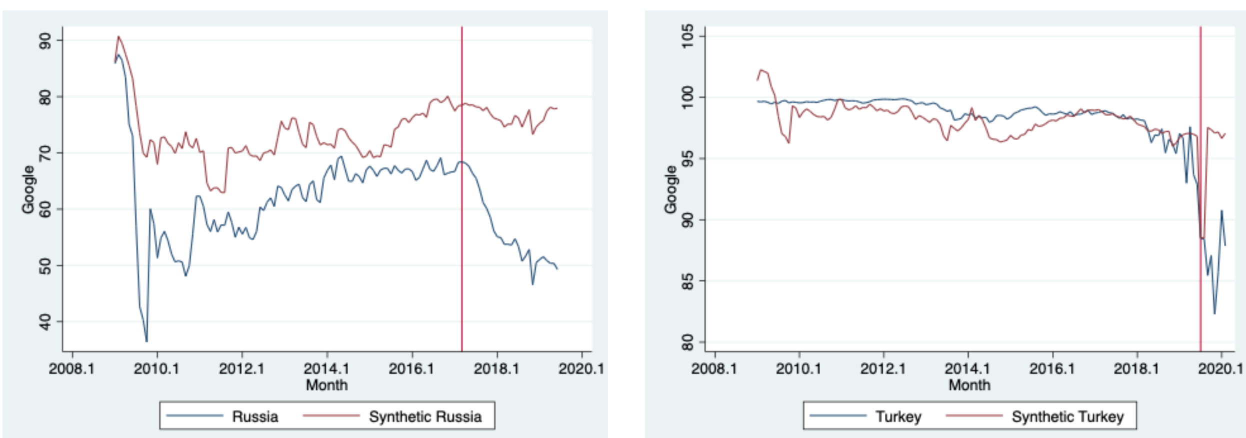
We employ the synthetic control technique proposed in Abadie et al. (2010) to identify and quantify the causal effect of the three interventions. For each one of the thee antitrust remedies, we construct the synthetic group consisting of the European and OECD countries that most closely resemble the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

Figure A.6: Synethetic Control Estimator of the EEA Remedy



In particular, in Figure A.6, Figure A.7a, and Figure A.7b, 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.7: Synethetic Control Estimator of the Russian and Turkish Remedy



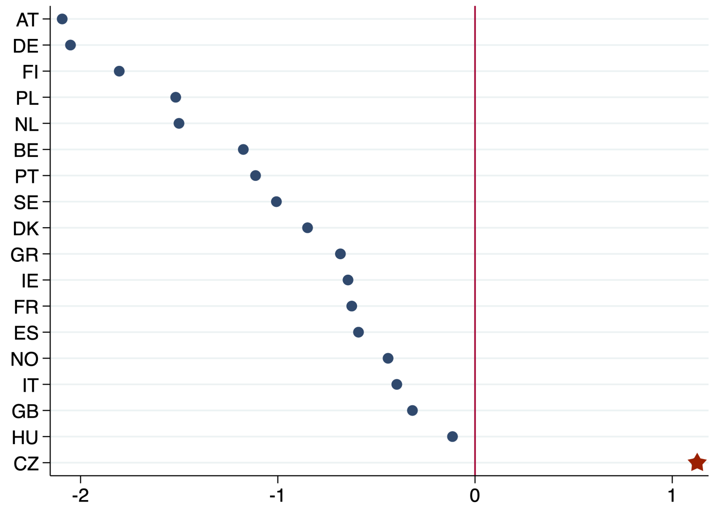
(a) Russia

(b) Turkey

A.9 Heterogeneous Effects of the EEA Remedy by Country

We estimate the weighted difference-in-differences model in equation (6) 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.8.

Figure A.8: Difference-in-Differences Estimates by Country



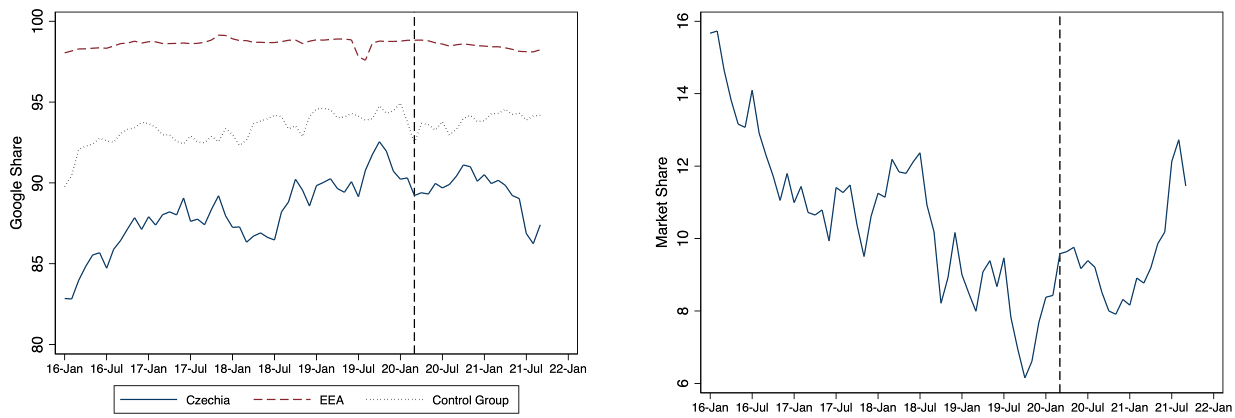
Notes: the sample used in the weighted difference-in-difference models includes Czechia, which is removed in all other analyses of the EEA remedy.

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. Indeed, Seznam was established in Czechia in 1996, before Google was even founded. The Czech search engine was still the most used search provider in Czechia in December 2013, when Google was already the dominant search engine in all other EU member states. 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.[57] 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.[58] According to Seznam, Google was able to gain market shares in the mobile segment by tying its search engine services with the Android mobile operating system.[59] 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". Figure A.9 plots the evolution of Google and Seznam market shares in Czechia in the four years leading up to the EEA choice screen.

Czechia is the only treated European country where Google's market share tends to be lower than its average market share in the control group consisting of other European and OECD countries. Moreover, the increasing trend in Google's shares we observe before the treatment is likely the result of Google gaining market shares from Seznam. Seznam's market share decreases before the remedy (from 16% in 2016 to about 8% in 2020) in a way that is comparable to the corresponding increase we observe in Google's shares (from 83% to about 90%).

[57] See `https://www.digitalnewsreport.org/survey/2017/czech-republic-2017/`.
[58] See `https://www.economist.com/babbage/2014/02/24/searching-for-answers`.
[59] See `https://www.nytimes.com/2022/02/02/technology/google-seznam-antitrust-czech-republic.html`.

Figure A.9: Mobile Market Share Trends in Czechia

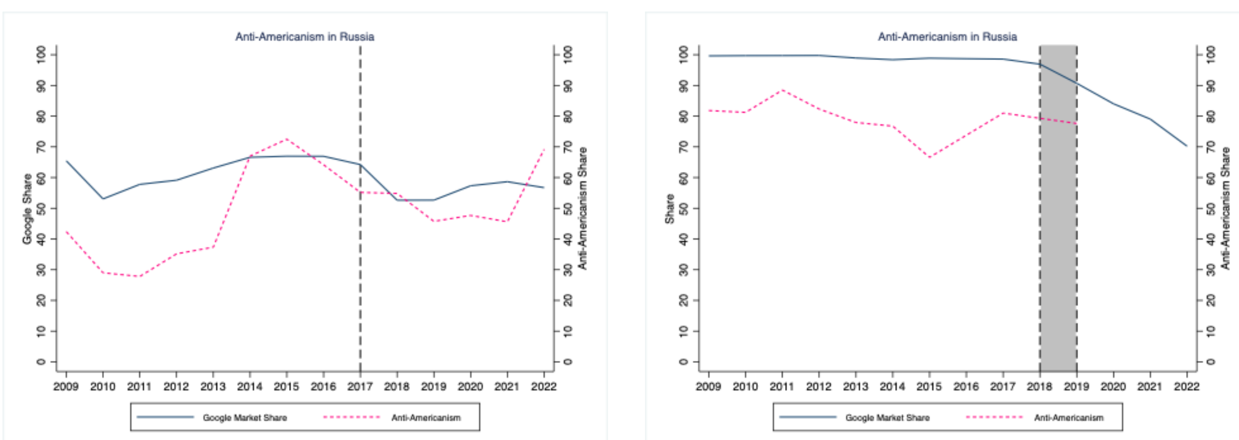


(a) Google (b) Seznam

A.10 Anti-Americanism

Anti-American sentiment characterizes a non trivial share of the population of Russia and Turkey. Changes to 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.[60] 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.[61]

Figure A.10: Anti-American Sentiment and Google Mobile Market Share



(a) Russia (b) Turkey

[60]See `https://www.pewresearch.org/global/database/indicator/1`.
[61]See `https://www.levada.ru/en/about-us/`.

In Figure A.10a and Figure A.10b, 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.[62] 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.

Table A.14: 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

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The time frame is all 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.

To further investigate this relationship, we incorporate anti-Americanism into our baseline model for the Russian intervention.[63] 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.14, we find that anti-Americanism has no effect on the intervention's impact. As in our baseline estimates, all estimates in Table A.14 indicate a causal decline in Google's market share induced by the Russian choice screen.[64]

A.11 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

[62] 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.

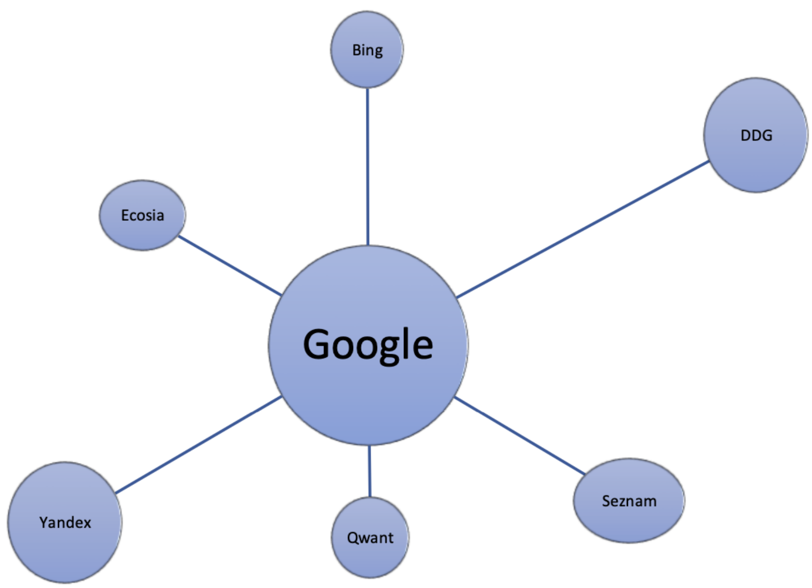
[63] For Turkey, instead, the available data do not cover a time horizon that allows estimating a DD model.

[64] 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.

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 A.11. 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, one search engine in the consideration set must be the incumbent firm g, and the other one is the competing search engine that the user is most familiar with.

Figure A.11: Remedy in the European Economic Area



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 ϵ_{ij} is the idiosyncratic awareness for user i. We assume that each ϵ_{ij} is independently and identically distributed with the standardized Gumbel (Type I Extreme Value) distribution. As a consequence, firm j will be chosen in the user's consideration set only if $W(i,j) > W(i,j')$ for all competing firms accessible to the user such that $\forall j' \in \{1, 2, ...J\} \neq j$. 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.

A.12 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:

1. Let b_i be the initial stock of mobile devices;
2. Let δ be the fraction of the initial stock that gets destroyed each period;
3. Let $ship_i$ be the number of mobile devices shipped to group i in each period;
4. Let γ_i be the fraction of shipped devices that become active in each period;
5. Let λ_i be the fraction of Android mobile devices out of total devices;
6. Let σ_i be the number of online searches made by each active device;
7. Let μ_i be the baseline market share for Google in mobile search;
8. Let θ be the rate at which users select Google from the choice screen ("CS").

Devices and Market Shares

Total mobile devices in group i at period t are given by:

$$dev_{it} = \underbrace{b_i \times (1-\delta_i)^t}_{\text{remaining stock}} + \underbrace{ship_i \times \gamma_i \times t}_{\text{shipments}} \tag{8}$$

Android devices are computed as:

$$Android\_dev_{it} = \lambda_i \times dev_{it} \tag{9}$$

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

$$cs\_dev_{et} = \begin{cases} 0 & t < t^* \\ \underbrace{\lambda_e \times ship_e \times \gamma_e}_{\substack{\text{choice screen} \\ \text{devices activated}}} \times \underbrace{(t - t^* + 1)}_{\substack{\text{periods} \\ \text{treated}}} & t \geq t^* \end{cases} \tag{10}$$

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:

$$Google_{it} = \frac{[(dev_{it} - cs\_dev_{it}) \times \mu_i \times \sigma_i] + [cs\_dev_{it} \times \theta \times \sigma_i]}{\underbrace{\underbrace{[(dev_{it} - cs\_dev_{it}) \times \mu_i \times \sigma_i]}_{\text{non CS device searches}} + \underbrace{[cs\_dev_{it} \times \theta \times \sigma_i]}_{\text{CS device searches}}}_{\text{Google searches}} + \underbrace{\underbrace{[(dev_{it} - cs\_dev_{it}) \times (1-\mu_i) \times \sigma_i]}_{\text{non CS device searches}} + \underbrace{[cs\_dev_{it} \times (1-\theta) \times \sigma_i]}_{\text{CS device searches}}}_{\text{competitors' searches}}} \tag{11}$$

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

$$Google\_Android_{it} = \frac{[(Android\_dev_{it} - cs\_dev_{it}) \times \mu_i \times \sigma_i] + [cs\_dev_{it} \times \theta \times \sigma_i]}{\underbrace{Android\_dev_{it} \times \sigma_i}_{\text{total Android searches}}} \tag{12}$$

Models

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

$$Google_{it} = \alpha + \beta_{\text{binary}}(Post_t \times Treat_i) + \psi Post_t + \phi Treat_i + \varepsilon_{it} \tag{13}$$

where $Post_t = \mathbb{1}(t \geq t^*)$ and $Treat_i = \mathbb{1}(i = e)$. Under the assumptions we made, it can be shown that the coefficient β_{binary} in regression (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:

$$\begin{aligned} \hat{\beta}_{\text{binary}} = & \underbrace{\left[\frac{1}{T - t^* + 1} \sum_{t=t^*}^{T} Google_{et} - \frac{1}{t^* - 1} \sum_{t=0}^{t^*} Google_{et} \right]}_{\text{treated group trend}} \\ & - \underbrace{\left[\frac{1}{T - t^* + 1} \sum_{t=t^*}^{T} Google_{ct} - \frac{1}{t^* - 1} \sum_{t=0}^{t^*} Google_{ct} \right]}_{\text{control group trend}} \end{aligned}$$

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

$$Google_{it} = \alpha + \beta_{\text{ship}}(Post_t \times Treat_i \times Android\_ship_i) + \rho Android\_ship_i + \psi Post_t + \phi Treat_i + \varepsilon_{it} \quad (14)$$

where $Android\_ship_i$ is the fraction of Android devices out of total mobile shipments in each period. It can be shown that, under our assumed configuration, the coefficient β_{ship} in regression (6) 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:

$$\hat{\beta}_{\text{ship}} = \underbrace{\left[\frac{1}{T - t^* + 1} \sum_{t=t^*}^{T} Google\_Android_{et} - \frac{1}{t^* - 1} \sum_{t=0}^{t^*} Google\_Android_{et} \right]}_{\text{treated group trend}} - \underbrace{\left[\frac{1}{T - t^* + 1} \sum_{t=t^*}^{T} Google\_Android_{ct} - \frac{1}{t^* - 1} \sum_{t=0}^{t^*} Google\_Android_{ct} \right]}_{\text{control group trend}}$$

Implications

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

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

- → If users select Google from the choice screen at a lower rate than its baseline market share, the estimated treatment effect is negative: $\theta \leq \mu_e \Longrightarrow \hat{\beta}_{\text{binary}} \leq 0$ 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 (θ) relative to its baseline market share (μ_e). If users select Google at a rate that is very close to its baseline share, the effect of the remedy is small. Moreover, note that the absolute value of both estimates is always smaller than the absolute value of the difference $|\theta - \mu_e|$. Intuitively, the two would coincide only if all mobile users were shown the choice screen. Since only a subset of users actually have access to the remedy, the effect $|\theta - \mu_e|$ is attenuated when measured on the broader population of Android users and even more so when measured in the population of overall mobile users.
- → The timing of the remedy: the effect of the remedy builds over time as more devices are exposed to the choice screen, hence if the treatment occurs at the end period ($t^* \to T$), 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 (δ), the per-period shipments ($ship_e$) and the activation rate (γ_e). Intuitively, these four parameters determine the mobile device accumulation pattern and the weight that devices with the choice screen have in the overall population of mobile devices. The smaller is the fraction of devices treated by the choice screen compared to the ones already circulating before the remedy, the smaller is the estimated effect.

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

→ As the fraction of Android devices falls, the two estimates will diverge more. Indeed, given our setting, λ_e measures the share of Android devices in mobile search. Intuitively, if all devices were Android $\lambda_e = 1$, then the two estimates would coincide $\hat{\beta}_{\text{binary}} = \hat{\beta}_{\text{ship}}$ as the effect on Android mobile search and on overall mobile search would be trivially the same. However, as the share of Android falls ($\lambda_e \to 0$), 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:

$$\hat{\beta}_{\text{ship}} = \frac{1}{\lambda_e} \times \hat{\beta}_{\text{binary}} \Longrightarrow |\hat{\beta}_{\text{ship}}| > |\hat{\beta}_{\text{binary}}| \tag{15}$$

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 levelling the playing field for competing search engines, the ATT is arguably more informative as it captures the effect on the sub-population affected by the remedy. We attempt to get an informative estimate of the effect of the choice screen remedy on treated consumers in the next section.

Inversion

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

Inverting equation (11), which determines Google's market share in overall mobile search, we can construct an estimate for θ as follows:

$$\hat{\theta} = \frac{(\overline{Google_e} \times \overline{dev_e}) - (\overline{dev_e} - \overline{cs\_dev_e}) \times \mu_e}{\overline{cs\_dev_e}} \tag{16}$$

where, on the right-hand-side, we have Google's baseline market share in the treatment group (μ_e) and averages over the post-treatment period for the treated group of Google's mobile market share ($\overline{Google_e}$), of the number of total devices ($\overline{dev_e}$) and of the number of choice screen devices ($\overline{cs\_dev_e}$) respectively.

From market size data (Newzoo), shipments data (Gartner) and market share data (StatCounter) at our disposal, we can compute the implied value $\hat{\theta}$ as in equation (16). We consider the 23 quarters between January 2016 and October 2021, with treatment occurring in March 2020. We focus on the 2016-2021 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 A.1. We exclude Russia and Turkey from the analysis as they are subject to their own interventions, and, following the discussion in Appendix A.9, 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:

(i) The initial stock of devices in each group (b_i);

(ii) The device destruction rate (δ);

(iii) The number of mobile devices shipped to each group in every quarter ($ship_i$);

(iv) The fraction of shipped devices that become active in each group in every quarter (γ_i);

(v) The share of Android devices in each group (λ_i);

(vi) Google's baseline market share in mobile search in each group (μ_i).

First, we assign values to the parameters that govern the mobile device accumulation pattern. From our market size data, we compute the total number of active smartphones as of 2016 in the EEA and in the control group and we assign the resulting values to the parameter b_i. We obtain a smartphone device stock equal to just below 560 million for the control group and to roughly 370 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 780 million while the EEA counted 470 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 (2016-2021), 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 2016-2021 period. On average, about 35 million devices are shipped in each quarter in the EEA and about 30 million to the control group. We assume that in both the treated and control group, 36% of shipped devices become active in each group.[65] The assumed destruction rate essentially sets the control group to an equilibrium number of mobile devices, whereby the inflow of shipped devices essentially compensates 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% of the initial stock in each period, which slightly exceeds the quarterly loss of devices, which we assumed to be 2.5% of the existing

[65] 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`.

stock.

Finally, we consider the parameters related to the mobile search market. In our setting, an important parameter is the share of Android in mobile search, captured by λ_i. From our shipments 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, 70.0% of shipped devices where Android, while in the control group this figure rises to 73.3%. By construction, as seen in equation (9), 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. We corroborate these assumed values with the data provided by StatCounter on mobile OS market shares for general internet traffic.[66] According to StatCounter, Android's average market share in Europe before the remedy, from January 2016 to February 2020, was 70.1% which perfectly matches our own figure. Lastly, we deal with the parameter related to Google's baseline market share in mobile search, captured by μ_i. From our search engine market share data, we compute the pre-treatment average market share of Google in mobile search both in the EEA and in the control group. From January 2016 to February 2020, Google had an average market share of 98.64% and 93.30% 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 (16).

Our estimate for Google's selection rate from the choice screen is equal to 95.59%. This value is smaller than the baseline market share of Google in mobile search in the EEA, which is equal to 98.64%. 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 6 the weighted and binary specifications yield very close estimates for the effect of the EEA remedy. This is likely due to the fact that θ is close to Google's baseline market share in the EEA. From equation (15), 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 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 6. Intuitively, since only new Android users had access to the choice screen, the effect is attenuated when measured on the

[66] For more information, please visit `https://gs.statcounter.com/`.

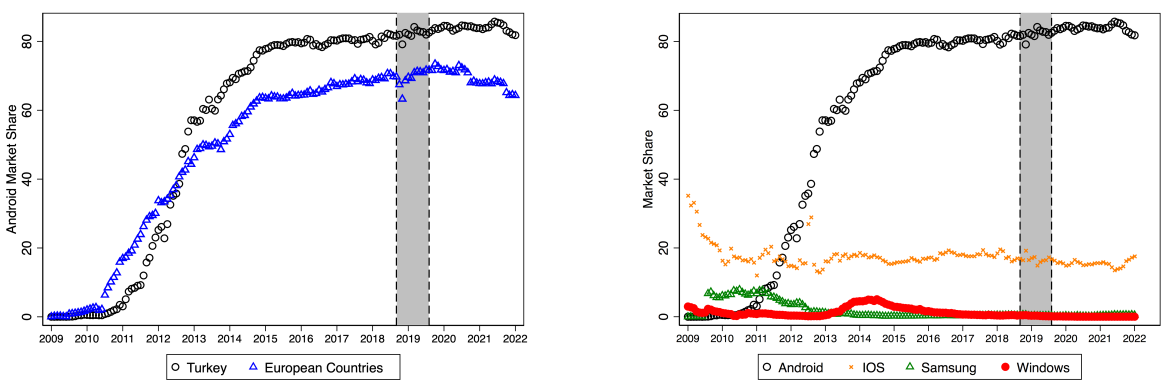
broader population of Android users and it decreases even more when measured in the population of overall mobile users.

A.13 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. To goal was to ensure 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 remains 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 A.12: 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 A.12a and Figure A.12b, 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:

$$Android_{ct} = \alpha + \beta(Turkey_c \times Post_t) + \lambda_c + \gamma_t + \varepsilon_{ct} \tag{17}$$

where $Android_{ct}$ is the mobile market share of the Android system in country c in period t. Our results in Table A.15 show no evidence of any significant change in the percentage of mobile devices

Table A.15: Mobile Operating System Market Share

	(1) Turkish Mobile OS	(2) Turkish Mobile OS	(3) Turkish Mobile OS	(4) Turkish Mobile OS
Turkey × Post	-1.352	-1.352	-0.826	-0.826
	(6.095)	(1.934)	(6.448)	(1.197)
Post 08/2019	8.828***		3.818***	
	(0.889)		(0.847)	
Turkey	13.008***		13.746***	
	(1.739)		(2.413)	
Month FE	No	Yes	No	Yes
Country FE	No	Yes	No	Yes
R-squared	0.038	0.906	0.020	0.967
Observations	4042	4042	2900	2900

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The first two models include all European and EEA countries and the last two models add OECD countries. The time frame of the first two models is between January 2013 and February 2020 and between January 2016 and February 2020 for the last two models.

adopting the Android operating system after the remedy. Therefore, we doubt the remedy generated any substantial change in the Android device price in Turkey.