

Competition and Defaults in Online Search*

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Abstract

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

Keywords: Online Advertising, Antitrust, Platform Competition

JEL Codes: C45, D44, G34, L13, L81, M37.

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

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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, United States v. Google LLC, 1:20-cv-03010 (D.D.C. 2020)*

1 Introduction

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

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

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

¹These 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.

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

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

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

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

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

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

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

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

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

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

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

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

engines respond to interventions in the online search market.

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

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

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

The second branch of the literature to which we contribute is that on behavioral economics. Choice screens might be interpreted as a tool to make certain choices more salient in the sense of Bordalo

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

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

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

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

2 Institutional Background

2.1 Search Engines

Internet search is a typical multi-sided market, connecting users surfing the web with advertisers wishing to attract eyeballs. Search engines supply links to content on the internet to users in response to their search queries. To do this, they index data from the public web and proprietary sources and return relevant content - ranked by an algorithm. In exchange for their services, search engines extract data and attention from users. Advertisers seeking to target consumers then pay search providers to display their ads, allowing search engines to offer their services free of charge to users. The mobile search market has experienced tremendous growth over recent decades due to the rapid adoption of smartphones. In 2021, mobile advertisement revenues accounted for over \$135 billion, more than double the revenues earned from advertisements on desktop devices.⁷ Google virtually monopolizes the search market, holding almost the entirety of the market. However, Google is not the only search engine available to consumers. Competitor search engines differ along many dimensions. Some pursue social causes (e.g., Ecosia and Panda Search), while others pride themselves on their strong protection of user privacy (e.g., DuckDuckGo). Some search engines focus on their local market (e.g., Qwant in France and Seznam.cz in Czechia), while others have global reach but differ in their geographical presence. Google, Bing, and DuckDuckGo are all based in the U.S., while Yandex is based in Russia. Among these, Bing seems to be the most viable competitor to Google in the U.S. and much of Europe. Indeed, several search engines, including DuckDuckGo, Ecosia, and Qwant, rely on Bing to provide search results.

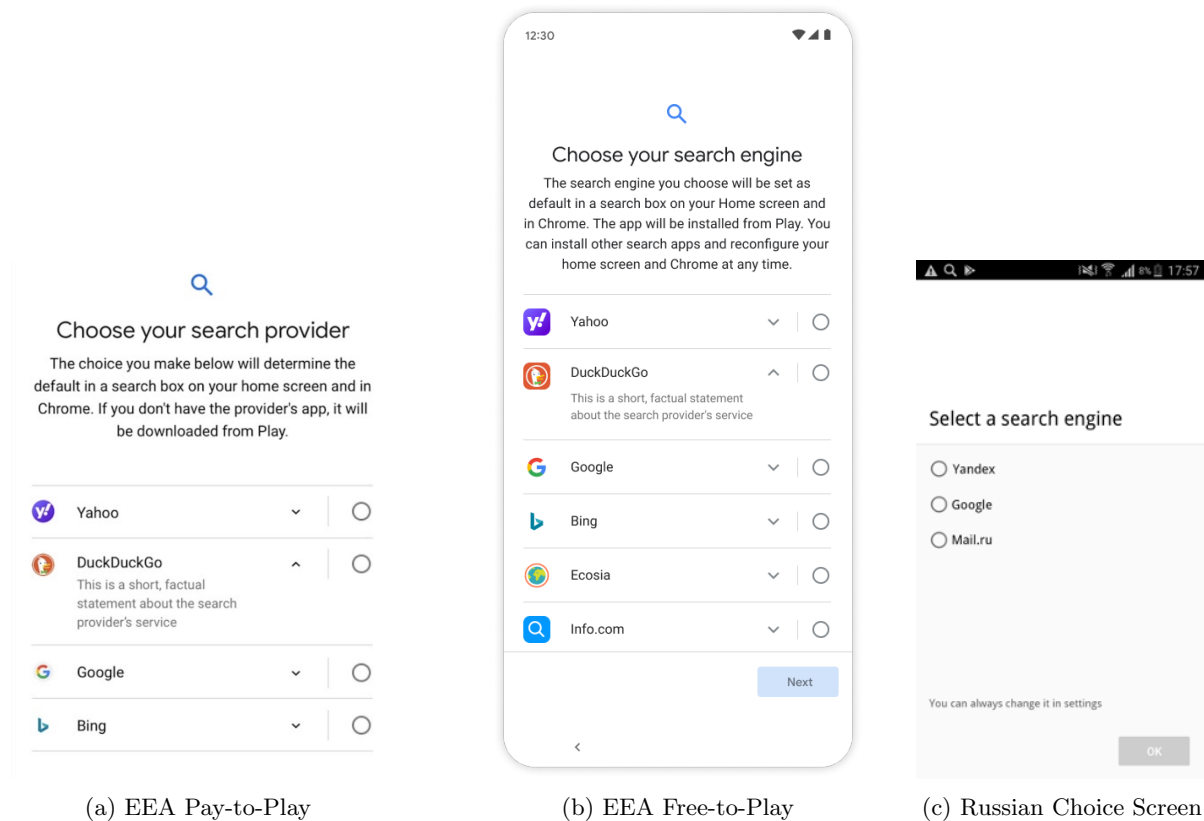
Mobile devices often come with several search access points pre-installed, each associated with a default search engine. Since mobile users suffer from inertia and status quo bias, being the default search engine is extremely valuable for search providers. To become the default search engine, search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

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

2.2 Remedy in the European Economic Area

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

Figure 1: Choice Screen Comparison



Following the EC decision, Google implemented a choice screen for general search providers on all new Android phones and tablets sold in the EEA and in the UK after March 2020. During the device setup, new Android users could select their preferred search provider on a screen offering a choice among four different providers. Choosing the provider (i) sets the search provider in a home screen search box; (ii) if Google Chrome is installed, makes the selected search provider Chrome’s default search engine; and (iii) prompts the downloading of the app of the selected provider. To appear on the choice screen (alongside Google), search providers have to participate in auctions, conducted quarterly and separately for each EEA member state, during which they bid the amount they are willing to pay Google each time a user selects them from the choice screen. The three

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

highest bidders win the auction and appear on the choice screen for that country (together with Google, all in random order) as shown in Figure 1. Each time a user chooses a search provider, the selected search engine has to pay Google an amount equal to the fourth-highest bid received in the auction. We refer to this as the “pay-to-play” choice screen.

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

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

2.3 Remedy in Russia

A similar antitrust investigation in Russia also resulted in a choice screen for mobile search providers. In April 2017, Russia’s Federal Antimonopoly Service (“FAS”) fined Google 438 million roubles¹¹ for violating the antimonopoly legislation. The abuse revolved around Google prohibiting the pre-installation of competing mobile applications of other developers.¹² The FAS determined that Google’s conduct constituted an abuse of dominance that distorted market competition. To restore competition, the FAS requested that Google (i) remove the exclusivity of Google applications on Android-based devices in Russia; (ii) stop restricting the pre-installation of competing search engines and applications; (iii) refrain from promoting pre-installation of Google as the only general

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

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

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

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

search engine; (iv) stop enforcing the clauses in its previously signed settlement contract with the FAS; and (v) ensure the rights of third party search engines to be included in the choice window.

Yandex and Mail.ru were the only two search engines that appeared on the choice screen alongside Google, as shown in Figure 1. For mobile and tablet devices that were already circulating before April 2017, users had the chance to choose their default search engine in the “choice window” that appeared upon the first system update, which took place on April 17th, 2017.¹³ For new devices sold in Russia after August 2017, a widget was developed that allowed users to select their preferred search engine from a new choice screen at first launch.

2.4 Remedy in Turkey

Following an investigation dating back to 2015, when the Russian search engine Yandex first initiated a complaint, the Turkish Competition Authority investigated and ultimately sanctioned Google for its restrictive terms imposed on original equipment manufacturers. In September 2018, the TCA imposed a fine of TRY 93 million¹⁴ on Google for forcing manufacturers to pre-install Google apps on their mobile devices through agreements. The TCA declared that Google held a dominant position in the market for licensable mobile operating systems and that it provided the Android OS with the conditions of having the manufacturers pre-installing Google as the default search engine and placing the search widget on the device’s main screen. The TCA concluded that the tying of Google’s mobile search services to its operating system constituted abusive behavior.¹⁵

Instead of introducing a choice screen to restore competition as in the EEA and Russia, the TCA required Google to modify its contracts with device manufacturers wishing to adopt the Commercial Android Operating System on their devices produced for sale in Turkey, to satisfy the following conditions:¹⁶ (i) removal of contractual provisions that require or directly/indirectly imply the exclusive placement of the Google search widget on the home screen as a condition of licensing, thereby guaranteeing the right of device manufacturers to choose the search provider; (ii) removal of the licence terms that require Google search to be assigned by default to all search access points within the existing design structure and included in the agreements, and not introducing new obligations to assign Google search by default to all search points that may arise as a result of design choices; (iii) removal of contractual provisions that require or directly/indirectly imply the installation of Google Webview¹⁷ as the default and exclusive in-app web browser as a condition of licensing; (iv) prohibition to provide incentives, financial or otherwise, in a manner that results in the conditions banned by the three obligations listed above. Furthermore, Google was also requested to remove from all existing agreements with device manufacturers (including Revenue Sharing Agreements) any obligation precluding competitor search engines from being preloaded on devices or set as default on any of the device’s search access points.

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

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

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

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

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

Google modified its contracts with mobile manufacturers in August 2019, but these efforts were considered unsatisfactory as they continued to prohibit changes to the devices’ default search engine.¹⁸ In November 2019, the TCA imposed a daily fine on Google at a rate of five per ten thousand of its turnover generated in Turkey until it addressed the outstanding issues.¹⁹ On January 9, 2020, Google submitted the final version of its revised contracts with device manufacturers to the TCA, which were deemed satisfactory by the competition agency. Device manufacturers were now free to negotiate with Google and any other competing search providers for access to the valuable search access points on mobile devices. In 2020, Yandex was chosen as the preset default search engine in Turkey by Huawei - among the largest OEMs in the country.²⁰

3 Data

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

3.1 Data Description

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

We also employ data from Gartner and Newzoo to measure the number of new and existing mobile phones. Gartner’s quarterly data cover device shipments in the largest 50 countries between the first quarter of 2016 and the third quarter of 2021. Shipments are recorded in each country by vendor,

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

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

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

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

OS, customer type, and device type. Newzoo’s data consist of annual measures of population, smartphone users, and active smartphones in 194 countries from 2016 to 2021. Together, these two data sources endow us with detailed information on the evolution of the stock of active mobile devices in each country. We also investigate app downloads based on data from AppTweak, an app store optimization tool that estimates the number of daily downloads of any app in over 70 countries. Further information and analyses based on these ancillary datasets can be found in the Online Appendix.

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

3.2 Data Patterns

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

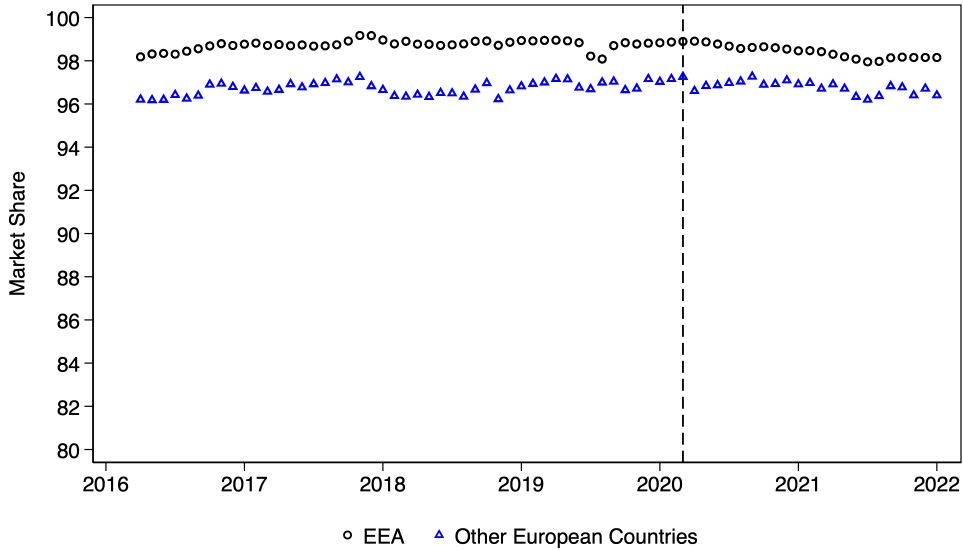
²²The complete list of treated and control group countries is provided in the Online Appendix.

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

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

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

Figure 2: Google Mobile Market Share



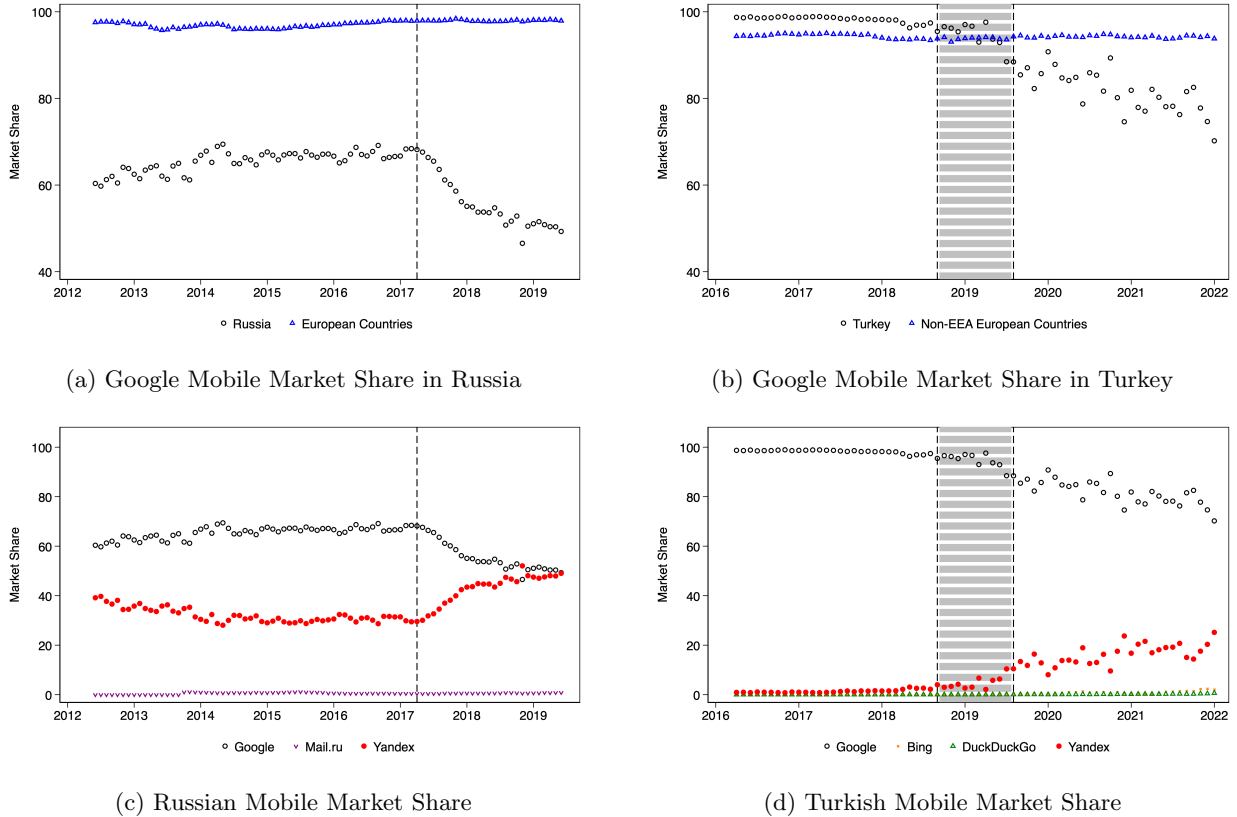
Notes: The vertical line corresponds to the introduction of the choice screen. We remove Russia and Turkey from the control group.

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

In Figure 3, we plot Google’s market share for Russia and Turkey compared to the European control countries and the evolution of the market shares for all of the main alternative search engines. In

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

Figure 3: Russian and Turkish Remedies



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

both cases, the trends appear to move in parallel before the interventions, but then diverge after the corresponding policies are implemented. We restrict our data to the time frame between June 2012 and June 2019 for the analysis of the Russian remedy (i.e., before the Russian government drafted the foreign ownership law in July 2019);²⁴ for Turkey, we consider the same period as the EEA (i.e., from April 2016 to January 2022). We observe that Google’s market share in Russia started to decrease in April 2017, when the choice screen was first shown to users, while Yandex’s market share increased. In April 2017, Google accounted for more than 60% of mobile searches and Yandex’s market share was around 30%. However, in July 2019, Yandex and Google shared almost the market equally.²⁵ Similar patterns are also observed for Turkey in Figure 3. Google’s market share began to decrease soon after September 2018, when the TCA asked Google to start working on its contracts with mobile manufacturers. This pattern persisted after August 2019, when Google

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

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

finished adjusting its contracts and officially submitted the compliance package to the TCA. After reviewing the main competing search engines in Turkey, we found that Yandex benefited the most from the TCA’s remedy on Google, as its market share kept increasing after this intervention.

4 Empirical Strategy and Results

4.1 Intervention Effect Analysis

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

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

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

where $Google_{ct}$ is Google’s market share in country c in 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 from zero to one for EEA countries after the policy is implemented (March 2020).

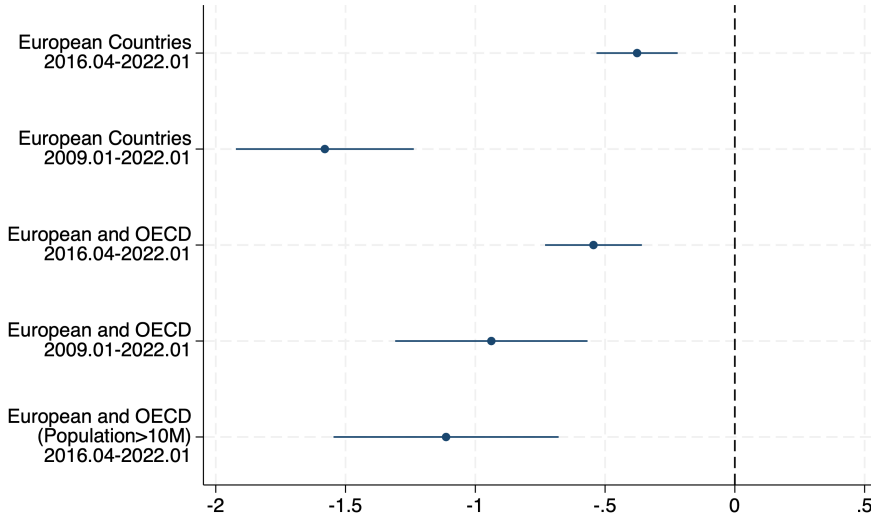
We apply the difference-in-differences model to a wide range of alternative sample choices, control groups, and regression specifications. Our first control group consists of all European countries not participating in the EEA remedy, and the baseline time frame is set between April 2016 and January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

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

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

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

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



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

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

Following the same methodology, we also analyze whether competitor search engines that won at least one “pay-to-play” auction gained from the remedy. These search engines include DuckDuckGo, GMX, Info.com, PrivacyWall, Bing, Qwant, Yandex, Seznam, Givero, and Ecosia. Among them, PrivacyWall, Info.com, GMX, and Givero have extremely low market shares and thus are not recorded by StatCounter. The market shares of Seznam, Qwant, and Ecosia are highly localized; thus, there are few observations in the European control group. We therefore focus on how the market shares of Bing, DuckDuckGo, and Yandex responded to the EEA remedy and compare these effects to the one suffered by Google in Table 2.²⁸ We find that Yandex, in particular, gained from the intervention, increasing its market share by over 1 percentage point. In terms of the magnitudes of the effects of the choice screen on competitor search engines, it is useful to consider the average market share of these search engines before the remedy was implemented. Indeed, the small increases in market shares we estimate are large compared to the tiny initial market shares

²⁷To ease the exposition, we summarize the main insights from the difference-in-differences estimates through figures (displaying the point estimate and its 95% confidence interval) and simplified tables (reporting exclusively the more relevant estimated coefficients). Readers can find in Appendix A.6.1 the complete set of results. The appendix also contains an extensive list of additional results that will be briefly described below.

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

of these search providers in EEA countries. The estimated effect of the choice screen for Yandex is about 0.106 percentage points, which is almost the same as its pre-treatment average market share in EEA countries of 0.11%.

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 \times Post	-0.377 (0.080)	-1.580 (0.175)	-0.545 (0.095)	-0.938 (0.189)	-1.113 (0.221)	0.019 (0.018)	0.060 (0.040)	0.106 (0.059)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.888	0.725	0.939	0.756	0.943	0.494	0.134	0.933
Pre-remedy Share	98.40	98.40	98.40	98.40	98.40	0.19	0.27	0.11
Observations	3010	6726	3780	8453	1416	3010	3010	3010

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

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

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

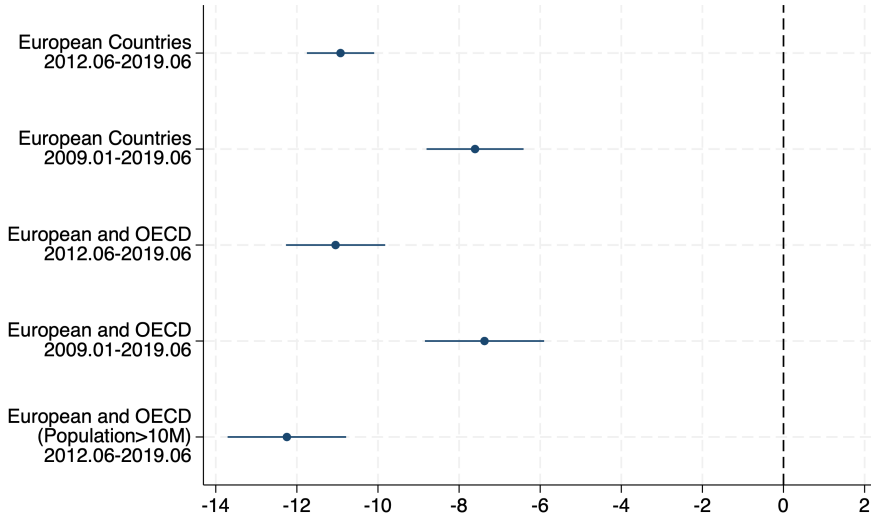
$$Google_{ct} = \alpha + \beta(Russia_c \times Post_t) + \lambda_c + \gamma_t + \varepsilon_{ct}, \quad (2)$$

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

²⁹The 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 July 2019 in our sample.

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

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



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

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

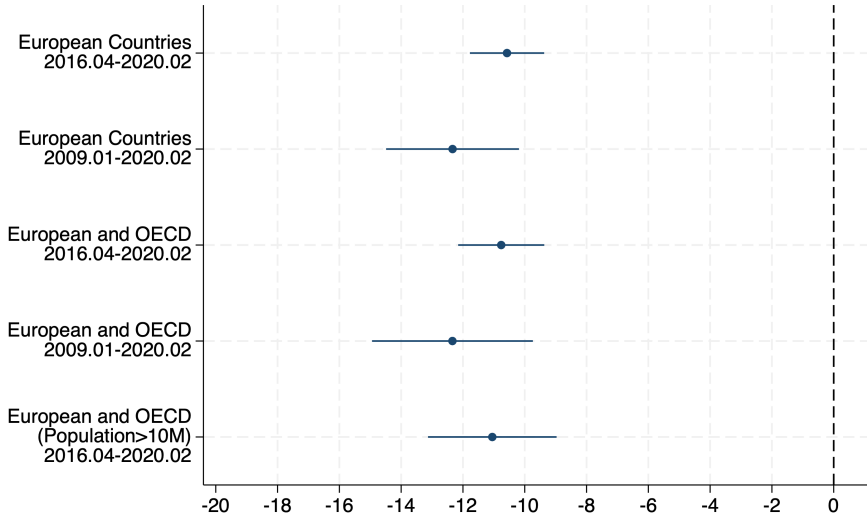
$$Google_{ct} = \alpha + \beta(Turkey_c \times Post_t) + \lambda_c + \gamma_t + \varepsilon_{ct}, \tag{3}$$

where $Turkey_c \times Post_t$ is a dummy variable that turns from zero to one for observations for Turkey after August 2019. The set of control countries is as described in the Russian case. To avoid having treated EEA countries in the control group, we restrict the sample to observations up to February 2020. In Figure 6, we report the estimated treatment for both the baseline case (a time frame between April 2016 and February 2020 and a control group of European countries) and alternative time frames and control groups. The complete set of estimates is reported in Table A.4. The estimates show a drop in Google’s market share of about 11 percentage points, which is equal to about five standard deviations of its pre-treatment mobile market share.³¹

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

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

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



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

Robustness We conduct multiple robustness checks to ensure the validity of our baseline findings. Our first set of checks focuses on the standard errors used to conduct inference for the remedy impacts. In particular, we take into account the potential issues of heteroskedasticity and error autocorrelation noted by Bertrand et al. (2004), as well as the challenge posed by having a small number of treated group units following Conley and Taber (2011). To account for these issues, we re-evaluate our baseline estimates through a battery of alternative methods described in Appendix A.6.2 along with the associated results. These results broadly confirm the baseline findings.

Our second set of robustness checks deals with the chosen estimators. In Appendix A.6.3, we relax the assumptions of static treatment effects and employ modern identification strategies developed by De Chaisemartin and d’Haultfoeuille (2024). We also explore the implications of relaxing the assumptions of homogeneous and static treatment effects in the Appendix A.6.4. Regarding the temporal dynamics of the treatment, we find that the effects tend to grow over time throughout the whole post-treatment sample period that we observe. In Appendix A.6.5, we estimate the impact of three remedies using the alternative synthetic control method of Abadie et al. (2010).

A third type of robustness check that we consider is one targeted to the Russian and Turkish cases and accounts for the dynamic of anti-Americanism (i.e., anti-US sentiment). Specifically, we check whether the drop in Google’s market share associated with the regulatory interventions occurs simultaneously with local spikes in anti-Americanism. Based on the anti-Americanism data and analysis described in Appendix A.6.6, we find no evidence of an association between anti-Americanism dynamics, the antitrust remedies, and the changes in Google’s market share. Indeed, our findings remain qualitatively unchanged even after incorporating anti-Americanism measures as a control in our baseline model. The main insight from these three sets of robustness checks is that the baseline findings are qualitatively robust.

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

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

4.2 Mechanisms

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

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

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

where $MobileChange_{ck}$ is the mobile market share change by search engine k in country c ;³³ $desktop_{ck}$ is the desktop market share of search engine k before the treatment; and, finally, Y_{ck} collects a dummy for whether search engine k is founded domestically in country c . The desktop share is a reasonable proxy for awareness because, as argued in the CMA report mentioned in the introduction, users tend to make more active choices of their search engine on desktops, meaning the share in the desktop search market is a good indicator of how aware users are of the different

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

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

Table 3: Bidding Strategy Estimates

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

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

search engines available. Moreover, the desktop market share, to some extent, also reflects the quality of search engines in the local market: intuitively, desktop users should prefer to use search engines with accurate search results.

The estimates reported in Table A.5 and Table A.6 reveal a positive and significant relationship between the mobile market share gain and the pre-remedy desktop share for most search engines, while there is no significant effect of the dummy for the domestic nature of the search engine. Interestingly, there is also a difference among competing search engines, with Bing being the only search engine whose interaction with the desktop share is negative and significant. This might be explained by desktop users of Bing not being keen to switch to it on their mobile phones.

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

The estimates are listed in Table 3. Across all of the models estimated, we find that a search engine is more likely to win an auction if it has a larger pre-remedy share in the desktop market in that country. Similarly, the pre-remedy mobile market share also has a positive effect, although the magnitude and significance vary across models. The controls for domestic search engines, as well

as those for the country characteristics included in the models of columns (3) and (4), are never significant, but they alter the size and significance of the two pre-remedy market share variables. Interestingly, in column (4), where we add search engine fixed effects, the magnitude of the desktop share effect grows relative to the other specification, which is explained by Bing behaving differently than the other search engines. Similar to the finding above on user choice, Bing’s desktop share is not predictive of winning auctions. Hence, it appears overall that search engines in the EEA auctions display a behavior that is coherent with user choices.

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

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

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

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

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

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

Notes: The time frames considered in these regressions span from 2016 to 2022 for EEA countries, from 2015 to 2022 for Russia, and from 2016 to 2022 for Turkey. The control group consistently includes Australia, Brazil, Canada, and the USA. Volume and revenue are recorded in thousands. Table A.8 to Table A.10 expand on the estimates in this table.

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

4.3 Counterfactual Analysis

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

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

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

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

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

Table 5: Google EEA Remedy Weighted Treatment Estimates

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

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

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

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

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

EEA Remedy Enhancing Visibility of the Top Competitor To evaluate this counterfactual, we exploit the differences across the EEA countries in the frequency with which the top competitor

wins a pay-to-play remedy auction to estimate what would have happened to Google’s market share had the EEA choice screen always displayed this top rival.

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

$$DiD_c = \alpha + \beta CompetitorFreq_c + \delta X_c + \gamma Y_c + \varepsilon_c \quad (6)$$

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

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

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

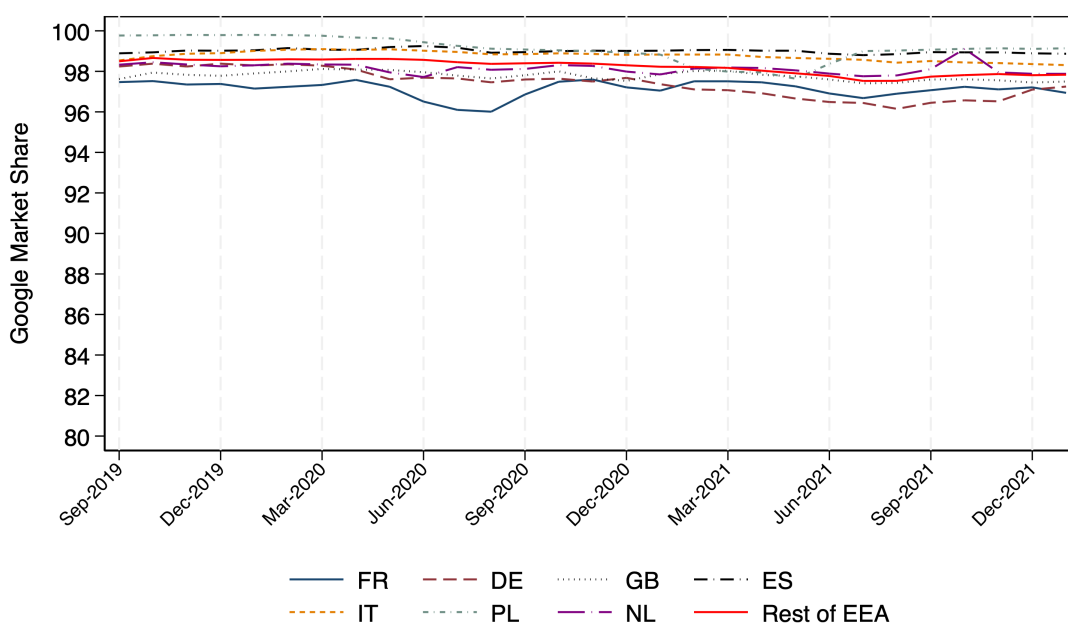
4.4 Quality Improvements and Search Defaults

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

appealing.

In 2019, Google anticipated revenue losses due to the EEA choice screen. In response, it launched a plan called “Go Big In Europe” aimed at enhancing the quality of its services for EEA users and increasing its chances of being selected as the preferred option in the choice screen.³⁴ Initially focusing on France and Germany in 2019 and 2020, Google aimed to improve its search services by adding post-game soccer video highlights, more local content and news, pronunciation practice for different languages, and more information on local television options available for streaming. According to the documents presented by the DOJ in court, Google intended to hire more than 80 new employees and spend more than \$200 million on the initiative. The updates were planned to be rolled out successively in the UK, Spain, Italy, Poland, and the Netherlands.

Figure 7: Go Big in Europe and Google Market Shares



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

Despite the limited information revealed in the ongoing court case, we attempt to assess the effect of Google’s Go Big in Europe plan by comparing how its market share changed in the seven EEA countries where the plan was implemented with the remaining EEA countries in Figure 7. Google’s market share did not seem to change drastically in the targeted countries, even compared to the rest of the EEA. Finally, in Table 6, we present regression estimates that dissect the impact of the EEA remedy on countries affected by Google’s Go Big in Europe plan. We estimate our baseline regression (1) distinguishing between the seven countries that were part of the plan and those that were not. We find that the effect of the remedy was remarkably consistent across both sets of countries, suggesting that the Go Big in Europe plan did not differentially alter the efficacy of the remedy within the targeted countries compared to non-targeted countries. However, it is important to note that the absence of an observable differential effect does not necessarily imply that the plan

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

was ineffective: the remedy might have led to more pronounced market share losses in the targeted countries if Google had not implemented its Go Big in Europe plan. Indeed, by forcing Google to make quality-enhancing investments, the EEA remedy may have greatly benefitted EEA users, despite the small effect on Google’s market shares.

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

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

Notes: Odd columns remove countries treated by Go Big in Europe (FR, DE, GB, ES, IT, PL, NL) from the treatment group, while even columns only consider countries treated by Go Big in Europe in the treatment group. Columns (1)-(4) only include European countries in the control group, while columns (5)-(8) add OECD countries to the control group. The time frame for all regressions is between April 2016 and January 2022.

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

Overall, the evidence arising from the US vs Google case indicates that regulatory interventions

³⁵For more details, please see <https://searchengineland.com/google-search-antitrust-trial-hearing-updates-431977>, (accessed February 24, 2024).

can have a broader impact than simply helping competitors to gain market share. Indeed, the reduction of the dominant firm’s market share should not be the sole indicator in welfare analysis. Although the impact of EEA remedy on Google’s market share might be small, such measures can encourage dominant companies to invest in improving their service quality. Also, the testimonies by Bing executives highlight the difficulties competitors face in matching Google’s level of quality, given that Google remains the default search engine on most devices. In fact, recent literature (Hovenkamp, 2023) suggests that policymakers should remove the entrenched default positions held by dominant firms to ensure a competitive playing field and promote welfare.

5 Conclusions

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

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

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

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

We find that the effectiveness of a remedy is determined by multiple factors, including nuances in intervention designs, user preferences, and characteristics of the local market. Investigating the potential factors determining the heterogeneous gains in market share across different search

engines, we show that competing search engines with higher pre-remedy popularity are more likely to be chosen by users in local markets. Further analyzing the EEA remedy during the pay-to-play period, we also observe consistent results showing that search engines with a larger existing user base and high popularity in the local market have strong incentives to participate in the remedy and to be visible to users.

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

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

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

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A.1 Appendix

A.1.1 Reduced-Form Analysis Tables

Table A.1: Google EEA Remedy Estimates

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

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

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

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

Notes: All models remove Turkey, Russia, Switzerland, and Czechia from the sample. The first two models include the European and OCED countries whose population exceeds 10 million and the time frame is between April 2016 and December 2021. The third and fourth models include all the European and OECD countries but exclude the period corresponding to the “play choice screen” from the period between January 2009 and January 2022. The fifth and sixth models restrict the sample to European countries and the time frame is between January 2019 and January 2021, when the downloads of VPN in Russia are quite stable as shown in Appendix ???. In the last two models, the sample include the European countries and the time frame is between April 2016 and January 2022.

Table A.3: Google Russian Remedy Estimates

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

Notes: The first four models include all European countries. The time frame of the first two models is between June 2012 and June 2019, and between January 2009 and June 2019 for the third and fourth models. All other models add OECD countries, with the last one selecting as control group only countries whose population exceeds 10 million. Among the last five models, the time frame of the first two and the last models is between June 2012 and June 2019, and is between January 2009 and June 2019 for the rest.

Table A.4: Google Turkish Intervention Estimates

	(1) Google	(2) Google	(3) Google	(4) Google	(5) Google	(6) Google	(7) Google	(8) Google	(9) Google
Turkey \times Post	-10.574 (2.710)	-10.574 (0.613)	-12.343 (2.810)	-12.336 (1.097)	-10.761 (3.118)	-10.761 (0.711)	-12.349 (3.070)	-12.340 (1.328)	-11.049 (1.061)
Post 08/2019	0.038 (0.395)		0.494 (0.410)		0.225 (0.409)		0.500 (0.403)		
Turkey	0.292 (1.046)		2.061 (0.642)		0.998 (1.203)		2.586 (0.702)		
Month FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	Yes
R-squared	0.008	0.951	0.004	0.853	0.004	0.950	0.003	0.818	0.949
Observations	2209	2209	6273	6273	2726	2726	7747	7747	1095

Notes: The first four models include all European countries. The time frame of the first two models is between April 2016 and February 2020, and between January 2009 and February 2020 for the third and fourth models. All other models add OECD countries, with the last one selecting as control group only countries whose population exceeds 10 million. Among the last five models, the time frame of the first two and the last models is between April 2016 and February 2020, and is between January 2009 and February 2020 for the rest. All models set August 2019 as the beginning month of the treatment.

Table A.5: Search Engine Market Share Gains

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

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

Table A.6: EEA Search Engine Market Gains

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

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

Table A.7: Number of Auctions Won OLS Estimates

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

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

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

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

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

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

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

Notes: The time frame is between 2015 and 2022 and the control group consists of Australia, Brazil, Canada, and USA.

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

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

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

Table A.11: Heterogeneous Effects across EEA Countries

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

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

A.1.2 Inference

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

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

Table A.12: Standard errors

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

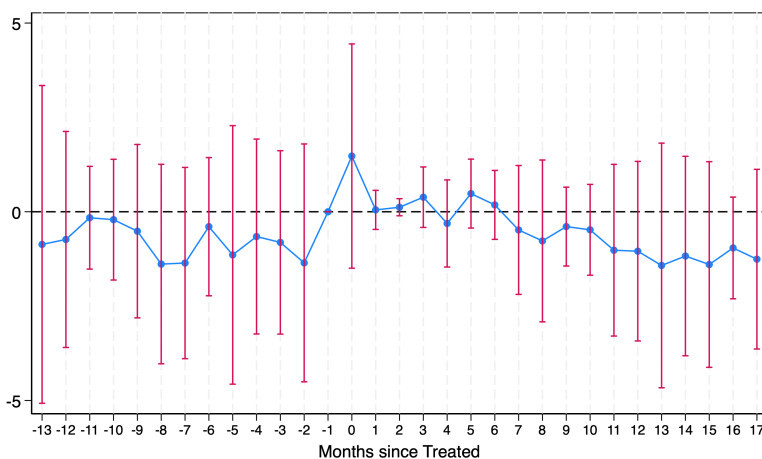
Notes: Confidence intervals (95% level) for the estimates from the regression specification of baseline models in Figures 4-6.

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

Russian and Turkish remedies, it is always the case that the treatment effect estimated by the DD is negative and statistically significant. For the EEA remedy, most results confirm the same evidence of the baseline estimates. In two cases (“Country Clusters” and “Conley & Taber”), the upper bound of the confidence interval is positive but very close to zero. Moreover, the interval in 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.1.3 Heterogeneous and Dynamic Treatment Effects

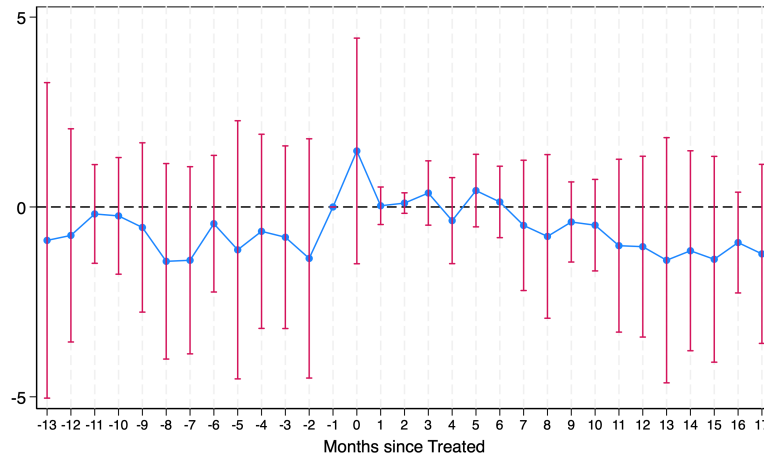
Figure A.1: Heterogeneous and Dynamic Effect of the EEA Remedy (Binary Specification)



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

We estimate the effect of the EEA remedy using the methodology proposed by De Chaisemartin and d’Haultfoeuille (2024). This strategy allows us to identify the treatment effect, allowing it to be heterogeneous across countries and allowing the current outcome in each country to depend also on the past values of the treatment. The only identification assumption required is the classic common trends assumption. Our estimates from the binary treatment specification in equation (1) and from the weighted treatment specification in equation (5) are shown in Figure A.1 and Figure A.2 respectively. According to the point estimates, there are negative cumulative effects of the remedy, as do all our previous results, but they lack statistical significance. The reason for this is probably that the estimation procedure clusters standard errors at the country-period level, since data is aggregated at that level before running the bootstrap. The two models yield very close estimates of the treatment effect, with the point estimates from the weighted treatment specification being slightly more negative than those from the binary treatment specification, and with both specifications pointing to effects that build over time. The average effect across all the instantaneous and dynamic effects estimated is equal to -0.4455 (SE: $.6209$) for the binary treatment specification and to -0.6461 (SE: $.8774$) for the weighted treatment specification. The estimation is performed with the `did_multiplegt` package.

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

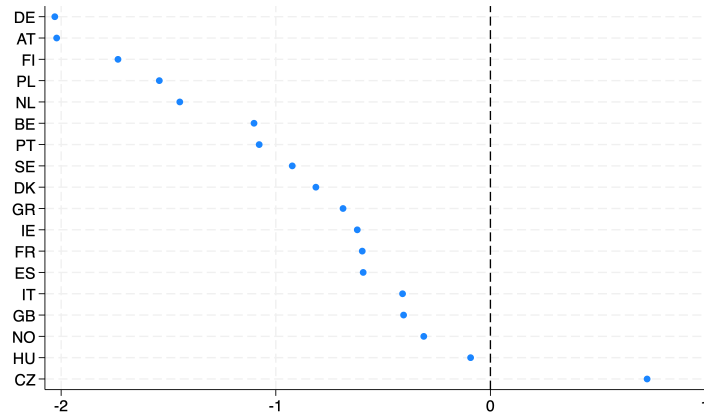


Notes: Each estimate, with its 95% CI, is the average cumulative effect of having been treated X periods ago. To the left of zero are placebo estimates testing the common trends assumption.

A.1.4 Heterogeneous Effects of the EEA Remedy by Country

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

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

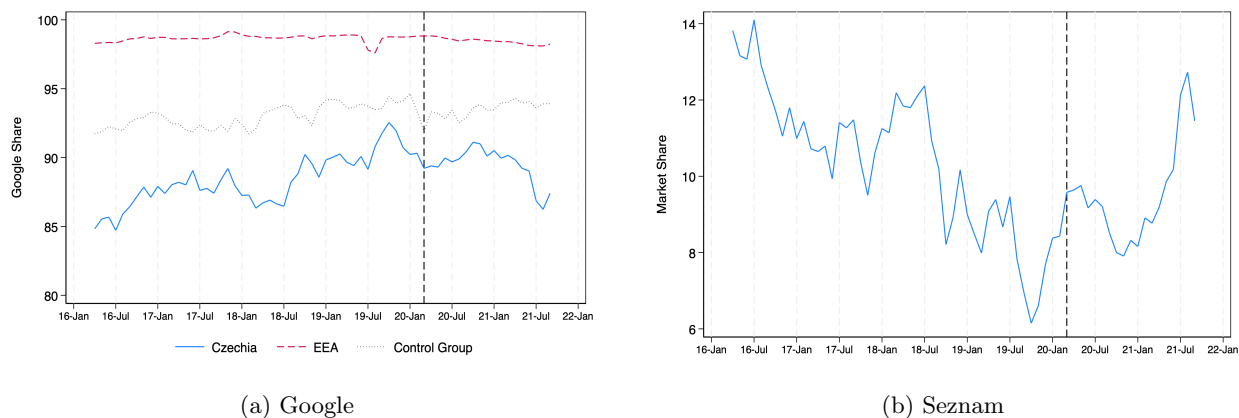


Notes: the sample used in the weighted difference-in-difference models includes Czechia, which is removed in all other analyses of the EEA remedy.

All treated countries exhibit a negative point estimate of the treatment effect, with the exception of Czechia, which seems to be an outlier. Czechia is unique compared to the other treated countries since Google is not as dominant there as it is in all other treated countries and faces competition from the domestic incumbent search engine, Seznam. As shown in Panel (a) of Figure A.4, Czechia is the only treated European country where Google’s market share is lower than its average market share in the control group consisting of other European and OECD countries. As Panel (b) shows, losses in Google market shares correspond to gains for Seznam. Throughout the whole period, the market share of Google has an upward trend until the fall 2019, after which it begins declining

in favor of Seznam. This reflects long-run competition between these two players in ways that we have no evidence to directly link to the EEA remedy.

Figure A.4: Mobile Market Share Trends in Czechia



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

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

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

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

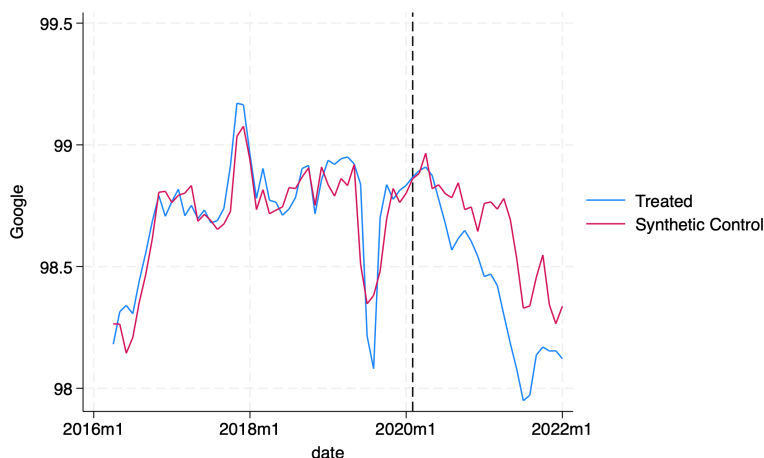
³⁸See <https://www.nytimes.com/2022/02/02/technology/google-seznam-antitrust-czech-republic.html> (accessed August 1st, 2024).

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

A.1.5 Alternative Estimator: Synthetic Control

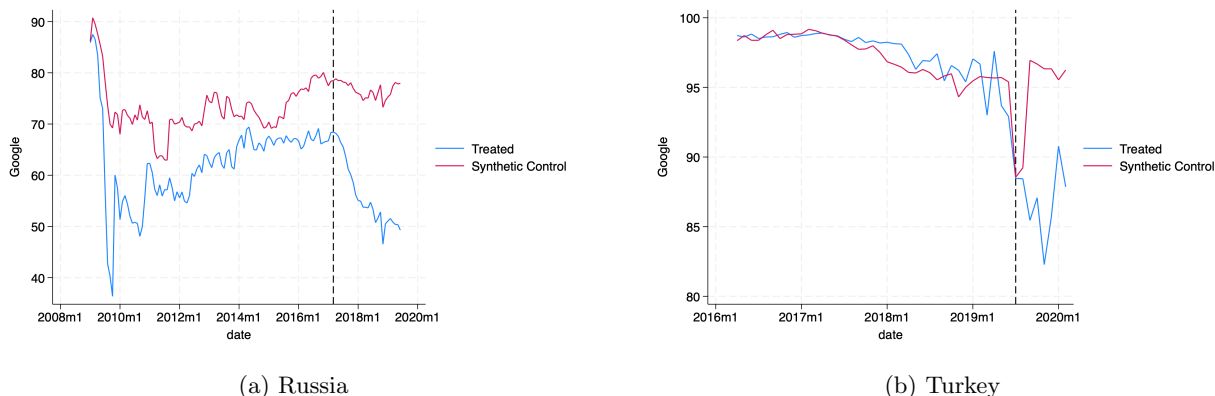
We employ the synthetic control technique proposed in Abadie et al. (2010) to identify and quantify the causal effect of the three interventions. For each one of the three antitrust remedies, we construct the synthetic group consisting of the European and OECD countries that most closely resemble the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

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



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

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

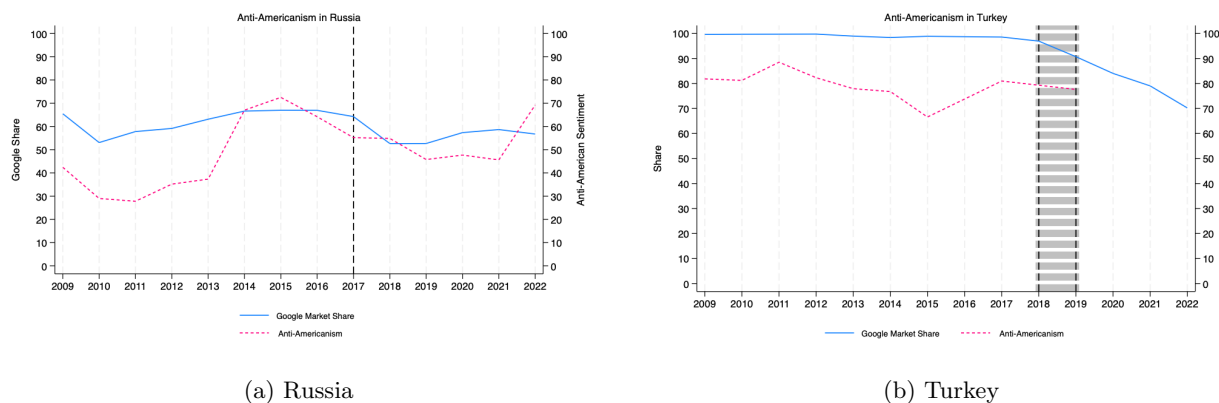


⁴⁰We use European and OECD countries as the control group and we drop Vatican City and San Marino from the synthetic control analysis as there are missing observations in these countries. We also drop Czechia and Switzerland from the EEA analysis due to its specialty as illustrated in Appendix A.6.3.

A.1.6 Anti-Americanism

Anti-American sentiment characterizes a nontrivial share of the population of Russia and Turkey. Changes in its intensity might partially drive changes in the Google market share if people were to associate Google and the US. To estimate whether anti-Americanism has any relevance to explain our findings, we employ survey data from the Pew Research Center (Pew) and Levada Analytical Center (Levada). Since its inception, the Global Attitudes Project conducted by Pew has interviewed over 600,000 people across 69 countries, recording their opinions of the United States between 2009 and 2019.⁴¹ We use the percentage of respondents who have somewhat unfavorable or very unfavorable opinions against the United States as a measure of anti-Americanism in each country. Levada, on the other hand, solely focuses on Russia, and its surveys cover a wide range of urban and rural populations across 50 regions in Russia between 1990 and 2022.⁴²

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



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

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

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

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

⁴³Note that the list of countries participating in Pew’s Global 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.

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

causal decline in Google’s market share induced by the Russian choice screen.⁴⁵

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

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

Notes: The first two models include all European countries between January 2013 and June 2019, during Vladimir Putin’s presidency. The last three models add OECD countries with the last model selecting as control countries only ones whose population exceeds 10 million, and the time frame is between January 2016 and June 2019.

⁴⁵Since 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.