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Competition Among Digital Services: Evidence From the 2021 Meta Outage

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Competition among digital services: Evidence from the 2021 Meta outage

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On October 4, 2021, all services provided by Meta Platforms, Inc. (then Facebook, Inc.) became unavailable unexpectedly for all its worldwide users for a period of about six hours. We use detailed high-frequency tracking data from smartphones, tablets and desktop computers of thousands of Meta users from Spain and the United States to study their behavioral responses during the outage. We find (1) the strongest substitution occurs within social media and messaging services, (2) evidence of substitution across service categories, (3) substitution patterns that vary across demographic groups, (4) substantially higher substitution rates among multi-homers, (5) substitution rates that increase over the course of the outage, (6) distinct differences in substitution patterns between countries, and (7) increased usage of non-Meta digital services after the outage. To our knowledge, this study presents the first comprehensive revealed-preference analysis of substitution patterns when an entire user population simultaneously seeks alternatives to major digital services.

Keywords: Digital services, Competition, Substitution, Attention markets, Outage
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1. Introduction

Assessing competition among digital services poses a unique set of challenges. These services are often based on multi-sided markets, exhibit network externalities, and are often free to consumers. These characteristics significantly complicate competition policy, for instance, for the delineation of relevant markets in the absence of observable prices. We analyze a natural experiment in which Facebook (including Messenger), Instagram, WhatsApp, and all other services provided by Meta Platforms, Inc. (then Facebook, Inc.) unexpectedly went offline worldwide for approximately six hours on October 4, 2021. This outage allows us to study consumer behavior when entire user populations simultaneously seek alternatives.

We focus on identifying "effective rates of substitution" in terms of usage time, capturing the "market for attention". Calvano and Polo (2021) provide an overview of the literature on attention markets. The effective rate of substitution quantifies the time reallocated from one service to another service. For example, a 10-minute increase in Twitter's usage time associated with a 20-minute decrease in Meta services' usage time indicates an effective substitution rate of 0.5. Our secondary results provide elasticities as well as substitution rates with respect to shares of device usage times. Our main identification strategy treats the outage as an instrumental variable (IV) for Meta services usage and estimates substitution rates by regressing non-Meta service usage times on Meta service usage times for a panel of individual users, while controlling for various fixed effects. The coefficient on Meta services' usage time identifies the effective substitution rate as a local average treatment effect. By using data from before, after and during the outage, this strategy corresponds to making in-sample counterfactual predictions for usage time. As a robustness check, we implement an alternative identification strategy with different identifying and econometric assumptions. We use time-series regressions to make out-of-sample counterfactual predictions for usage times during the outage for aggregates of users. The difference between predicted counterfactual and realization allows us to calculate effective substitution rates that can be compared to the ones from our main identification strategy.

The identification strategies are implemented using a comprehensive dataset of digital service usage behavior with millisecond time stamps. The data is collected by online panel providers through tracking panels, where panelists which usually take part in surveys, additionally install tracking software on their devices that monitors app and browser activity. The dataset also contains demographic information for each individual. To ensure that sample attrition does not bias our results, we balance the sample by only considering individuals with sufficient device usage. The balanced panel contains 11,858 individuals for the US and 2,420 for Spain between July 4, 2021 and November 4, 2021. Both panels have good coverage across various demographic variables.

Our key findings are as follows: First, non-Meta social media and messaging services are the strongest substitutes for Meta's services. Second, some substitution patterns cross commonly used service categories. For instance, video streaming services appear to be related to Meta's services. Third, the substitution patterns differ across demographic groups. Fourth, using non-Meta services before the outage is the strongest predictor of substituting toward these services during the outage, emphasizing the importance of multi-homing. For instance, while some users started using services such as Twitter or Telegram during the outage, the substitution rates among the previous users of these services are multiple times larger. Fifth, we observe inertia in behavioral responses. Substitution rates are larger in the second half of the outage, which indicates inertia in switching to using non-Meta services. Sixth, many of these results are different in magnitude between the US and Spain. Seventh, we find indicative evidence for greater usage of non-Meta services following the outage.

The external validity of our findings hinges particularly on whether we can generalize from short-term substitution rates to longer-term substitution rates. The estimated short-term substitution rates likely represent conservative estimates of longer-term substitutability, since users had limited time to explore alternatives and coordinate with others during the outage. This interpretation is supported by our analysis showing increased usage of non-Meta social media services in the weeks following the outage.

Our findings suggest two main policy implications. First, multi-homing significantly drives substitutability, with users familiar with multiple services showing higher substitution rates. This supports the Digital Markets Act (DMA)'s focus on enabling multi-homing through data portability and interoperability requirements. Second, the substantial heterogeneity in user responses across demographics and countries challenges uniform market definitions in digital services. This heterogeneity, combined with cross-category substitution patterns, questions the current category-based regulatory approach, as exemplified by YouTube's strong relationship with Meta's services despite being classified differently under the DMA.

We contribute to a growing body of literature on substitutes and complements among digital services. Our study is unique three ways: First, we identify substitution patterns when an entire group of major digital services temporarily exits the market. Second, most of Meta's services are based on social networks. The outage allows us to study how entire user populations coordinate and potentially migrate to other services. Third, we analyze revealed preferences from a large sample covering most demographic groups using comprehensive, fine-grained usage data.

Prior work has primarily relied on either stated preferences or revealed preferences from smaller, experimental samples. In the stated preference domain, Brynjolfsson, Collis, and Eggers (2019) and Coyle and Nguyen (2020) use choice experiments to estimate welfare effects and identify substitution patterns, while Dertwinkel-Kalt, Eulenberg, and Wey (2024) directly survey users about platform substitutes.

Studies using revealed preferences typically follow one of two approaches. The first approach pays selected users to forgo service usage. While Allcott et al. (2020) and Mosquera et al. (2020) rely on surveys to capture subsequent behavior, Allcott, Gentzkow, and Song (2022) and Collis and Eggers (2022) use tracking software to observe actual usage patterns. Similarly, Aridor (Forthcoming) tracks student behavior when incentivized to avoid specific services, documenting substitution across service categories. Bursztyn et al. (2023) elicit revealed preferences through incentivized experiments measuring college students' valuations for Instagram and TikTok.

The second revealed preference approach examines natural experiments. Xu et al. (2014) analyzes complementarity effects when a mobile news app is introduced, while Agarwal, Ananthakrishnan, and Tucker (2022) traces user migration after the shutdown of the Parler platform. However, these studies capture partial market effects since they examine either individual user choices or single-service changes, not a group of interconnected services. Our work advances this literature by providing the first comprehensive analysis of revealed substitution patterns when multiple user populations must simultaneously find alternatives. This allows us to capture the full network effects and coordination dynamics of mass service disruption, rather than individual responses when social networks remain largely intact. Additionally, our large sample with comprehensive demographic coverage provides broader external validity compared to previous studies focused on student populations or specific user segments.

We proceed as follows: First, we describe the timeline of events of the Facebook outage on October 4, 2021, and outline what makes it interesting for further investigation. Second, we describe the tracking data and demographics. Third, we present our main identification strategy, which leverages the outage. Fourth, we present the results of implementing this identification strategy. Fifth, we present results for an alternative identification strategy. Sixth, we discuss the external validity of our results and, seventh, their policy implications. Lastly, we conclude.

2. Meta outage on October 4, 2021 as a natural experiment

2.1. Timeline of events

On Monday, October 4, 2021, the services of Facebook, Inc. (now Meta Platforms Inc., hereinafter Meta) became unavailable worldwide at 15:40 Coordinated Universal Time (UTC) for a period of approximately six hours. The outage directly affected the company's social media platforms Facebook (including Messenger) and Instagram, its messaging service WhatsApp, and its other services such as Mapillary and Oculus.

According to Meta, the cause of the outage was a faulty command sent during a regular maintenance operation.[1] The command inadvertently disconnected all of

[1] Meta Platforms, Inc. 2021. More details about the October 4 outage. October 5. https://engineering.fb.com/2021/10/05/networking-traffic/outage-details/.

Meta's data centers, causing Meta's Domain Name System (DNS) servers to disable Border Gateway Protocol (BGP) advertisements. In essence, Meta stopped informing the outside internet of the location of its DNS servers. The purpose of these servers is to translate the web addresses we type into web browsers and which are used by apps into specific server IP addresses. Without available DNS servers, Meta's services could not be accessed by anyone. The length of the outage was due in part to the time it took to locate the problem, but also to the fact that Meta's engineers were unable to access the data centers.

The exact end of the outage is less clear. According to the cloud service provider Cloudflare, the DNS name `facebook.com` was available again around 21:20 UTC, about 5 hours and 40 minutes after the outage began.[2] This means that translation to the specific IP address was working again and users were being directed to the correct servers. While restoring services, Meta encountered some additional difficulties. The company reported that it had to be careful about bringing its data centers back online all at once, due to concerns about the surge in traffic and the corresponding sudden increase in power consumption of its data centers.[1] This resulted in a gradual return of services, which were generally available to users at approximately 22:45 UTC, approximately 7 hours after the outage began.

Table 1 shows the local times of the three major outage events: the start of the outage, the re-availability of the DNS servers and the general re-availability of the services to the end users. In the US, the outage occurs in the morning and afternoon, while in Europe it occurs in the late afternoon and continues into the evening.

TABLE 1. Outage Events in Local Times

Time zone	Time offset	(1)	(2)	(3)
Coordinated Universal Time (UTC)		15:40	21:20	22:45
Eastern Daylight Time (EDT)	UTC-4	11:40	17:20	18:45
Central Daylight Time (CDT)	UTC-5	10:40	16:20	17:45
Mountain Daylight Time (MDT)	UTC-6	09:40	15:20	16:45
Pacific Daylight Time (PDT)	UTC-7	08:40	14:20	15:45
Central European Summer Time (CEST)	UTC+2	17:40	23:20	00:45
Western European Summer Time (WEST)	UTC+1	16:40	22:20	23:45

Notes: The table shows the local times for three key outage events for the time zones present in our sample: (1) the start of the outage at 15:40 UTC, (2) the re-availability of the DNS servers at 21:20 UTC, and (3) the general re-availability of the services to the end users at 22:45 UTC.

2.2. Quasi-experimental variation

Meta's global outage allows to study its users' behavioral responses to an unexpected shock to the availability of Meta's online services. Since the outage was caused in the

[2]Cloudflare, Inc. 2021. Understanding how Facebook disappeared from the Internet. October 4. `https://blog.cloudflare.com/october-2021-facebook-outage/`.

server backend during regular maintenance work, without any connection to the user side, we can rule out immediate anticipatory effects. However, users might have expected outages to happen in general, even if major global outages are rare for large online service providers. Meta itself previously had major global outage events in 2008 and 2019.[3] So even if users might have expected outages to happen every once in a while, no user could have prepared for this particular time and day.

Two characteristics of the outage are of particular interest for competition policy. First, an entire group of services was affected by the outage. Facebook, Instagram and WhatsApp were simultaneously unavailable, representing three of the world's most widely used social media and messaging platforms. This simultaneous outage of multiple major services is particularly notable because these platforms serve distinct but overlapping purposes – Facebook for social networking and content sharing, Instagram for photo and video sharing, and WhatsApp for messaging. The concurrent unavailability of these complementary services forced users to find alternatives across multiple use cases simultaneously, rather than being able to fall back on other Meta services.

Second, since most of Meta's services have strong social network components, the outage affected entire social graphs and not only individual users. This differs from experimental settings where only selected individuals stop using a service while their social connections remain active. The simultaneous displacement of all users provides insights into network effects and coordination challenges when entire social graphs need to find alternative communication channels.

When studying substitution rates of Meta's services vis-à-vis other digital services, these rates might be downward-biased because Meta provides user authentication services to other websites and apps. For instance, users with a Facebook account can not only access other services provided by Meta, such as Instagram, but also use it to log into platforms like Netflix (discontinued in 2022) or Spotify. While users might have recovered access to these services by other means, the Meta outage might well have negatively affected their availability. Therefore, any substitution rates we estimate should be interpreted as conservative lower bounds, since the outage may have impaired users' ability to access and substitute toward alternative services that rely on Meta's authentication infrastructure.

3. Data

3.1. Scope

We use detailed, high-frequency app and browser usage data of individuals based in the US and Spain to capture behavioral responses to the outage. The data is obtained by online panel providers Luth Research for the US and Netquest for Spain. Panelists

[3] Subin, Samantha. 2021. Facebook is back online after suffering its worst outage since 2008. *CNBC*, October 4. `https://www.cnbc.com/2021/10/04/facebook-instagram-and-whatsapp-are-down.html`.

in this setting are paid by the companies to have an app installed on their devices that passively records their app and browser usage in addition to taking part in online surveys on different topics. All companies are fully CCPA and GDPR compliant and the data is fully anonymized.

Panelists might be tracked on their smartphones, tablets or desktop computers. Some panelists are tracked on multiple devices. The panel consists of 62.5% (45.2%) smartphones, 31.4% (44.9%) desktop computers and 6.1% (9.8%) tablets for the US (Spain). The sample covers mostly Android (60.1% US, 52.6% Spain) and Windows (31.4% US, 42.5% Spain) devices. Apple's iOS makes up only a small fraction of devices (8.5% US, 2.8% Spain) in both countries. This is in part due to Apple's release of iOS 15 in September 2021, which added additional privacy protections for users, and led to temporary difficulties in tracking iOS devices.[4]

The data covers the period from July 4, 2021 to November 4, 2021. It is an unbalanced panel with late entries and early exits of panelists. We create a balanced panel of regular device users that register at least five minutes of device usage on 90% of the days during the four weeks before Meta's outage on October 4, 2024 and the four weeks after the outage. Additionally, we filter out all individuals which did not use any Meta service in the four weeks prior to the outage, and are therefore not directly affected by the outage. Our main balanced panel consists of 11,858 individuals for the US and 2,420 for Spain.[5]

3.2. Processing

The tracking data is structured as follows. One row in the app data represents a single instance of an individual opening an app on a device. The time of the instance and the length of usage are recorded to the millisecond. The activity within the app is not recorded. One row in the browser data represents an instance of an individual opening a specific URL in their browser. If an individual visits multiple URLs of a website, these are recorded in separate rows. A URL is only recorded if it is in the active browser tab and the browser itself is the active window on the screen. Again, the time of the instance and its length are recorded.

The identification of the most used digital services in each country was done manually based on the balanced panel of users. Digital services can be accessed via an app or a web address in a browser. With app and browser traffic being recorded separately, it is necessary to account for both means of usage. To this end, apps and web addresses need to be matched to the corresponding digital services. Additionally, slight differences in the naming of apps and web addresses in the data for different operating systems need to be corrected to identify all instances of a service. We manually

[4]"iOS 15 is available today". *Apple*. 2021, October 4. `https://www.apple.com/newsroom/2021/09/ios-15-is-available-today/`

[5]The balancing requirements are rather strict and could potentially be relaxed. The unbalanced sample for the period between July 4, 2021 and October 4, 2021 consists of 147,292 individuals for the United States and 5,000 for Spain.

match app names and web addresses to services to solve these issues. The procedure is as follows.

First, we define the selection of app names and web addresses to be assigned to services in a data-driven way. To do so, we manually assign services to the instances of app names and subdomain-domain tuples that account for the most traffic in the app and browser data. We rank the instances of app names and subdomain-domain tuples in the data by total usage time during the data collection period. For web addresses, we use subdomain-domain tuples to account for different services of the same provider. For example, the web addresses of digital services by *Google LLC* share the same domain, but can be distinguished by their subdomain. The web address of its e-mail service *Gmail* is `mail.google.com`, its navigation service *Google Maps* can be found at `maps.google.com`.

To keep the number of services tractable, we concentrate of the most relevant services for the manual matching procedure. We define a relevance threshold of 0.25% of total app or browser usage. All app names or subdomain-domain tuples that account for at least 0.25% are manually assigned to a service. This leaves us with the 55 (44) most used app names and the 35 (34) most used subdomain-domain tuples for the US (Spain). With this approach, we capture all services, for which either the usage of their app or their web address are above the threshold. Appendix A shows all 65 services for the US and 52 services for Spain that are assigned with this approach.

For these services, we search for string patterns in both app and browser data and manually assign all instances of app names and subdomain-domain tuples to a service. For app names, this means that we account for different apps of the same service and small naming inconsistencies between operating systems. For web addresses, we use either the domain or the subdomain-domain tuple to assign the service. For example, both the tuples (`facebook, www`) for the service's regular website and (`facebook, m`) for the mobile version of its website are assigned to the same service. In total, the manually assigned services account for 66.9% of total app traffic and 54.7% of total browser traffic during the data collection period in the US, and 74.1% of total app traffic and 48.7% of total browser traffic for Spain. After identifying and selecting the relevant services, we assign each service to a service category based on its functionality. The mapping is provided in Appendix A. For instance, we distinguish between social media services, messaging services as well as other means of communication and entertainment.

Table 2 presents the identified services for the largest fractions of total app and browser traffic, respectively, in the US and Spain. The table underscores the relevance of Meta's services in both countries. Particularly in Spain, Meta's share of usage time is high due to the additional importance of WhatsApp. The table shows that similar social media, streaming and email services are used in both countries. By contrast, dedicated messaging services differ between countries. In Spain, WhatsApp and Telegram are the most used, while in the US, only the default Android messaging apps are

TABLE 2. Most used identified digital services

Apps			Web browser		
#	App name	% of usage	#	Domain	% of usage
US					
1	Facebook	13.55	1	YouTube	8.81
2	YouTube	10.97	2	Gmail	8.55
3	TikTok	4.36	3	Facebook	8.19
4	Instagram	3.65	4	Yahoo Mail	4.26
5	Clock	2.44	5	Google Search	3.34
6	Google Search	2.09	6	Outlook	2.43
7	Gmail	2.08	7	Amazon	2.19
8	Samsung Messages	1.99	8	Google Docs	1.68
9	Google Messages	1.76	9	Twitter	1.65
10	Snapchat	1.60	10	AOL Mail	1.59
11	Netflix	1.27	11	Bing	1.39
12	Daydream	1.20	12	Reddit	0.92
13	Phone/Dialer	1.18	13	Twitch	0.91
14	Amazon	1.16	14	MyPoints	0.77
15	Current Cash Rewards	1.03	15	Swagbucks	0.77
Spain					
1	WhatsApp	14.59	1	Facebook	10.42
2	Facebook	8.65	2	YouTube	9.16
3	Instagram	7.75	3	Google Search	4.46
4	Mi Locker	6.70	4	Gmail	2.90
5	YouTube	6.11	5	Outlook	2.56
6	Twitter	2.50	6	Twitter	2.18
7	TikTok	2.49	7	Twitch	2.03
8	Launcher	2.34	8	WhatsApp	1.76
9	Google Search	2.14	9	Netflix	1.61
10	Phone/Dialer	1.76	10	Amazon	1.55
11	Candy Crush	1.66	11	Instagram	0.91
12	Telegram	1.47	12	Yahoo Mail	0.81
13	Google Maps	1.41	13	Prime Video	0.75
14	Netflix	1.09	14	Marca	0.73
15	Gmail	1.02	15	Google Docs	0.68

Notes: This table presents a ranking of the identified digital services by their usage time. The first set of columns lists the services with most usage time with respect to app activity, the second set of columns with respect to web browser activity.

among the most used services. Additionally, some system utilities like launcher apps, clock apps or *MiLocker*, a lock screen app, are identified. *Daydream*, an Android virtual reality service, is also among the most used services, driven by few heavy users. Inherent to our sample, we also identify some online earning services like *Swagbucks* or *Current Cash Rewards* among the most used services.

To construct a panel for identification, we aggregate the usage time for a service within specified time intervals for each individual. We primarily use 6-hour intervals and align the intervals with the start of the outage, i.e. the 6-hour intervals start at 15:40 UTC, 21:40 UTC, 03:40 UTC and 09:40 UTC. The length of 6 hours covers the entire period of the DNS servers being entirely offline. Additionally, we use 3-hour intervals with the same alignment to identify temporal dynamics in the first and second halves of the outage. The number of observations for both intervals is reported in Table 3.

3.3. Summary statistics

For each individual, we have self-reported demographic data that was collected by the respective market research firms. This includes information on gender, age, education, and income. In Table 3 we present summary statistics for the balanced sample. The sample differs from a representative sample of the populations of the US and Spain. In the US, we have about 10 percentage point (pp) more women than the representative population. For both the US and Spain, our balanced sample is significantly younger than the population. In the US, individuals with higher educational attainment and income levels are underrepresented, which is typical for online panels.[6] The correct reference to assess the representativeness of the samples would be the population of Meta's or other services' user bases, which are likely to deviate from a country's overall population. Unfortunately, most digital services don't publish demographic data of their user base on a per-country basis. As a result, conclusively assessing the representativeness in this context is not feasible.

4. Identification

4.1. Market and estimand of interest

We are interested in the market for digital services to consumers. Most of these services are free to them. Consumers "pay" by providing eyeballs for advertising (Calvano and Polo 2021). Meta is a particularly large player in this "market for attention". Usage time is the most economically relevant unit of exchange in this market, since it is positively related to the potential to present advertisements. [7]

[6] We don't have access to education and income information for the Spanish sample.

[7] Transforming (or essentially binarizing) usage time data to choice data in order to apply the commonly used discrete-choice toolchain would probably lose valuable information on usage intensities, which we can easily address by working with usage time directly.

TABLE 3. Summary statistics

	US		Spain	
	Sample	Population	Sample	Population
Individuals	11,858	–	2,420	–
Observations (6-h)	1,671,978	–	341,220	–
Observations (3-h)	3,343,956	–	682,440	–
Gender (in %)				
Female	62.3	50.8	48.0	51.0
Male	37.6	49.2	52.0	49.0
Other	0.1	–	–	–
Age (in %)				
18 to 34 years	35.0	29.6	21.1	22.0
35 to 49 years	35.8	24.3	36.3	27.8
50 to 64 years	21.2	24.5	32.3	26.1
65 years and over	8.0	21.7	10.3	24.1
Education (in %)				
Less than high school	8.4	10.8	–	–
High school	27.1	27.3	–	–
Some college / associate degree	36.6	29.5	–	–
Bachelor degree or higher	24.4	32.4	–	–
No Info	3.4	–	–	–
Income (USD, in %)				
Less than 25,000	32.5	17.4	–	–
25,000 to 49,999	30.6	19.1	–	–
50,000 to 74,999	15.9	16.8	–	–
75,000 to 99,999	8.4	12.8	–	–
100,000 or more	9.2	34.0	–	–
No Info	3.4	–	–	–
Device usage time per day (in hours)				
Mean	6.769	–	3.935	–
Standard deviation	6.246	–	2.221	–

Notes: This table presents summary statistics for the balanced panel of regular device users that register at least five minutes of device usage on 90% of the days during the four weeks before and after Meta's outage on October 4, 2021. Population statistics are from the US Census Bureau's American Community Survey and Spain's Instituto Nacional de Estadística for 2021.

We aim at identifying the "effective rates of substitution" between Meta's services and other digital services, quantified by changes in usage time. For example, a 10-minute increase in Twitter's usage time, contrasted with a 20-minute decrease in Meta services' usage time indicates an effective substitution rate of 0.5. While this does not correspond to the theoretically appealing marginal rate of substitution, we deem this to be the most intuitive measure of substitutability suitable to the setting at hand, in which individuals simultaneously faced a non-marginal change in the availability of a group of digital services within a potentially complex web of digital complements and substitutes, and had to consider network effects within the user graph of some of these services. Identifying marginal rates of substitution would require strong assumptions with respect to all of these concerns.

4.2. Identification strategy

The main challenge to identify the effective rates of substitution is the lack of a control group of users not affected by the outage. Therefore, we estimate the counterfactual usage times of a given service, had the outage not occurred, using data from before and after the outage. Our main identification strategy implicitly estimates the counterfactual by treating the outage as an IV for Meta services usage and estimates substitution rates by regressing non-Meta service usage times on Meta service usage times for a panel of individual users. The exclusion restriction for this IV strategy is likely violated since Meta's authentication services were also unavailable during the outage, potentially directly affecting usage of non-Meta services that rely on Facebook login. However, this violation would bias our substitution rate estimates toward zero, making our results conservative lower bounds. We use data for the four weeks prior and one week after the outage to estimate these regressions. These five weeks serve as the baseline against which the behavioral responses during the outage are measured.

We implement the identification strategy with standard IV regression methods. The estimated equations are of the following form:

$$
\begin{aligned}
U_{it} &= \alpha_0 + \alpha_1 \widehat{M_{it}} + h_t d_t + p_i + \mu_{it} \\
M_{it} &= \gamma_0 + \gamma_1 \mathbb{1}_{\text{outage}} + h_t d_t + p_i + \nu_{it}
\end{aligned}
\tag{1}
$$

with U_{it} denoting the usage time of a particular service or service category for individual i at time t, M_{it} denoting the usage time of Meta's services, p_i denoting individual fixed effects, and h_t and d_t are indicator variables for the time of day and the day of the week, respectively.[8] M_{it} is instrumented with $\mathbb{1}_{\text{outage}}$, an indicator variable which is one in the period of the outage and zero otherwise. Our analysis focuses on the coefficient α_1, which captures the relationship between the usage time of Meta's services

[8]For the US, we additionally include an indicator for the individual's timezone and interact it with the time indicator variables to account for differences in daily and weekly usage patterns across timezones when using standardized UTC time.

and the usage time for a particular service or category. This corresponds to our estimand of interest, the effective substitution rate. A negative α_1 implies substitution, meaning that a disruption to Meta's services leads to an increase in the usage time of another service. Conversely, a positive α_1 implies complementarity, meaning that a disruption to Meta's services results in a decrease in the usage time of another service. Reflecting our primary focus on substitution, we refer to α_1 as the "substitution rate", and explicitly distinguish cases where a positive coefficient α_1 reflects a complementarity effect.

We estimate these regressions for each country separately. To analyze heterogeneity in substitution rates within a country, we also split the set of individuals by their demographic characteristics or they pre-outage behavior with respect to multi-homing. This yields the following estimated equations:

$$\begin{aligned} U_{it} &= \alpha_0 + \alpha_1 \widehat{M_{it}} + \alpha_2 \widehat{S_i M_{it}} + h_t d_t + p_i + \mu_{it} \\ M_{it} &= \gamma_0 + \gamma_1 \mathbb{1}_{\text{outage}} + h_t d_t + p_i + \nu_{it} \\ S_i M_{it} &= \gamma_0 + \gamma_1 \mathbb{1}_{\text{outage}} + h_t d_t + p_i + \nu_{it}, \end{aligned} \tag{2}$$

with S_i denoting the binary variable along which the set of individuals is split. α_1 corresponds to the effective substitution rate for $S_i = 0$, while α_2 captures the difference from this baseline for individuals with $S_i = 1$.

One implicit assumption of this specification is that the substitution rate is linear in usage time. This functional form assumption might not be fully appropriate, as substitution behavior could exhibit diminishing returns or threshold effects. For example, users might substitute proportionally more Meta usage time when the reduction is small (e.g., checking Twitter instead of Facebook for 5 minutes) compared to when it's large (e.g., finding alternatives for several hours of social media use). Additionally, some services might only become viable substitutes after a certain minimum threshold of Meta usage reduction, as users need time to set up and explore alternative services.

To address these functional form concerns, we re-estimate our baseline specification using inverse hyperbolic sine (asinh) transformations of both the dependent variable and Meta services usage. The asinh transformation primarily allows us to test whether the substitution relationships hold under a different functional form assumption, as it approximates a log transformation for large values while remaining defined at zero. As such, the asinh transformation approximates elasticities (Bellemare and Wichman 2020). As an additional benefit, it reduces the influence of extreme values while preserving zero observations, reducing sensitivity to outliers in usage time, which are common in digital service data. The transformed regression equations take the form:

$$
\begin{aligned}
\operatorname{asinh}(U_{it}) &= \alpha_0 + \alpha_1 \widehat{\operatorname{asinh}(M_{it})} + h_t d_t + p_i + \mu_{it} \\
\operatorname{asinh}(M_{it}) &= \gamma_0 + \gamma_1 \mathbb{1}_{\text{outage}} + h_t d_t + p_i + \nu_{it},
\end{aligned}
\tag{3}
$$

Additionally, we estimate substitution in terms of shares in the digital "market for attention". In order to do so, we calculate substitution rates for relative usage time, the share of the usage time for a given service or service category in an individual's total device usage time across all of the recorded devices. The substitution rates for relative usage times (or market shares) are estimated as:

$$
\begin{aligned}
\frac{U_{it}}{D_{it}} &= \alpha_0 + \alpha_1 \frac{\widehat{M_{it}}}{D_{it}} + h_t d_t + p_i + \mu_{it} \\
\frac{M_{it}}{D_{it}} &= \gamma_0 + \gamma_1 \mathbb{1}_{\text{outage}} + h_t d_t + p_i + \nu_{it},
\end{aligned}
\tag{4}
$$

with D_{it} denoting the total device usage time for individual i at time t.

Changes in market shares defined as such are net of off-device substitution. The interpretation of relative usage measures implicitly assumes users first decide to use a device before choosing specific services. However, this assumption is problematic since notifications and other service-initiated prompts often drive device usage, creating simultaneous device and service choice decisions. This simultaneity is particularly evident at high frequencies where individual notification-driven sessions are observable. Therefore, we place greater weight on absolute usage times when analyzing user behavior at higher frequencies, especially during the outage.

At lower frequencies like daily aggregates, both absolute and relative usage measures have tradeoffs. Absolute measures may capture true substitution patterns better but are sensitive to external factors affecting overall device usage (e.g., weather, local events) that time fixed effects may not fully capture. Relative measures control for these factors but rely on stronger assumptions about user decision processes. Given that external factors are likely to be more influential over longer time periods, we place greater weight on relative usage measures when analyzing lower frequency data. This particularly concerns the longer-term effects of the outage.

In all cases, the identification strategy makes standard assumptions common for IV methods regarding functional forms in the first and second stage regressions and error term distributions. We use "sampling-based" inference in the sense of Abadie et al. (2020), treating our sample as drawn from a population and quantifying uncertainty about whether our findings generalize to that population. To remain conservative, we cluster standard errors simultaneously at both the individual and time-interval levels.

5. Results

5.1. Descriptive analysis

The Meta outage can be easily spotted in time series of the aggregate usage time of all users. Figure 1 shows the total device usage time in hours, the device usage time for the aggregate of all Meta services and all identified non-Meta services. The outage is indicated by the gray areas. All three time series exhibit strong hour-of-day patterns, reflecting users' daily routines. When the outage begins, device usage drops temporarily as users appear to briefly disengage from their devices, before returning to levels consistent with typical daily patterns. It is notable that the onset of the outage coincides with the daily peak of devices usage during the evening in Spain. For the US, the outage occurs before the daily peak of device usage. Meta service usage drops sharply during the outage, though not completely to zero. This reflects users' repeated attempts to access these services despite their unavailability. Those attempts are recorded in the tracking data. Simultaneously, usage of non-Meta services increases above typical levels, suggesting substitution toward alternative digital services during the outage period. After the outage ends, usage levels seem to return to their original levels.

5.2. Off-device substitution

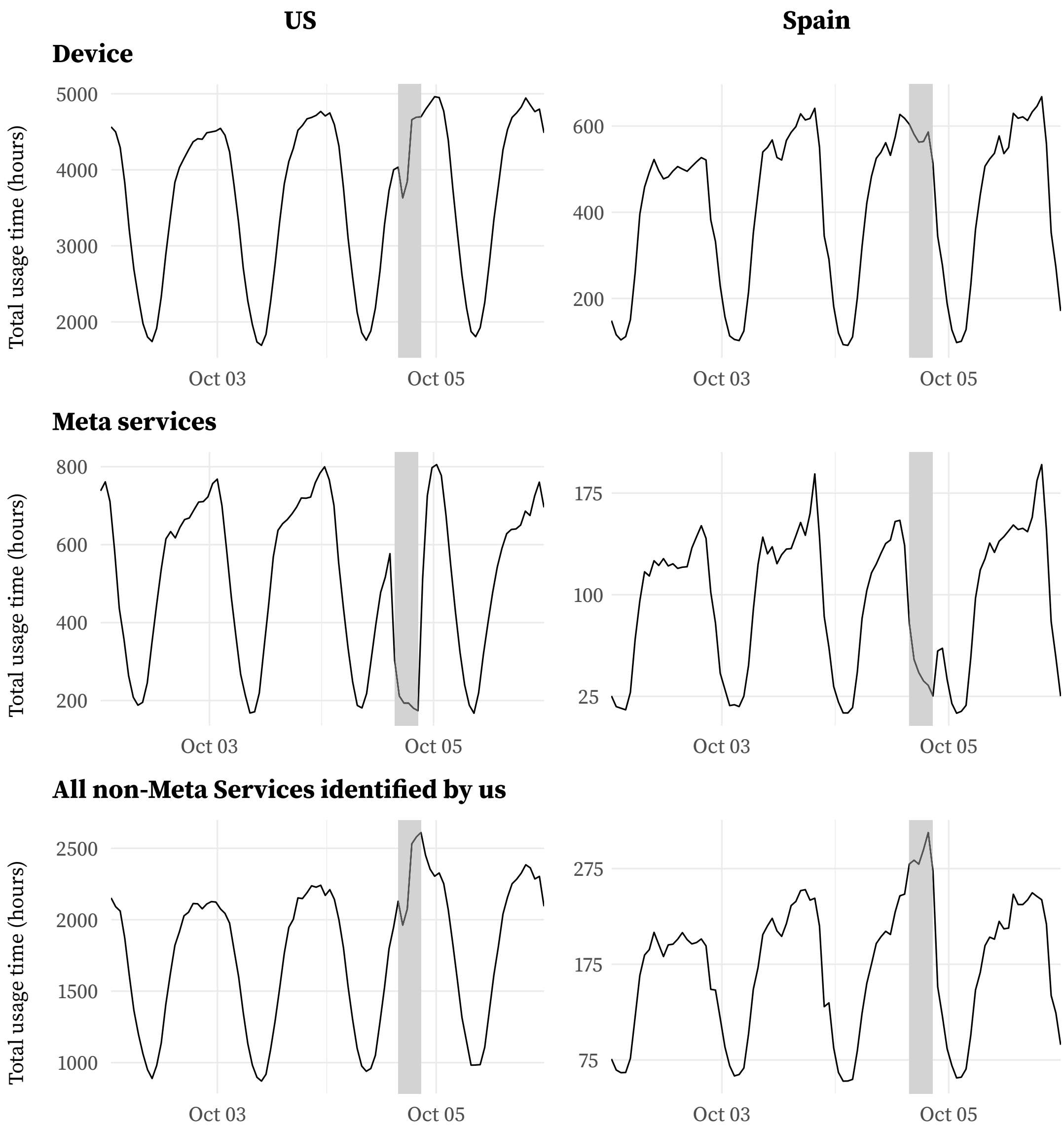
The usage time series in Figure 1 indicates that Meta's outage might have led to less device usage. To quantify this effect, we run an event study-type panel regressions of the following form:

$$D_{it} = \alpha_0 + \alpha_1 \mathbb{1}_{\text{outage}} + h_t d_t + p_i + \mu_{it}, \tag{5}$$

with D_{it} denoting total device usage, $\mathbb{1}_{\text{outage}}$ denoting an indicator variable, which is one for the period of the outage and zero otherwise, h_t and d_t denoting indicator variables for the time of the day and the day of the week, respectively, and p_i denoting individual fixed effects. The coefficient α_1 reflects the absolute changes in total device usage during the outage relative to baseline usage patterns. On average, we observe a reduction in individuals' device usage of 17.2 minutes (95% CI: 13.9, 21.2) in the US and 6.1 minutes (95% CI: 4.8, 7.4) in Spain during the six hours of the outage. The average usage time during the same time interval, i.e. Mondays 15:40 to 21:40 UTC, in the four weeks prior to the outage was 143.7 minutes and 90.4 minutes for the US and Spain, respectively. Compared to these benchmarks, the changes constitute a reduction in device by 12.0% and and 6.4%.

Using the linear specification of Equation 1 and the asinh specification Equation 3 shows how this device usage time change converts into an effective substitution rate for off-device activities. The results are shown in the first row of Table 4. For the linear specification, columns (1) and (4) report a statistically significant estimate for α_1 in

FIGURE 1. Total device and relative usage time



Notes: The figure shows the aggregate usage time among all individuals in the balanced panel at hourly frequency 72 hours before and 24 hours after the start of the outage. The gray area indicates the outage period.

both countries. The results imply that a one-minute decrease in the usage time of Meta's services results in a decrease in total device usage time of 1.297 minutes (95% CI: 0.94, 1.65) in the US and of 0.371 (95% CI: 0.30, 0.44) in Spain. This is consistent with off-device substitution. For the asinh specification, presented in columns (2) and (5), the estimates for α_1 are insignificantly different from zero.

These results suggest different patterns depending on the specification used. The linear specification indicates potential off-device substitution in both countries, with a notably stronger effect in the US. A coefficient above one in the USA means that the reduction in device usage time exceeds the reduction in Meta usage time. This could reflect Meta's role as a gateway to other digital activities. Users might often start their device sessions by reacting to social media notifications, which could then lead to using other services. Additionally, Meta's authentication services enable access to various third-party applications, potentially making Meta usage complementary to broader device engagement.

However, when using the asinh transformation, which reduces the influence of extreme values while preserving zero observations, the substitution rates become statistically indistinguishable from zero in both countries. This contrast between specifications suggests that the linear results may be driven by a subset of heavy users or extreme observations, rather than representing a consistent pattern across all usage intensities. The asinh results indicate that proportional changes in Meta usage do not consistently correspond to proportional changes in overall device usage, cautioning against strong conclusions about systematic off-device substitution patterns.

5.3. On-device substitution

The substitution rates for digital service categories are presented in Table 4. Columns (1) and (4) display the results for the linear specification in Equation 1. For the US, the substitution rate for the aggregate of all assigned non-Meta services is not statistically different from zero. The primary substitution effects occur within categories, particularly in social media and messaging services. A one-minute decrease in the usage time for Meta's services during the outage results in an average increase of 0.069 and 0.061 minutes respectively. As shown in Table A3, the substitution within the social media category is largely driven by TikTok, Snapchat, and Twitter, while in the messaging category, the default messaging services for Android devices—Google Messages and Samsung Messages—are the main drivers of substitution. Furthermore, streaming services and entertainment services have statistically significant positive coefficients, implying that their aggregate usage time decreases together with Meta's services. This complementarity effect is primarily driven by YouTube, whereas classical video streaming services, such as Netflix and Amazon Prime Video, act as substitutes.

For Spain, we find more pronounced online substitution effects. For instance, a one-minute reduction in Meta's services leads to a 0.425-minute increase in the us-

TABLE 4. Substitution rates

	US			Spain		
U_{it}	M_{it} (1)	asinh(M_{it}) (2)	M_{it}/D_{it} (3)	M_{it} (4)	asinh(M_{it}) (5)	M_{it}/D_{it} (6)
Device	1.297***	0.085	—	0.371***	-0.051	—
	(0.182)	(0.094)	(—)	(0.035)	(0.034)	(—)
All non-Meta services	-0.086	-0.064	-0.777***	-0.425***	-0.451***	-0.673***
	(0.092)	(0.108)	(0.060)	(0.007)	(0.040)	(0.004)
Social media	-0.069***	-0.184***	-0.161***	-0.111***	-0.981***	-0.149***
	(0.009)	(0.013)	(0.001)	(0.008)	(0.044)	(0.004)
Messaging	-0.061***	-0.257**	-0.158***	-0.116***	-1.167***	-0.115***
	(0.013)	(0.099)	(0.019)	(0.005)	(0.056)	(0.003)
Streaming	0.038***	-0.027	-0.122***	-0.050**	-0.352***	-0.069***
	(0.007)	(0.030)	(0.005)	(0.023)	(0.057)	(0.008)
Entertainment	0.010***	0.040***	0.004**	-0.012*	-0.157***	-0.032***
	(0.002)	(0.004)	(0.002)	(0.006)	(0.017)	(0.005)
Voice or video calls	-0.017	-0.152	-0.056***	-0.035***	-0.824***	-0.056***
	(0.012)	(0.151)	(0.018)	(0.005)	(0.041)	(0.004)
Email	-0.010	-0.142	-0.116***	-0.049***	-0.583***	-0.079***
	(0.053)	(0.144)	(0.027)	(0.008)	(0.089)	(0.006)
News	0.003	-0.015**	-0.005	-0.012***	-0.389***	-0.018***
	(0.005)	(0.007)	(0.003)	(0.003)	(0.042)	(0.001)
Other	0.020	-0.037	-0.163***	-0.040***	-0.448***	-0.155***
	(0.019)	(0.089)	(0.004)	(0.012)	(0.030)	(0.002)

Notes: This table shows estimated substitution rates during the Meta outage. Standard errors are in parentheses. Statistical significance levels are denoted as follows: * 90%, ** 95%, *** 99%. Colums (1) and (4) are estimated according to Equation 1, columns (2) and (5) according to Equation 3 and columns (3) and (6) according to Equation 4. The disaggregated numbers underlying this table can be found in Table A3 and Table A4.

age of non-Meta services. When factoring in the time substituted away from the device, the majority of usage time reallocated within the device during the outage is accounted for by our assigned services. Similar to the US, the strongest substitution effects are observed in the social media and messaging categories. A one-minute decrease in usage of Meta's services results in an increase in these services' usage of 0.111 and 0.116 minutes, respectively. In Spain, cross-category substitution is stronger and additionally included entertainment and other communication methods, such as direct voice and video communication or email during the outage. Table A4 provides the substitution rates for individual services. Similar to the US, Twitter and TikTok are the primary substitutes within the social media category. By contrast, the composition of the messaging category differs from the US, with Telegram being the only significant substitute. The Android default messaging services do not even meet the threshold to be assigned. In the streaming category, Netflix and Amazon Prime Video display substitution effects, whereas YouTube does not show a statistically significant effect. Overall, the results indicate that Spain exhibits higher on-device substitution rates across all categories compared to the US.

Columns (2) and (5) present the results for the asinh transformation, as specified in Equation 3, for the US and Spain, respectively. The estimated substitution rates correspond to average percentage point changes during the outage relative to the baseline level of each individual at this day of the week and time of day. The asinh transformation accounts for such level differences. The results are qualitatively similar to those obtained from the linear specification in both countries, with larger effective substitution rates for Spain than for the US. The rates for social media and messaging services are particularly large. For example, a 1% reduction in Meta's services leads to a 1.167% increase in Telegram usage[9], and a 0.981% increase in overall social media usage. In the US, these elasticities are smaller but still notable, with a 0.184% increase in social media usage and a 0.257% increase in the usage of messaging services. The substantial change in usage relative to baseline levels resulted in disruptions in some services due to increased traffic. For instance, Twitter issued a statement apologizing for server issues.[10]

Columns (3) and (6) report substitution rates in relative usage time following Equation 4. A 1 pp decrease in the market share of Meta's services results in a 0.777 and 0.673 pp increase in the share of all other recorded digital services for the US and Spain, respectively. This finding implies that our assigned services account for the majority of market share gains resulting from Meta's outage in both countries. Cross-category substitution of relative usage time is more pronounced than in the other specifications. In both countries, social media and messaging services remain the primary category substitutes.

5.4. Cross-sectional heterogeneity in on-device substitution

The granularity of the tracking data allows us to examine heterogeneity in substitution patterns across different consumer groups. We follow the notation of Equation 2. The instrumented variable M_{it} is interacted with the dummy variable S_i to differentiate between the cohorts. The coefficient α_1 represents the substitution rate for individuals with $S_i = 0$, while α_2 captures the difference from this baseline for individuals with $S_i = 1$.

Table 5 reports the results for single-homers and multi-homers. A multi-homer is

[9] The messaging category in Spain consists only of Telegram, as shown in Table A2. No other dedicated messenger services met the threshold to be assigned.

[10] Timsit, Annabelle and Sofia Diogo Mateus. 2021. 'Hello literally everyone': Twitter flooded with users during Facebook, Instagram outage. *The Washington Post*, October 4. `https://www.washingtonpost.com/technology/2021/10/05/twitter-users-facebook-outage-instagram-whatsapp/`.

TABLE 5. Substitution rates for multi- and single-homers

	US		Spain	
U_{it}	M_{it} (1)	$S_i M_{it}$ (2)	M_{it} (3)	$S_i M_{it}$ (4)
Social media	-0.005***	-0.072***	-0.001***	-0.133***
	(0.000)	(0.014)	(0.000)	(0.010)
Messaging	-0.001*	-0.097***	-0.034***	-0.183***
	(0.000)	(0.021)	(0.002)	(0.013)
Streaming	-0.012***	0.051***	-0.009	-0.041*
	(0.003)	(0.014)	(0.008)	(0.024)
Entertainment	-0.000*	0.046**	-0.009***	-0.012
	(0.000)	(0.022)	(0.001)	(0.032)
Voice or video calls	-0.002	-0.022	-0.000	-0.051***
	(0.043)	(0.017)	(0.000)	(0.007)
Email	-0.001	-0.010	-0.000***	-0.049***
	(0.002)	(0.059)	(0.000)	(0.012)
News	-0.000***	0.010	-0.002***	-0.014***
	(0.000)	(0.013)	(0.000)	(0.005)
Other	-0.000	0.020	-0.000	-0.040***
	(0.002)	(0.028)	(0.000)	(0.012)

Notes: This table shows estimated substitution rates during the Meta outage. Standard errors are in parentheses. Statistical significance levels are denoted as follows: * 90%, ** 95%, *** 99%. Each row shows regression coefficients following Equation 2, with columns (1) and (2) showing the base effect and columns (3) and (4) the interaction effect. The disaggregated numbers underlying this table can be found in Table A8 and Table A9.

defined as an individual who had a nonzero usage time of a given service or service category ($U_{it} > 0$) in the four weeks preceding the outage.[11] This distinction allows for the examination of substitution along both the intensive margin (multi-homers) and the extensive margin (single-homers). Columns (1) and (3) present the estimated coefficients for α_1, i.e. the substitution rates for single-homers ($S_i = 0$). Columns (2) and (4) present the estimated coefficients for α_2, which capture the difference in substitution rates for multi-homers ($S_i = 1$) relative to single-homers.

The coefficients on M_{it} show small but often statistically significant substitution rates. This reflects that adoption of services within the respective categories by single-homers is small. The most pronounced effects for single-homers are observed in social media and streaming services in the US, and messaging and entertainment services in Spain. Table A8 and Table A9 report the results for individual services. In the

[11]Since our sample consists only of Meta users, all individuals record nonzero usage of Meta's services ($M_{it} > 0$) during this period.

US, single-homers show sizable substitution rates for Twitter and YouTube, whereas in Spain, the substitution rates for Telegram, Twitter, and YouTube are also substantial. Columns (2) and (4) show that that substitution rates are significantly higher for multi-homers in the same service categories where notable substitution effects are found in the aggregate results, as reported in Table 4. By definition, multi-homers also drive the complementarity effects observed in the aggregate results, e.g. for streaming services in the US. Single-homers can adopt a service but cannot reduce their baseline usage, which is zero.

Overall, the results show that the observed substitution and complementarity effects are primarily driven by multi-homers. This finding likely reflects differences in switching costs between single-homers and multi-homers. Consumers expected Meta's services to be restored at some point, so they had to decide whether it was worth incurring the cost of switching to an alternative service or waiting until the outage was resolved. For multi-homers, the cost of switching to alternative services is lower, as they are familiar with the quality of these services and the extent to which they can substitute functionality and maintain their social graph.

We further examine substitution patterns across demographic groups, focusing on age and education. In this context, our study complements prior deactivation experiments in the literature (Aridor Forthcoming; Bursztyn et al. 2023) which studies substitution patterns in a sample of university students.

First, to assess differences by age, we use the interaction term in Equation 2 to divide the sample into two cohorts. We define two different age cohorts, individuals aged 35 years and older ($S_i = 0$), and individuals between 18 and 34 years ($S_i = 1$). The results are reported in Table A5 and Table A6. Off-device substitution does not differ significantly by age in either the US or Spain. In the US, younger individuals substitute more toward social media services, particularly TikTok, Snapchat, and Discord, while substitution for Twitter does not differ between cohorts. Additional differences exist in the substitution rates for Netflix and Spotify. In Spain, younger individuals exhibit higher substitution rates for social media and messaging services, whereas older individuals substitute more within the "other" category. Within the social media category, the younger cohort substitutes significantly more for TikTok and, unlike in the US, also for Twitter.

Second, to assess differences by education, we define two education cohorts, individuals with a high school degree or less ($S_i = 0$) and individuals with more than a high school degree ($S_i = 1$). This analysis is conducted only for the US, as educational data is unavailable for the Spanish sample. The results are reported in Table A7. Individuals with higher educational attainment substitute more toward off-device activities and messaging services, but have lower substitution rates for social media and streaming services.

5.5. Temporal heterogeneity in on- and off-device substitution

Motivated by apparent dynamics in behavioral responses during the outage, as shown in Figure 1, we test for temporal heterogeneity. We estimate IV regressions following Equation 2 but split the sample temporally rather than cross-sectionally, dividing the outage into two halves. For this analysis, we use data at a 3-hour frequency rather than a 6-hour frequency. In this specification, α_1 corresponds to the substitution rate in the first half of the outage, α_2 captures the difference in substitution rates between the first and second halves. Table A10 and Table A11 show the results. For the US, stark differences emerge in substitution rates between the two periods. The estimates for α_1 are significantly positive for overall device usage time and the aggregate usage time of all assigned non-Meta services, implying complementarity effects during the first half of the outage. For device usage time, we refer to this complementarity effect as off-device substitution. The estimates for α_2 are significantly negative in both cases, indicating a shift in behavior in the second half of the outage. The aggregated estimate $\alpha_1+\alpha_2$ is significantly positive for device usage, reflecting that off-device substitution persisted in the second half of the outage. By contrast, the aggregated estimate $\alpha_1+\alpha_2$ for all assigned non-Meta services is significantly negative. This implies an overall substitution effect of these services during the second half of the outage. Similar reversals are observed for most service categories and some individual services. This pattern is particularly pronounced for email services, where major providers such as AOL Mail, Gmail, Outlook and Yahoo Mail shift from being complements in the first half to substitutes in the second half.

While we can only speculate about the underlying behavioral mechanisms, several factors may explain this pattern. In the first half, positive substitution rates could reflect users repeatedly checking Meta services and their devices, hoping services would return. The shift to negative rates in the second half may indicate users eventually accepting the outage's persistence and actively seeking alternatives. The delayed substitution behavior could also reflect coordination challenges inherent to services with strong network effects, as users needed time to coordinate with their social networks on alternative platforms.

These temporal dynamics suggest that the aggregate substitution rates reported for the entire outage in subsection 5.3 may understate the longer-term substitution rates between Meta's services and potential alternatives. Although the outage was relatively brief overall, it was sufficiently long to capture these temporal shifts, such that the latter half might serve as a reasonable approximation of longer-term substitution rates. Given more time to adapt, users might show even stronger substitution patterns. This might particularly be the case for single-homers.

5.6. Longer-term effects

The interpretation of necessary adaptation time or inertia in responding to the outage is supported by our findings on the longer-term effects of the outage. To quantify these potential long-term effects, we estimate the level shifts in market shares due to the outage and trace the changes in substitution rates before and after the outage. To estimate the level shifts, we estimate event study-type regressions of the following form:

$$\frac{U_{it}}{D_{it}} = \alpha_0 + \alpha_1 \mathbb{1}_{\text{post outage}} + d_t + p_i + \mu_{it}, \tag{6}$$

with U_{it}/D_{it} denoting relative usage time of a given service category, $\mathbb{1}_{\text{post outage}}$ denoting an indicator variable, which is one for the period after the outage and zero otherwise, h_t and d_t denoting indicator variables for the time of the day and the day of the week, respectively, and p_i denoting individual fixed effects. The baseline period covers 4 weeks prior to the outage and the post-outage period is 3 weeks. To reduce noise, the data are aggregated to 24-hour intervals. The 24-hour period of the outage is dropped from the data to avoid confounding the baseline or post-outage period.

We deem relative usage time to be the appropriate measure for long-term effects because it abstracts from potential time trends or variation in overall device usage. Variation in usage times can be the result of outside factors such as the weather (Minor, Moro, and Obradovich Forthoming). Notably, α_1 in Equation 6 does not yield a substitution rate, but captures changes in relative usage time for different service categories post-outage compared to the baseline period before the outage. The coefficient should not be interpreted causally, since other events may have also driven usage post-outage, and hence, may confound a causal interpretation. In particular, on October 5, 2021, Frances Haugen, a former Meta employee and whistleblower, testified before the US Congress.[12]. However, given the unprecedented scale and duration of the outage, a substantial portion of the observed behavioral changes should be attributable to this event.

Table 6 shows the results for Equation 6 for the US and Spain. In the US, the market shares for Meta's services decreased by 0.211 pp following the outage. By contrast, the market share of Meta is not statistically different from the baseline period in Spain. In both countries, the relative usage time of other social media increases, by 0.240 pp in the US and 0.223 pp in Spain. In the US, the aggregate of all assigned non-Meta services increases by 0.907 pp after the outage. This effect more than offsets the decrease in Meta's market share, suggesting that during the post-outage period, user switched from smaller services below our assignment threshold to the larger services, which we have assigned. This pattern is unlikely to be driven by outage itself.

To estimate changes in substitution rates following the outage, we use the same

[12]Frenkel, Sheera. 2021. Key takeaways from Facebook's whistle-blower hearing. *The New York Times*, October 5. `https://www.nytimes.com/2021/10/05/technology/what-happened-at-facebook-whistleblower-hearing.html`

TABLE 6. Level shifts in market shares after the outage

	$\mathbb{1}_{\text{post outage}}$	
U_{it}/D_{it}	US (1)	Spain (2)
All non-Meta services	0.907*** (0.145)	0.246 (0.164)
Meta platforms	-0.211** (0.094)	-0.003 (0.162)
Social media	0.240*** (0.046)	0.223*** (0.073)
Messaging	0.052* (0.031)	0.030 (0.032)
Streaming	0.157** (0.066)	-0.059 (0.120)
Entertainment	-0.022 (0.028)	-0.014 (0.063)
Voice or video calls	0.029 (0.021)	0.043 (0.041)
Email	0.210*** (0.048)	0.053 (0.077)
News	-0.014 (0.012)	-0.125*** (0.035)
Other	0.256*** (0.085)	0.094 (0.116)

Notes: This table shows the comparison of substitution rates before and after the outage following Equation 6. Standard errors are in parentheses. Statistical significance levels are denoted as follows: * 90%, ** 95%, *** 99%.

data at 24-hour frequency to estimate regressions similar to Equation 2, but without instrumenting the relative usage time of Meta's services. Instead, we define a temporal split as in the event study regression in Equation 6. This leads to the following specification:

$$\frac{U_{it}}{D_{it}} = \alpha_0 + \alpha_1 \frac{M_{it}}{D_{it}} + \alpha_2 \mathbb{1}_{\text{post outage}} \frac{M_{it}}{D_{it}} + d_t + p_i + \mu_{it}, \tag{7}$$

with α_1 corresponding to the substitution rates before the outage and α_2 capturing the difference in the substitution rates post-outage relative to the baseline period. As in Equation 6, we use relative usage times to abstract from trends or variation in overall device usage over time.

The results are presented in Table 7. Columns (1) and (3) report the estimates for α_1, the substitution rates before the outage. We find that the relative usage time of all assigned non-Meta services is strongly negatively correlated with the relative usage time of Meta's services in both countries. This relationship can be interpreted as a substitution rate. On average, individuals who allocate 1 pp more of their device time to Meta's services use the other assigned services 0.437 (0.353) pp less in the US (Spain). In the US, the estimates for α_1 are statistically significant and negative across all service categories. In particular, streaming services show a strong negative correlation. In Spain, we observe qualitatively similar results, although there are no significant estimates for messaging services or voice and video communication services.

Comparing these results with the substitution rates during the outage reported in Table 4, we find that substitution rates during the outage are higher than those observed before the outage for all assigned non-Meta services and most service categories. For streaming services and the "other" category, the substitution rates before the outage are similar to those observed during the outage in the US. In Spain, however, the substitution rates for streaming services before the outage are higher than those during the outage. A conceptual difference between the substitution rates presented here and the ones for the outage itself is, that the substitution rates here are likely to be "more marginal", because they are estimated for smaller changes in usage time. This is different to the effective substitution rates based on a non-marginal change in usage time due to the outage.

Columns (2) and (4) of Table 7 report the estimates for α_2, the coefficient on the interaction term $\mathbb{1}_{\text{post outage}} \frac{M_{it}}{D_{it}}$. We do not find evidence that substitution rates change significantly following the outage. While the level shifts in relative usage times following the outage, as reported in Table 6, are consistent with a potential change in substitution rates, these shifts cannot be directly attributed to a change in substitution rates. A change in substitution rates would indicate that users became systematically more or less likely to switch between Meta and non-Meta services after experiencing the outage. The absence of such changes (given the statistical power we have) suggests that while some users may have permanently shifted some of their usage to non-Meta services (as indicated by the level shifts), the underlying substitution patterns between services remained stable.

6. Alternative identification strategy

In-sample counterfactual predictions, as in our main identification strategy, may suffer from information from after the outage "leaking" into them, which could potentially bias the results. Therefore, we confirm the robustness of our main results in subsection 5.2 and subsection 5.3 with a second identification strategy, which consists of making strictly out-of-sample counterfactual predictions for usage times during the

TABLE 7. Comparison of substitution rates before and after the outage

U_{it}/D_{it}	US M_{it}/D_{it} (1)	US $\mathbb{1}_{\text{post outage}} M_{it}/D_{it}$ (2)	Spain M_{it}/D_{it} (3)	Spain $\mathbb{1}_{\text{post outage}} M_{it}/D_{it}$ (4)
All non-Meta services	-0.437***	-0.001	-0.353***	-0.003
	(0.006)	(0.004)	(0.010)	(0.006)
Social media	-0.047***	0.001	-0.024***	-0.002
	(0.002)	(0.001)	(0.003)	(0.002)
Messaging	-0.022***	0.002	-0.002	0.000
	(0.002)	(0.001)	(0.001)	(0.001)
Streaming	-0.157***	-0.001	-0.153***	0.005
	(0.004)	(0.002)	(0.007)	(0.004)
Entertainment	-0.020***	0.001	-0.021***	-0.003
	(0.001)	(0.001)	(0.003)	(0.002)
Voice or video calls	-0.014***	0.000	0.002	-0.002*
	(0.001)	(0.001)	(0.002)	(0.001)
Email	-0.034***	-0.002	-0.039***	0.001
	(0.002)	(0.002)	(0.003)	(0.003)
News	-0.004***	-0.000	-0.008***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Other	-0.139***	-0.002	-0.109***	-0.003
	(0.003)	(0.002)	(0.006)	(0.004)

Notes: This table shows in the substitution rates for relative usage time before and after the outage following Equation 7. Standard errors are in parentheses. Statistical significance levels are denoted as follows: * 90%, ** 95%, *** 99%.

outage and comparing them with observed usage times to obtain substitution rates.

To implement this identification strategy, we use time series regressions to make predictions. As in our main identification strategy, we focus on 6-hour time intervals. For these intervals, we aggregate usage times over all individuals in each country. The time series regressions are regularized with cross-validated Elastic Net penalties and are of the following form:

$$U_{t+k} = \alpha + \beta_1 U_t + \beta_2 U_{t-1} + \cdots + \beta_L U_{t-L} + h_{t+k} + d_{t+k} + \varepsilon_{t+k}, \tag{8}$$

with U_{t+k} denoting the k-step-ahead prediction for the usage time of a service. For 6-hour intervals, $k = 1$, because we only need one prediction to capture the entire outage. $U_t, U_{t-1}, \ldots, U_{t-L}$ denoting the lags of the usage time up to lag L, and h_{t+k} and d_{t+k} denoting indicator variables for the time of the day and the day of the week of the period to be predicted, respectively. We derive the effective substitution rates from the counterfactual predictions using the absolute differences between the predicted usage $\widehat{U_{t+k}}$ and the actual usage time U_{t+k} for a respective service. We denote the difference $\widehat{U_{t+k}} - U_{t+k}$ with Δ^{t+k}. To compute the effective substitution rates, we divide $\Delta^{t+k}_{\text{service}}$ by $\Delta^{t+k}_{\text{Meta}}$ for each service.

To quantify prediction uncertainty, we use Ensemble Batch Prediction Intervals (EnbPI) (Xu and Xie 2021), which adapts the conformal prediction framework (see, for instance, Shafer and Vovk 2008) for non-exchangeable time series data. To calibrate the prediction model and the prediction intervals, we use data from July 4, 2021, until the outage on October 4, 2021. EnbPI and other conformal prediction methods provide theoretical coverage guarantees only for in-sample prediction intervals. Setting a nominal coverage level of 95% during (in-sample) calibration does not guarantee the same coverage level for out-of-sample predictions. Therefore, we consider the nominal coverage level used when calibrating EnbPI to be a tunable hyperparameter, which we set such that the out-of-sample coverage in the seven days prior to the outage is at least 95%. We assume that the coverage level immediately before the outage is similar to that during the outage. For tuning the hyperparameter, we evaluate EnbPI prediction intervals on a grid of nominal coverage levels between 90% and 99% and choose the level which leads to a out-of-sample coverage level of at least 95%.[13]

The out-of-sample strategy assumes that we can make unbiased point predictions of counterfactual outcomes using the functional form laid out in Equation 8. Using conformal prediction methods allows us to quantify uncertainty in these point predictions without any distributional assumptions. For valid inference, we only have to assume that the accuracy of the point predictions and the coverage of the prediction intervals stay the same for the out-of-sample predictions right before and during the outage. Given the unexpected nature of the outage, we consider this assumption to be justified. The alternative identification strategy employs "design-based" inference where the sample is treated as fixed and uncertainty about what would have happened without the outage is quantified (Abadie et al. 2020). This is in contrast to the "sampling-based" inference used in the main identification strategy. Using a second mode of inference provides a robustness check with respect to quantifying uncertainty.

The results from the alternative identification strategy closely align with those of our main approach. Table A12 and Table A13 present these findings. We observe similar off-device substitution rates to those reported in the main results for absolute usage time. The point estimates for substitution rates across all service categories are also consistent with the main results. As in the main analysis, we find generally higher substitution rates in Spain compared to the US.

[13]We choose to optimize with the help of a grid since EnbPI and conformal prediction methods in general are computationally demanding, such that it is infeasible to iteratively optimize for an optimal nominal coverage level of exactly 95%.

7. External validity

The external validity of our results hinges on whether we can generalize from the case of Meta to other digital services and on the extent to which short-term substitution rates are informative for longer-term substitution rates. Generalizing the substitution rates to other digital services is difficult, because we can only speculate on how consumers of other digital services would have responded to a similar short-term outage. Answering this question depends on the comparability of these services, but also on the population of their users. Meta's services are among the most widely used digital services globally, with significant network effects and established user habits. Other social networks and messenger services with similar characteristics might respond similarly. A particularity of the Meta outage is that Meta's services span various categories and all of them went offline simultaneously. The observed behavioral responses might not be easily transferable to other more specialized services going offline individually.

To address the question of the informativeness of the short-term substitutability for longer-term substitutability further analysis are needed using post-outage data. In general, we expect the observed substitution rates to be rather conservative estimates of longer-term substitution rates given that users expected Meta's services to be restored at some point. This might have prevented many users from incurring the cost of switching to other services, which involves exploring alternatives, coordinate with other users and familiarize themselves with other services. In particular, our results underestimate the longer-term effects on the extensive margin, because we likely underestimate the substitution rates for single-homers, which incur higher switching costs, and are therefore less likely to substitute other services in a short-term outage. With more time, users—especially single-homers—would likely discover and adopt more alternative services. Our results support this interpretation in two ways. First, in subsection 5.5 we observe higher substitution rates in the latter half of the outage. Second, our analysis of the longer-term effects on usage in Table 6 shows an increase in relative usage time of non-Meta social media services after the outage.

8. Policy implications

The policy implications of our findings depend on their external validity, particularly concerning long-term substitution rates, which are of interest to competition policy. To the extent that the short term substitution rates are informative for the longer term substitution rates, our results suggest two key policy implications.

First, multi-homing activity appears to be a strong driver of our observed substitution patterns. Users engaging with multiple services before the outage showed significantly higher substitution rates, indicating that familiarity with alternatives lowers switching costs. This supports the DMA's approach of mandating specific multi-homing enablers, for instance, requiring platforms to allow data portability, ensuring interoperability of basic messaging features and prohibiting restrictions on using competing services. However, the effectiveness of these measures may depend on users' willingness to actively maintain multiple service relationships.

Second, cross-sectional heterogeneity in behavioral responses has implications for the delineation of markets of digital services. The uncovered heterogeneity across countries, demographic characteristics and service categories calls into question uniform digital service market definitions. If the relevant market is substantially different across age cohorts and countries, a one-size-fits-all market delineation might be inappropriate. Additionally, the observed substitution patterns across common service categories call into question category-based market definitions, such as those used by the European Commission to enforce the European Union (EU)'s DMA. For instance, Youtube is shown to be strongly related to Meta's services, but is classified in a different "core platform service" category, as defined by the European Commission (EC). On a conceptional level, competition authorities have to address the trade-off between the high level of aggregation necessary for practical regulation and the finer granularity at which consumer welfare should be protected.

9. Conclusion

We use a global outage of Meta on October 4, 2021, in which all its services went offline for a period of about six hours, as a natural experiment to identify substitution and complementarity patterns among digital services. Using detailed high-frequency tracking data from individuals in Spain and the US, we provide the first comprehensive analysis of revealed substitution patterns when an entire user population must simultaneously find alternatives to a major digital service provider. We identify effective substitution rates between Meta's services and other digital services, yielding seven key findings: First, substitution toward other social media and messaging services—the categories in which Meta's services are typically classified—is the highest. Second, we observe substitution across common service categories. Third, substitution patterns differ significantly across demographic groups. Fourth, multi-homing emerges as a key driver of substitution, as users already familiar with alternative services exhibit significantly higher substitution rates. Fifth, we observe inertia in behavioral responses, with substitution rates increasing over the course of the outage. Sixth, most of these findings differ in magnitude between both countries. Seventh, we find indicative evidence of greater usage of non-Meta services in the weeks following the outage, particularly for social media services.

We are currently analyzing additional data from the post-outage period to assess longer-term effects of the outage in more detail. Given the outage's significance, Meta's users may have updated their expectations about service reliability and quality, potentially leading to increased multi-homing behavior, as users either discover alternatives or seek to hedge against future outages. Our preliminary analysis of the longer-term effects points in this direction. Analyzing these longer-term effects in greater detail may yield substitution rates that better approximate theoretically appealing marginal rates of substitution, since the quality shift is more marginal on longer time scales. Additionally, users have more time to discover alternatives, social networks have more time to mobilize, and equilibrium effects play out over time.

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Appendix A. Service category definitions

TABLE A1. Service category definitions: US

Category	Services
Meta platforms	Facebook, Instagram, WhatsApp
Social media	Discord, Pinterest, Reddit, Snapchat, TikTok, Twitch, Twitter
Messaging	Google Messages, Samsung Messages, Message+, Motorola Messages
Streaming	Hulu, Netflix, Prime Video, Roku, YouTube, YouTube Vanced, Spotify, YouTube Music
Entertainment	Pokémon GO, Candy Crush, Daydream, Amazon Kindle, Archive of Our Own
Voice or video calls	Phone/Dialer, Contacts, Google Duo
Email	Gmail, Yahoo Mail, Outlook, AOL Mail
News	NewsBreak, MSN, ESPN
Other	Google Docs, Google Drive, Google Maps, Safari, Samsung Browser, Google Search, Bing, Current Cash Rewards, S'more Cash, DoorDash, Swagbucks, MyPoints, InboxDollars, Hideout.tv, PrizeRebel, Amazon Mechanical Turk, Amazon, Walmart, PayPal, eBay, Clock, LG Home, Settings, Moto Display, Google Play Store, Amazon Photos, Google Photos, Samsung Gallery

TABLE A2. Service category definitions: Spain

Category	Services
Meta platforms	Facebook, Instagram, WhatsApp
Social media	TikTok, Twitch, Twitter
Messaging	Telegram
Streaming	YouTube, Netflix, Prime Video, Movistar Plus, Spotify, XVideos, RTVE, Mitele, Atresplayer, Disney+
Entertainment	Candy Crush, Pokémon GO, Township, Farm Heroes Saga, Homescapes, Parchisi, Gardenscapes, Clash Royale
Voice or video calls	Phone/Dialer, Contacts
Email	Gmail, Outlook, Yahoo Mail
News	AS, Marca, MSN, 20 Minutos, El Pais
Other	Google Maps, Google Drive, Google Docs, Google Calendar, Mi Browser, Google Search, Coin Master, Maximiles, AliExpress, Wallapop, Amazon, Mi Locker, Launcher, Xperia Home, Clock, Settings, Camera

Appendix B. Main results

B.1. Substitution rates

B.1.1. All users

TABLE A3. Substitution rates: US

U_{it}	M_{it} (1)		asinh(M_{it}) (2)		M_{it}/D_{it} (3)	
Device	**1.297*****	**(0.182)**	**0.085**	**(0.094)**	**—**	**(—)**
All non-Meta services	**-0.086**	**(0.092)**	**-0.064**	**(0.108)**	**-0.777*****	**(0.060)**
Social media	**-0.069*****	**(0.009)**	**-0.184*****	**(0.013)**	**-0.161*****	**(0.001)**
Discord	-0.004	(0.004)	-0.021***	(0.004)	-0.008***	(0.001)
Pinterest	0.003**	(0.001)	0.004	(0.011)	-0.005***	(0.001)
Reddit	0.007	(0.006)	-0.014**	(0.007)	-0.000	(0.002)
Snapchat	-0.022***	(0.002)	-0.063***	(0.015)	-0.053***	(0.003)
TikTok	-0.039***	(0.005)	-0.115***	(0.008)	-0.062***	(0.005)
Twitch	0.005**	(0.002)	-0.002	(0.002)	-0.003**	(0.002)
Twitter	-0.019***	(0.005)	-0.157***	(0.016)	-0.029***	(0.002)
Messaging	**-0.061*****	**(0.013)**	**-0.257****	**(0.099)**	**-0.158*****	**(0.019)**
Google Messages	-0.027***	(0.004)	-0.088**	(0.040)	-0.052***	(0.005)
Motorola Messages	-0.001*	(0.001)	-0.020***	(0.006)	-0.010***	(0.001)
Samsung Messages	-0.031***	(0.007)	-0.136***	(0.044)	-0.087***	(0.012)
Message+	-0.002	(0.001)	-0.013***	(0.005)	-0.009***	(0.002)
Streaming	**0.038*****	**(0.007)**	**-0.027**	**(0.030)**	**-0.122*****	**(0.005)**
Hulu	0.001	(0.003)	-0.005	(0.005)	-0.004***	(0.002)
Netflix	-0.012***	(0.004)	-0.057***	(0.005)	-0.020***	(0.001)
Prime Video	0.003***	(0.001)	0.004	(0.005)	0.001	(0.001)
Roku	0.001	(0.001)	0.011***	(0.004)	-0.003**	(0.001)
Spotify	-0.003	(0.002)	0.021*	(0.012)	-0.007***	(0.001)
YouTube	0.054***	(0.006)	0.022	(0.021)	-0.076***	(0.006)
YouTube Music	-0.004**	(0.002)	-0.013**	(0.006)	-0.010***	(0.002)
YouTube Vanced	-0.001	(0.002)	-0.000	(0.001)	-0.003**	(0.001)
Entertainment	**0.010*****	**(0.002)**	**0.040*****	**(0.004)**	**0.004****	**(0.002)**
Amazon Kindle	0.002	(0.001)	0.008***	(0.002)	0.001	(0.001)
Archive of Our Own	0.000	(0.003)	-0.000	(0.002)	-0.001***	(0.000)
Candy Crush	-0.002	(0.002)	-0.001	(0.001)	-0.005***	(0.002)
Daydream	0.004	(0.004)	0.011***	(0.004)	0.003	(0.002)
Pokémon GO	0.005***	(0.001)	0.025***	(0.004)	0.007***	(0.001)
Voice or video calls	**-0.017**	**(0.012)**	**-0.152**	**(0.151)**	**-0.056*****	**(0.018)**
Contacts	-0.003	(0.002)	-0.100	(0.070)	-0.009***	(0.003)
Google Duo	-0.001*	(0.001)	-0.029***	(0.005)	-0.006***	(0.001)
Phone/Dialer	-0.013	(0.008)	-0.093	(0.111)	-0.041***	(0.014)

TABLE A3. Substitution rates: US

U_{it}	M_{it}		asinh(M_{it})		M_{it}/D_{it}	
	(1)		(2)		(3)	
Email	**-0.010**	**(0.053)**	**-0.142**	**(0.144)**	**-0.116*** **	**(0.027)**
AOL Mail	-0.004	(0.005)	-0.006*	(0.003)	-0.005**	(0.003)
Gmail	-0.017	(0.027)	-0.123	(0.120)	-0.074***	(0.015)
Outlook	0.006	(0.013)	-0.026	(0.031)	-0.014**	(0.006)
Yahoo Mail	0.004	(0.013)	-0.010	(0.018)	-0.024***	(0.005)
News	**0.003**	**(0.005)**	**-0.015** **	**(0.007)**	**-0.005**	**(0.003)**
ESPN	0.002	(0.001)	0.010***	(0.004)	0.001	(0.001)
MSN	0.001	(0.003)	-0.012***	(0.004)	-0.004***	(0.001)
NewsBreak	-0.000	(0.001)	-0.015***	(0.003)	-0.002	(0.002)
Other	**0.020**	**(0.019)**	**-0.037**	**(0.089)**	**-0.163*** **	**(0.004)**

TABLE A4. Substitution rates: Spain

U_{it}	M_{it} (1)		asinh(M_{it}) (2)		M_{it}/D_{it} (3)	
Device	**0.371*** **	**(0.035)**	**-0.051**	**(0.034)**	**—**	**(—)**
All non-Meta services	**-0.425*** **	**(0.007)**	**-0.451*** **	**(0.040)**	**-0.673*** **	**(0.004)**
Social media	**-0.111*** **	**(0.008)**	**-0.981*** **	**(0.044)**	**-0.149*** **	**(0.004)**
TikTok	-0.042***	(0.009)	-0.270***	(0.012)	-0.052***	(0.004)
Twitch	0.010	(0.007)	-0.055***	(0.004)	-0.001	(0.005)
Twitter	-0.079***	(0.009)	-0.879***	(0.022)	-0.097***	(0.002)
Messaging	**-0.116*** **	**(0.005)**	**-1.167*** **	**(0.056)**	**-0.115*** **	**(0.003)**
Telegram	-0.116***	(0.005)	-1.167***	(0.056)	-0.115***	(0.003)
Streaming	**-0.050** **	**(0.023)**	**-0.352*** **	**(0.057)**	**-0.069*** **	**(0.008)**
Atresplayer	-0.002	(0.002)	-0.009***	(0.003)	-0.001	(0.003)
Disney+	0.003	(0.003)	0.021**	(0.010)	0.001	(0.002)
Mitele	-0.001	(0.002)	-0.012***	(0.003)	0.000	(0.002)
Movistar Plus	-0.001	(0.005)	-0.003	(0.007)	0.000	(0.003)
Netflix	-0.019**	(0.009)	-0.070***	(0.015)	-0.013***	(0.004)
Prime Video	-0.013***	(0.005)	-0.073***	(0.012)	-0.007*	(0.004)
RTVE	-0.003	(0.002)	0.013	(0.015)	0.002	(0.003)
Spotify	0.001	(0.001)	0.029***	(0.005)	-0.002	(0.003)
XVideos	0.002	(0.001)	0.013**	(0.006)	0.000	(0.002)
YouTube	-0.016	(0.013)	-0.303***	(0.047)	-0.049***	(0.008)
Entertainment	**-0.012* **	**(0.006)**	**-0.157*** **	**(0.017)**	**-0.032*** **	**(0.005)**
Candy Crush	-0.004	(0.004)	-0.055***	(0.005)	-0.011***	(0.003)
Clash Royale	-0.003*	(0.002)	-0.038***	(0.007)	-0.002	(0.002)
Farm Heroes Saga	-0.001	(0.003)	-0.022***	(0.002)	-0.004	(0.003)
Gardenscapes	-0.005	(0.003)	-0.022***	(0.003)	-0.005***	(0.001)
Homescapes	0.002	(0.003)	-0.052***	(0.009)	-0.007***	(0.001)
Parchisi	0.007*	(0.004)	-0.000	(0.004)	0.005	(0.003)
Pokémon GO	-0.004**	(0.002)	-0.003	(0.007)	-0.004	(0.003)
Township	-0.005*	(0.003)	-0.001	(0.003)	-0.004	(0.003)
Voice or video calls	**-0.035*** **	**(0.005)**	**-0.824*** **	**(0.041)**	**-0.056*** **	**(0.004)**
Contacts	-0.010***	(0.002)	-0.348***	(0.001)	-0.009***	(0.002)
Phone/Dialer	-0.025***	(0.004)	-0.615***	(0.035)	-0.048***	(0.003)
Email	**-0.049*** **	**(0.008)**	**-0.583*** **	**(0.089)**	**-0.079*** **	**(0.006)**
Gmail	-0.014**	(0.006)	-0.373***	(0.053)	-0.029***	(0.006)
Outlook	-0.026***	(0.003)	-0.356***	(0.055)	-0.038***	(0.005)
Yahoo Mail	-0.008***	(0.003)	-0.088***	(0.008)	-0.012***	(0.002)
News	**-0.012*** **	**(0.003)**	**-0.389*** **	**(0.042)**	**-0.018*** **	**(0.001)**
AS	-0.001	(0.001)	-0.047***	(0.012)	-0.003	(0.003)
El Pais	-0.001**	(0.000)	-0.142***	(0.029)	-0.000	(0.002)
Marca	0.001	(0.001)	-0.017	(0.022)	-0.002	(0.002)
MSN	-0.005***	(0.001)	-0.078***	(0.007)	-0.007***	(0.001)
20 Minutos	-0.006***	(0.002)	-0.155***	(0.005)	-0.006***	(0.002)

TABLE A4. Substitution rates: Spain

U_{it}	M_{it} (1)		$\text{asinh}(M_{it})$ (2)		M_{it}/D_{it} (3)	
Other	**-0.040*** **	**(0.012)**	**-0.448*** **	**(0.030)**	**-0.155*** **	**(0.002)**

B.1.2. Cross-sectional heterogeneity in on-device substitution

TABLE A5. Substitution rates for different age groups: US

U_{it}	M_{it} (1)		$S_i M_{it}$ (2)	
Device	**1.324*****	**(0.213)**	**-0.074**	**(0.170)**
All non-Meta services	**-0.090**	**(0.114)**	**0.012**	**(0.071)**
Social media	**-0.025*****	**(0.001)**	**-0.124*****	**(0.024)**
Discord	0.002	(0.003)	-0.018**	(0.008)
Pinterest	0.002***	(0.001)	0.002	(0.003)
Reddit	0.005	(0.005)	0.005	(0.014)
Snapchat	-0.004*	(0.002)	-0.050***	(0.008)
TikTok	-0.013***	(0.005)	-0.073***	(0.009)
Twitch	0.004	(0.004)	0.004	(0.011)
Twitter	-0.021***	(0.007)	0.007	(0.015)
Messaging	**-0.059*****	**(0.015)**	**-0.005**	**(0.007)**
Google Messages	-0.024***	(0.005)	-0.008	(0.005)
Motorola Messages	-0.001	(0.001)	-0.000	(0.002)
Samsung Messages	-0.032***	(0.010)	0.002	(0.007)
Message+	-0.002	(0.002)	0.001	(0.002)
Streaming	**0.041*****	**(0.014)**	**-0.010**	**(0.024)**
Hulu	-0.001	(0.003)	0.005	(0.010)
Netflix	0.003	(0.005)	-0.041***	(0.012)
Prime Video	0.001	(0.003)	0.006	(0.006)
Roku	0.001	(0.003)	0.001	(0.004)
Spotify	0.002	(0.002)	-0.013***	(0.004)
YouTube	0.046***	(0.014)	0.022	(0.022)
YouTube Music	-0.008***	(0.002)	0.011**	(0.004)
YouTube Vanced	-0.001	(0.001)	-0.000	(0.005)
Entertainment	**0.003**	**(0.008)**	**0.021**	**(0.014)**
Amazon Kindle	0.002	(0.003)	-0.000	(0.006)
Archive of Our Own	-0.002	(0.002)	0.007	(0.008)
Candy Crush	-0.005*	(0.003)	0.009***	(0.003)
Daydream	0.004	(0.006)	0.000	(0.008)
Pokémon GO	0.004***	(0.001)	0.005***	(0.001)
Voice or video calls	**-0.019**	**(0.013)**	**0.007****	**(0.003)**
Contacts	-0.004	(0.003)	0.004*	(0.002)
Google Duo	-0.003	(0.002)	0.006	(0.004)
Phone/Dialer	-0.012	(0.010)	-0.002	(0.005)
Email	**-0.026**	**(0.070)**	**0.046**	**(0.049)**
AOL Mail	-0.004	(0.006)	0.001	(0.009)
Gmail	-0.030	(0.032)	0.037	(0.024)
Outlook	0.002	(0.015)	0.012	(0.011)

TABLE A5. Substitution rates for different age groups: US

U_{it}	M_{it} (1)		$S_i M_{it}$ (2)	
Yahoo Mail	0.006	(0.020)	-0.005	(0.019)
News	**0.005**	**(0.007)**	**-0.005**	**(0.008)**
ESPN	0.004	(0.004)	-0.005	(0.006)
MSN	0.002	(0.004)	-0.001	(0.004)
NewsBreak	-0.001	(0.002)	0.001	(0.003)
Other	**-0.009**	**(0.035)**	**0.082***	**(0.044)**

TABLE A6. Substitution rates for different age groups: Spain

U_{it}	M_{it} (1)		$S_i M_{it}$ (2)	
Device	**0.362*****	**(0.031)**	**0.034**	**(0.025)**
All non-Meta services	**-0.418*****	**(0.038)**	**-0.025**	**(0.073)**
Social media	**-0.087*****	**(0.002)**	**-0.091*****	**(0.012)**
TikTok	-0.035***	(0.004)	-0.024**	(0.011)
Twitch	0.005	(0.004)	0.019	(0.024)
Twitter	-0.056***	(0.009)	-0.086***	(0.021)
Messaging	**-0.107*****	**(0.007)**	**-0.033*****	**(0.013)**
Telegram	-0.107***	(0.007)	-0.033***	(0.013)
Streaming	**-0.056****	**(0.023)**	**0.022**	**(0.051)**
Atresplayer	-0.002	(0.002)	0.003	(0.004)
Disney+	0.000	(0.002)	0.009	(0.011)
Mitele	-0.002	(0.002)	0.003	(0.005)
Movistar Plus	-0.002	(0.007)	0.003	(0.007)
Netflix	-0.009	(0.009)	-0.040**	(0.016)
Prime Video	-0.014**	(0.006)	0.005	(0.010)
RTVE	-0.000	(0.003)	-0.009*	(0.005)
Spotify	-0.000	(0.003)	0.002	(0.004)
XVideos	0.001	(0.002)	0.004*	(0.002)
YouTube	-0.027	(0.017)	0.040	(0.035)
Entertainment	**-0.012**	**(0.008)**	**0.002**	**(0.008)**
Candy Crush	-0.004	(0.006)	0.002	(0.005)
Clash Royale	-0.003	(0.002)	0.000	(0.003)
Farm Heroes Saga	-0.000	(0.003)	-0.002	(0.006)
Gardenscapes	-0.005	(0.004)	0.001	(0.007)
Homescapes	0.004	(0.005)	-0.007	(0.006)
Parchisi	0.008	(0.005)	-0.002	(0.005)
Pokémon GO	-0.005***	(0.002)	0.005	(0.003)
Township	-0.007	(0.005)	0.005	(0.005)
Voice or video calls	**-0.035*****	**(0.006)**	**0.002**	**(0.008)**
Contacts	-0.013***	(0.003)	0.012***	(0.003)
Phone/Dialer	-0.022***	(0.005)	-0.009	(0.007)
Email	**-0.051*****	**(0.012)**	**0.010**	**(0.012)**
Gmail	-0.010	(0.006)	-0.018**	(0.007)
Outlook	-0.030***	(0.003)	0.016***	(0.002)
Yahoo Mail	-0.011***	(0.004)	0.012***	(0.004)
News	**-0.015*****	**(0.005)**	**0.012****	**(0.005)**
AS	-0.001	(0.002)	0.001	(0.002)
El Pais	-0.000	(0.001)	-0.003***	(0.001)
Marca	0.001	(0.001)	-0.000	(0.000)
MSN	-0.006**	(0.003)	0.005**	(0.002)
20 Minutos	-0.009***	(0.002)	0.009***	(0.002)

TABLE A6. Substitution rates for different age groups: Spain

U_{it}	M_{it} (1)		$S_i M_{it}$ (2)	
Other	**-0.054*****	**(0.015)**	**0.051***	**(0.027)**

TABLE A7. Substitution rates for different educational backgrounds: US

U_{it}	M_{it} (1)		S_iM_{it} (2)	
Device	**1.073*** **	**(0.150)**	**0.551***	**(0.288)**
All non-Meta services	**-0.178** **	**(0.071)**	**0.329** **	**(0.161)**
Social media	**-0.086*** **	**(0.013)**	**0.047***	**(0.027)**
Discord	-0.002	(0.004)	-0.007	(0.009)
Pinterest	0.003	(0.002)	-0.003	(0.002)
Reddit	0.009	(0.006)	-0.010	(0.014)
Snapchat	-0.029***	(0.002)	0.029***	(0.002)
TikTok	-0.045***	(0.007)	0.024*	(0.014)
Twitch	-0.001	(0.005)	0.008	(0.008)
Twitter	-0.021***	(0.008)	0.006	(0.015)
Messaging	**-0.059*** **	**(0.014)**	**-0.020** **	**(0.008)**
Google Messages	-0.026***	(0.006)	-0.010	(0.008)
Motorola Messages	-0.001	(0.001)	-0.004*	(0.002)
Samsung Messages	-0.032***	(0.008)	0.000	(0.007)
Message+	-0.000	(0.001)	-0.006**	(0.003)
Streaming	**-0.005**	**(0.011)**	**0.134*** **	**(0.041)**
Hulu	-0.001	(0.002)	0.000	(0.010)
Netflix	-0.015***	(0.005)	0.010	(0.013)
Prime Video	0.002	(0.003)	0.006	(0.005)
Roku	0.001	(0.002)	0.002	(0.004)
Spotify	-0.004	(0.002)	-0.001	(0.005)
YouTube	0.018	(0.012)	0.113***	(0.031)
YouTube Music	-0.004	(0.003)	0.001	(0.003)
YouTube Vanced	-0.002	(0.002)	0.003	(0.003)
Entertainment	**0.013*** **	**(0.005)**	**-0.013**	**(0.021)**
Amazon Kindle	0.003	(0.002)	-0.004	(0.006)
Archive of Our Own	0.000	(0.002)	0.001	(0.013)
Candy Crush	-0.001	(0.002)	-0.001	(0.006)
Daydream	0.004	(0.004)	-0.003	(0.009)
Pokémon GO	0.007***	(0.002)	-0.006	(0.005)
Voice or video calls	**-0.015**	**(0.012)**	**-0.003**	**(0.007)**
Contacts	-0.000	(0.003)	-0.013***	(0.005)
Google Duo	-0.001	(0.002)	-0.001	(0.003)
Phone/Dialer	-0.015*	(0.008)	0.011*	(0.006)
Email	**-0.033**	**(0.041)**	**0.100**	**(0.099)**
AOL Mail	-0.006	(0.004)	0.008	(0.018)
Gmail	-0.025	(0.017)	0.037**	(0.018)
Outlook	0.002	(0.010)	0.023	(0.029)
Yahoo Mail	-0.004	(0.012)	0.031	(0.028)
News	**0.000**	**(0.006)**	**0.015**	**(0.010)**
ESPN	0.001	(0.003)	0.004	(0.008)

TABLE A7. Substitution rates for different educational backgrounds: US

U_{it}	M_{it} (1)		$S_i M_{it}$ (2)	
MSN	0.000	(0.003)	0.008	(0.006)
NewsBreak	-0.001	(0.002)	0.003	(0.003)
Other	**0.007**	**(0.008)**	**0.069*** **	**(0.017)**

B.1.3. Users split by multi-homing prior to outage

TABLE A8. Substitution rates for multi- and single-homers: US

U_{it}	M_{it} (1)		$S_i M_{it}$ (2)	
Social media	**-0.005*** **	**(0.000)**	**-0.072*** **	**(0.014)**
Discord	-0.000***	(0.000)	-0.039	(0.033)
Pinterest	-0.000***	(0.000)	0.008**	(0.004)
Reddit	-0.001***	(0.000)	0.026	(0.019)
Snapchat	-0.000***	(0.000)	-0.059***	(0.008)
TikTok	-0.001***	(0.000)	-0.069***	(0.011)
Twitch	-0.000***	(0.000)	0.064	(0.053)
Twitter	-0.004***	(0.000)	-0.030**	(0.014)
Messaging	**-0.001***	**(0.000)**	**-0.097*** **	**(0.021)**
Google Messages	-0.000	(0.001)	-0.109***	(0.018)
Motorola Messages	-0.000***	(0.000)	-0.030	(0.025)
Samsung Messages	-0.000	(0.000)	-0.100***	(0.023)
Message+	-0.000	(0.000)	-0.036	(0.026)
Streaming	**-0.012*** **	**(0.003)**	**0.051*** **	**(0.014)**
Hulu	-0.000***	(0.000)	0.005	(0.023)
Netflix	-0.002***	(0.000)	-0.029**	(0.012)
Prime Video	-0.001***	(0.000)	0.018	(0.012)
Roku	-0.000***	(0.000)	0.011	(0.017)
Spotify	-0.000	(0.000)	-0.012	(0.009)
YouTube	-0.023***	(0.002)	0.080***	(0.007)
YouTube Music	-0.000	(0.000)	-0.032*	(0.017)
YouTube Vanced	-0.000	(0.000)	-0.187	(0.306)
Entertainment	**-0.000***	**(0.000)**	**0.046*** *	**(0.022)**
Amazon Kindle	-0.000***	(0.000)	0.023	(0.022)
Archive of Our Own	-0.000	(0.000)	0.037	(0.238)
Candy Crush	-0.000	(0.000)	-0.021	(0.025)
Daydream	-0.000	(0.000)	0.140	(0.124)
Pokémon GO	-0.000	(0.000)	0.104***	(0.031)
Voice or video calls	**-0.002**	**(0.043)**	**-0.022**	**(0.017)**
Contacts	-0.001***	(0.000)	-0.003	(0.003)
Google Duo	-0.003***	(0.000)	0.008***	(0.003)
Phone/Dialer	-0.001***	(0.000)	-0.023	(0.016)
Email	**-0.001**	**(0.002)**	**-0.010**	**(0.059)**
AOL Mail	-0.000**	(0.000)	-0.052	(0.080)
Gmail	-0.002**	(0.001)	-0.018	(0.038)
Outlook	-0.001***	(0.000)	0.035	(0.063)
Yahoo Mail	-0.000	(0.000)	0.015	(0.043)
News	**-0.000*** **	**(0.000)**	**0.010**	**(0.013)**
ESPN	-0.000	(0.000)	0.020	(0.024)

TABLE A8. Substitution rates for multi- and single-homers: US

U_{it}	M_{it} (1)		$S_i M_{it}$ (2)	
MSN	-0.000***	(0.000)	0.011	(0.017)
NewsBreak	-0.000**	(0.000)	-0.002	(0.010)
Other	**-0.000**	**(0.002)**	**0.020**	**(0.028)**

TABLE A9. Substitution rates for multi- and single-homers: Spain

U_{it}	M_{it} (1)		$S_i M_{it}$ (2)	
Social media	**-0.001*** **	**(0.000)**	**-0.133*** **	**(0.010)**
TikTok	-0.001***	(0.000)	-0.103***	(0.025)
Twitch	-0.000	(0.000)	0.066	(0.051)
Twitter	-0.007***	(0.000)	-0.099***	(0.012)
Messaging	**-0.034*** **	**(0.002)**	**-0.183*** **	**(0.013)**
Telegram	-0.034***	(0.002)	-0.183***	(0.013)
Streaming	**-0.009**	**(0.008)**	**-0.041* **	**(0.024)**
Atresplayer	-0.001***	(0.000)	-0.008	(0.016)
Disney+	-0.001**	(0.001)	0.034	(0.025)
Mitele	-0.000	(0.000)	-0.012	(0.017)
Movistar Plus	-0.000	(0.000)	-0.008	(0.039)
Netflix	-0.002***	(0.001)	-0.047*	(0.028)
Prime Video	-0.000***	(0.000)	-0.040***	(0.015)
RTVE	-0.000***	(0.000)	-0.010	(0.008)
Spotify	-0.000***	(0.000)	0.001	(0.005)
XVideos	-0.001***	(0.000)	0.017	(0.011)
YouTube	-0.011***	(0.003)	-0.006	(0.014)
Entertainment	**-0.009*** **	**(0.001)**	**-0.012**	**(0.032)**
Candy Crush	-0.000	(0.000)	-0.044	(0.091)
Clash Royale	-0.003***	(0.001)	-0.017	(0.065)
Farm Heroes Saga	0.000	(0.000)	-0.042	(0.101)
Gardenscapes	-0.004***	(0.000)	-0.019	(0.131)
Homescapes	-0.002***	(0.000)	0.102	(0.112)
Parchisi	-0.001	(0.001)	0.321**	(0.139)
Pokémon GO	0.000	(0.000)	-0.078	(0.078)
Township	-0.000	(0.000)	-0.385*	(0.202)
Voice or video calls	**-0.000**	**(0.000)**	**-0.051*** **	**(0.007)**
Contacts	-0.000***	(0.000)	-0.017***	(0.004)
Phone/Dialer	-0.000***	(0.000)	-0.040***	(0.007)
Email	**-0.000*** **	**(0.000)**	**-0.049*** **	**(0.012)**
Gmail	-0.001***	(0.000)	-0.015**	(0.008)
Outlook	-0.000	(0.000)	-0.043***	(0.008)
Yahoo Mail	-0.000***	(0.000)	-0.074***	(0.023)
News	**-0.002*** **	**(0.000)**	**-0.014*** **	**(0.005)**
AS	-0.000***	(0.000)	-0.002	(0.006)
El Pais	-0.002***	(0.000)	0.001	(0.003)
Marca	-0.001***	(0.000)	0.006	(0.004)
MSN	-0.001***	(0.000)	-0.019***	(0.005)
20 Minutos	-0.001***	(0.000)	-0.018***	(0.006)
Other	**-0.000**	**(0.000)**	**-0.040*** **	**(0.012)**

B.1.4. Temporal heterogeneity in on- and off-device substitution

TABLE A10. Substitution rates for first or second half of outage: US

U_{it}	M_{it} (1)		$S_i M_{it}$ (2)	
Device	**2.026*** **	**(0.223)**	**-1.343*** **	**(0.311)**
All non-Meta services	**0.310*** **	**(0.096)**	**-0.730*** **	**(0.128)**
Social media	**-0.014**	**(0.011)**	**-0.102*** **	**(0.008)**
Discord	-0.000	(0.003)	-0.008***	(0.003)
Pinterest	0.002*	(0.001)	0.002*	(0.001)
Reddit	0.017***	(0.006)	-0.018***	(0.004)
Snapchat	-0.012***	(0.003)	-0.019***	(0.002)
TikTok	-0.032***	(0.012)	-0.013**	(0.006)
Twitch	0.005	(0.004)	-0.000	(0.003)
Twitter	0.007	(0.008)	-0.047***	(0.002)
Messaging	**-0.050*** **	**(0.013)**	**-0.021**	**(0.017)**
Google Messages	-0.023***	(0.005)	-0.007*	(0.004)
Motorola Messages	-0.001	(0.001)	-0.001	(0.001)
Samsung Messages	-0.028***	(0.006)	-0.006	(0.008)
Message+	0.002*	(0.001)	-0.006***	(0.001)
Streaming	**0.095*** **	**(0.012)**	**-0.106*** **	**(0.015)**
Hulu	0.006	(0.005)	-0.010***	(0.003)
Netflix	-0.007*	(0.004)	-0.009*	(0.005)
Prime Video	0.006***	(0.002)	-0.006***	(0.002)
Roku	0.002	(0.002)	-0.001	(0.001)
Spotify	-0.003	(0.002)	-0.000	(0.002)
YouTube	0.095***	(0.011)	-0.076***	(0.012)
YouTube Music	-0.003	(0.002)	-0.003	(0.002)
YouTube Vanced	-0.001	(0.002)	-0.001	(0.001)
Entertainment	**0.013*** **	**(0.005)**	**-0.006**	**(0.005)**
Amazon Kindle	0.004*	(0.002)	-0.003*	(0.002)
Archive of Our Own	0.000	(0.003)	0.001	(0.002)
Candy Crush	0.000	(0.002)	-0.004	(0.002)
Daydream	0.005	(0.003)	-0.002	(0.003)
Pokémon GO	0.004*	(0.002)	0.003*	(0.002)
Voice or video calls	**-0.022***	**(0.012)**	**0.010**	**(0.015)**
Contacts	-0.005**	(0.002)	0.003**	(0.002)
Google Duo	-0.003	(0.002)	0.003**	(0.001)
Phone/Dialer	-0.015*	(0.009)	0.004	(0.011)
Email	**0.168*** **	**(0.056)**	**-0.328*** **	**(0.077)**
AOL Mail	0.015***	(0.004)	-0.035***	(0.004)
Gmail	0.056**	(0.026)	-0.135***	(0.036)
Outlook	0.032**	(0.016)	-0.048***	(0.017)

TABLE A10. Substitution rates for first or second half of outage: US

U_{it}	M_{it}		$S_i M_{it}$	
	(1)		(2)	
Yahoo Mail	0.064***	(0.012)	-0.110***	(0.016)
News	**0.010****	**(0.005)**	**-0.012*****	**(0.004)**
ESPN	0.002	(0.002)	-0.001	(0.003)
MSN	0.004	(0.004)	-0.005	(0.003)
NewsBreak	0.003***	(0.001)	-0.006***	(0.001)
Other	**0.110*****	**(0.030)**	**-0.165*****	**(0.026)**

TABLE A11. Substitution rates for first or second half of outage: Spain

U_{it}	M_{it} (1)		$S_i M_{it}$ (2)	
Device	**0.334*** **	**(0.059)**	**0.062**	**(0.043)**
All non-Meta services	**-0.431*** **	**(0.035)**	**0.011**	**(0.023)**
Social media	**-0.115*** **	**(0.009)**	**0.007**	**(0.010)**
TikTok	-0.037***	(0.006)	-0.009	(0.006)
Twitch	-0.001	(0.005)	0.018***	(0.005)
Twitter	-0.078***	(0.008)	-0.003	(0.004)
Messaging	**-0.089*** **	**(0.007)**	**-0.047*** **	**(0.003)**
Telegram	-0.089***	(0.007)	-0.047***	(0.003)
Streaming	**-0.047* **	**(0.024)**	**-0.005**	**(0.018)**
Atresplayer	0.005**	(0.002)	-0.011***	(0.002)
Disney+	0.001	(0.002)	0.002*	(0.001)
Mitele	0.002	(0.002)	-0.005*	(0.003)
Movistar Plus	-0.004	(0.003)	0.005	(0.004)
Netflix	-0.031***	(0.006)	0.021***	(0.007)
Prime Video	-0.021***	(0.005)	0.013***	(0.003)
RTVE	-0.004*	(0.002)	0.002	(0.002)
Spotify	-0.004	(0.003)	0.008***	(0.003)
XVideos	0.005***	(0.002)	-0.005***	(0.002)
YouTube	0.004	(0.019)	-0.034**	(0.015)
Entertainment	**-0.005**	**(0.013)**	**-0.011**	**(0.007)**
Candy Crush	-0.002	(0.007)	-0.002	(0.004)
Clash Royale	-0.004*	(0.002)	0.002	(0.003)
Farm Heroes Saga	-0.004	(0.003)	0.005	(0.003)
Gardenscapes	0.004	(0.003)	-0.014***	(0.003)
Homescapes	0.010**	(0.005)	-0.014***	(0.003)
Parchisi	0.010*	(0.005)	-0.004	(0.005)
Pokémon GO	-0.008*	(0.005)	0.008**	(0.004)
Township	-0.010**	(0.004)	0.009***	(0.003)
Voice or video calls	**-0.046*** **	**(0.006)**	**0.019*** **	**(0.003)**
Contacts	-0.015***	(0.005)	0.008***	(0.001)
Phone/Dialer	-0.031***	(0.004)	0.011***	(0.003)
Email	**-0.075*** **	**(0.015)**	**0.045*** **	**(0.011)**
Gmail	-0.030***	(0.010)	0.027***	(0.008)
Outlook	-0.035***	(0.006)	0.016***	(0.004)
Yahoo Mail	-0.009**	(0.004)	0.001	(0.003)
News	**-0.016*** **	**(0.004)**	**0.006**	**(0.004)**
AS	-0.001	(0.002)	0.001	(0.003)
El Pais	-0.002	(0.002)	0.002	(0.002)
Marca	0.003*	(0.002)	-0.003	(0.002)
MSN	-0.009***	(0.002)	0.006***	(0.001)
20 Minutos	-0.006***	(0.002)	-0.000	(0.003)

TABLE A11. Substitution rates for first or second half of outage: Spain

U_{it}	M_{it}		$S_i M_{it}$	
	(1)		(2)	
Other	**-0.039*****	**(0.014)**	**-0.002**	**(0.011)**

Appendix C. Alternative identification strategy

TABLE A12. Substitution rates for alternative identification strategy: US

Service	Realization (hours)	Prediction (hours)	Relative deviation		Substitution rate	
Meta platforms	**1,256.3**	**4,056.8**	**-0.690****	**[-0.65, -0.73]**	**1.000****	**[1.00, 1.00]**
Facebook	1,050.3	3,308.4	-0.683**	[-0.64, -0.73]	0.806**	[0.81, 0.81]
Instagram	167.1	639.3	-0.739**	[-0.65, -0.83]	0.169**	[0.17, 0.16]
WhatsApp	39.0	106.7	-0.635**	[-0.49, -0.81]	0.024**	[0.03, 0.02]
Device	**24,680.7**	**27,790.2**	**-0.112****	**[-0.06, -0.16]**	**1.110****	**[1.49, 0.66]**
All non-Meta services	**13,425.8**	**13,128.4**	**0.023**	**[0.06, -0.01]**	**-0.106**	**[0.02, -0.28]**
Social media	**1,910.3**	**1,698.1**	**0.125****	**[0.19, 0.05]**	**-0.076****	**[-0.03, -0.13]**
Discord	119.9	107.3	0.118	[0.25, -0.05]	-0.005	[0.00, -0.01]
Pinterest	45.7	55.6	-0.177	[0.01, -0.45]	0.004	[0.01, -0.00]
Reddit	166.3	175.1	-0.050	[0.12, -0.22]	0.003	[0.01, -0.01]
Snapchat	327.5	276.6	0.184**	[0.30, 0.08]	-0.018**	[-0.01, -0.03]
TikTok	796.3	686.5	0.160**	[0.24, 0.08]	-0.039**	[-0.02, -0.06]
Twitch	90.1	96.0	-0.061	[0.19, -0.32]	0.002	[0.01, -0.01]
Twitter	364.5	304.3	0.198**	[0.33, 0.06]	-0.022**	[-0.01, -0.04]
Messaging	**1,015.1**	**884.7**	**0.147****	**[0.22, 0.09]**	**-0.047****	**[-0.03, -0.07]**
Google Messages	415.3	361.0	0.151**	[0.23, 0.07]	-0.019**	[-0.01, -0.03]
Motorola Messages	57.0	53.3	0.070	[0.19, -0.04]	-0.001	[0.00, -0.00]
Samsung Messages	471.9	400.1	0.179**	[0.27, 0.10]	-0.026**	[-0.01, -0.04]
Message+	70.8	63.3	0.118	[0.27, -0.03]	-0.003	[0.00, -0.01]
Streaming	**3,090.3**	**3,125.5**	**-0.011**	**[0.04, -0.05]**	**0.013**	**[0.05, -0.04]**
Hulu	113.7	120.9	-0.059	[0.10, -0.25]	0.003	[0.01, -0.00]
Netflix	263.8	222.5	0.186*	[0.34, 0.01]	-0.015*	[-0.00, -0.03]
Prime Video	45.6	48.3	-0.055	[0.23, -0.39]	0.001	[0.01, -0.00]
Roku	31.2	32.4	-0.039	[0.33, -0.46]	0.000	[0.00, -0.00]
Spotify	119.4	107.8	0.108	[0.27, -0.05]	-0.004	[0.00, -0.01]
YouTube	2,370.9	2,461.5	-0.037	[0.01, -0.08]	0.032	[0.06, -0.01]
YouTube Music	106.7	95.5	0.118	[0.29, -0.08]	-0.004	[0.00, -0.01]
YouTube Vanced	38.9	32.7	0.189	[0.43, -0.16]	-0.002	[0.00, -0.01]
Entertainment	**280.9**	**305.0**	**-0.079**	**[0.06, -0.28]**	**0.009**	**[0.03, -0.01]**
Amazon Kindle	36.6	39.5	-0.074	[0.19, -0.37]	0.001	[0.01, -0.00]
Archive of Our Own	27.5	22.7	0.208	[0.67, -0.68]	-0.002	[0.01, -0.01]
Candy Crush	61.6	55.0	0.120	[0.33, -0.12]	-0.002	[0.00, -0.01]
Daydream	98.3	107.3	-0.084	[0.15, -0.41]	0.003	[0.02, -0.01]
Pokémon GO	57.0	77.9	-0.268	[0.01, -0.50]	0.007	[0.01, -0.00]
Voice or video calls	**468.8**	**449.3**	**0.044**	**[0.10, -0.03]**	**-0.007**	**[0.00, -0.02]**
Contacts	107.0	105.3	0.016	[0.11, -0.10]	-0.001	[0.00, -0.00]
Google Duo	52.0	48.8	0.065	[0.31, -0.23]	-0.001	[0.00, -0.01]
Phone/Dialer	309.9	287.0	0.080	[0.15, -0.00]	-0.008	[0.00, -0.02]
Email	**2,840.0**	**2,926.4**	**-0.030**	**[0.01, -0.07]**	**0.031**	**[0.07, -0.01]**
AOL Mail	242.3	225.8	0.073	[0.18, -0.05]	-0.006	[0.00, -0.02]

TABLE A12. Substitution rates for alternative identification strategy: US

Service	Realization (hours)	Prediction (hours)	Relative deviation		Substitution rate	
Gmail	1,533.3	1,533.3	-0.000	[0.05, -0.06]	0.000	[0.03, -0.03]
Outlook	411.9	430.2	-0.042	[0.02, -0.11]	0.007	[0.02, -0.00]
Yahoo Mail	652.6	676.3	-0.035	[0.02, -0.10]	0.008	[0.02, -0.01]
News	**192.6**	**224.4**	**-0.141**	**[0.03, -0.35]**	**0.011**	**[0.03, -0.00]**
ESPN	52.6	88.1	-0.403*	[-0.10, -0.90]	0.013*	[0.03, 0.00]
MSN	86.3	76.3	0.131	[0.32, -0.06]	-0.004	[0.00, -0.01]
NewsBreak	53.7	52.8	0.018	[0.20, -0.23]	-0.000	[0.00, -0.00]
Other	**3,627.7**	**3,646.7**	**-0.005**	**[0.06, -0.06]**	**0.007**	**[0.07, -0.08]**

TABLE A13. Substitution rates for alternative identification strategy: Spain

Service	Realization (hours)	Prediction (hours)	Relative deviation		Substitution rate	
Meta platforms	**268.5**	**965.4**	**-0.722****	**[-0.67, -0.78]**	**1.000****	**[1.00, 1.00]**
Facebook	89.2	349.3	-0.745**	[-0.67, -0.84]	0.373**	[0.39, 0.36]
Instagram	43.8	199.4	-0.781**	[-0.68, -0.88]	0.223**	[0.23, 0.21]
WhatsApp	135.5	405.4	-0.666**	[-0.60, -0.76]	0.387**	[0.41, 0.37]
Device	**3,389.8**	**3,776.6**	**-0.102****	**[-0.06, -0.15]**	**0.555****	**[0.75, 0.35]**
All non-Meta services	**1,710.9**	**1,443.3**	**0.185****	**[0.24, 0.12]**	**-0.384****	**[-0.23, -0.54]**
Social media	**258.3**	**176.5**	**0.463****	**[0.56, 0.34]**	**-0.117****	**[-0.08, -0.15]**
TikTok	81.6	58.6	0.394**	[0.59, 0.20]	-0.033**	[-0.02, -0.05]
Twitch	42.3	43.0	-0.014	[0.17, -0.27]	0.001	[0.02, -0.01]
Twitter	134.3	74.3	0.808**	[0.93, 0.64]	-0.086**	[-0.06, -0.11]
Messaging	**114.7**	**32.6**	**2.523****	**[2.72, 2.29]**	**-0.118****	**[-0.10, -0.14]**
Telegram	114.7	32.6	2.523**	[2.72, 2.29]	-0.118**	[-0.10, -0.14]
Streaming	**434.9**	**381.9**	**0.139****	**[0.26, 0.01]**	**-0.076****	**[-0.00, -0.15]**
Atresplayer	7.2	4.7	0.526*	[0.93, 0.04]	-0.004*	[-0.00, -0.01]
Disney+	4.2	4.8	-0.129	[0.51, -1.22]	0.001	[0.01, -0.00]
Mitele	6.5	6.0	0.088	[0.65, -0.86]	-0.001	[0.01, -0.01]
Movistar Plus	18.6	15.7	0.180	[0.64, -0.52]	-0.004	[0.01, -0.02]
Netflix	65.5	49.5	0.321**	[0.51, 0.06]	-0.023**	[-0.00, -0.04]
Prime Video	31.7	22.1	0.432	[0.85, -0.08]	-0.014	[0.00, -0.03]
RTVE	8.6	7.9	0.099	[0.78, -0.92]	-0.001	[0.01, -0.01]
Spotify	10.3	10.4	-0.004	[0.31, -0.50]	0.000	[0.01, -0.00]
XVideos	5.7	5.6	0.025	[0.46, -0.50]	-0.000	[0.00, -0.00]
YouTube	276.7	253.2	0.093*	[0.18, 0.00]	-0.034*	[-0.00, -0.07]
Entertainment	**122.3**	**112.4**	**0.088**	**[0.20, -0.06]**	**-0.014**	**[0.01, -0.03]**
Candy Crush	48.8	43.1	0.131	[0.32, -0.11]	-0.008	[0.01, -0.02]
Clash Royale	7.1	5.0	0.417	[0.71, -0.10]	-0.003	[0.00, -0.01]
Farm Heroes Saga	9.7	9.2	0.060	[0.45, -0.53]	-0.001	[0.01, -0.01]
Gardenscapes	12.2	5.8	1.096**	[1.75, 0.21]	-0.009**	[-0.00, -0.02]
Homescapes	10.0	8.7	0.155	[0.50, -0.37]	-0.002	[0.00, -0.01]
Parchisi	4.5	8.5	-0.465*	[-0.04, -1.15]	0.006*	[0.01, 0.00]
Pokémon GO	14.3	12.7	0.125	[0.53, -0.55]	-0.002	[0.01, -0.01]
Township	15.7	13.0	0.202	[0.47, -0.16]	-0.004	[0.00, -0.01]
Voice or video calls	**79.5**	**55.9**	**0.422****	**[0.60, 0.20]**	**-0.034****	**[-0.01, -0.05]**
Contacts	12.4	5.7	1.175**	[1.49, 0.45]	-0.010**	[-0.00, -0.01]
Phone/Dialer	67.1	49.2	0.364**	[0.55, 0.16]	-0.026**	[-0.01, -0.04]
Email	**166.8**	**140.9**	**0.183****	**[0.31, 0.03]**	**-0.037****	**[-0.01, -0.07]**
Gmail	75.7	65.3	0.159	[0.31, -0.03]	-0.015	[0.00, -0.03]
Outlook	70.5	60.1	0.175*	[0.28, 0.03]	-0.015*	[-0.00, -0.03]
Yahoo Mail	20.6	11.9	0.731**	[1.22, 0.09]	-0.012**	[-0.00, -0.02]
News	**47.5**	**37.9**	**0.256***	**[0.42, 0.01]**	**-0.014***	**[-0.00, -0.02]**
AS	8.0	7.6	0.056	[0.34, -0.40]	-0.001	[0.00, -0.00]
El Pais	6.6	4.0	0.639	[0.99, -0.37]	-0.004	[0.00, -0.01]

TABLE A13. Substitution rates for alternative identification strategy: Spain

Service	Realization (hours)	Prediction (hours)	Relative deviation		Substitution rate	
Marca	11.6	15.9	-0.269*	[-0.03, -0.59]	0.006*	[0.01, 0.00]
MSN	9.2	4.9	0.873*	[1.27, 0.09]	-0.006*	[-0.00, -0.01]
20 Minutos	12.2	5.6	1.176**	[1.60, 0.49]	-0.009**	[-0.00, -0.01]
Other	**486.8**	**445.1**	**0.094***	**[0.18, 0.00]**	**-0.060***	**[-0.00, -0.12]**

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