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Ph.D. thesis

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Essays on smartphones' effects on attention and behavior

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Summary

Since the introduction of the iPhone in 2007, smartphones have become an integrated part of human life. Smartphones are excellent tools that help us access information, coordinate journeys, connect with friends and family, and much, much more. However, in parallel with the proliferation of smartphones, more and more concerns about adverse effects on human life have been raised. Research has shown that smartphones can be addictive, affect cognitive abilities, negatively influence social and intimate relationships, reduce academic performance, and correlate with depression and low well-being.

In this Ph.D. dissertation, I analyze how smartphones affect human life through three separate chapters. Though examining different domains of human life, the chapters have several things in common. First, they all relate to how smartphones affect human attention. Second, they all use data collected from smartphones to examine the influence of smartphones. Third, in all three chapters, analyzes are made based on advanced data structuring and the use of econometric models seeking to establish causal claims when possible.

How constant internet access affects human behavior - the case of free roaming

The first chapter is called "How constant internet access affects human behavior - the case of free roaming". I am the first-author of this chapter, which is written together with Sigga Svala Jonasdottir. We use smartphone data from more than 20,000 Europeans collected over two years to causally assess how mobile internet affects human behavior. Specifically, we examine daily smartphone screen use, app use, and mobility patterns when traveling in another EU country before and after the implementation of the Roam-Like-at-Home initiative, which removed roaming (using your phone in another country) tariffs within the EU.

After accounting for individual and place-specific factors, we show that there was a sharp increase in smartphone use when traveling between EU countries after June 15th, 2017, when tariffs were removed. We see this as causal evidence that the Roam-Like-at-Home initiative increased smartphone use, with an average daily increase in screentime of 6 percent. This increase is primarily driven by social media apps, browser and search apps, and map apps. Further, we investigate the effect on mobility patterns and find that while travelers due to free roaming visit 6% more locations a day, they spent 5% less time on transportation like cars and trains. This suggests that mobile internet access help travelers visit more places and travel more efficient.

Nature unplugged or interrupted?

The second chapter is called "Nature unplugged or interrupted? A two-year panel study of smartphone use and digital impulse inhibition in natural and urban environments". I am the first-author, together with Kelton Minor, on this chapter, which we co-wrote with Aaron J. Schwartz, Christopher Danforth, Sune Lehmann, and Andreas Bjerre-Nielsen.

An extensive literature has studied how natural areas affects human well-being positively. Natural areas can, for example, be recreational areas, like parks and recreational grounds, or nature areas, like forests and nature reserves. We examine both the effect of natural areas overall (both recreational and nature areas) and recreational and nature areas separately. Time spent in natural areas have been shown to correlate with improved mental health, reduced stress, and improved cognitive outcome, among other things. In recent generations time spent in natural areas have fallen, leading some researchers to fear an "extinction of experience".

However, how smartphones might mediate or mitigate the positive effect of natural areas on individuals, has not been adequately studied, as we show in our systematic literature review. We use data from the Copenhagen Network Study, to follow 701 young adults' phone use for two years and use fixed effects models to account for individual-specific and time-specific effects. We show that exposure to natural areas in general (including nature areas and recreational areas) only slightly affects smartphone use, relative to being in urban areas. However, we find that these effects differ substantially over the type of natural areas. While being in nature (e.g., forests or nature reserves) *reduces* smartphone screentime, texting, and calling by 4%, 6%, and 7%, respectively, being in recreational areas (e.g., parks or recreational grounds) has no effect on smartphone screentime, but *increases* texting and calling by 11% and 17% respectively. Further, we show that the effect of being in a specific environment changes depending on how long time you have been in the specific environment and that nature reduces smartphone use more when users are staying still in nature, compared to moving through nature. Finally, we find that the users who spent the most time in nature also lowers their phone use the most when being in nature. In contrast, infrequent nature visitors increase their screentime when being in nature.

This chapter highlights that smartphone use should be accounted for when assessing the role of natural spaces on well-being, and that this requires detailed data.

Smartphone use is socially contagious

The third chapter is called "Smartphone use is socially contagious." I am the first-author on this chapter, which I have written together with co-authors Asger Andersen and Andreas Bjerre-Nielsen. In this chapter, we show that smartphone use spread between individuals that are near each other. The spread of smartphone use only occurs between individuals who have a social relation. We, therefore, conclude that smartphone use spreads through social mechanisms. We show this by using data from a large-scale field study running for more than two years, which has the unique feature that it includes detailed information about nearby individuals. To causally identify the effect of one individual's screentime on nearby individuals, we use the arrival of text messages (SMS) as quasi-random natural experiments and track phone use for all co-present individuals before and after the arrival of the text message. We, further, compare these to similar situations where the same people are present but where no text messages are received. This matching setup enables us to causally assess whether smartphone use is contagion.

Showing that smartphone use is contagious has the potential to change the way we think about smartphone use. Because it is contagious, individuals' smartphone use goes from exclusively affecting the individual to also affecting nearby peers. Since there are indications that additional smartphone use is harmful to the individual, smartphone use arguably exhibits a negative externality, which would be an argument for regulation. This can be compared to second-hand smoking, where evidence of adverse effects on co-present individuals has led to heavy regulation.

Since it is unclear how smartphone use would be taxed, the regulation that would be easiest to implement would prohibit smartphone use in specific settings. This regulation could be enforced either by formal regulation (e.g., banning smartphones in a school class) or by social norms (e.g., by making smartphone use in social settings frowned upon). Since we show that smartphone use is socially contagious, I find no argument that these regulations should include public settings like public transport or waiting areas. Possible regulation should focus on settings that contain social interactions and where interruptions and inattention are adverse. Examples could be educational settings or intimate relationships.

Other work and dissemination

In addition to the chapters in this dissertation, I also produced other work during my Ph.D.

I have written the commentary "Big data and ethnography", together with Andreas Bjerre-Nielsen, which is currently revise and resubmit at the journal Big Data and Society. This chapter explores similarities and differences between "big data" and ethnographic data, and the methods used to examine them. Further, we make recommendations on how big data and ethnographic data can be combined and discuss why this may benefit research. Thereby, we contribute the methodology in the field that seeks to combine quantitative big data methods with qualitative ethnographic methods, sometimes called "machine anthropology."

In the midst of the lockdown caused by the Covid-19 pandemic, I analyzed the mood of the public opinion on Twitter, together with several colleagues from SODAS. Among other things, we found that the mood of tweets concerning Covid-19 improved significantly after the lockdown measures were announced, suggesting that Twitter users felt more secure after the Prime Minister announced the lockdown measures. The results were published on the SODAS Covid-19 blog.

To fulfill my dissemination requirements, I have written an article to the medical magazine "BestPractice" together with Sune Lehmann Jørgensen, about how to optimally vaccinate from a theoretical point of view, and how social media data and telecom data might help. Further, I have appeared as an expert in an article on DR.dk, in the podcast Adapter, and on the radio show Go'morgen P3.

Contents

How Constant Internet Access Affects Human Behavior - the Case of free Roaming

Kristoffer Lind Glavind Sigga Svala Jonasdottir

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Abstract

The proliferation of smartphones and mobile internet has made people all over the world Permanently Online and Permanently Connected. This unprecedented change has been hypothesized to have both adverse and beneficial effects on human life. However, since the proliferation of mobile internet has been gradual, it is confounded with other simultaneous societal changes, making the causal effects difficult to examine. We follow 21,489 Europeans over two years and exploit a major policy change that overnight removed fees on phone use when traveling inside the EU. This enabled us to identify the causal effects of having access to mobile internet. We find that travelers' average screentime increased by 6% and that the change was driven by increased use of social media, browsers, and maps. Further, the number of locations visited each day increased by 6%, while time spent in transport decreased by 5%, suggesting that mobile internet access increases mobility while making it more efficient.

Abstract

I takt udbredelsen at smartphones og mobilt internet er størstedelen af den vestlige verdens befolkning blevet Permanent Online og Permanent Forbundne. Det har medført spådomme om både store positive og negative konsekvenser. Men fordi udbredelsen af mobilt internet har været gradvis og er sket samtidig med andre samfundsudviklinger, er effekten svær at isolere. Vi følger 21.489 europæere i to år, og udnytter en stor reform der betød, at gebyrer på mobiltelefonbrug i andre EU lande, blev afskaffet fra den ene dag til den anden. Vi finder at rejsendes gennemsnitlige skræmtid steg med 6 procent, og at stigningen var drevet af højere brug af sociale medier, browsere og kort. Endvidere finder vi, at antallet af steder rejsende besøgte hver dag steg med 6 procent, samtidig med at den daglige transporttid faldt med 5 procent. Det indikerer, at adgang til mobilt internet øger den individueller mobilitet, og samtidig gør den mere effektiv.

Introduction

With the proliferation of smartphones and mobile internet access, a large part of the world's population is now permanently online and permanently connected (POPC). How the "always-on" state affects human life has led to fear and controversy, and extensive media coverage (Twenge, 2017; Bhattacharjee, 2019; Lusinski, 2018). While some emphasize that smartphones with access to mobile internet ease coordination and access to information (Bezerra et al., 2015; WorldBank, 2016), others fear that humans will turn into never-present smartphone zombies ("Smombies") (Duke and Montag, 2017; Tom Chatfield, 2016). However, since the proliferation of smartphones and mobile internet has happened gradually over the course of the last 15 years and has been simultaneous with the development of other societal phenomenons (e.g., social media), the effect on human life is difficult to assess. In the present study, we use a global, large-scale smartphone dataset, together with a policy intervention which changed mobile internet access for most Europeans overnight. This way, we are able to causally identify how mobile internet access affects behavior.

With the European Union's Roam-Like-at-Home (RLaH) initiative, fees on roaming (using your mobile phone in another EU country) were abolished on June 15 2017[1]. The RLaH initiative was praised by EU-leaders as "one of the greatest and most tangible successes of the EU" (EU, 2017), and following the implementation roaming data usage rose sharply (Blackman and Forge, 2018). However, it has not been studied how this intervention, which made it possible for millions of individuals to be permanently online and permanently connected, affected behavior. We examine this by looking at changes in individual smartphone use and mobility pattern.

Permanently Online and Permanently Connected

Smartphones enable users to access the internet anywhere. Vorderer et al. (2017) divides the effect of constantly having access to mobile internet into "permanently online" - and being "permanently connected". "Permanently online" refers to the constant ability to retrieve information from the internet (e.g., looking up routes or accessing news), while "permanently connected" refers to the constant ability to access online communication (e.g., social media and messaging apps).

Since the introduction of the mobile phone, the guiding principle of virtual communication has gradually changed from geographic addressability to individual addressability Ling (2017).

[1]The initiative affected all countries in the European Economic Area (EEA). All EEA countries are included in the analysis, however, we will refer to the affected area as EU to ease interpretability.

Whereas communication was previously linked to geographically fixed locations (e.g. landline and phone booths), the mobile phone allows for one-to-one communications using text or mobile voice, and the smartphone further adds multisided interactions on messaging apps and social media (Ling, 2017).

Constant individual addressability does not only entail possibilities but also commitments in the form of social expectations. By now, abstaining from communication is an action that requires planning and justification (Klimmt et al., 2017; Bayer et al., 2016). Likewise, we are drawn to our smartphones by both endogenous cues (inner desires to use the smartphone) and exogenous cues (e.g., sound or vibration from notifications) (Wilmer et al., 2017). Further, using mobile social network sites can lead to the feeling of information overload (Matthes et al., 2020), and smartphone addiction seems to be increasing across the world (Olson et al., 2020).

Though a lot has been written about the "always-on" technologies, real-world causal evidence is scarce (Schneider et al., 2017). The present study seeks to contribute by assessing how access to mobile internet 1) affects overall smartphone use, 2) affects use of individual apps and 3) whether it influences individual mobility patterns. We find that access to mobile internet, on average, increases daily smartphone use by around 6% and that this increment is primarily driven by higher use of social media (5%), browser (9%), and maps (15%). Further, we find that access to mobile internet leads to an increase in the daily number of unique places visited (6%), while time spent on transport decreases (5%).

Results

We structure the analysis into three parts. *Part one* examines whether the Roam-Like-at-Home initiative affected how much time people spent actively using their smartphones (screentime) when traveling. *Part two* decomposes this effect into the usage of specific apps and app categories. *Part three* explores the effect on the daily mobility patterns of individuals by studying the time spent in transport, spatial entropy and the number of places visited.

We use a large-scale smartphone dataset collected conditionally on user consent, containing data on mobility, overall phone use and use of individual apps aggregated on the daily level. We limit the sample to only include EU residents, who traveled to another EU country both before and after the introduction of the RLaH initiative. To limit the number of users who had free roaming subscriptions before the RLaH initiative, we further exclude users who spent more than 6 weeks in another EU country, during the two years surrounding the implementation of RLaH. Further, the first and last two weeks of the year are excluded, due to the changes in travel behavior related to the Christmas and Epiphany holidays. In the final sample, we have 21,489 users from 30 different countries, with a total of 4,512,602 days of observations, of which 92.4% are observed in the home country, 6.1% in another EU country and 1.4% in a country outside the EU (See data section).

Since phone use and mobility are very person- and place-dependent aggregated raw data can hide causal patterns. Therefore, we use a fully dynamic fixed effects model (Angrist and Pischke, 2008) following the development in screentime over time, while controlling for stable individual factors such as demographic characteristics and area-specific mobility patterns (see methods section for further details).

To isolate the effect of mobile internet access, we compare affected observations with non-affected. While observations are only affected when users travel to another EU country, unaffected observations can either occur when the user is at home or when the user is traveling to a non-EU country. We, therefore, compare affected users to the two counterfactuals separately. If the RLaH initiative is driving a change in mobile use and behavior, we expect the affected users to develop differently to both counterfactuals.

How mobile internet access affects screentime

In this subsection, we examine how individuals' screentime was affected by RLaH. Figure 1 plots the results of the fully dynamic fixed effects model with data aggregated on a biweekly level. The figure shows the development in screentime for EU residents in each of the three contexts: in home country, in another EU country and in a non-EU country.

Figure 1a plots the development relative to the two-week period before the implementation of RLaH. We see that while the development in screentime over all three contexts is quite stable before RLaH, it increases sharply at the time of implementation and reaches a new level around 10 minutes higher a day. We do not observe a similar pattern for screentime at home or in non-EU countries, which seems to be stable or mildly decreasing.

Figure 1b and 1c show respectively the difference in screentime development between EU travel and home, and between EU travel and non-EU travel. Similarly to Figure 1a we see a sharp increase at the time of implementation and stabilization at a higher level around 8 and 11 minutes a day higher than the reference for 1b and 1c respectively. To estimate the average causal change, we use a difference-in-difference fixed effects model and find an increase of 6.9 minutes (s.e. 0.62) comparing EU travel to home and an increase of 9.1 minutes (s.e. 1.9) when comparing EU travel to non-EU travel. Both estimates are statistically significant from

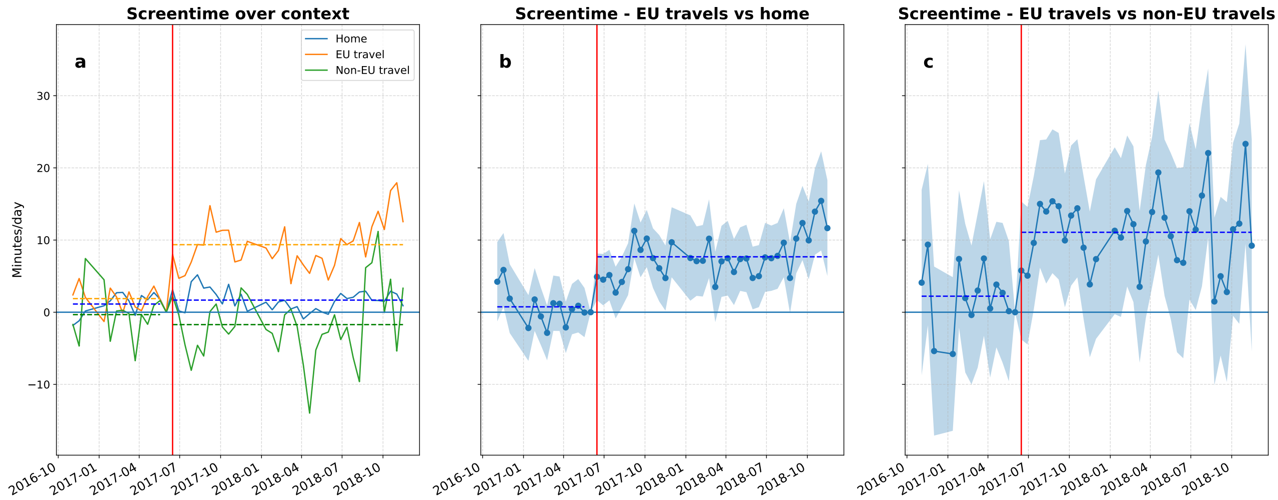

Figure 1: Development in screentime over context. Panel **a)** shows the development in mean screentime when being in the home country, traveling to another EU country and traveling to a non-EU country. Panel **b)** and **c)** illustrate the development in the difference between screentime when traveling in an EU country and screentime when being at home and traveling in a non-EU country, respectively. All estimates are outputs from a two-way fixed effects linear model. The vertical red line shows the timing of implementation of RLaH. Dashed lines show the mean before and after. Blue areas indicate 95% confidence intervals. Standard errors are clustered on the level of individuals.

zero, but not from each other. With average screentime when traveling in another EU country before RLaH being 1 hour and 54 minutes, this corresponds to a relative increase of 6 and 8 percent respectively.

We interpret these results as causal evidence that the RLaH initiative increased smartphone use for EU residents traveling in another EU country.

App specific changes

In this part, we decompose the change in screentime at the app level. We start by exploring the app categories in the Google Play store. Figure 2 shows the relative changes for categories where the change is significant at the 10 percent level both when comparing to being at home and outside the EU. We see that there are significant changes in the categories "Communication", "Social" and "Travel Local". Compared to being at home, daily usage increased by around 5 percent both in the "Communication" and "Social" category, while screentime in the "Travel Local" category increased by 18 percent. Compared to being in a non-EU country, the relative effect is 15 percent on "Communication", 8 percent on "Social" and 10 percent on "Travel Local". This indicates that the increased screentime is driven by social activities and travel planning, and, potentially, exploration in unfamiliar environments.

As illustrated in Table 1, the Google Play categories are rather broad and diverse. For

Play Category	**Examples**
Communication	Google Chrome, WhatsApp, Facebook Messenger, Gmail
Social	Facebook, Instagram, Twitter, Snapchat, Grindr, Tumblr
Travel & Local	Google Maps, Foursquare, Booking.com, Tripadvisor

Custom Category	**Examples**
Browsers and Search	Google Chrome, Firefox, Opera, Google Search Box, Wikipedia
Social Media	Facebook, Instagram, Twitter, Snapchat, Pinterest, LinkedIn, Jodle
Maps	Google Maps, Waze, WeGo-CityMaps, Sygic GPS Navigator
Messaging apps	Whatsapp, Facebook Messenger, Telegram, WeChat

Table 1: Example of apps in Google Play Categories and Custom categories

example, "Communication" contains browser apps such as Google Chrome as well as messaging apps like WhatsApp, while the "Travel Local" category contains both maps and booking apps. To get a deeper understanding of which types of apps are driving the observed increase, we make custom categories based on the 1000 most used apps in our data. Figure 3 shows the relative effects for these custom categories. Comparing EU travel to home country, we see that the change is significant in social media apps (5%), apps related to browsers and search (9%) and map apps (15%), however, there is no change relating to messaging apps. The estimates comparing EU travels with non-EU travels are generally not significantly different from the estimates reported above. The only exception is messaging apps for which the estimate is statistically significant when comparing to non-EU travels.

We conclude that this is evidence that the RLaH initiative increased the use of apps in the "Social Media", "Browser and Search" and "Map" categories, but that the evidence is insufficient to conclude an increase in the messaging app category. Looking at the absolute effect sizes in Figure **??**, this corresponds to an average increase of around 1.5 minutes/day for both social media apps, browser apps and map apps.

We interpret this as consistent evidence that these three categories account for most of the observed increase in screentime. This implicates that RLaH has made users both more Permanently Online, searching for information, using browsers and maps, and more Permanently Connected virtually staying in touch with peers on social media.

Changes in mobility patterns

We now turn to the effect on mobility patterns. We examine three measures: Unique locations visited, day level entropy and time spent in transport. Unique locations visited count all locations visited during a day, only counting locations visited several times once. Spatial entropy tells us about the predictability of a person's movement and can be interpreted as

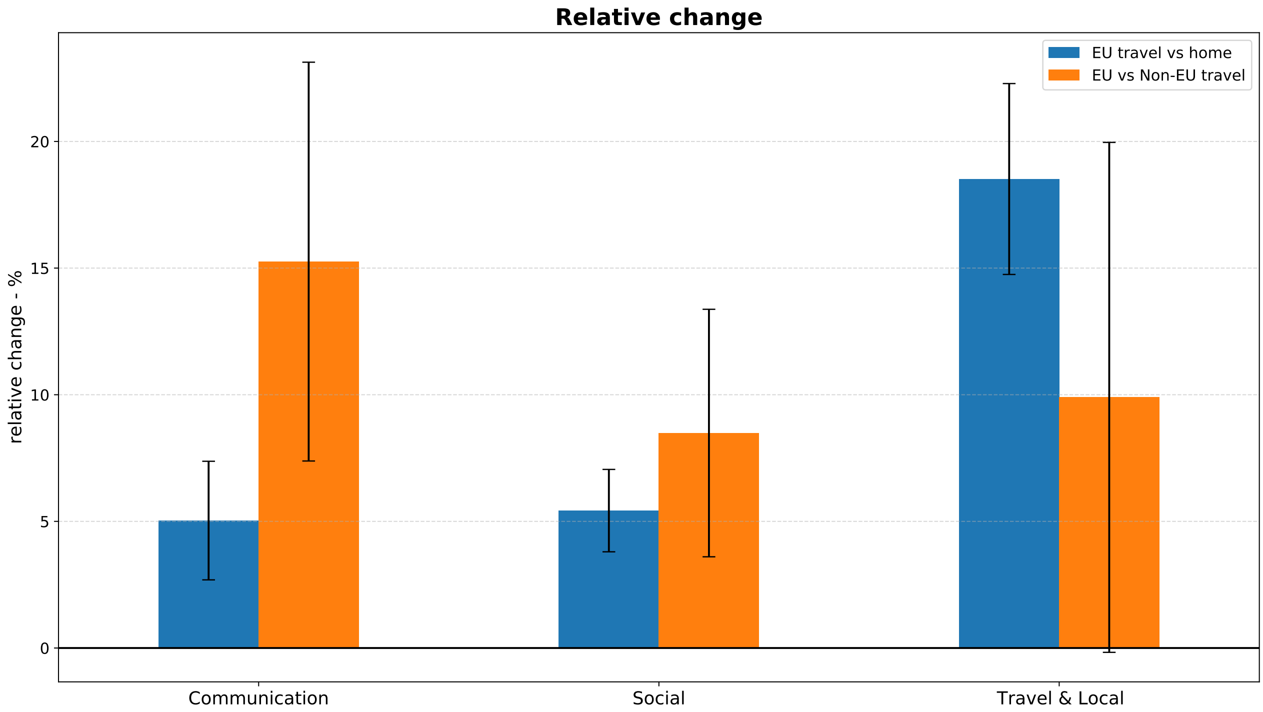

Figure 2: Effect estimates of relative change in use for the Play Store categories. Blue and orange columns represent difference-in-difference estimates when comparing EU travels to being at home and traveling outside the EU, respectively. Error bars show 95% confidence intervals, with standard errors clustered on the individual level.

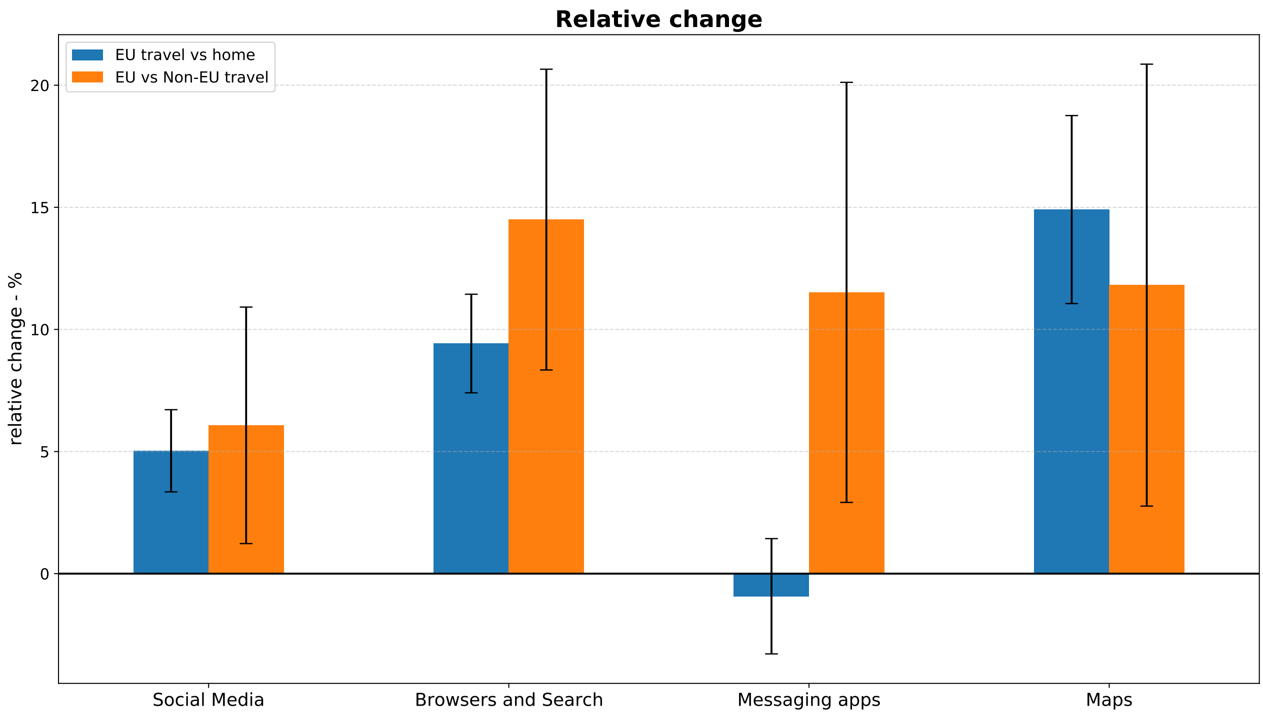

Figure 3: Effect estimates of relative change in use for custom app categories. Blue and orange columns represent difference-in-difference estimates when comparing EU travels to being at home and traveling outside the EU, respectively. Error bars show 95% confidence intervals, with standard errors clustered on the individual level.

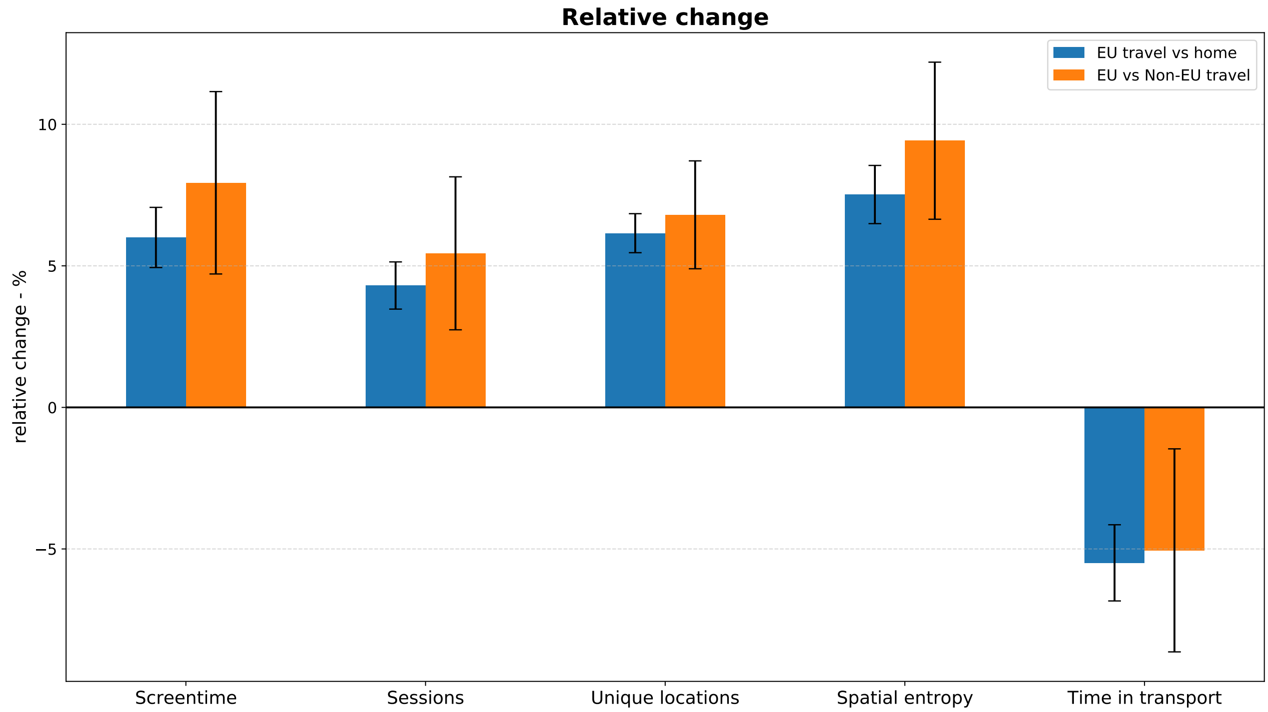

Figure 4: Effect estimates of relative change in variables relating to phone use and mobility patterns. Blue and orange columns represent difference-in-difference estimates when comparing EU travels to being at home and traveling outside the EU, respectively. Error bars show 95% confidence intervals, with standard errors clustered on the individual level.

the number of yes/no questions a person needs to ask to be at least 50% certain about where another person is if he/she knows all the possible places the other person could be that day. Time in transport represents the time spent in transportation like cars and trains.

Figure 4 summarizes the overall results of our primary variables of interest. As previously described screentime increases by 6% (7 minutes/day). Further, we see that the number of daily phone sessions, which count the number of times a user activates an app, increases by 4% (2.5 sessions/day).

Unique locations visited increase by 6% (0.15 locations a day), indicating that travelers explore more locations when they have mobile internet access. Spatial entropy increases by 7.5% (0.04 units), indicating that individual mobility patterns become less predictable.

Interestingly, even though more unique places are visited, less time is spent in transport like cars and trains. Daily time spent in transport falls by 5% (5.5 minutes). Thus, even though more places are visited, the time spent moving between those places decreases. This indicates that transport becomes more efficient, which is consistent with the hypothesis that mobile internet access can make travel more efficient.

	In home country	Another EU-country	Non-EU country
Before RLaH	124.3	114.4	132.8
After RLaH	124.1	122.6	137.3
Difference	-0.27	8.2	4.5
Difference (%)	-0.22	6.7	3.3

Table 2: Mean daily minutes of screenuse before and after implementation of the RLaH initiative.

Discussion

We have shown that access to mobile internet changes human behavior, both in terms of overall phone use, app usage (specifically Social Media, Browsers and maps) and mobility patterns. This shows that the RLaH initiative implemented by the European Union had substantial implications.

The analysis shows the effect of getting free access to mobile internet during travels in another EU country. Looking at the raw total screentime across contexts, we find indications that after the RLaH initiative was implemented, phone use during travel between EU countries became more similar to phone use at home. As Table 2 conveys, average screentime in the home country showed no difference before and after RLaH, being constant at 2 hours and 4 minutes. Conversely, average screentime when traveling to another EU country increased 8.2 minutes a day, from 1 hour and 54 minutes to 2 hours and 3 minutes, almost the same as average screentime at home. When traveling to non-EU countries, users, on average, used their phone more than when being in their home country or traveling in EU countries. Before the implementation of the RLaH initiative average screentime when traveling in non-EU countries was 2 hours and 13 minutes, increasing by 4.5 minutes to 2 hours and 17 minutes after RLaH was implemented.

Although the overall means in Table 2 are informative differences can be driven by changes in sample competition (e.g., due to change in individual travel patterns). Therefore, we use fixed effects models to control for individual and destination-specific behavior in the analysis.

That screentime in the home country and another EU country are at the same level after the implementation of RLaH, can be interpreted as an indication that smartphone use in these two contexts does not differ when the user has access to mobile internet. This would implicate that the effects reported in this study would be similar for users who gain access to mobile internet in their home country.

However, although screentime at home and during within-EU traveling became similar after

RLaH was implemented, there are reasons why the effect of gaining free internet access at home and while traveling may differ. First, users are likely to have less information about their travel locations than they have about locations in their home country, which will make the gain from seeking information online - like looking up routes, restaurants or attractions - higher. Second, travelers' urge to share experiences with peers might be different. On the one hand, the urge might be higher because users have exciting experiences or because they are physically separated from peers. On the other hand, users may feel less drawn to social media because the exciting travel experiences reduce their need to socialize. However, even if our results should only generalize to the realm of travel, the implications would still be significant.

Vacation is a highly valued and demanded good all over the world. In 2019 tourism employed over 300 million people globally and accounted for more than 10 percent of GDP and 7 percent of global trade. Further, 1.5 billion international tourists spent \$1.6 trillion (Nations, 2020; Goretti et al., 2021). Vacations have been found to positively affect family life, social life, cultural life, job performance, perceived health and wellness and overall life satisfaction and well-being (Uysal et al., 2016; Durko and Petrick, 2013; Chen and Petrick, 2013). The positive effects on well-being are strongest during the vacation but already starts before the vacation, and can last several weeks after returning home (Gilbert and Abdullah, 2004; Nawijn et al., 2010; Nawijn, 2011b). Vacations only affect well-being positively if the stress levels on the vacation was low. Smartphones can potentially influence vacation stress levels in several ways. For example, commuting and figuring out logistics during vacation adds substantially to vacation stress (Zehrer and Crotts, 2012). Another crucial factor in determining vacation happiness is the attitude of fellow travelers toward each other Nawijn (2011a), where smartphones can both reduce and increase conflict levels Yu et al. (2018). Our study suggests that access to mobile internet can help travel planning and shorten commutes, which will likely reduce travel stress. It also shows that social media use increases, which might in some situations lead to conflicts in families. Overall, it seems that the constant opportunity to access information online (Permanently Online) has clear benefits in terms of reducing inefficient transport time. In contrast, the effect of constantly being able to connect with non-present peers (Permanently Connected) seems more ambiguous.

Some users might already have had data subscription packages that included roaming in some or all EU countries before the implementation of free roaming. We partly account for this by excluding users who spent more than six weeks of in another EU country in the two years surrounding the implementation of RLaH, since they would have benefited more from data packages including roaming. However, it is possible that some users in the analysis already had

EU roaming packages before RLaH, which would lead us to underestimate the effects.

The effect of gaining access to mobile internet might differ across users. We have studied the average daily effect of the RLaH initiative on smartphone users. However, since smartphone use varies by age, gender and country of residence (Van Deursen et al., 2015; Andone et al., 2016; Blackman and Forge, 2018), it would be interesting to analyze how the effects are heterogeneous by these demographic indicators. Likewise, it would be interesting to examine if the RLaH initiative has changed travel patterns, for example, by making travelers more likely to travel to another country or more likely to choose destinations within the EU. We leave these explorations to future research.

Methods

Data

The analysis was based on a dataset provided by a global smartphone and electronics company extracted through a smartphone app. The dataset includes data on GPS, overall screen usage and usage of individual apps. We use data from November 3rd, 2016, to November 28th, 2018. All data analysis was carried out in accordance with the European Union's General Data Protection Regulation 2016/679 (GDPR) and the Danish Data Protection Act.

Day locations were identified applying the algorithm "infostop" to GPS trajectories (Alessandretti et al., 2020; Aslak and Alessandretti, 2020). Daily country and subregion were defined by the location in which most time was spent during each day. Countries and subregions were categorised using GADM 3.6 administrative boundaries for countries (level 0) and subregions (level 2) (Hijmans et al., 2018). Home country was defined as the country where most days were spent. Daily entropy was calculated following the temporal-uncorrelated entropy in Song et al. (2010). Time spent in transport is provided from the data supplier and were calculated using sensor data and methods resembling those described in Martin et al. (2017) and Shafique and Hato (2015). Time spent in transport covers time in transportation vehicles like trains and cars.

When calculating daily screentime, apps were limited to the most used apps within each category, only keeping the apps accounting for 75% of the total usage within each category. Apps that could potentially expose sensitive information were excluded. Further, when calculating use on individual app categories, apps not identified in the Google Play store and others maintenance apps (running in the background) were filtered out. In the sample used in the analysis, each year's first and final two-week period were excluded, because of irregular mobility and screentime patterns relating to the Christmas and Epiphany holidays. Likewise, only subregions with more than 200 days of travel observations were included, and only users having at least one day of data in both their home country and in another EU country both before and after implementation of RLaH were included.

The final sample used for analysis contained 4.512.602 daily observations and 21.489 individual users. 38% of users identified as female, and self-reported age, which half of the users reported, had a median of 40 years. The dataset contained information from 103 countries and 1,247 subregions.

Fixed effects models

Three fixed effects models were used for the analysis. In the first part of the analysis two fully dynamic fixed effects models (Models 1 and 2) were used (Angrist and Pischke, 2008; Borusyak et al., 2021). In the rest of the analysis a difference-in-difference fixed effect model was used (Model 3) (Angrist and Pischke, 2008; Imbens and Wooldridge, 2007).

Fully dynamic fixed effects models are used to follow trajectories of causal effects over time while accounting for recurring patterns (in our case within individuals, subregions and weekdays). For each context, the model contains an indicator variable for every time period (except for the reference period). These estimates are plotted to show the trajectory for screentime in each context (see Figure 1).

$$
\begin{aligned}
Y_{i,d} = & \sum_{\substack{t=t_0 \\ t \neq t_{ref}}}^{t_{max}} \sum_{c \in C} \tau_{t,c} \mathbb{1}(T_{i,d} = t) * \mathbb{1}(c_{i,d} = c) + \gamma_i + \omega_{w(d)} \\
& + \sum_{r \in R} \sum_{c \in C} \rho_{r,c} \mathbb{1}(r_{i,d} = r) * \mathbb{1}(c_{i,d} = c) + \epsilon_{i,d}
\end{aligned} \tag{1}
$$

Model 1 describes the fully dynamic fixed effects model used to produce Figure 1. In Model 1, Y represents user's daily screentime, i indexes users, d indexes day user is observed, c indexes contexts ($C = \{$in home country, in another EU country, in non-EU country$\}$), t indexes unique 14-days bins centered around implementation of RLaH, with the excluded reference (t_{ref}) being the two-week period before implementation. t_{max} represents the last two-week interval in the sample. $\mathbb{1}(T_{i,d} = t)$ and $\mathbb{1}(c_{i,d} = c)$ are binary indicators showing whether the observation belong to period t and context c respectively. γ_i represents fixed effects for individuals allowing for person-specific factors that may affect behavior, including individual time-invariant factors such as average screen use, mobility patterns, demographic characteristics and other unknown factors. ρ represents fixed effects for each context for every subregion. Separate indicators for context-specific indicators for each subregion were included to allow the subregion effect to differ between users for which the specific subregion is their home country and users for which the subregion is not in their home country. $\omega_{w(d)}$ indexes fixed effects for each day of the week, taking out recurring weekly patterns. ϵ represents the error term. Standard errors were clustered on user-level.

To explicitly examine the difference between being in another EU country and being in one's home country simultaneously with the difference between being in another EU country and being in a non-EU country (see Figure 1b and 1c), model 1 was modified by adding a general time fixed effect, and limiting the interaction terms between time and context to $C_{-} = \{\text{in home country, in non-EU country}\}$. This was done in model 2.

$$\begin{aligned} Y_{i,d} = \sum_{\substack{t=t_0 \\ t \neq t_{ref}}}^{t_{max}} \beta \mathbb{1}(T = t_{i,t}) + \sum_{\substack{t=t_0 \\ t \neq t_{ref}}}^{t_{max}} \sum_{c \in C_{-}} \tau_{t,c} \mathbb{1}(T_{i,d} = t) * \mathbb{1}(c_{i,d} = c) + \gamma_i + \omega_{w(d)} \\ + \sum_{r \in R} \sum_{c \in C} \rho_{r,c} \mathbb{1}(r_{i,d} = r) * \mathbb{1}(c_{i,d} = c) + \epsilon_{i,d} \end{aligned} \tag{2}$$

In the remaining analysis, the average daily effect of the RLaH initiative was examined using a two-period difference-in-difference fixed effects model - model 3. This model compares levels in the variable of interest before and after the implementation of RLaH for each context while accounting for individual, subregional and weekday fixed effects. Thereby estimating the average causal effect of having access to mobile internet when traveling in another EU country relative to being at home (δ), and relative to traveling in a non-EU country (η).

$$\begin{aligned} Y_{i,d} = \alpha post + \beta nonEU + \delta(home * post) + \eta(nonEU * post) \\ + \gamma_i + \omega_{w(d)} + \sum_{r \in R} \sum_{c \in C} \rho_{r,c} \mathbb{1}(r_{i,d} = r) * \mathbb{1}(c_{i,d} = c) + \epsilon_{i,d} \end{aligned} \tag{3}$$

Like the previous models, model 3 has fixed effects for users, day of the week and separate region fixed effects for home country and foreign country. Y is the dependent variable of interest. Further, to obtain difference-in-difference estimates, model 3 has indicator variables for the period after implementation of RLaH (*post*), being in another EU country (*nonEU*), and interactions between being in the post period and being in the home country ($home * post$) and being in a non-EU country ($nonEU * post$). Note that there was not included an indicator for being at home since this is controlled by the regional fixed effects. This model gives the difference-in-difference model with the difference-in-difference estimates of interest being δ and η.

Identifying assumptions and fixed effects

In this section, we briefly discuss assumptions required for the causal estimates in our models to be well identified. Then we briefly discuss the recent criticism of fixed effects models in event studies and why it is not relevant for this study case.

The two main assumptions of the models used are "parallel trends" and "no anticipation effects", and Figure 1 can help us assess both[2]. The parallel trend assumption states that development in pre-treatment periods (in this case before the introduction of RLaH) should not systematically differ across contexts. The assumption of no anticipation effects implicates no selection into treatment and that pre-treatment behavior does not change because of the anticipation of treatment. Figure 1 shows no indication of behavioral change in the periods before implementation of RLaH.

In the analysis, we use fully dynamic fixed effects models. Recently, there has been much discussion concerning models similar to these. Some parts of this criticism is irrelevant to our case, while the other parts highlight implicit assumptions and interpretation of estimates. Here, we briefly address two points from recent literature.

The first concern relates to the use of two-way fixed effects (TWFE) models in datasets with staggered adoption, where treated individuals stay treated and individuals are treated at different times (also called panel event studies). In this setting, it is common to include fixed effects for individuals and for time periods (therefore two-way), and further having either dynamic treatment effects (including indicators for relevant lead and lags in treatment) or static treatments effects (in which a single treatment indicator is included, thereby assuming treatment effects are constant over time). As shown e.g., in De Chaisemartin and d'Haultfoeuille (2020) estimating this in a standard way (OLS) might lead to negative weights because it makes "forbidden" comparisons. This may lead to bias estimates unless strong homogeneity assumptions are satisfied (Borusyak et al., 2021).

[2]A further assumption is that there is no unit root auto-correlation in the error term. That is, errors from one period can carry over to the next period but decay within a finite number of periods. If this assumption is violated, we would expect the graphs in figure 1 to exhibit random walk behavior, which we do no

However, since treatment occurs at the same time for all individuals, we do not use TWFE models. Instead, we have a fully dynamic individual fixed effects model. Therefore, in the case considered in this study, the model will (to the best of our knowledge) not generate negative weights.

The second concern relates to heterogeneous treatment effects across individuals and treatment timing. When we have an unbalanced panel and heterogeneous treatment effects across users, the (unweighted) estimated coefficient will not, in general, be the average treatment effect on the treated (ATT). This is important to have in mind in our case, where the reported estimates should be interpreted as the average effect on travel days across all users since users with more travel days implicitly weighing higher. Further, much effort has been put into investigating heterogeneous treatment effects across treatment time, which might lead to biased treatment estimates if not addressed. However, since the RLaH initiative was implemented at the same time for all individuals, this is not relevant in our case.

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Appendices

A The Roam-Like-at-Home Initiative

Background

The Roam-Like-at-Home initiative was the culmination of the EU's effort to fix the market failures in the EU roaming market (EU, 2017). As we will see in this section, the regulatory process leading up to the effectuating of the initiative on June 15th, 2017, was long and difficult (see e.g., (Blackman and Forge, 2018)).

As the market for mobile communication (primarily voice calls) grew throughout the 90s and early 2000s, various regulatory policies were introduced. The "Normal Network Tariffs" regulation scheme, which capped wholesale prices to foreign providers at the domestic "normal retail tariff" plus a 15% markup, was gradually replaced by the "Inter-Operator Tariff" (IOT) scheme from May 1998 to April 1999. Under the IOT scheme, tariffs were to be negotiated bilaterally by mobile network operators and did not have to reflect actual wholesale costs. It was hoped that the prices would be reduced when going from cost-based prices (including markup) to competition-based prices.

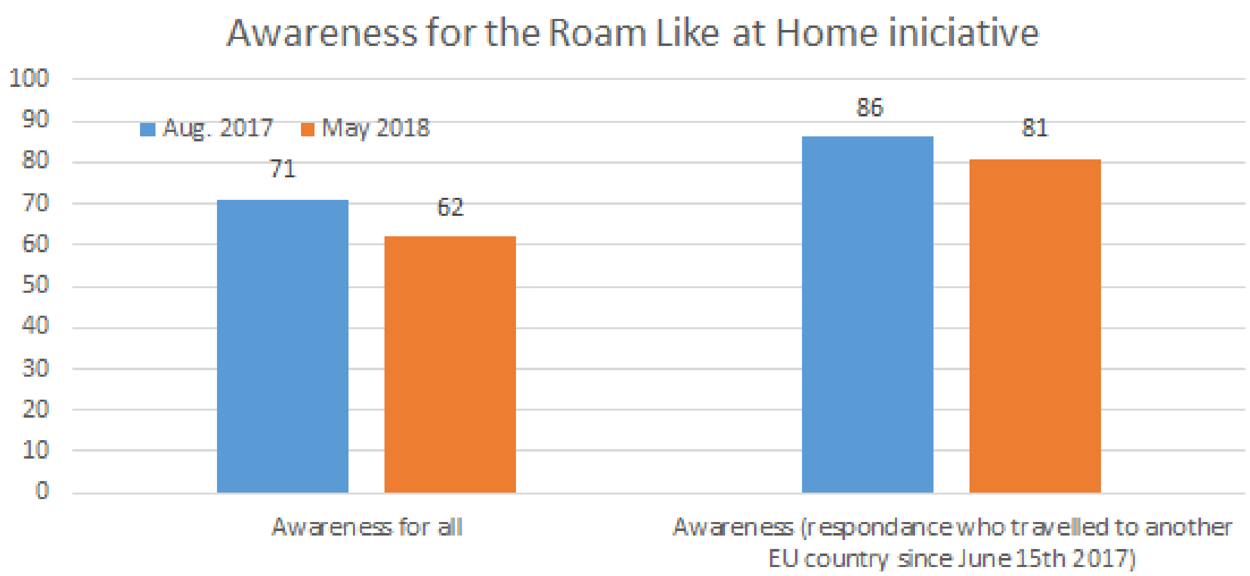
However, the change did not lower prices or promote competition as hoped. On the contrary, the link between wholesale prices and market share disappeared, so that the volume of roaming services sold by domestic Mobile Network Operators (MNO) to foreign MNOs became solely determined by the domestic MNO's market share (and not the offered wholesale roaming prices) (Blackman and Forge, 2018). The inelastic demand led the MNO's to raise wholesale roaming prices. As a working group launched by the European Commission summarized it: "Over the period in review [1997-2000] the wholesale tariffs have clearly converged towards a higher overall level that does not appear to bear any relation to cost." (Competition, 2000).

The IOT was the primary regulation until Spring 2007, when the first of several regulation packages that would eventually become the Roam-Like-at-Home initiative was passed in the European Parliament. Since regulators had found that regulation based primarily on costs and competition had not worked satisfactorily, they now turned to price caps as the primary tool. From 2007 to 2012 regulation was passed, which gradually lowered the prices on roaming calls and text messages (SMS), and from 2012 also including data roaming. Price caps on data roaming were introduced at 45 cent/MB in July 2013, lowered to 20 cent/MB in July 2014 and

5 cent/MB in April 2016, before the fees were abolished at June 15th, 2017 [3].

Fair use policy

Following the Roam Like at Home initiative, domestic subscription terms also apply when traveling in the European Union. For example, if a subscriber has a data package with 10 GB of free data, it does not matter whether the data is used in the home country or in another EU country. However, MNO's may limit roaming services to prevent "abusive" or "anomalous" roaming behavior. For example, if over a 4-month period, a subscriber has used more time abroad than at home, and roaming usage exceeds domestic usage, the MNO may apply a (capped) surcharge to the customer (not exceeding wholesale price) on future roaming. However, MNO's only seem to have applied these restrictions to a very limited degree (Blackman and Forge, 2018).



Source: Flash Barometer 468 (June 2018). Share anwsering "yes" to the question: Are you aware that since 15 June 2017 European Union residents can use their mobile phone while traveling in the European Union and pay the same as they would at home? Right columns only shows respondence who travelled to another EU country since June 15th 2017.

Figure 5: Awareness about the Roam Like at Home initiative.

Awareness of the Roam-Like-at-Home Initiative

As shown in figure 5 the awareness of the Roam Like at Home initiative was generally immediately following the implementation. Two months after implementation, in August 2017, 71%

[3] The initially planned price cap glide path and Roam Like timetable was adjusted in 2016. The regulation is due to expire June 30th, 2022, however, in February 2021, the European Commission introduced a proposal to extend the regulation another ten years (and expand it in terms of speed and quality requirements)

of EU citizens and 86% of people who had traveled to another country in the EU were aware of the change. Curiously, a little less than a year after implementation, in May 2018, overall awareness had fallen to 62% and awareness for travelers to 81%.

Effect of data traffic

To get a picture of the the RLaH initiative's overall effect on data usage, we examine the development in data roaming traffic within the EU. In figure 6 and 7 we see that data roaming volumes have been increasing steadily, roughly doubling every year since 2011. We see a tendency that years when price caps were introduced saw an extra increase. For example, in the year starting July 1st, 2014, when caps were lowered to 0,2 cent/MB, data volumes increased by 193 %, relative to the year before. However, when the fees on roaming were abolished in the middle of June 2017, the data roaming traffic in the EU increased dramatically, growing by 323% comparing the year starting 1st 2017, with one year earlier.

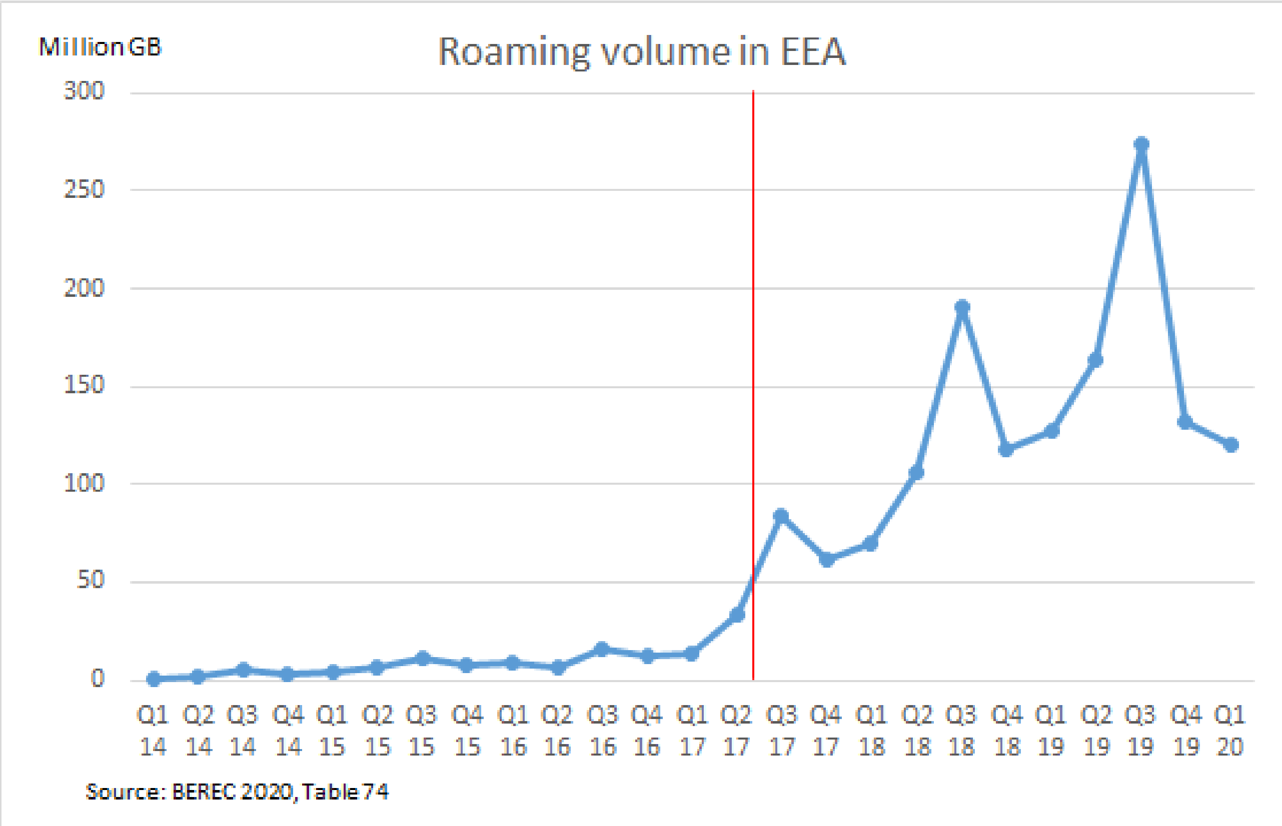


Figure 6: Development in quarterly roaming traffic in the European Economics Area. Red line indicate the implementation of the Roam-Like-at-Home initiative.

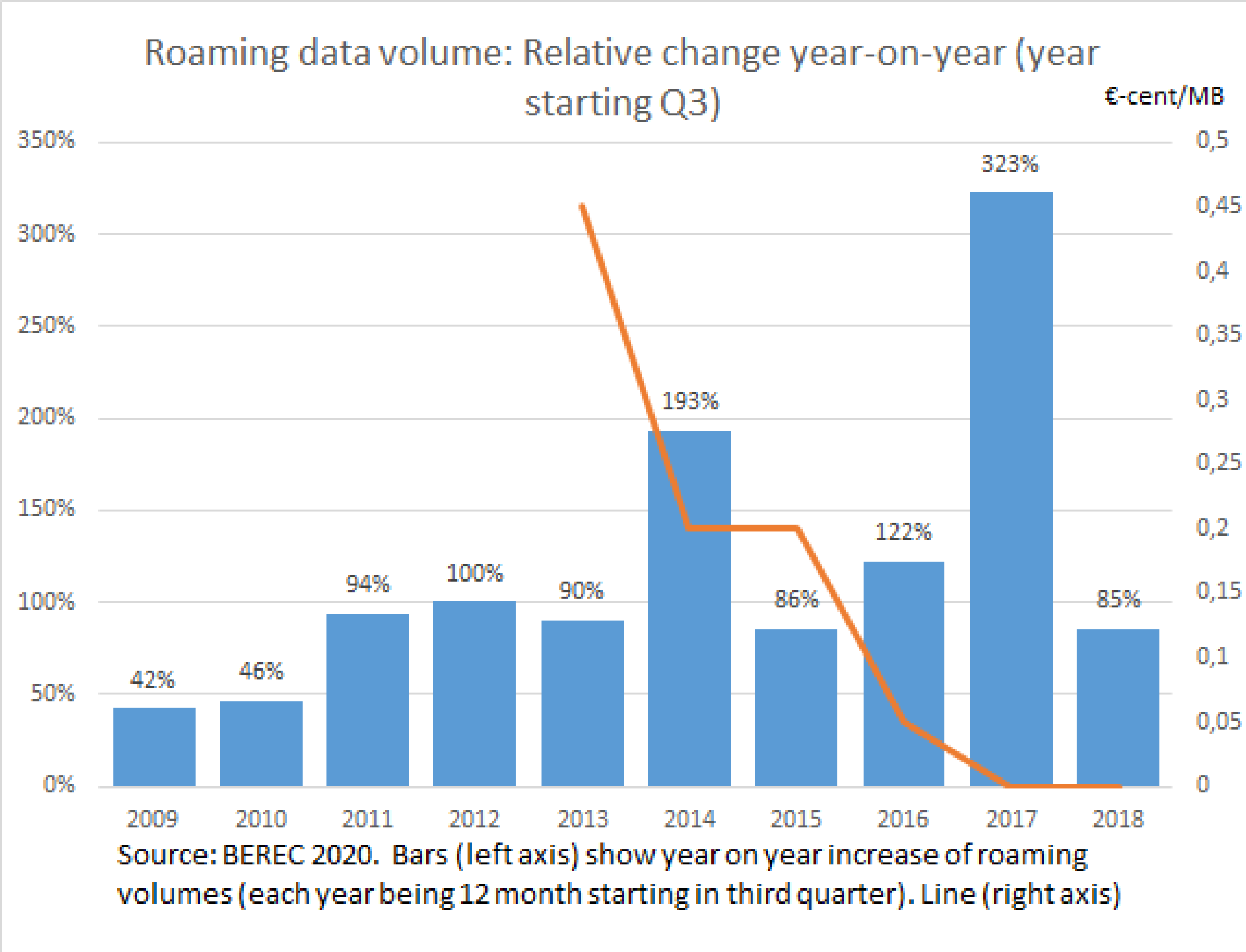


Figure 7: Year-on-year change in roaming fees with year starting in the third quarter. Calculated by the authors using data from the BEREC 2020 report. Bars show relative change from a year earlier, numbers on top indicating precise rise in percent. Orange line shows maximum allowed tariff on roaming data in €-cent per megabyte. Before 2013 no price cap was in place.

B Representativeness

To understand how representative the data is for the population in Europe, we 1) compare user share to population and 2) compare travel days in our data set to nights spent at accommodations by foreign travelers.

Figure 8 shows how the users in the sample are distributed over countries relative to the population distribution. The figure shows that users are broadly distributed across Europe. There is a tendency that the Nordic and Baltic countries have a larger share of users in the sample, than in the population. On the contrary, certain Southern European countries (e.g., Italy and Spain) have a lower share of the sample than the population size would suggest. However, it is important to note that most of the major countries in Europe still have a substantial number of users (e.g., there are 531 users from Italy and 659 users from Spain). The correlation between the two series is 0.74.

Figure 9 shows the distribution of travel observations in the sample and the number of nights spent in accommodations by foreigners. This is included to provide an illustration of the extent to which the travel patterns in the sample corresponds to the actual travel patterns. Nights spent in accommodations by foreigners is a crude proxy because it contains non-EU travelers, so we would not expect a 1:1 overlap. However, we still find the comparison helpful. The figure shows that travel observations in the sample are broadly distributed across all European countries. Some countries have a lower proportion of observations than overnight stays (e.g., Italy, Spain and the UK), while others have higher (e.g., Germany, Poland and Sweden). We notice that the number of observations for most countries is still substantial, with the mean (median) being 9,893 (5,997). The correlation between the two data series is 0.83.

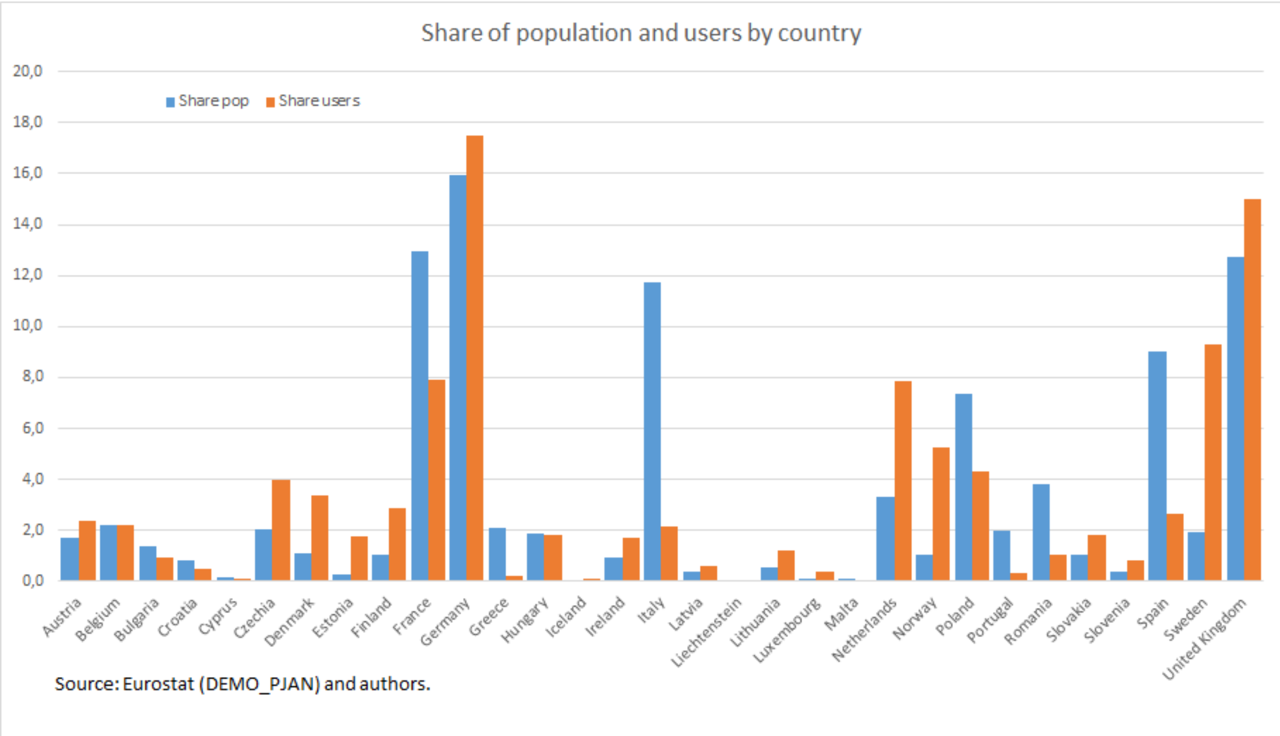


Figure 8: Share of users in sample relative (orange bars) to population size (blue bars).

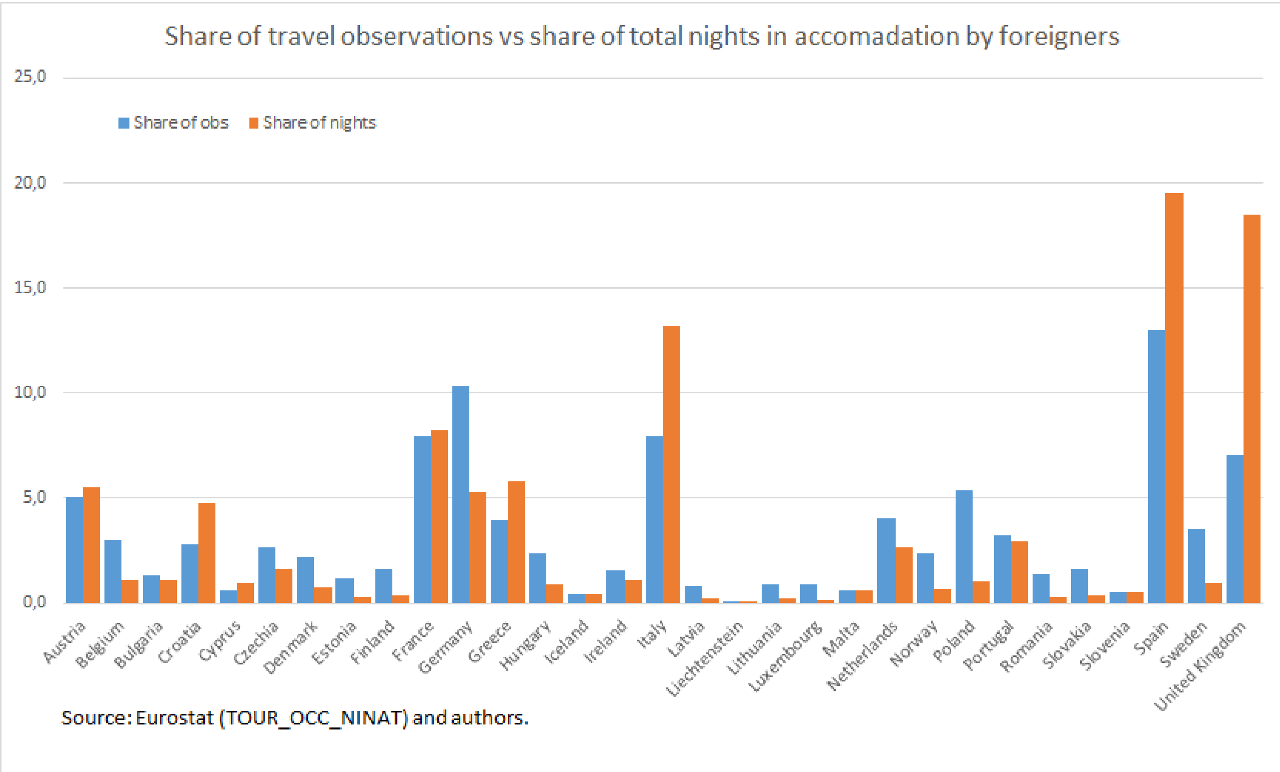


Figure 9: Share of travel day observations in sample by country (blue bars), and share of all travel days in within the EU by country.

Nature unplugged or interrupted? A two year panel study of smartphone use and digital impulse inhibition in natural and urban environments

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Abstract:

Extensive evidence links exposure to natural environments with restorative benefits to human cognition and well-being, yet nature contact is reportedly declining for younger demographics. Although Attention Restoration Theory (ART) posits that natural environments can free attentional resources by eliciting soft fascination, it remains unknown whether exposure to natural settings is disrupted by smartphone-directed attention. Here, we monitored minute-level smartphone screen use, communication and environmental exposures for 701 Danish young adults over two years. On average, participants spent over twice as much time on their smartphones per week than in natural environments. Relative to urban environments, exposure to natural settings decreased smartphone screen use slightly, while texting and calling did not significantly change. However, these relationships differed by the type and dose of natural environment exposure: smartphone social activities increased during short visits to recreational areas while smartphone use declined markedly over the first three hours in nature areas, suggesting that natural areas may support digital impulse inhibition in-situ. Paradoxically, increased daily smartphone use was associated with marginally reduced time in natural environments overall but an elevated probability of visiting them.

Abstract:

Omfattende forskning viser, at ophold i grønne områder kan have positive effekter for menneskelig kognition og velbefindende. På trods af dette bruger nutidens unge mindre tid i grønne områder end tidligere generationer. Selv om ophold i grønne områder, ifølge Attention Restoration Theory, kan frigøre kognitive ressourcer til opmærksomhed gennem "blød fascination", er det stadig uvist om denne proces bliver afbrudt, hvis opmærksomheden er rettet mod en smartphone. I dette studie følger vi på minutniveau 701 unge danskeres skærmtid, kommunikation og hvilke områder, de opholder sig i, i løbet af to år. Deltagerne bruger i gennemsnit dobbelt så meget tid på deres telefon hver uge, som de bruger i grønne områder. I forhold til ophold i byområder sænker ophold i grønne områder skræmtid en smule, mens SMS'er og opkald ikke bliver påvirket signifikant. Effekterne afhænger dog både af typen af grønne områder og længden af opholdet i et område. Kommunikation via smartphones stiger i løbet af korte besøg i rekreative områder (som parker og kirkegårde), mens den falder betydeligt i løbet af de første tre timer, de er i et naturområde (som skove eller nationalparker). Det tyder på, at naturområder – men ikke rekreative områder – hjælper med at undertrykke impulser til at bruge digitale teknologier. Paradoksalt nok er højere dagligt smartphoneforbrug forbundet med marginalt mindre tid i grønne områder, men højere sandsynlighed for at besøge dem.

Introduction:

"*The enjoyment of scenery employs the mind without fatigue and yet exercises it; tranquilizes it and yet enlivens it; and thus, through the influence of the mind over the body gives the effect of refreshing rest and reinvigoration to the whole system*." – Frederick Law Olmsted (1865)

The belief that nature in general - and green spaces specifically - can support health and well-being is deep-seated in many cultures, far preceding the recent emergence of a vast empirical research program exploring the socioecological, psychosocial, and public health effects of natural settings[1–8]. In particular, the theory that time spent immersed in natural spaces can restore cognitive attentional resources has motivated extensive research, seeded landscape and planning interventions, informed policy recommendations, inspired preventive medicine programs and has been featured extensively in the media[6,9,10]. Yet, unlike when Kaplan and Kaplan first developed their influential Attention Restoration Theory (ART)[11], today information technologies are no longer limited to indoor use. Now, smartphones regularly accompany their owners' every action and respite, shadowing them into nature. Indeed, smartphones and digital media have been engineered to engage focal attention and hold it[12], possibly challenging attention restoration in natural areas and urban green spaces[13]. Conversely, the recent rise of nature-based digital detox recommendations, regimens and retreats is indicative of an increasingly popular view that certain settings in the biosphere may permit an escape from the "always-on" social and informational demands of the cybersphere[14,15]. Yet evidence in this setting is extremely sparse. Does nature exposure influence device-directed attention and relatedly, does increased daily smartphone use relate to changes in time spent in natural environments?

Modern urban lifestyles have led to what some researchers have described as an "extinction of experience" for younger generations, a lack of interaction with the natural environment on which life in the biosphere depends, with potential consequences for human well-being and environmental stewardship[16–20]. Indeed, evidence from cross-sectional surveys and retrospective cohort analyses indicate that in recent years nature exposure has fallen precipitously, with the greatest declines observed for youth and young adults relative to prior generations[21–23]. This deficit in nature exposure has been attributed to a variety of factors including accelerating urbanization and increased immersion in digital media from television[24], the internet[25], and more recently mobile devices[26,27]. Several psychological, public health and sustainability scholars have deemed these trends to be disconcerting because of the myriad documented anthropocentric and ecocentric benefits linked to time spent in natural environments[17,28,29]. With over half of the world's population now residing in cities, most human experiences of nature increasingly transpire within or near highly connected urban settings, with potential implications for planetary health and human well-being[30,31].

Evidence spanning multiple disciplines has shown that nature contact is associated with improved mental health[32–35], positive affective states[2], reduced stress[36–40], reduced risk of preterm birth[32], lower risk of premature mortality[41], increased physical activity[8,42] and improved cognitive outcomes[4,43], including self-discipline[44]. A Danish registry-analysis of public health records for nearly 1 million people found that low levels of nearby green space (natural vegetation) in childhood - controlling for socioeconomic status - was strongly associated with developing mental illness and several psychiatric disorders in later life[45]. Beyond correlational evidence suggesting cumulative positive psychological effects of nearby nature[41,46–48], there is accruing experimental and longitudinal evidence that time in nature can impart acute cognitive and mood benefits, even during short exposures[49]. Several field experiments have shown that compared to individuals randomly assigned to spend time in urban settings, those assigned to natural settings demonstrate near-immediate improvements in affect and cognition[50–52], as well as reductions in rumination[53] and physiological stress[54]. Such work has drawn renewed attention to understanding the specific qualities of natural settings that are restorative[55], as well as the underlying processes involved[6,13,33,41,56–58].

Although investigation of the mechanisms underlying the psychological benefits of nature contact is ongoing, at least three primary pathways have been widely supported by the extant literature[59]: 1) natural settings may restore mental and physiological capacities via rejuvenated attentional resources and stress recovery, 2) they may reduce harm by diminishing exposure to environmental stressors and 3) they may build physical and social capacity by affording exercise and social cohesion. Of the theoretical and conceptual frameworks that have gained currency for characterizing this first pathway, Attention Restoration Theory (ART) and Stress Recovery

Theory (SRT) are among the most established. According to ART, people have finite cognitive resources to engage in directed attention and inhibit other distracting impulses, resulting in mental fatigue[11,60]. A core premise of ART suggests that nature contact allows a person to engage with *softly fascinating* natural stimuli that effortlessly hold one's attention while providing mental bandwidth for reflection, facilitating the restoration of cognitive resources exhausted by effortful fixation[60,61]. Similarly, SRT and the biophilia hypothesis draw on psycho-evolutionary theory to suggest that people have 'the innate tendency to focus on life and lifelike processes' and therefore have a low-level affective preference for safe environments reminiscent of those our species developed among, promoting stress recovery[2,16,36]. In their original theoretical and conceptual development, the Kaplans, Ulrich and Wilson variously cited lifestyle changes driven by urbanization and media technologies as potential challenges to human attention and nature contact[11,16,18]. Yet when these scholars first proposed their complementary theoretical frameworks in the mid-to-late 80s, virtually connected information technologies had reached the living room but were still far afield from the outdoor natural areas, parks and green spaces that they theorized about[62].

In the intervening years, the advent of mobile computing devices has allowed virtual stimuli from the cybersphere to cross over into daily activities[63], and social relationships[64–66], largely irrespective of one's spatiotemporal context in the biosphere[67]. Today, a growing proportion of humanity spends an increasing fraction of their waking life attending to screen-based stimuli, modulating individual and collective attention dynamics[68–72]. For instance, people tend to attend to new mobile phone notifications within seconds to minutes, regardless of whether their phone is silenced or not[73]. In an increasing number of countries, adults and adolescents now rarely leave the house without their smartphones, with around 94% of young adults in the EU accessing the internet on the move from their mobile devices[74]. Despite the communicational and functional capabilities enabled by these technologies, a recent multinational consumer survey found that nearly half of young adults in nordic countries also report negative, distractive side effects of smartphone use, in-line with a rapidly growing body of research linking excessive smartphone use with adverse behavioral, mental and cognitive outcomes[70,75–80]. However, deriving directional inferences from this literature - most of which has relied on cross-sectional designs and inaccurate self-report measures - is made difficult by likely confounding and measurement error due to omitted variable and recall biases[81–86], with scholars emphasizing the need for objectively logged, high resolution and longitudinal behavioral measurements of device use to provide a more robust evidence base to guide both policy and design[87–90].

Similarly, research on the attentional and behavioral correlates of environmental exposures has long relied on self-reported or indirect measures of nature exposure and task-based cognitive tests that may lack ecological validity[6,13,34,41,91]. Interestingly, outside of studies that continuously measured physiological responses to nature, little is known about how physically spending time in natural and urban environments influences attention and impulse inhibition *during* the course of exposure. In this regard, the proliferation of ubiquitous mobile devices and connectivity have created new opportunities to study dynamic person-environment interactions across overlapping physical and virtual settings[67,82,92–94]. For instance, recent large-scale studies leveraging social media data and time-series mobile GPS data have uncovered consistent associations between improved mood and recent exposure to urban greenspace, but have yet to research the relationship between natural settings and smartphone use in situ[95–98]. Indeed, increasing digital connectivity may alter opportunities for restoration in natural settings in several key ways, leading some to conclude that videophilia - human affinity for digital media - may be supplanting biophilic interactions[24,25,99]. Specifically, we hypothesize that electronic device use may modify in-person nature exposures indirectly by *displacing* time available for encounters with natural areas. Separately, mobile device use may interrupt nature contact directly by *emplacing* distracting digital stimuli inside natural settings during visits, engaging attentional resources away from restorative environmental features. Lastly, device use may substitute for nature interaction by *replacing* physical nature encounters with same-day virtual activities outside of natural environments.

To review prior investigations of the relationship between greenspace exposure and electronic device use across these hypothesized pathways, we conducted a systematic review of recent research published in the journals *Environment and Behavior*, *Journal of Environmental Psychology*, *Psychological Science*, *Frontiers in Psychology*, and *Health & Place* (Fig. 1A). We used each journal's online search index to query articles with the keyword phrase "attention restoration." A total of 394 articles meeting this search criteria were returned. We then further filtered these articles to only include those that explicitly investigated attention restoration in natural environments as indicated by the inclusion of any of the following nature indicator key words in the abstract: "nature” OR “green space” OR “greenspace” OR “park” OR “forest” OR “natural space” OR “natural environment.” 238 articles meeting these criteria were then parsed for occurences of terms containing the root word(s) “phone” OR “device” using the full texts (see Supplementary File 1). Excluding experimenter phone use (i.e. to conduct telephone interviews), only 35 of these articles mentioned at least one mobile device term. Of these, only 5 explicitly addressed the potential confounding influence of device use by telling participants to refrain from using their mobile devices during the study, only 3 articles operationalized device use as a variable of interest, and no studies included objective measures of smartphone use (Fig 1A). One cross-sectional survey study of 546 US adolescents found negative relationships between self-reported media use (a single measure item for all screen use, including computers and television) and both recalled outdoor time spent in nature and perceived nature connection, consistent with the replacement hypothesis[26]. In a separate experimental study, participants randomly assigned to spend a break in green space without a laptop showed significantly higher improvement on cognitive tests than participants in all other device and setting conditions, supporting the idea that digital stimuli may disrupt the restorative attentional and cognitive benefits derived from green space, in line with the emplacement hypothesis[100].

However, unlike laptops, smartphones are designed to be accessed while mobile and may be a more salient source of digital stimuli for young adults -- particularly in natural environments -- a concern voiced by several authors[14,101,102], but as of yet uninvestigated with objective measures of coinciding smartphone and environmental exposures during daily living. A relevant experimental study found that exposing students to a stressful initial condition and then assigning them to play a game of their choosing on their phone in either an outdoor school courtyard or indoor windowless setting reduced concentration recovery and diminished positive affect in both settings, but that time spent outside improved concentration - overall - compared to the indoor setting, even when gaming outside. This analysis featured only 20 participants in the outdoor mobile phone condition for a short 20 minute exposure, and did not control for individual baseline measures of concentration, mood, or objective smartphone use that would be needed to rule out regression to the mean, as noted by the authors. Indeed, if the restorative benefits of nature contact - as currently theorized - depend on connecting with natural elements[16], specifically through soft fascination and low-level involuntary attention to environmental features[11], the lure of smartphone use may distract focal attention in natural spaces and plausibly prevent recovery of the inhibitory mechanism needed for directed-attention[6,103]. Further, recent evidence suggests that smartphones may limit the mental bandwidth for reflection and dissolve the sense of being away[61], potentially disrupting core tenets of restorative environments described by ART[60]. However, it remains unclear how automatically logged smartphone use compares and relates to nature visitation for highly connected young adults, and moreover, whether natural settings differentially influence within-person smartphone use and inhibition in these settings compared to in urban environments. Nevertheless, nature experiences are increasingly prescribed as part of so-called digital detoxes[14,15], even though evidence largely lags practice.

To investigate these emerging relationships we pose two primary and four exploratory research questions. First, how do objective measures of smartphone use in a highly-connected student community of young adults compare to time spent in natural settings? Second, does exposure to natural environments influence smartphone use, impulse inhibition and outgoing phone-based communication compared to urban settings? To explore whether environmental or behavioral factors may moderate the relationship between natural environment exposure and smartphone behaviors, we further inquire whether the relationship between environmental exposure and smartphone behavior varies with the type of natural environment visited, the dose of exposure experienced (short vs. long visits) or the state of mobility used (moving vs. staying) during human environment interactions. We further assess whether the relationship between nature exposure and mobile device use varies according to one's baseline level of smartphone use and typical nature use, respectively. Lastly, we investigate whether within-person fluctuations in daily smartphone use are associated with changes in visiting natural environments. Due to the sparsity of existing behavioral and socioecological evidence in this domain, we refrain from formulating directional hypotheses about the expected patterns of association and instead adopt a data-driven socioecological approach to inspect the relationships of within-person changes in device use during free living routines when participants were exposed to natural environments compared to when they were exposed to urban settings (Methods). Specifically, we logged student location, smartphone screen use, outgoing texting and calling continuously using a mobile app for a large cohort of n=701 Danish university students over a two year period from September 1st, 2013 to August 31st, 2015 as a part of the Copenhagen Networks Study (CNS)[104].

Methods

Participating students in the Copenhagen Networks Study received a smartphone with an onboard data-logging app that continuously recorded several behavioral measures over the duration of the study, including location-based mobility from geolocation data, smartphone screen use and phone-based social interactions via texting and calling. The study was approved by the Danish Data Supervision Authority in 2013 and featured dynamic informed consent whereby students who agreed to participate were able to view and download their own logged data, and could withdraw from the study and delete their data at any point. This data set has previously been used to study several dimensions of human behavior including dynamics in social networks[105,106], human mobility[107,108], epidemic tracing[109], and academic performance[82,110,111]. All observations located within the national borders of Denmark were included and data collection concluded after 2 years due to the costs of maintaining data collection and replacing broken or lost phones. Participants were included in the final analyses who logged a minimum of 672 15-minute-level observations (>= 168 hours of total data), and a minimum of 7 days with at least 12 hours of data per day. After filtering on these inclusion criteria, a total of 701 participants (n_female = 151) were included in the final analyses, with a median period of observation of 507 days (Q1: 343, Q3: 629).

Environmental Exposures

In the current study, we investigated the relationship between environmental exposures and smartphone-directed attention by linking timestamped individual mobile screen activity and geolocation data - aggregated to the 15 minute level - with contextual location information (Fig. 1B). Geolocation data included automatically-registered spatial points retrieved through the Google Location API which utilizes a combination of GPS, Wi-Fi traces and nearby cell phone towers to interpolate latitude and longitude coordinates[104]. To link location data with environmental context information, we used geo-referenced contextual categories from Open Street Map (OSM). OSM provides a global land use - land cover map. We categorized these land cover types into two primary contexts (natural vs. urban environments), with natural environments consisting of the two nested subcontexts of nature areas (meadows, forests, nature reserves, heath or scrub land cover) and recreational areas (parks, grasses, recreation grounds or cemeteries) (Table 1). For each fifteen minute interval, we labelled a user's geometric median location with the corresponding environmental context and sub-context. We further registered whether participants were moving or staying during each 15-minute interval using the unsupervised machine-learning DBSCAN algorithm utilized in previous studies on human mobility[112].

Table 2 | Environmental Context Categories

Natural Environments		**Urban Environments**
Nature Areas	**Recreational Areas**	**Urban Areas**
Meadow	Park	Commercial
Forest	Grass	Residential
Nature Reserve	Recreation Ground	Industrial
Heath or Scrub	Cemetery	Military

Smartphone Use

Within each 15 minute time interval, we logged three measures of smartphone use. First, we recorded the fractional amount of screen use when the participant's smartphone screen was activated, a proxy for smartphone-directed attention[82]. We interpreted within-person decreases in smartphone-directed attention relative to their use in urban settings as behavioral evidence of impulse inhibition - the capacity to reduce "execution of an over learned or prepotent response"[33], and conversely, increases in smartphone use were viewed as evidence of digital impulse promotion. Second, we recorded whether the participant sent out a text message within each 15-minute interval and additionally registered whether the participant made a phone call within each interval (Table 2). To investigate whether environmental exposures were linked with changes in participant-initiated digital behaviors, we focused on outgoing communication activities rather than incoming calls or messages, although such use was included in our general measure of screen use which integrated over all smartphone activities.

Investigating Displacement

Our analysis consisted of multiple stages, moving from data-driven description of virtual and physical exposures in our sample, to statistical inference concerning our theoretical relationships of interest using statistical methods for analyzing panel data. First, to investigate the displacement hypothesis that time allocation to virtual smartphone stimuli may limit time available, we sought to descriptively compare weekly exposures to natural environments versus smartphone screens, employing automatically logged measures of spatial and virtual interactions. Thus for each participant, we computed average measures of smartphone screen time and time spent in natural environments respectively, extrapolating these measures to the week-level (Fig. 1G). Further, we computed the percent of total 15 minute observation windows during which participants spent at least some time on their smartphones, in natural areas, in recreational areas or in urban settings, and plotted these distributions for comparison (Fig. 1H).

Investigating Emplacement

In the second phase, we aimed to assess the emplacement hypothesis: whether exposure to natural environments influenced within-person smartphone use in these settings relative to use in urban contexts. We excluded observations originating from participants' home and university (Technical University of Denmark) locations, to compare device use in natural environments to baseline use in urban settings that were also outside of home and school. We further constrained our analysis to the universe of all observed environmental exposures lasting between 0-12 hours in duration when participants were completely situated in a single context at the level of analysis, excluding observations at the boundaries of separate, but overlapping, context categories. Thus, for our primary analysis comparing the relationship between smartphone screen use in natural environments to screentime in urban settings (Eq. 1), natural environment observations located jointly within the sub-contexts of nature areas and recreational areas were included (Fig. 2A), whereas for our sub-context analyses (Eq. 2 - 5) such joint observations were excluded to evaluate whether setting-screen use relationships differ between nature areas and recreational areas (Fig. 2B). In order to examine the relationship between daily environmental exposures and smartphone use, we specified a type of time-series model known as a two-way fixed effects panel regression model, due to its capacity to provide consistent estimation of model parameters while controlling the association between exposure and use for all stable personal and temporal characteristics, even when these potentially confounding factors were unobserved[82,113,114].

Person-level fixed effects linear panel regression model - natural context vs. urban context

$$S_{ithd} = \beta C_{ithd} + \mu_{ih} + \nu_{d} + \epsilon_{ithd} \quad (1)$$

Equation 1 describes the linear fixed effects model employed for modelling the effect of environmental exposure on each smartphone outcome, β. In this model, *i* indexes individuals, *t* indexes unique 15-minute time bin of the day, *h* indexes unique hour of the week, and *d* indexes unique date of the study period. Our independent variable of interest was natural environment exposure C_{ithd}, an indicator variable for being located inside of a natural environment with urban context exposure omitted as the baseline category. Unobservable person-specific and temporal factors may also impact smartphone use. Since mobile device use and media consumption have been shown to vary idiosyncratically across days of the week based on individual schedules and routines[115], we included μ_{ih} representing person-by-hour-of-the-week fixed effects, resulting in 168 fixed effects for each individual (one for each hour of the day by day of the week). These fixed effects controlled for both stable and time-varying psychological characteristics that may influence individual smartphone use and also coincidentally correlate with greenspace exposure, including individual baseline attention characteristics, cognitive abilities, weekly behavioral routines (e.g., fixed schedules, recurring in-person and virtual social obligations, scheduled exercise, repeating practices), regular media use, and other unmeasured time-varying background factors. Additionally, they controlled for other demographic factors, including age, gender, individual socioeconomic status, latent environmental preferences and residential location, the latter of which previous research has shown to be highly associated with proximity to natural environments, especially in urban regions[116–118].

Further, unobserved daily factors, such as specific days of the week (weekends vs. weekdays), days of the year (holidays and vacation days), seasonal changes in daylight and daily fluctuations in weather may influence outdoor natural environmental behaviors in a way that also spuriously correlates with mobile device use. To control for these temporal confounds, we include ν_{d}, representing unique date of study fixed effects over the two year period of observation. We interpreted the estimated model coefficients from C_{ithd} as the effect of natural environmental exposure on individual smartphone use, relative to their smartphone use in urban settings outside of home and work. We estimated *Eq. 1* using ordinary least squares and adjusted for possible serial correlation in ϵ_{ithd} by employing heteroskedasticity-robust standard errors clustered at the individual level. We omitted non-contextual control variables in *Eq. 1* due to our inclusion of a comprehensive set of fixed effects that control for all stable individual-level demographic and hour-of-week temporal controls as well as date-specific factors, and to avoid generating bias in our parameters of interest. Separate models were run with different dependent variables S_{ithd} for each smartphone use outcome (screen use, outgoing texting, outgoing calling)

Table 3 | Primary Smartphone Activity Outcome Measures

Outcome Variable	Metric
Screen use	The fraction of time within each 15 minute interval that the participant's smartphone screen was active
Outgoing SMS	1 if the participant sent a text message within the interval; else 0
Outgoing call	1 if the participant made a phone-call within the interval; else 0

To provide scale for the estimated effect of exposure to specific types of environments on device use, we plotted the relative magnitude of the within-person effect of natural environment exposure compared to the urban exposure baseline (% of average individual urban smartphone use) computed by dividing the model coefficients by the mean of the urban reference condition and multiplying by 100 to convert to a percent value.

Person-level fixed effects linear panel regression model - natural subcontexts vs. urban context

$$S_{ithd} = \beta^{nat} C^{nat}_{ithd} + \beta^{rec} C^{rec}_{ithd} + \mu_{ih} + \nu_d + \epsilon_{ithd} \quad (2)$$

Equation 2 substituted the single overarching natural environmental context variable used in *Eq. 1* with natural environment sub-context indicator variables C^{nat}_{ithd} representing nature areas and C^{rec}_{ithd} representing recreational areas. Thus, *Eq. 2* estimated the effects of natural environment exposure type (nature area or recreational area), relative to the omitted urban baseline.

Person-level fixed effects linear panel regression - dose response model

$$S_{ithd} = f^{nat}(T^{nat}_{ithd}) + f^{rec}(T^{rec}_{ithd}) + f^{urb}(T^{urb}_{ithd}) + \mu_{ih} + \nu_d + \epsilon_{ithd} \quad (3)$$

We complemented our primary linear specification with a secondary flexible specification exploring whether the duration of time spent in different types of natural environments was related to smartphone use in a dose-dependent manner. *Equation 3* mirrored *Eq. 2*, but included the function f^k consisting of flexible interaction terms, represented by a set of dummies for the total time, T^k_{ithd}, spent in a specific environmental context, k. Consistent with prior literature investigating natural environment dose response relationships, we employed 1 hour binned exposure increments[119]. We interpreted the resulting estimates from in f^k as the marginal effects of *T* hours of environmental exposure on mobile device use, relative to the baseline category of less than 1 hour of urban exposure (Fig. 3A-C). The inclusion of these semi-parametric bins permitted estimation of a non-linear relationship between dose of exposure and smartphone use.

Person-level fixed effects linear panel regression - mobility state interaction model

$$S_{ithd} = \sum_{k\in\{nat,rec\}} \left[\beta^{k,0} C^k_{ithd} (1 - M_{ithd}) + \beta^{k,1} C^k_{ithd} M_{ithd} \right] + \mu_{ih} + \nu_d + \epsilon_{ithd} \quad (4)$$

Similarly, the effect of exposure to natural settings on smartphone use may depend on other contextual characteristics, including one's state of mobility. *Equation 4* substituted one's mobility state M_{ihtd}- an indicator variable denoting whether the participant was moving or staying in place in context k, with moving as the omitted baseline.

Person-level fixed effects linear panel regression - stratified subgroup models by quartiles of typical natural environment use and smartphone use

$$S_{ithd} = \beta^{nat,q} C^{nat}_{ithd} + \beta^{rec,q} C^{rec}_{ithd} + \mu_{ih} + \nu_d + \epsilon_{ithd}, \quad (5)$$

Since the relationship between natural environment exposure and smartphone use may vary by the amount of typical screen time or green time, we performed subgroup analyses comparing participants across the distribution of each of these measures. Specifically, we delineated subgroups by quartiles of typical environmental and smartphone engagement respectively (each participant was assigned to one quartile group based on their average use over the study period), and then ran stratified models for each quartile group in the sample. We interpret Cn_{ithd} and Cr_{ithd} in *Equation 5* as the marginal effect of the type of natural environmental exposure on smartphone screen use for the stratified quartile *q,* relative to the estimated baseline smartphone response in urban settings within the same quartile group.

Investigating Replacement

In the final phase we investigated the replacement hypothesis: whether within-person fluctuations in daily total smartphone use -- summing over all daily observations including those made while participants were at home and at school -- were associated with changes in daily nature visitation and exposure duration, after controlling for other unobserved individual and daily temporal environmental factors.

Person-level linear probability fixed effects model - daily natural context visitation

$$C_{idw} = \nu\, ln(S_{id}) + \mu_{iw} + \nu_d + \sum_{t=48}^{96} \Theta_{it} 1_t(\#_{idw}) + \epsilon_{idw} \quad (6)$$

Equation 6 describes the fixed effects linear probability panel model for estimating the association between daily individual smartphone use and natural environment visitation. In this equation, *i* indexes individuals and *d* indexes the unique date spanning the two year period of observation. We included a binary environmental context indicator variable C_{idw} as the dependent variable, representing whether an individual visited a natural environmental setting (C_{idw}= 1) on a given date. Our independent variable of interest was captured by the log of individual daily smartphone screen time $ln(S_{id})$. Since unobserved individual factors may exist that confound the relationship between daily smartphone use and natural context visitation, we included person weekday fixed effects μ_{iw} for each day of the week for each participant tracked in the study. These indicators controlled for all stable unobserved psychological, physiological, behavioral and demographic individual factors, including socioeconomic status, primary residential location and environmental preferences, as well as weekly person-specific routine behaviors. Moreover, there may have been unobserved daily factors or seasonal time trends that influenced individual smartphone use and also spuriously correlated with nature exposure. For instance, both smartphone use and natural environment visitation may have been elevated on weekends and holidays for reasons unrelated to the theoretical relationships of interest in this study. To address this concern, we include ν_d a vector of date indicators for every day over the two year period of observation. Further, since both the probability of visiting a natural environment and total daily screen time may be associated with the duration that an individual's phone battery retained power on a given day, we included participant-level data coverage coefficients,Θ_{it},for the total daily count of 15-minute observations, $\#_{id}$ (where $1_t(\cdot)$ is an indicator variable for whether the input equals t). We define the log by adding 1 to daily screen time to account for rare days when participants did not use their smartphones at all. Thus the screen time coefficient of this linear probability specification represents the estimated percentage point change in the probability of daily nature visitation given a doubling in daily screen time.

Person-level fixed effects panel linear regression - daily natural context visit duration

$$T_{idw} = \beta^{day} ln(S_{id}) + \mu_{iw} + \nu_d + \sum_{t=48}^{96} \Theta_{it} 1_t(\#_{idw}) + \epsilon_{idw} \quad (7)$$

Equation 7 details the linear fixed effects model used to estimate the relationship between total daily screen time and total daily green time, the total duration spent in natural environments on a given date. This specification substitutes in the total daily time spent in natural environments T_{idw} for the previous binary context visitation outcome in *Eq. 6,* while including the log of daily screen time $ln(S_{id})$ as our independent variable of interest. We define the log of screen time by adding 1 as in *Eq. 6*.

Results

Drawing on 2,454,420 automatically logged observations spanning the two year study period, we found that all student participants visited natural environments at least once during the course of the study, consistent with a recent nationally representative Danish survey that found that only

0.9% never visit green space[120]. Summing up participant-level weekly natural environmental and smartphone exposures, participants spent a median of 4.67 hours (Q1: 1.54, Q3: 14.04) in natural settings and registered a median 10.88 hours (Q1: 6.43, Q3: 16.93) of smartphone use per week (Fig. 1G). On average, 92.3% (Q1: 88.0%, Q3: 94.7%) of participant observations were registered in urban environments, 4.4% (Q1: 2.6%, Q3: 7.4%) were recorded in nature areas, 3.6% (Q1: 2.2%, Q3: 5.9%) were logged in natural recreational areas and 38.8% (Q1: 31.7%, Q3: 45.8%) of observations contained smartphone use (Fig. 1H).

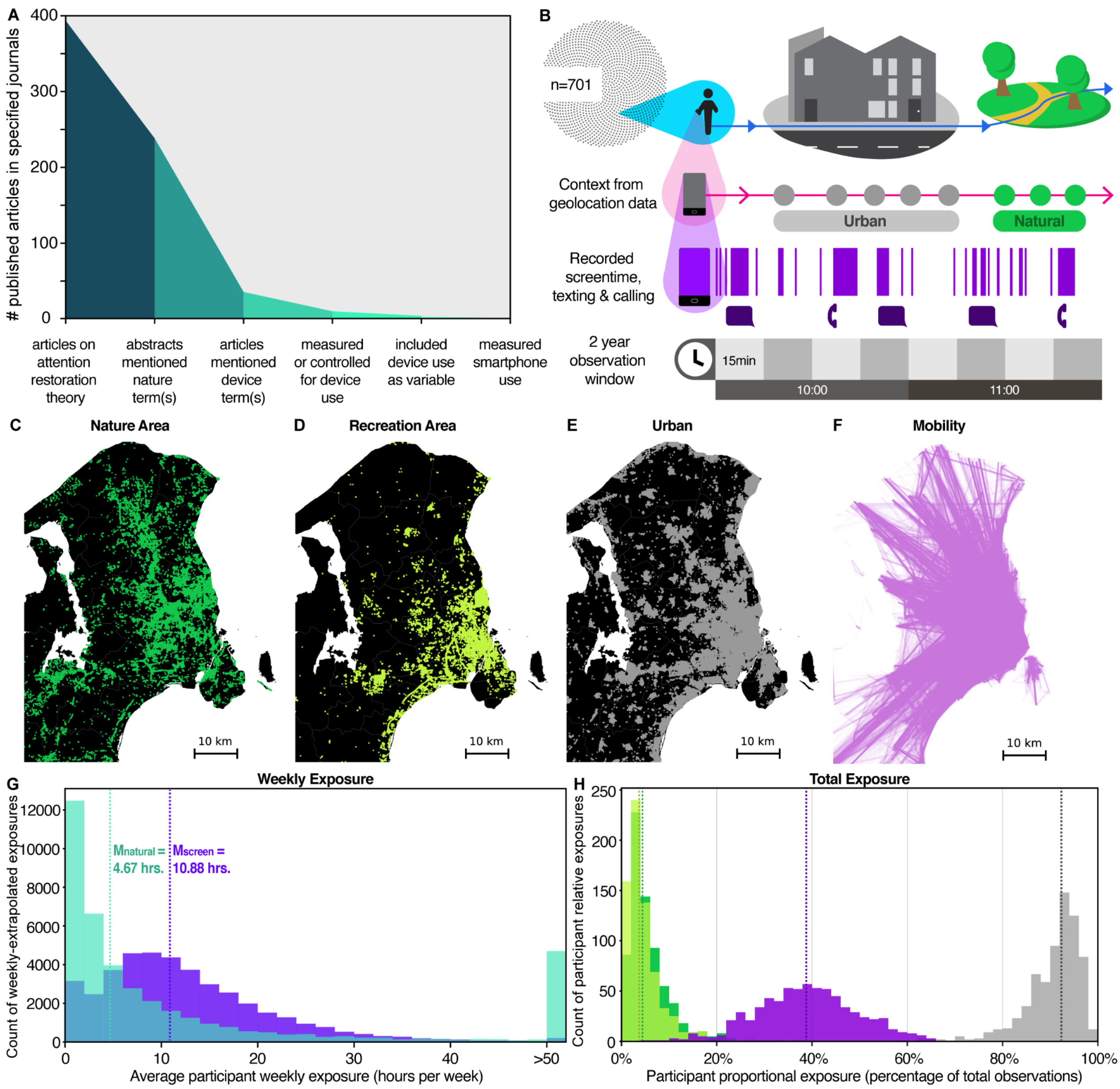

Fig. 1 | Measuring natural environmental and smartphone-based virtual exposures. (A) Visualization of the proportion of systematically reviewed articles investigating attention restoration theory in natural settings while mentioning, controlling for and lastly measuring mobile device use. (B) Mobile sensing framework deploying smartphones as socioecological sensors to track overlapping biospheric and cyber-spheric interactions. (C-F) Maps of natural, recreational and urban exposures and functional mobility among the sample of 701 young adults for the month of September 2014. (G) Distributions of participant natural environmental exposures (cyan) and smartphone use (purple) over the study period, extrapolated to the weekly level. Colored lines indicate the median exposure value for each distribution. (H) Distributions of the % of total participant-level observations spent in nature areas (dark green), recreational areas (yellow-green), urban settings (grey), and containing smartphone use (purple). Colored lines depict median values.

The results from the primary fixed effects panel model specification (Methods, Eq. 1) showed that within-person smartphone use in natural environments was estimated to decrease by -2.35% (95% CI: -4.47% – -0.22%) relative to use in urban settings, controlling for all stable individual characteristics and fixed temporal factors (Fig. 2A). By contrast, smartphone-based social activities did not significantly change within-participants when they were situated in natural environments, with the estimate for outgoing text messaging being 1.02% (-1.84% – 3.89%) and outgoing calls increasing by 3.43% (-0.75% – 7.60%) relative to being in urban settings.

A fixed effects panel model with the overarching context category of natural environments broken out into the constituent sub-contexts of nature areas and recreation areas (Methods, Eq. 2) showed that smartphone use, outgoing texting and outgoing calling significantly declined in nature areas by -4.39% (-7.21% – -1.57%), -5.74% (-9.21% – 2.27%) and -7.17%(-12.97% – -1.37%), while outgoing texting and calling increased in recreational areas by 10.96% (5.88% – 16.04%) and 16.63% (9.61% – 23.65%) respectively, relative to the corresponding smartphone behavior baselines in urban environments (Fig. 2B). Smartphone use slightly increased by 0.91% (-2.36% – 4.18%) in recreational areas relative to use in urban environments but this increase was not significantly different with the confidence interval containing the estimated average urban screen use response.

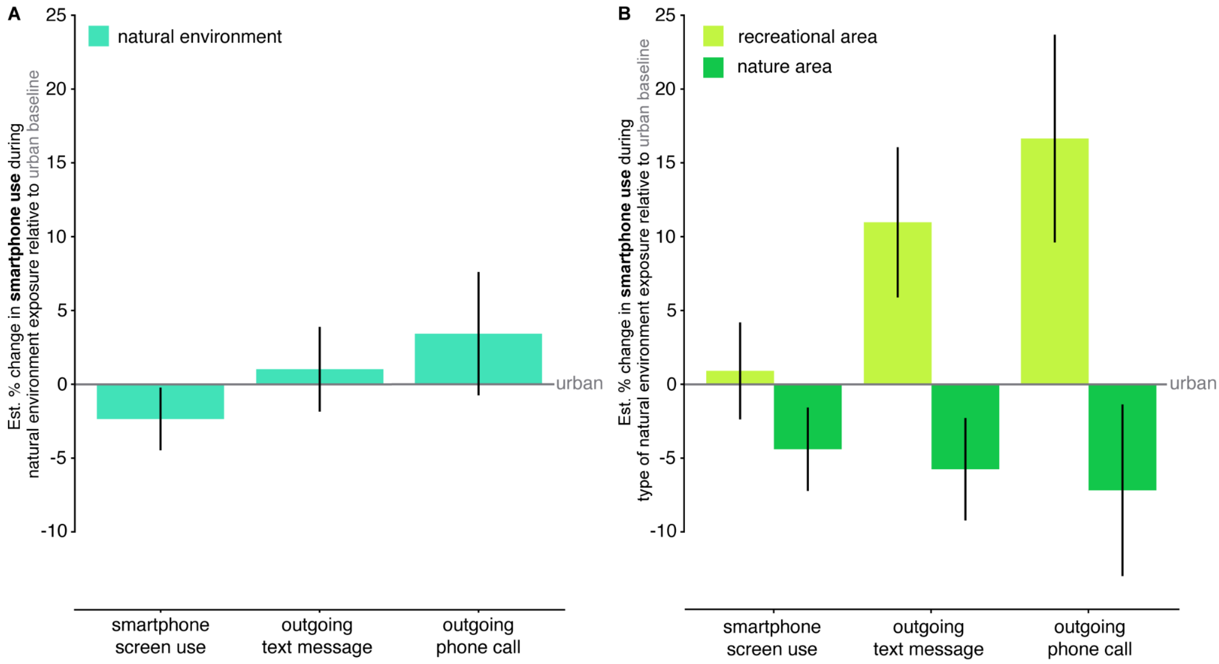

Fig. 2 | Within-Person Effects of Natural Environment Exposures on Smartphone Use and Communication. (A) The cyan bars show the estimated within-individual change (%) in smartphone use during general natural environmental exposure compared to the person-specific urban setting baseline. From left to right, bars represent the response for total screen use, outgoing text messages sent, and outgoing phone calls made. Error bars represent 95% confidence intervals. (B) Estimated within-person change (%) in smartphone use by type of natural environmental exposure, relative to the urban baseline (grey line). Colored bars show the marginal individual smartphone use responses for each smartphone activity measure in natural recreational environments (yellow green) and nature areas (dark green), relative to the urban baseline (grey line).

As can be seen in Fig. 3, the estimated relationships between environmental exposures and smartphone activity (screen use, texting and calling) varied by the type of environment and duration of environmental exposure. Across all environments and smartphone behaviors, long environmental exposures greater than 3 hours were marginally associated with reduced Whsmartphone activity within-individuals compared to short 0-1 hour exposures in urban settings. Smartphone use and outgoing communication activities significantly declined with the dose of exposure to nature areas over the first three hours, plateauing beyond 3 hours. Compared to an exposure of equivalent duration in urban settings, exposure to nature areas was associated with reduced screen use across all doses, with no evident overlap in the corresponding confidence intervals bounding the nature area and urban environment smartphone use response estimates (Fig. 3A). 2-3 hour exposures to nature areas were associated with the largest marginal reductions in smartphone activity within individuals from the previous dose bin. Screen use decreased within-person from -20.04% (-26.17% – -13.91%) during 1-2 hour nature exposures to -41.89% (-48.85% – -34.93%) during 2-3 hour nature exposures, outgoing texting decreased from -24.89% (-32.51% – -17.27%) to -43.86% (-53.13% – -34.59%), and outgoing calling declined from -20.78% (-33.27% – 8.29%) to -43.61% (-57.27% – -29.95%), relative to individual baseline use during short (0 - 1 hour) exposures in urban areas.

Model estimates indicated that only recreational area exposure durations greater than an hour were significantly associated with reductions in smartphone screen use compared to urban exposures of similar lengths. By contrast, outgoing texting slightly increased by 2.94% (1.00% – 4.88%) during moderate 1-2 hour recreational area exposures, before significantly declining during longer exposures relative to the 0-1 hour urban baseline, although the outgoing texting response in recreational areas was similar in magnitude and functional form to urban environmental exposures of equivalent duration, with overlapping confidence intervals evident (Fig. 3B). Similarly, outgoing calls were estimated to significantly increase by 40.8% (25.75% – 55.85%) in recreational areas during moderate exposures of 1-2 hours relative to the urban baseline of 0-1 hours, before substantially declining during longer exposures. Estimates of outgoing calling activity in recreational environments were also elevated relative to urban exposures of equivalent duration during exposures less than 3 hours, with exposures of 1-2 hours in urban settings associated with an increase of 18.84% (15.76% – 21.92%), and exposures of 2-3 hours associated with a relative decrease of -21.82% (-25.47% – -18.17%) in urban areas, and a non-significant change of -2.4% (-20.08% – 15.28%) in recreational areas.

Mobility state moderated the relationship between environmental exposure and smartphone use (Fig. 3D-F). Compared to the baseline mobility state of moving in urban contexts, staying in place was associated with within-person reductions in smartphone screen use across all contexts. Although staying in place was associated with significant reductions in smartphone use and outgoing communication activities for both urban settings and nature areas, staying in nature was associated with the largest reductions in smartphone screen use (-20.90%, -25.33% – 16.47%), outgoing texting (-20.40%, -26.14% – -14.66%) and calling (-18.55%, -27.82% – -9.28%) compared to the mobile urban baseline. By contrast, smartphone screen use was estimated to only slightly and non-significantly deviate from the urban baseline while moving in natural areas

(-3.15%, -8.60% – 2.30%), and recreational areas (3.8%, -2.67% – 10.27%). Conversely, staying in place in recreational areas was associated with a small increase in outgoing texting (6.74%, -0.51% – 13.99%) within participants as well as a significant and substantive increase in calling (21.49%, 11.28% – 31.70%) relative to corresponding individual smartphone activity in urban settings.

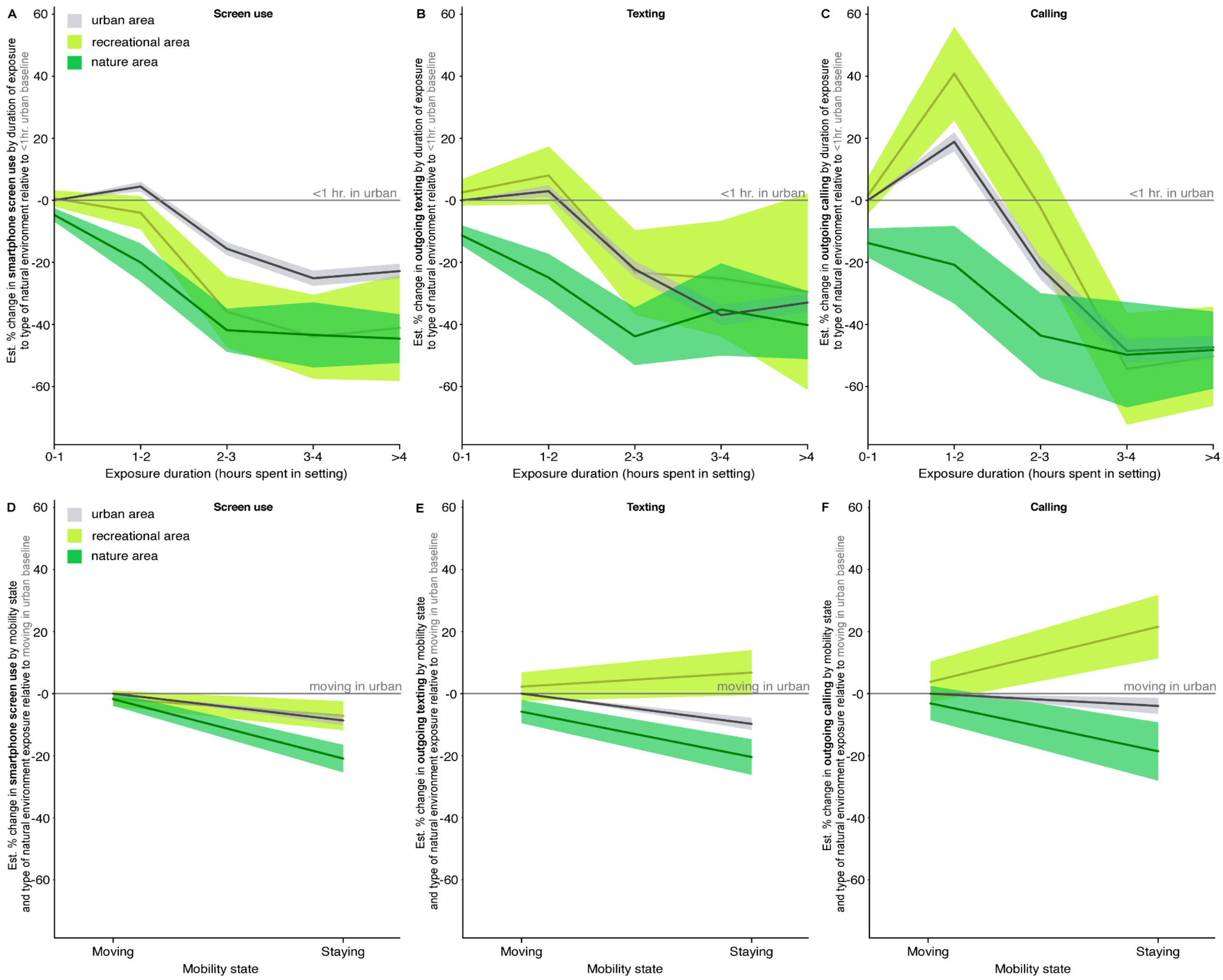

Fig. 3 | Setting Exposure Dose and Smartphone Use Response Relationships. (A-C) Colored lines depict the estimated smartphone use response by environmental exposure type and dose in 1 hour bins, compared to the <1hr urban exposure baseline. The relative smartphone response is shown for urban settings (dark grey line), recreational natural environments (yellow-green line) and natural areas (dark green line). Shaded intervals represent 95% CIs. (D-F) Lines show the estimated relative effect of environmental exposures on smartphone use by mobility state (actively moving vs. staying in place) in urban settings (grey), natural recreational environments (yellow-green) and natural areas (dark green) compared to the mobile urban baseline. Shaded intervals show 95% CIs.

Stratified model estimates indicated that while participants at all levels of typical smartphone screen time reduced their mobile device use in nature areas, those in the quartile with the highest average smartphone screen time over the study period were the only group found to significantly reduce their smartphone activity in nature areas (-7.05%, -11.64% – -2.46%) compared to in urban settings (Fig. 4A). By comparison, smartphone use in recreational areas did not significantly differ from use in urban settings irrespective of level of typical screen time, although the smartphone use response in the lowest quartile of average screen time indicated that smartphone activity marginally increased (6.92%, -2.68% – 16.52%) during recreational area exposures.

Similarly, stratified model estimates suggested that people with higher typical exposure to natural environments over the study period experienced larger marginal reductions in smartphone screen use while in nature areas (Fig. 4B). Those in the third and fourth quartiles of natural environment visitation over the study period were found to significantly reduce their smartphone screen use in nature areas by -4.92% (-9.21% – -0.63%) and -9.60% (-14.83% – -4.37%) respectively relative to in urban settings. By comparison, participants in the lowest quartile of typical natural environment visitation over the study period were found to marginally increase their smartphone use in nature areas by 5.96% (-0.27% – 12.19%) relative to use in urban settings within this same quartile. No significant differences in smartphone use were observed in recreational areas relative to the urban baseline across all study period quartiles of green time.

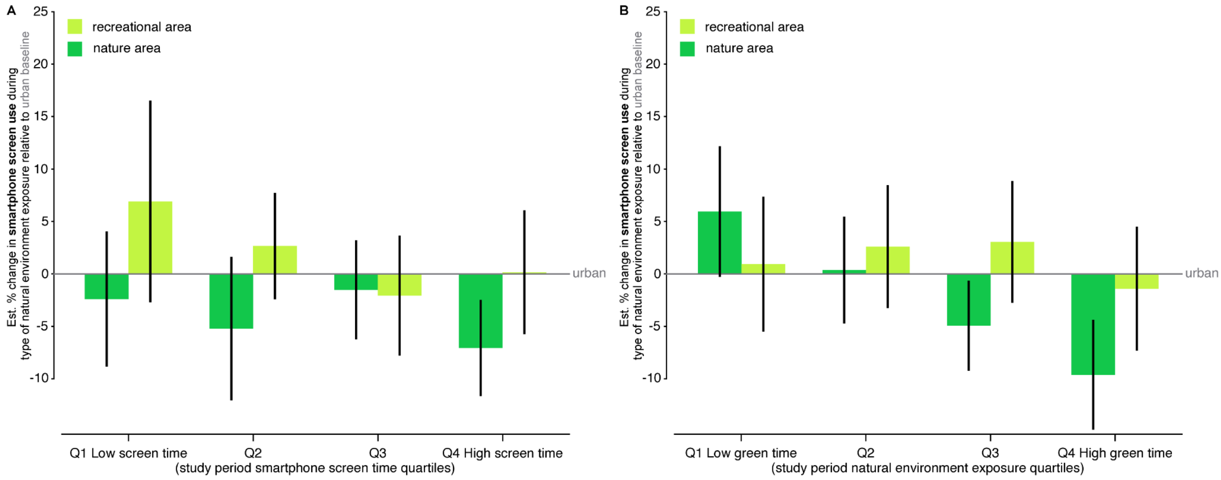

Fig. 4 | Subgroup plots of the estimated effects of natural environmental exposures on smartphone use by quartiles of average mobile device usage and typical natural environmental visitation. A) Colored bars depict the estimated relative within-person smartphone use response to being in recreational natural environments (lime-green) and natural areas (dark green) compared to the urban setting baseline (grey), by quartiles of smartphone usage, ranging from participants with light to heavy typical device usage over the study period. Error bars represent 95% confidence intervals. B) The estimated average within-person smartphone use response to environmental exposures, relative to the urban baseline, across quartiles of natural environment visitation over the course of the study.

Table 1 | Results from linear probability and linear fixed effects regression models investigating daily replacement

Outcome	**Predictor**	**Estimate**	**Std. Error**	**t-statistic**	**p-value**
Natural Environment Visitation (Yes | No)	Log(Daily screen time)	0.0637	0.0061	10.370	<2e-16
Minutes Spent in Natural Environment	Log(Daily screen time)	-5.441	2.806	-1.939	.0529

The estimates from the linear probability fixed effects model indicated that increased smartphone use above the individual baseline was significantly positively associated with increased probability of visiting natural environments. Doubling daily smartphone screen use from the average level of observed use was associated with a 6.37 (5.17 – 7.57) percentage point increase in the probability of visiting natural environments on the same day. Conversely, a fixed effects model assessing the relationship between screen time and time spent in natural settings found that elevated smartphone usage was marginally negatively associated with natural environmental exposure duration. A doubling in daily smartphone usage was associated with a reduction of -5.44 minutes of daily natural environment exposure (-10.94 – 0.06 minutes).

Discussion

Over the last half-century, humanity's virtual surroundings have become increasingly salient in our physical environments, presenting complex adaptive challenges for people and the planet[28,63]. Although time spent in nature is increasingly prescribed as a form of digital detox from screen-based technologies, it has remained an open question whether exposure to natural settings is associated with altered patterns of smartphone use in situ, or conversely, whether daily virtual demands may interrupt in person human-nature connection[14]. Differing from most prior research reliant on self-report methods or brief interventions, the present study continuously registered objective measures of minute-by-minute screen use and natural environmental exposures for 701 young adults over two years, using smartphones as socioecological sensors. Drawing on over 2 million unobtrusive observations of coupled physical and virtual activity, we found behavioral evidence that participants spent over twice as much time per week on their smartphones than in natural environments. Controlling for unobserved stable individual characteristics and behavioral routines, as well as time-varying social and environmental factors, we uncovered evidence that levels of smartphone screen use in natural environments were slightly lower compared to screen use in urban environments within individuals. In contrast, social communication activities were not found to significantly change in natural settings. These findings provide some behavioral evidence for the emplacement of digital stimuli into young adult encounters with natural environments, and indicate that social attentional demands of mobile devices may spill over into certain natural contexts.

Critically, however, participants' capacity to disconnect from their mobile devices varied in sign and magnitude according to the type and dose of environmental exposure. All observed smartphone activities declined substantially within-individuals in nature areas over the first three hours whereas outgoing smartphone communication increased in recreational green spaces - such as parks and grass areas - during visits shorter than two hours, with calling significantly amplified. By contrast, smartphone screen use increased during 1-2 hour exposures to urban environments. ART conveys that exposure to settings and situations that do not demand directed attention can permit mentally fatigued individuals to rest and restore the inhibitory mechanism required for focused attention[11,60]. Thus our results suggest that certain natural environments - specifically nature areas - may contribute to digital impulse inhibition in-situ, with exposure to these settings tending to coincide with within-person reductions in smartphone use, relative to the urban individual baseline.

This pattern is in agreement with both theory and accruing evidence indicating that more vegetated, and possibly more biodiverse, natural areas may provide enhanced restorative benefits compared to more programmed urban recreational green spaces[60,95,121–123]. For instance, visual and sensory characteristics of natural elements in these settings, such as fractal patterns in vegetation, may invite involuntary attention and promote soft fascination[11,61]. Our finding that smartphone usage significantly declined the most in both nature areas and recreational green spaces during visits exceeding two hours, is in line with growing evidence showing larger salutary effects from longer exposures to natural environments[119,124,125]. However, since longer environmental exposures were associated with reductions in mobile device use irrespective of environment, exposures to nature areas lasting 1-3 hours were estimated to provide the greatest marginal reductions in smartphone screen use compared to equivalent exposure doses in urban environments. Thus even nature visits of short to moderate duration may enable meaningful improvements in digital impulse inhibition compared to urban environments. Further, the magnitude of the associated reduction in smartphone screen use in natural environments was larger when staying in place compared to being on the move, consistent with a prior multi-study analysis that found mobility in green spaces was associated with truncated mental health benefits[126].

Why did some social smartphone activities increase in certain natural environments, relative to urban settings? It has long been apparent that natural landscapes can support in-person social interactions with both close contacts and loose ties, and thus facilitate social cohesion[127–130]. However, the possible use of natural settings for virtual communication has been largely ignored by prior research. Our findings suggest that urban virtual interactions may spill over into recreational areas such as parks and grass areas, with these settings serving as a semi-private space to engage in remote social interaction. Thus, certain environmental qualities that promote restoration in natural settings - such as being physically removed from the sites of daily obligations - may also increase the salience of smartphone-accessible remote social contacts. Hence, these findings dovetail with recent experimental evidence to raise questions about whether merely being in green space for short exposures is sufficient to achieve meaningful connection with nature in the digital age, particularly if attention is directed elsewhere[100]. Our results hint at a potential tradeoff: spending time in common urban recreational green spaces may support the maintenance of remote social ties but interrupt individual contact with restorative natural elements. This tradeoff parallels prior evidence indicating that in-person social interactions in natural settings may reduce their restorative potential[130,131].

Those with different baseline levels of screen time or green time may respond to natural exposures differently. For instance, people with high-levels of screen time may be especially prone to directed attention fatigue, and thus may both plausibly stand to benefit more from time spent in nature but also be more inclined to use their devices there. Our finding that reductions in smartphone screen use in nature were significantly pronounced among participants in the highest quartile of smartphone screen time over the study period indicates that time in nature may indeed provide an acute marginal improvement in digital impulse inhibition for those that use their mobile devices the most. Separately, previous studies have shown that the benefits conferred from time in nature may be greater for people who engage with these settings more. This converges with our results showing that only those with higher than average green time over the study period experienced statistically significant reductions in smartphone screen use in nature areas, while those in the lowest quartile of green time marginally increased device use in nature areas (Fig. 4B). Although future research is warranted to investigate the causal relationship of prescribed nature exposures on smartphone use, the present within-person field study provides strong initial behavioral evidence that people who use their phone relatively more or spend more time in natural environments may experience improved digital impulse inhibition in nature areas, but not necessarily in recreational green spaces. Thus, prescribing more time in the natural biosphere to provide a reprieve from the cybersphere may be a relevant intervention for young adults in need of a digital break.

While we primarily interpreted our results through the theoretical lens of Attention Restoration Theory (ART), our findings appear relevant for other perspectives. For instance, perceptual contact with nature is a critical part of the salutary cognitive and affective channels theorized by ART, SRT and biophilia[16], yet such direct contact can be interrupted when attending to smartphone stimuli. Thus an alternative interpretation of our results is that more wild and less urban natural environments may draw people away from the synthetic stimuli of their devices via deeply encoded psycho-evolutionary cues. Such an explanation is congruent with our finding that nature areas - more than recreational areas - were associated with a greater decline in smartphone use, although other explanations were equally plausible. For instance, it has been hypothesized that natural settings may confer benefits by buffering individuals from ambient environmental stressors[1]. Indeed urban life has long been characterized by a high density of stimuli, including noise, air pollution, traffic, and crowding, contributing to overload and potentially overwhelming the human capacity to engage in directed attention[132]. Our study implies that urban settings and recreational green spaces may also be sites of amplified digital demands and connectivity, adding a virtual dimension to the classic information-overload framework[67,133,134]. Consistent with this framework, mobile information demands may have been muted in more remote natural settings due to reduced cellular service or data coverage. However, the spatial distributions of nature and recreational area exposures in our sample were highly interspersed (Fig. C-E), challenging such an interpretation. Nevertheless, future research should strive to directly identify the extent to which digital impulse inhibition in nature may be driven by reduced connectivity alone versus restorative environmental characteristics that drive involuntary attention. Since cell and mobile internet coverage is projected to continue to expand, such a question has relevance for both planning and the future of human environment relationships.

Several lines of evidence suggest that human-nature interactions may be in decline, with younger generations visiting natural spaces more infrequently than previous generations[17]. Although we found that participants regularly visited natural environments, the percentage of observations containing screen time was approximately an order of magnitude larger than those containing exposures to nature or recreational areas (Fig. 1H). Thus, despite the historically recent advent of smartphone screen stimuli in the human social environment, our descriptive results provide initial behavioral evidence that smartphone screens alone may now occupy more time and attention for highly connected young adults than in-person experiences of nature (Fig. 1G). These estimates - derived from digital trace data - are consistent with a recent survey-based study that found self-reports of general category media use was greater than self-reported time in nature[26], and with cohort evidence from time diaries that showed the proportion of time spent on media activities increased while time outdoors declined in recent decades[23]. However, prior studies have been unable to rigorously investigate whether these diverging trends in screen time and green time are related or instead linked to other unobserved technological, social or economic developments that transpired over the same period, weakening inference about whether the observed displacements are indicative of actual substitution. Drawing on extensive longitudinal individual-level panel data, we uncovered mixed evidence for the replacement hypothesis: increased daily smartphone use was marginally associated with reduced same-day time in natural environments, but paradoxically, was also significantly associated with an elevated probability of same-day nature visitation.

How should we interpret the diverging associations between daily smartphone use and, respectively, daily nature visitation and daily time spent in natural environments? Given the small negative association between daily smartphone use and time spent in nature, our longitudinal findings suggest that smartphone use alone may not be a predominant competing leisure activity with nature-based visitation. Further, and counter to the popular perspective that digital media use directly substitutes for time in natural settings[14,26,27], we find within-person evidence that increased smartphone use from the individual baseline may be positively associated with same-day nature visits. This finding adds nuance to the complexity of human nature relations in the digital age, and is consistent with frameworks that emphasize precursors to nature contact as deeply situated in sociocultural and sociotechnical systems[28,63,135,136]. As Kaplan and Kaplan noted, people may be motivated to connect to nature by a desire to escape from the modern demands of urban life[11]. Seen through this lens, young adults may engage in device use to plan, navigate or accompany their journeys and then reduce usage upon entering into restorative nature areas, a pattern consistent with the estimated relationships observed in this study. Taken together, these patterns may have implications for the benefits conferred from time in natural settings. Longer visits to nature are associated with lower rates of high blood pressure and depression, while more frequent visits have been linked to greater levels of social cohesion[124]. Thus, increased smartphone use may stand to strengthen social connections while slightly curtailing salutogenic exposures to natural environments, although future research is warranted.

Several considerations should be weighed when interpreting the results of the present study. Recognizing that personal and sociocultural factors can color experiences of nature, the current investigation measured person-level variation in exposure to multiple categories of nature. Nevertheless, we acknowledge that the diversity of natural contexts far exceeds the Northern European natural settings encountered by the participants. Further, although we found that time spent in nature areas was associated with a reduction in smartphone use, smartphones may still occupy individual attention even when not in use. Thus, a decline in the behavioral salience of smartphones in the presence of natural areas does not invariably imply a similar decline in the cognitive salience of smartphones[71,137,138]. Although the present study improves over studies that relied on self-reported green space use and/or screen time, the use of only three dimensions of smartphone activity only enabled an initial exploration of possible heterogeneity in the relationship between natural environmental exposures and on-screen behaviors. For instance, it would be valuable to know the extent to which smartphone use in urban greenspaces is composed of time spent on goal-directed vs. involuntary smartphone use, and how time varies across email, social media, games or other digital activities that center attention away from one's setting, versus environmentally responsive activities such as taking or sharing photos of natural elements. Indeed, some evidence suggests that nature-based mobile app guides[139,140], or games like Pokemon Go can increase physical activity and encounters with certain natural settings[141–143], although their influence on attention restoration remains unclear.

Further, we assumed that smartphones closely shadowed their owners, but it is possible that we may have undersampled time spent in nature if people selectively left their phones behind when entering natural settings. In such a case, the estimated magnitude of the negative association between nature exposure and in situ smartphone use may underestimate the magnitude of the actual relationship. Additionally, although we draw upon longitudinal observations to identify the relationship between within-person changes in natural environment exposure and registered changes in device use, controlling for all stable individual characteristics, recurring routines and date-specific temporal factors, the choice to visit natural contexts was not random, preventing a causal interpretation. For instance, it is possible that emergent goal-directed behaviors or specific unobserved activities transpiring in natural environments may underlie the relationships uncovered. However, our results were robust, even when controlling for individual mobility (Fig. 3D-F). Lastly, the relationships we identify between daily within-person variations in smartphone use and natural environment visitation have a weaker identification strategy than the one used to investigate emplacement, where we exploit the arrival timing into the environment. Thus this component of the analysis is more likely to be spurious and driven by confounders. For instance, idiosyncratic person-specific leisure time that deviates from their baseline weekly schedule may be associated with both daily increases in smartphone use and nature visitation, rather than a mechanistic relationship between smartphone use and nature encounters per se.

Over the past few decades researchers from environmental psychology, environmental health and the environmental social sciences have marshalled evidence about numerous salutary effects linked to natural settings[1,3,29,31,144]. However, past studies largely omit a now pervasive digital layer of the social environment. Such engagement with virtual environments in urban and natural settings, as documented by the current study, may constitute a confounding variable for research on restorative environments. Our findings suggest that objective measures of mobile device use, almost entirely absent from previous studies on the restorative effects of nature (Fig. 1A), should be included or explicitly accounted for in future observational and experimental investigations. Moreover, even the act of restricting participant smartphone use may lead to illusory restorative benefits of nature exposures. Since self-reported behavioral measures may poorly recover actual exposures, and since unobserved individual characteristics may jointly influence both smartphone use and nature exposure, we recommend that researchers studying the restorative effects of nature employ objective measurements of both device use and environmental exposures over prolonged time horizons. We conclude that links between human biospheric and cyber-spheric interactions may be both more pervasive and complex than previously hypothesized. Urban areas and recreational green spaces may be characterized by not only a higher density of stimuli in the physical environment but also in the digital environment. By contrast, nature areas may provide respite from digital demands.

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Smartphone use is socially contagious

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Abstract

Over the past decades digital devices have become an integral part of modern human life. But in spite of growing concerns of their adverse effects on human life, little is known about what causes smartphone use. We focus on the social aspects of smartphone use and ask whether such usage is contagious even in physical space. We leverage a unique, large field study with 779 participants covering social interactions over the course of 2 years. To establish causal measures of contagion effects in smartphone screentime we exploit the randomness in the arrival of text messages. We find that when an individual receives a text message, other physically nearby related individuals' smartphone use increase in the following 2 minutes. Since we do not find evidence of spread to nearby non-related individuals, we conclude that smartphone contagion works through social mechanisms. Further, we find exploratory evidence that the magnitude of social contagion depends on gender composition, relative social status, and relative conscientiousness within the dyad, but find no evidence that it depends on differences in other personality traits. Finally, we argue that the aggregated effects of social smartphone contagion have big societal consequences, and discuss possible consequences for policy interventions.

Abstract

I løbet af de sidste årtier er smartphones blevet en central del af moderne menneskers liv. På trods af stigende bekymring for, at smartphonebrug kan have negative konsekvenser, ved vi kun lidt om, hvordan smartphonebrug opstår. I dette studie fokuserer vi på de social aspekter af smartphonebrug, og undersøger om smartphonebrug smitter mellem personer, der er fysisk tæt på hinanden. Vi bruger et unikt storskala feltstudie, der fulgte 779 deltagere i to år. Vi udnytter den tilfældige timing af SMS'er til at måle smartphonesmitte kausalt. Vi viser, at når én person modtager en SMS, så stiger smartphoneforbruget for personer, der er fysisk tæt på de næste to minutter. Da vi ikke finder nogen indikationer på, at smartphonebrug spredes mellem personer, der ikke kender hinanden, konkluderer vi, at smartphonesmitte sker gennem sociale mekanismer. Vi finder endvidere indikationer på, at styrken af den sociale smitte afhænger af kønssammensætning, relativ social status og relativ samvittighedsfuldhed (conscientiousness) i situation, men ingen indikationer på, at smitten afhænger af forskel i andre personlighedstræk. Afslutningsvis argumenterer vi for, at social smartphonesmitte kan have store samfundsmæssige konsekvenser, og vi diskuterer, hvordan smartphonebrug bedst reguleres.

Introduction

The increasing ubiquity of smartphones and digital devices allow people to connect across time and space and access a wealth of information and services. However, the growing adoption has been met with increased worry and scrutiny over how these digital devices affect human life. Recent evidence documents how smartphone use impairs cognitive ability [60] and is associated with lower academic performance [8] as well as personal well-being [17, 40]. However, we still have limited knowledge about long term effects and the mechanisms through which smartphones affect human lives, which have lead to calls for research using better data [35].

One of the mechanisms that we lack understanding of is if, and how, smartphone use spreads between individuals who are physically close to each other (co-present). Establishing that smartphones are contagious in the physical world, can potentially have far-reaching consequences on how we think about smartphone use. If smartphones are contagious then using a smartphone will go from being a choice only affecting the individual, to being a choice affecting nearby individuals potentially imposing a negative externality. Like in the case of second-hand smoking, evidence that smartphone use affects nearby individuals could justify tougher smartphone regulation.

To examine whether smartphone use is contagious between individuals who are co-present, we use the Copenhagen Network Study (CNS) dataset and utilize its unique depth, precision and scope. CNS was a large-scale field study running for more than two years. All students of a university freshmen cohort (N$\sim$1,000) were offered a high-end smartphone. The phones collected precise measures for a range of features including individual screentime, phone communication (calls and texts), location and (using Bluetooth) on co-present individuals and distance to them. Further, surveys about participant characteristics and personality traits were conducted, and social media accounts were followed to obtain participants' social networks. The reliance on sensor data allows us to overcome limitations of using self-reported measures on social interactions and screentime, which have been shown to exhibit systematic biases [12, 39]. Having access to accurate, high resolution data on where people were, who they were together with, their phone use, and their social network, allows to overcome previous limitations and assess whether, and how, smartphone use is contagious in real-life settings.

We study 56,219 situations where only two people were present, and one of the participants received a text message (SMS). We look at how screentime develops 10 minutes before and after the arrival of the text for both the individual receiving the text message ("recipient") and the co-present individual ("peer"). Further, we compare this to 145,230 similar situations where the same users were present but we did not condition on the arrival of a text. By comparing these two groups of observations, we can causally identify how phone use spread from recipients to peers. We find that smartphone use is contagious. We conclude that this mechanism works through disturbances in social interactions (i.e., social contagion) since we find no effect when co-present peers have no social connection. Therefore, we rule out alternative spreading mechanisms, e.g., through direct visual or audible sensory exposure to others' notifications or observing non-related others react to incoming text messages.

We find that a text to a recipient, on average, increases screentime of the co-present related peer by 3.2 percent over the following four minutes, corresponding to 2/3 of a second. We find that when recipient's screentime increases screentime of the co-present related peer increases by 7.24 percent of recipients' increase in screentime. Further, since our analysis most likely includes situations with no social interaction, we believe that the estimates constitute a lower bound and that the actual effects are probably higher.

Our estimated effect from each specific text message on screentime is modest. However, the direct and indirect aggregated contagion effect of smartphone use has vast consequences. Due to the omnipresence of smartphones, we estimate that the aggregated effect of notifications on nearby peers corresponds to at least an additional eight and a half years of human life used on smartphones every day in the United States alone. In addition, many other factors lead individuals to increase their smartphone use, both external sources and sources internal to the individual [28, 60], which substantially increases the number of situations where smartphone contagious is relevant. Finally, the increased smartphone use due to social contagion is likely to persist over time through habit formation in usage [4] and in turn spiral out and affect other peers.

According to classic consumption theory, one could argue that since smartphone use is an individual choice, the chosen amount of smartphone use is most likely optimal. Nevertheless, this ignores crucial differences between smartphones and other standard consumption goods. [48] argues that, due to evolutionary mismatch, smartphone notifications trigger deep evolutionary tendencies that make individuals use smartphones more than would be optimal. [4] find that people have self-control problems leading to smartphone use that is over 30 percent higher than desired by the individual. Combined with the adverse personal effects of smartphone use and the fact that smartphones can erode a social relations [11, 20], this calls into question whether and how smartphone use should be regulated or banned in certain environments.

A pioneering study on the causal peer effects of devices use is [46]. They show causally that individual laptop use can impair nearby peer's learning. Although their data is obtained in an experimental setting, they cannot measure the learning outcome (test results) or others' device use in real-time and thus cannot examine the mechanisms in the micro development. Our study provides evidence that one plausible mechanism through which classmates' device use affects peers' learning is through increased device use by the peers themselves, as opposed to merely grabbing their attention.

Our study further contributes to an extensive literature concerning smartphones' impact on individuals and social relations. [60] review the literature on smartphone and cognition, providing evidence that smartphones affect human attention, memory, and patience. [38, 40] find that smartphone use in adolescence negatively correlates with well-being for some individuals, and [13] links smartphone use to depression. Although the found average effects tend to be small, there is a worry that adverse effects of smartphone use may target already vulnerable individuals, thereby exacerbating existing inequalities [37]. Regarding smartphones' effects on social relations, it has been shown that lower perceived responsiveness due to smartphone interruptions negatively affects close and intimate relationships [48]. Likewise, higher smartphone use within relationships can lead to lower relationship satisfaction [20, 45].

Few studies have looked at smartphone contagion in real life. [22] use ethnographic methods to look at how cell phone use affects nearby individuals initiating a kind of dance between call recipient and co-present peers, and [14] finds a positive correlation in smartphone use between peers eating lunch. Neither provided causal evidence.

Further, our work also relates to the literature on social contagion in networks science [26, 56], which examines how social phenomenons propagate through networks. In the context of the network science literature, we focus on the dynamics between two nodes only.

For a more comprehensive review of the literature, see appendix D.

Approach

We use data from Copenhagen Networks Study [47, 51] that continuously collected behavioral data from the smartphones of 779 university students over two years. The data allows us to detect whether the smartphones' screens are turned on or off at any time, register all incoming and outgoing text messages, and calls and measure the distance between the phones when they are within range of each others' Bluetooth scanners. We define two individuals as *co-present peers* when they are estimated to be within 3m using the Bluetooth sensor data.

Causally measuring behavioral contagion is tricky since co-movements in smartphone use between two people might be a result of a common influence, like the bell ringing or a movie being boring [32]. Therefore we need external variation, which only directly affects one of the individuals in the dyad. We use situations where one of the members receives an incoming text message, which we call a *cue*. To qualify as a peer for the cue, the other person must be co-present both in the 10 minutes before and after the text message was received and there must be at least 3 minutes between the measurements before and after cue. We aggregate screentime at the 30 seconds level, which results in 40 bins of 30 seconds for each cue. For further details on data collection and structuring, see the Data section.

For each cue, we analyze the screentime of the recipient and the co-present peer. To reduce the complexities of measuring social spillovers, we limit our study to situations with only two people together for the 10 minutes before and after cues. See Appendix A for results where screentime is aggregated at the 5-second level.

We regard the timing of the cue as quasi-random, and therefore we view the cue as an external shock. This enables us to compute causal measures of how the cue affects the co-present peer by simply measuring the change in screentime. To address potential confounding of the exogenous variation, such as the cue being caused by a text message that the recipient had sent briefly before, we restrict that recipient has not communicated with the person sending the text message in the 5 minutes before the cue. Further, to ensure that the co-present peer is not directly affected by the cue, we condition that the peer does not receive a text from the same person 15 seconds before or after the cue. The conditions on communications ensure exogeneity but can have implications for the counterfactual screentime trajectories in the absence of cues, which may bias our estimates. To address this concern, we construct control situations without the arrival of text messages to act as measures of counterfactual behavior. We refer to situations without cues as *controls* while those with cues we refer to as *treated*. The key assumption for causal identification is that the development in treated and controls, would, on average, have been the same in the absence of the cue.

To compute the treatment effects, we employ matching estimation by matching treatment situations to control situations that are close in time and consist of the same people (see Methods for precise conditions). In the matched observations, we keep the roles in terms of cue recipient and its peer the same.

We estimate a fully dynamic two-way fixed effects model with intercepts for each cue and its associated matches. We compute the standard errors of coefficients by clustering at match level, which includes all observations in the 10 minutes before and after the arrival of the text message for both treated observations and its controls.

As a reference point for smartphone use, we use the time-bin 0-30 seconds before cue for the recipient and 30-60 seconds before cue for the peer. The latter corresponds to adjusting for the temporal displacement in the smartphone clocks, which leads to a lack of synchronization between phones leading to underestimation of the results. For details about the adjustment, see Appendix B. The level of smartphone use is centered at the level of the reference period before the cue. See the Method section for details.

Results

To test our hypothesis that smartphone use is contagious, we first focus on screentime use in the time surrounding the arrival of a cue. Figure 1 plots the mean screentime for both the recipients and the peers in the 10 minutes before and after the cue.

Figure 1a shows raw mean screentime for recipients when they receive a cue and when they do not. Examining this figure allows us to examine the exogeneity of the cue arrival and its effect on the recipient. The figure shows that screentime before the cue arrival is not entirely flat due to the condition of no communication with the cue sender 300 seconds before the arrival of the cue. Although this development may seem inconsistent with the parallel pre-trends assumption, two factors make this point irrelevant: 1) compared with the discontinuous jump in screentime after the arrival of the cue, the movement before the cue is an order of magnitude smaller; 2) the level of screentime is constant in the 30 seconds before the cue arrival when measured at a resolution of 5 seconds, see Appendix A for details.

Figure 1b plots the difference between treated and controls, estimated in a fixed effects model (see Methods). It shows that the arrival of a text message more than doubles the recipient's screentime in the next 30 second period, increasing 13%-points. We see that this effect gradually dies out (in a fashion that resembles exponential decay), falling to around half 60-90 seconds after the cue and stabilizing around pre-condition levels after around 500 seconds ($\sim$8 minutes). The median time it takes for the effect of the cue to die out is around 90 seconds.

Figure 1c shows mean raw screentime measures for the co-present peers when a cue arrives and when it does not, which are respectively the treated observations and their matched controls. We note that the screentime of the treated co-moves with their matched controls before the arrival of the cue.

Figure 1d shows the difference between the treated and controls and the estimated confidence intervals. The stable pre-trend shows no significant difference in development between the treated and controls before the cue arrival. We see that mean screen time for peers increases after the cue, topping at an increase of 0.4%-point, before gradually falling and disappearing

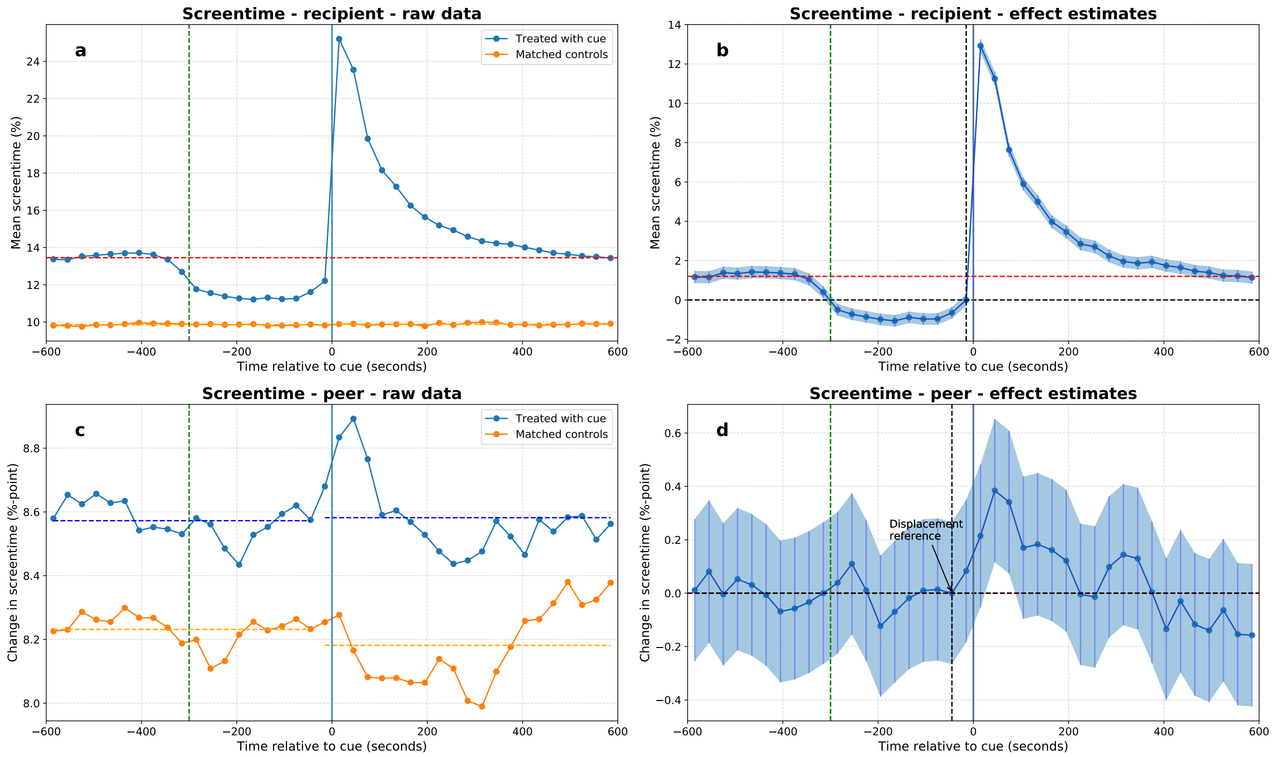

Figure 1: Mean screentime for the recipients and the peers 10 minutes before and after cue arrival in treated (blue) and control (orange) situations. Panels a and c show raw mean screentime. Panels b and d show the effect estimates. The effect is measured as the difference between treatment and matched control computed using a fixed effect model where the intercepts and standard errors clusters are at the match level. The green lines show the timing of conditioning on no communication between the sender and recipient in the time before cue, and the red line shows the average screentime of the recipient before this condition. The dashed black lines show the timing of reference. Note that the reference period for the peer is adjusted to account for clock displacement between the phones.

after around 200 seconds. Note that due to the displacement effect in the smartphone clocks, for peers, we use the 30-60 seconds before the arrival of the cue as reference.

We see this as evidence that smartphones are contagious. In the following section, we examine the mechanisms of this contagion.

Social or non-social contagion

The word "contagion" originates from the Latin word "contagio" which means to "touch" or "influence" [58]. We define social contagion as "the spread of affect, attitude or behavior from one person (in our case the "recipient") to another (the "peer"), where the receiver did not display any intention of getting the peer to do as he/she did". This, to a large extent, follows the definitions of [29] and [31]. We define non-social contagion as contagion that is not social. For example, reacting to cues, like sounds, in the nearby environment or seeing someone you are not having a social interaction with using their phone.

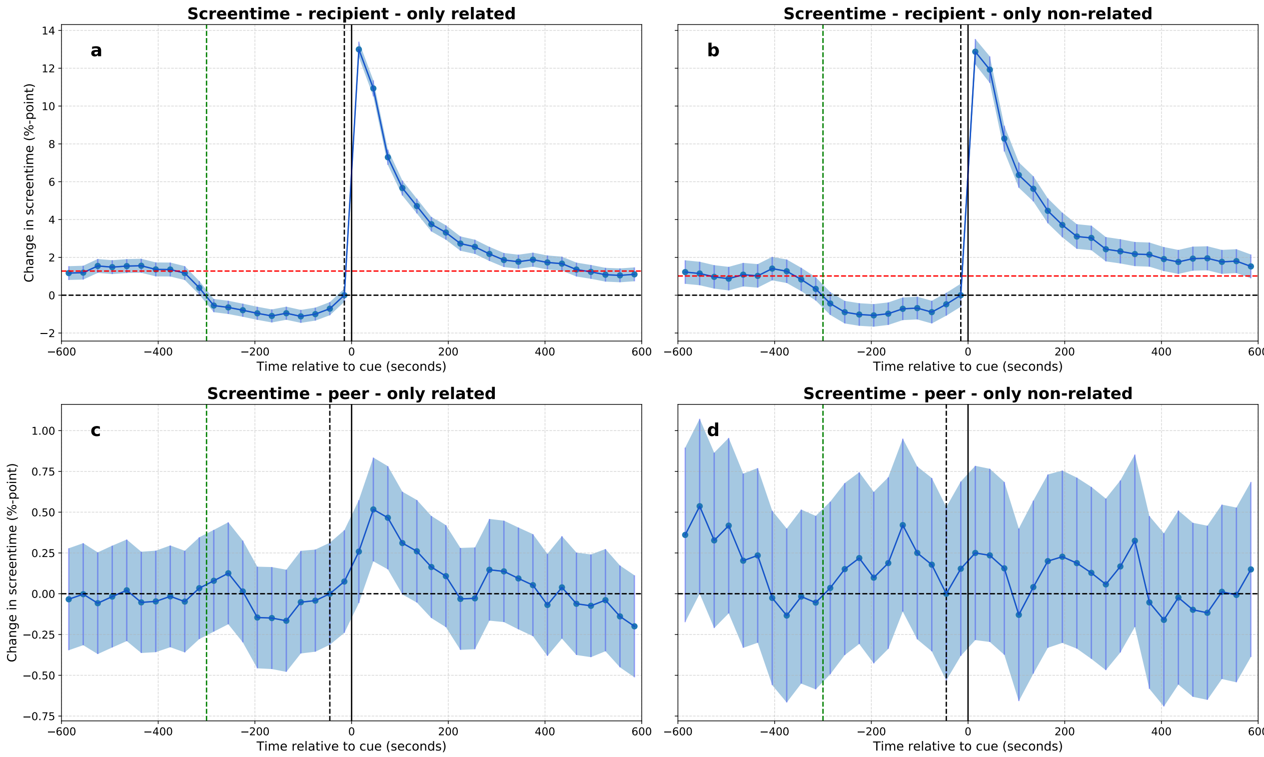

Figure 2: Estimated effects on screentime for recipient and peer. The effect is measured as the difference between treatment and matched control computed using a fixed effect model where the intercepts and standard errors clusters are at the match level. The estimates were split according to whether or not the peer is related - panels a,c show estimates when the peer is related and b,d when the peer is not related. The green lines show the timing of conditioning on no communication between the sender and recipient in the time before cue, and the red line shows the average screentime of the recipient before this condition. The dashed black lines show the timing of reference. Note that the reference period for the peer is adjusted to account for clock displacement between the phones.

To disentangle social and non-social contagion, we split the analysis on whether or not dyads are related defined as having had previous phone contact (text or call) or being friends on Facebook. If contagion is purely social, we expect an effect for related dyads and no effect for unrelated dyads. If contagion is purely non-social, we expect the same effect for related and unrelated dyads. If contagion is both social and non-social we expect an effect for both related and unrelated dyads, with the strongest effect being within related dyads.

Panel **a** and **b** in Figure 2 show similar effect of the arrival of a cue on the recipient's screentime for related or non-related dyads. However, panel **c** and **d** show that the cue only affects peer's smartphone use if the individuals in the dyad are related. This leads us to conclude that smartphones are only socially contagious and, thus, not non-socially contagious.

Relative and cumulative effects Table 1 contains the effect estimates in the first 4 minutes after the reference period when the recipients and the peers are socially related. The absolute

	0-29	30-59	60-89	90-119	120-149	150-179	180-209	210-239	Mean
Recipient absolute change (%-point)	13.00	10.93	7.29	5.67	4.71	3.75	3.31	2.73	6.42
Recipient relative change (%)	107.8	90.66	60.49	46.99	39.07	31.13	27.49	22.63	53.28
Peer absolute change (%-point)	0.07	0.26	0.52	0.47	0.31	0.26	0.16	0.11	0.27
Peer relative change (%)	0.88	3.05	6.11	5.50	3.67	3.07	1.93	1.27	3.19
Relative change ratio (%)	0.82	3.37	10.09	11.71	9.39	9.88	7.04	5.63	7.24

Table 1: Point estimates for relative and absolute change for receiver and peer in 30 seconds intervals over the first 4 minutes after reference - only related users. The relative effects are calculated using screentime in the reference period being 12.06 for the recipients (reference 0-30 seconds before cue) and 8.5 for the peers (reference 30-60 seconds before cue). Relative change ratio shows peers' relative change divided by receivers relative change in percent.

effects are identical to the effect estimates shown in Figure 2a and 2c. The mean absolute effect in the first 4 minutes is 6.4 percentage points for the recipients and 0.27 percentage points for the peers corresponding to a total increase in screentime over the following 4 minutes by 15.4 seconds for the recipients and 0.65 seconds for the peers. Looking at the relative change in screentime, by comparing to pre-cue screentime levels, we see that a cue on average increases recipients' screentime by 53% in the 4 minutes following the cue, while peers' screentime increases by 3.2%.

To estimate the marginal effect on the peer when the recipient takes up the smartphone, we calculate the relative change ratio by dividing relative change in peers' screentime with the relative change in recipients' screentime. This way, we account for the fact that not all recipients react to the cue. Thus, the relative change ratio is our preferred estimate of how much the recipient's screentime directly affects the peer. We see that the relative change ratio reaches its maximum value after $1\frac{1}{2}$-2 minutes at 11.7% and that the average relative change ratio over the first four minutes is 7.24%.

Text messaging around the cues

To examine the dynamics of contact with external users in relation to the cue situation, we analyze the rate of incoming and outgoing text messages. This examination provides a check of the core assumptions of quasi-randomness in whether the peers also experience a spike in text messages around the cue since this could pose a problem for our identification strategy.

Figure 3 shows the rate of incoming and outgoing texts for recipients and peers. In panel **a** we see that all treated recipients (by construction) receive a text in the 30 second period starting with the arrival of the cue. In the periods before the cue, the share receiving an incoming text is stable and at the same level as controls, showing no difference in pre-trends. In the periods after the cue, incoming texts are consistently higher than pre-cue levels, persisting until the end of the observed period. This is consistent with the fact that the probability of an outgoing text

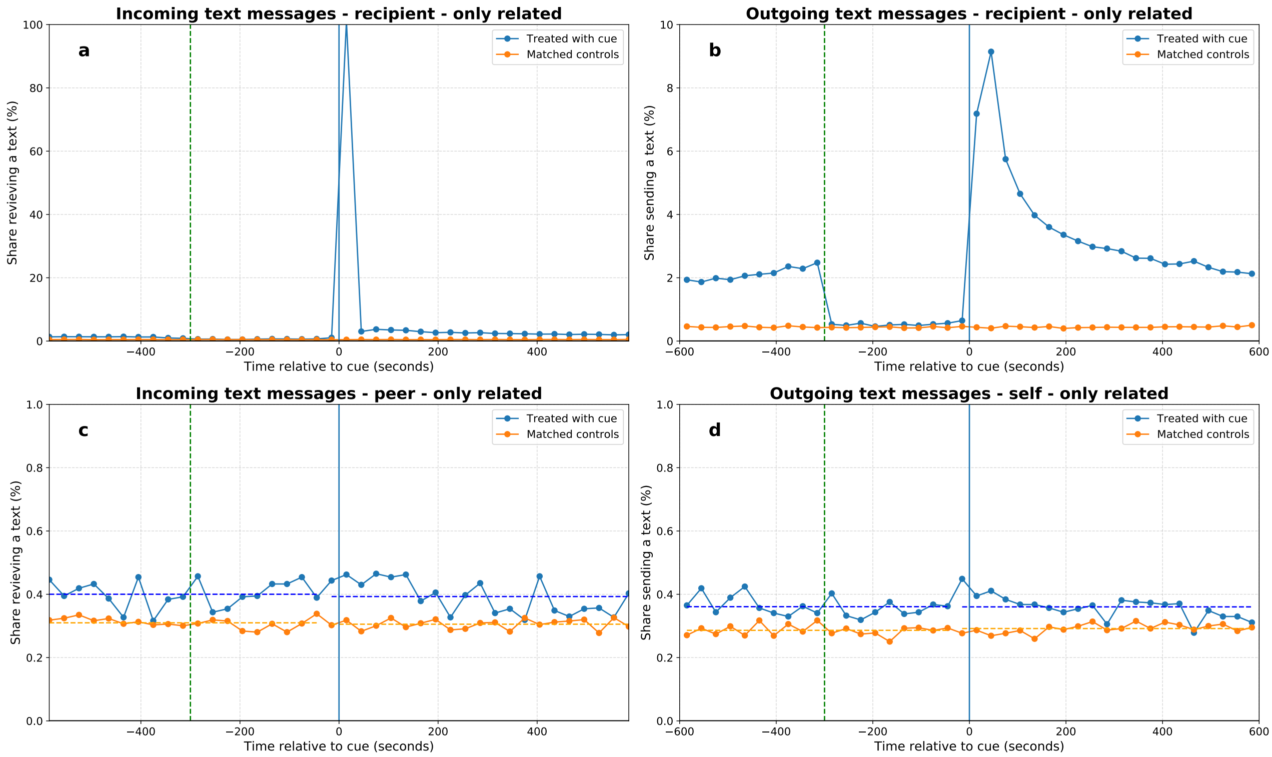

Figure 3: Share who receives or sends at least one text message 10 minutes before and after cue arrival in treated (blue) and control (orange) situations. Panels a,b show measures for recipients while panels c,d contain measures for the peers. The dashed blue and orange lines show the average likelihood before and after the reference. The green lines show the onset of imposing the conditioning of no communication between the sender and recipient of the cue. Note that the scale of the vertical axis of panels a and b are respectively 100 and 10 times larger than that of panels c and d.

for the recipients (panel **b**) is higher in the post-period, which suggests that the first text raises the probability of back and forward communication. Further, we notice that the distribution of outgoing texts in the post-period seems to exhibit exponential decay, resembling recipients' screentime distribution.

Turning to incoming texts for peer (panel **c**), we see that the development is relatively stable over the period and does not show indications of a spike around treatment. We see the same pattern for outgoing texts, though there might be a slight tendency of a spike in the period before treatment of the recipients. As discussed earlier, this is within the treatment period of the peers since phones are not perfectly synchronized. Had this spike been more substantial, it would have been an indicator that the initial text, through social contagion, triggers a new text from the peer to a person outside the social situation. However, we do not find sufficient evidence for such an effect, though we cannot entirely reject it.

Heterogeneous effects

We proceed with an exploration of whether certain kinds of social ties conduct social contagion better than others. We maintain the focus on individuals who know each other in addition to being physically co-present. We analyze how the magnitude of the cues' effect on the recipient's and peer's screentime depends on the individual characteristics of the two people present with respect to similarities and differences in their gender, network centrality, and personality traits.

When analyzing heterogeneous effects, we follow [7] in looking at relative difference in the composition of the dyad. Thus, we look at same-sex dyads vs. difference-sex dyads and the relative level within the dyad of centrality and personality traits, respectively.

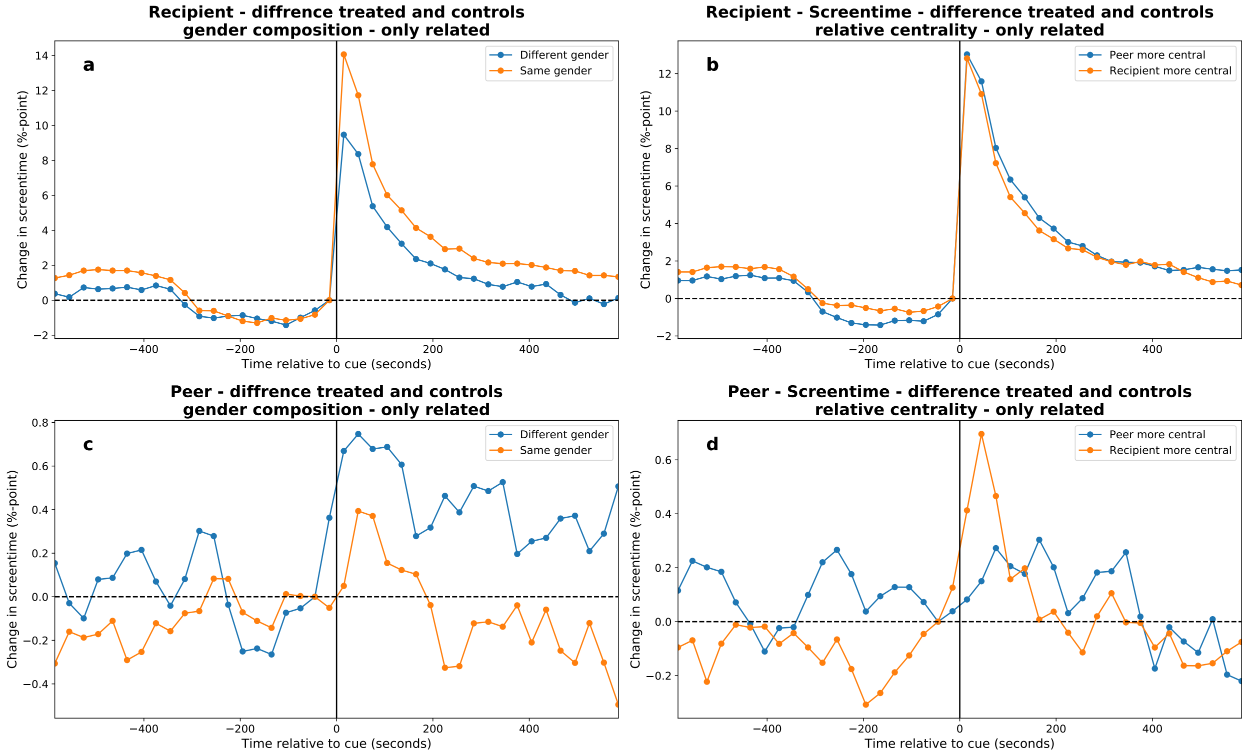

Figure 4: Screentime split on gender composition (Panel a and c) and relative eigenvector centrality (Panel b and d). Shows difference between matches and controls centered in the reference period. Green lines show timing of conditioning on no communication between texter and recipient in time before cue. Dashed black lines indicate the reference.

Gender We explore how smartphone contagion depends on the gender composition of the dyad, motivated by gender sociologists who argue that gender is the primary cultural frame for coordinating social behavior and that gender inequality is continuously reproduced in face-to-face social interactions [43, 44]. Further, men and women have been found to have different phone etiquette [16]. Figure 4a and 4c shows that whereas the cue's effect on the recipient's screentime is stronger for same-sex dyads, its effect on the peer's screentime is stronger for different-sex dyads.

Centrality In sociology, network centrality has long been seen as an indication of an individual's social status or influence [23]. We look at how relative eigenvector centrality within the dyad affects our results. Eigenvector centrality measures how many well-connected individuals an individual is connected to and has often been interpreted as an individual's influence or prestige within a network [36]. Figure 4b and 4d show that whereas the cue's effect on the recipient's screentime does not depend on whether the recipient or the peer has the highest eigenvector centrality, social contagion is only present when the recipient has the highest centrality measure.

Personality traits Figure 5 explore heterogeneity depending on the big five personal traits, which are central indicators within the field of psychology [21]. Figure 5 shows the differences in development in screentime depending on whether recipient or peer has a higher value of the given personal trait. Looking at the left side of Figure 5, it does not seem that the relative composition of the different personal traits matter much in terms of recipients reaction.

However, there are indications that the peer's reaction is stronger when the peer has the highest conscientiousness. High conscientiousness is associated with having high self-discipline and being less impulsive. It might seem counter-intuitive that the peers with higher conscientiousness react more strongly. However, it could indicate that less impulsive people, who have control over endogenous cues, react stronger to exogenous cues. However, this result is only exploratory and requires further research. Looking at the other personal traits, we do not find substantial differences.

Conclusive discussion

We have shown that smartphone use is socially contagious. This shows that smartphone use is not just an individual choice but also a collective choice. As previously mentioned, smartphone use can possibly have negative consequences for mental health and for social relations. This implies that individuals have a moral obligation to consider how their smartphone use affects others. Further, our results can point to the need for smartphone regulation (either through rules or social norms) in certain settings, where interruptions might be especially harmful to productivity or social relations, such as schools, workplaces, or social and intimate relations. However, since we find no evidence of environmental contagion, we find no support for general

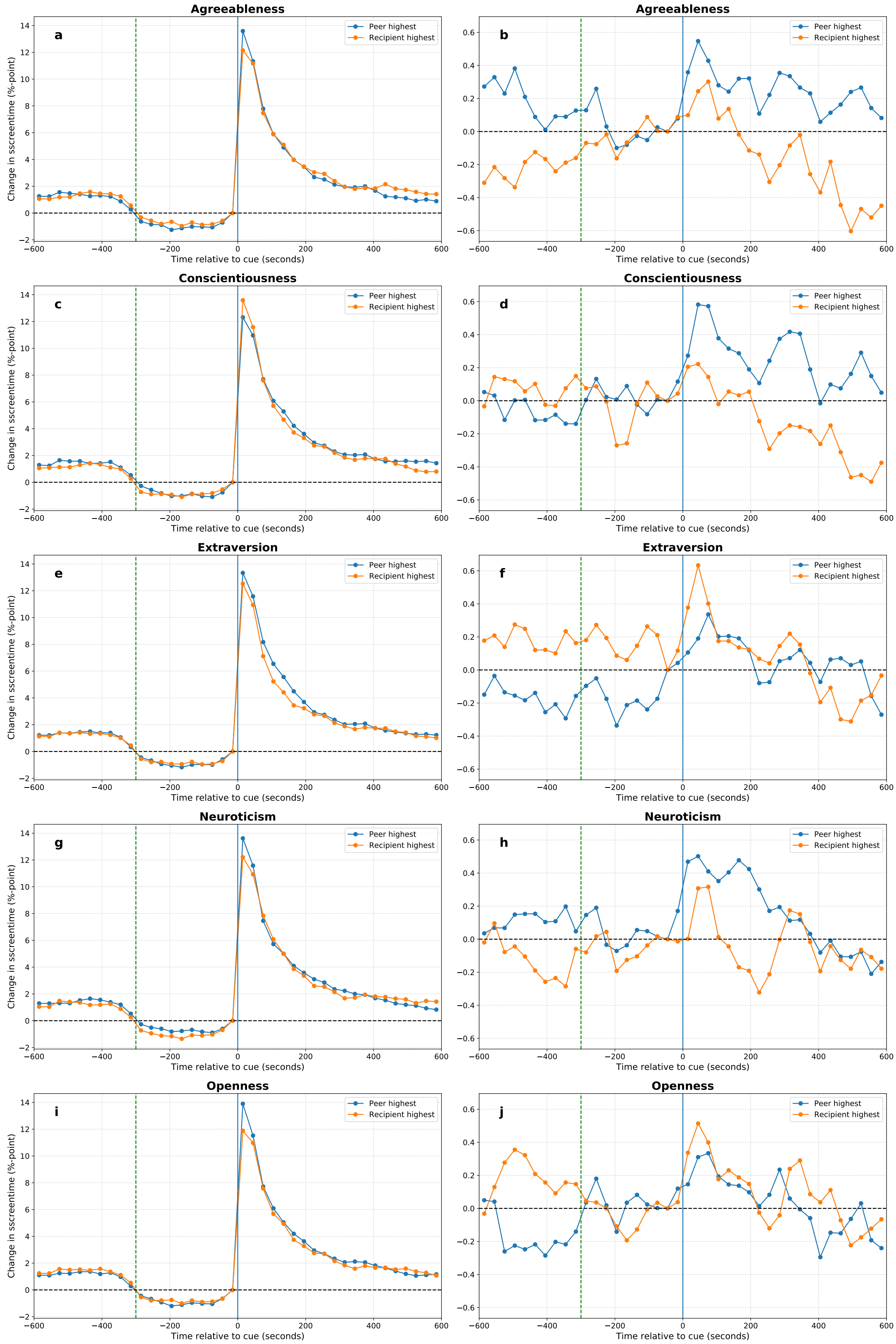

Figure 5: Development in screentime split on who has the highest score in each of the big 5 personality traits (if same score peer is counted has highest). Only related dyads. Shows difference between matches and controls centered in the reference period. Green lines show timing of conditioning on no communication between texter and recipient in time before cue. Dashed black lines indicate the reference.

regulation of smartphones in public spheres such as public transport, parks, or cafes.

As shown in Table 1 we find an average increase for related peers screentime of 0.27 percentage points over the 4 minutes following the reference, which corresponds to an average of 2/3 seconds of additional screentime for each received text message. There are several reasons to believe that this estimate underestimate the actual effect substantially.

First, the estimates reported so far, can be described as "intention to treat"-estimates, since it covers the average effect of all cues. Since only roughly 1 in 8 (13 percent on average) of receivers start looking at their phone when the cue arrives, only a subset of the peers in this analysis is actually exposed to the behavioral effects stemming from the cue. Therefore, we believe the actual peer effect to be substantially higher. When we condition on situations where the recipient switches to start using the phone, our effect estimate on the screentime is three times larger, see Appendix C.

Second, though related peers are co-present, they might not be engaged in social interaction. For example, they might sit together studying on separate assignments or at separate tables in the campus canteen. It is also possible that phones are not a part of the social situation but put in separate back bags in a corner. Both examples will lead to an underestimation of the effect. Our data do not allow us to control for examples like these. Further, since not all students at the campus are included in the study, we cannot exclude that in some situations, the dyad is not the only people present, which might also lower the effect.

Though some interruptions might be brief, they can still have extended consequences. As discussed in the introduction, even small interruptions or moments of inattention might have consequences. For example, [34] shows that small interruptions increase the risk of errors when returning to the present task ("resumption errors"). Further, the feeling of being phubbed or that your conversation partner is less responsive can have substantial negative consequences for the development of close social relations and intimacy [48].

Aggregated effect

Interruptions from notifications have become a big part of modern life. In 2018 the average American smartphone user received 46 push messages every day [2]. A separate report finds that on average 7% of notifications are reacted to - this corresponds to a little more than half of the reaction effect we find (13%) [1]. According to Pew Research Center, 85% of adults in the USA own a smartphone [3], which corresponds to 175 million people. Suppose we assume an average peer effect on notifications on half of our findings from SMS (2/3 seconds), and that

1/10 notifications are received in social settings, the accumulated peer effects correspond to 8.5 years of human life (3,100 days) every day in the US alone. We believe that these back of the envelope calculations illustrate how small average effects can have massive consequences on a societal scale.

Is phone use always optimal?

From an evolutionist or a rationalistic point of view, it is possible to argue that if an individual decides to look at his/her phone, it is probably optimal. However, this is not necessarily the case. [48] argue that there is an "evolutionary mismatch" between attending to the smartphone and maintaining high-quality close relationships. An evolutionary mismatch can happen because humans have begun living in environments that diverge vastly from those in which they evolved, and therefore critical aspects of psychological mechanisms may no longer be linked to the environment in the same way [30].

A classic and oft-cited example of an evolutionary mismatch is humans' desire for sweet-tasting food, which signaled nutritional value in ancestral environments. In most industrialized societies, these signals are now used to sell sugar-enhanced foods, which leads to adverse health outcomes. Similarly, directing attention to cues like sounds and vibrations might have been optimal in ancestral environments, even during deep social interactions. However, in present days, attention-grabbing devices can take advantage of the evolved tendencies by artificially cueing our subconsciousness. [57] call these cues "supernormal". In short: Reacting to cues similar to smartphone cues was beneficial in the past but can be adverse today.

A rationalistic argument why reacting to a match phone cue might be adverse in social settings is to view collective attention as a common good that can only be sustained if all individuals' attention is directed to the social situation. When receiving a text, it might be optimal for the individual to break the collective attention by looking at the phone, but sub-optimal for the group as a whole. In this view, some kind of restriction on phone use would be optimal. This could either be in the form of banning phones from certain situations (e.g. school) or social norms disapproving asocial phone behavior.

Materials and Methods

Data

The data for this study was collected data from September 2013 until September 2015 as part of the Copenhagen Networks Study (CNS) [51]. The participants in CNS were students from the Technical University of Denmark who volunteered to receive a smartphone that continually monitored a broad range of behavioral measures. These measures included timestamps for each time the phone screen was turned on or off and the distance to nearby participants, as measured by the strength of the Bluetooth signal between the participants' phones. The participants consented to take part in the study, had access to their own data and could withdraw, and have the data deleted at any time (for more details, see [51]). CNS was approved by the Danish Data Supervision Authority in 2013. Before the start of the study, the data collection period was planned to terminate after two years.

Our dataset is constructed from aggregating smartphone usage at the 5-second level, from which we construct 5.33 billion screentime observations. Each observation measures the percentage of time the screen of the phone was turned on during the 5 seconds. See [8] for details about how the measure was computed from the raw data, including how the raw data was cleaned by removing data points where the phone sensors were not functioning properly.

We observe the participants receive 2.01 million text messages over the study period. After filtering out observations with any missing data 10 minutes before or after receiving a text message, there are 1,768,352 text messages. This corresponds to 424 million screentime observations in the 20-minute window around the time the text message is received. We further limit the sample to situations containing two individuals (dyads), where the text is not between the recipient and the peer, the peer and the texter (the user sending cue) have not communicated (by call or text) 5 minutes before the cue, and no text is sent between the peer and the texter 15 seconds before and after cue. After filtering in this way, we end up with a treated dataset consisting of 56,219 cues, each monitored on 5-second intervals 10 minutes and after giving a total of 13,492,560 observations. The dataset consists of 779 individuals forming 10,745 unique dyads.

To observe a counterfactual setting, we constructed a control data set, which does not condition on recipients receiving at a cue at time 0. However, both recipients and peers could still receive and send texts over the 20 minute period. To find these counterfactuals for each cue, we found observations where only the same dyad was present, maximum four weeks from the cue. We further conditioned the control observations to not be on the same day, but at the same time of day +-1 hour, and we matched weekends with weekends, and the same for weekdays, and observations attending or not attending class. For each cue, a maximum of 5 observations we kept. The final control dataset consisted of 34,855,200 5 seconds intervals distributed on 145,230 unique situations. 40 percent of the treated situations had at least 5 matches, 4.2 percent had 4 matches, 5.5 percent had 2 matches, 8.9 percent had 1 match, while no match was found for 34.1 percent of treated observations. Thus, we have an unbalanced matching dataset, which is partly due to that non-related dyads have fewer interactions. We control for this, by doing the analysis separately on related and non-related dyads, and by having fixed effects on the match-level and cluster standard errors on the match-level.

The exact definition of co-present peers is participants who scan each other using the Bluetooth sensors and where the associated signal strength (=RSSI) exceeds -83, which corresponds to 3m distance between phones [49]. When further removing observations where there are no social peers or there is missing screentime data for peers, we are left with 180,493 text messages.

Method

Our primary analysis uses a fully dynamic fixed effects model implemented on the match level using the equation below. The equation is based on matching situations where a cue arrived with situations were no cue arrived.

$$S_{s,m,t} = \sum_{\substack{h=t_0 \\ h\neq -1}}^{t} \beta \mathbb{1}_h(T_{s,t}) + \sum_{h=t_0}^{t} \tau \mathbb{1}_h(T_{s,t})\mathbb{1}_1(c_s) + \rho_m + \epsilon_{s,m,t} \tag{1}$$

Equation 1 shows a fully dynamic fixed effects matching model [5, 9], where the outcome $S_{s,m,t}$ represents the share of the period where the user's smartphone screen was activated. β and τ are vectors of coefficients, with τ containing the effect estimates for treated situations, which are our primary coefficients of interest. s indexes the social situation containing 10 minutes before and after the cue, t indexes the 40 30-seconds intervals within each 20-minute social situation, with the period before the cue as reference. m represents the match level, e.i., the treated observations, and all the observations matched to it. c_s indicates whether or not a cue arrived in the situation or not.

The function $\mathbb{1}_a(\cdot)$ is an indicator function that equals 1 if the input is equal to a and otherwise 0. The variable $T_{s,t}$ indicates the difference in the index of the time intervals for the observation and the index of the time interval of the cue. ρ_m represents a fixed effect on match level m (treated observation and observation matched to it). ϵ represents the error term. The equation is estimated separately for recipients and peers. We use robust standard errors clustered on the match level [61], allowing correlation in the error term within matched situations. Further, standard errors are allowed to be correlated over time, as long as the is no unit root, which corresponds to the effect dying out over time [61], which our data support.

Matching models are often used to construct counterfactual situations in setups where all individuals are treated at some point [24]. Model 1 uses such a matching setup, by matching each treated situation, with up to 5 similar untreated situations. The fundamental identifying assumption is that treated situations, on average, have developed as matches situations, had the recipient no received a text message. We find this plausible, since trends develop in parallel before the cue. This way, we can identify the causal effect on both recipients and peers when a text message is received.

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Appendices

A Raw screentime 5 seconds level

Figure 6 shows development in screentime on a 5 seconds level for treated and control observations, respectively. The data used to constructed Figure 6a and 6b is the same used to construct Figure 1a and 1c, the difference being, that Figure 6 in only aggregated on the 5-second level. In accordance, we see that the figures are very similar, though graphs on the 5-second level are noisier.

Note how there is no increase in recipients screentime in the 30 seconds before the cue is received. We see this as evidence that recipients do not anticipate the arrival of the text message.

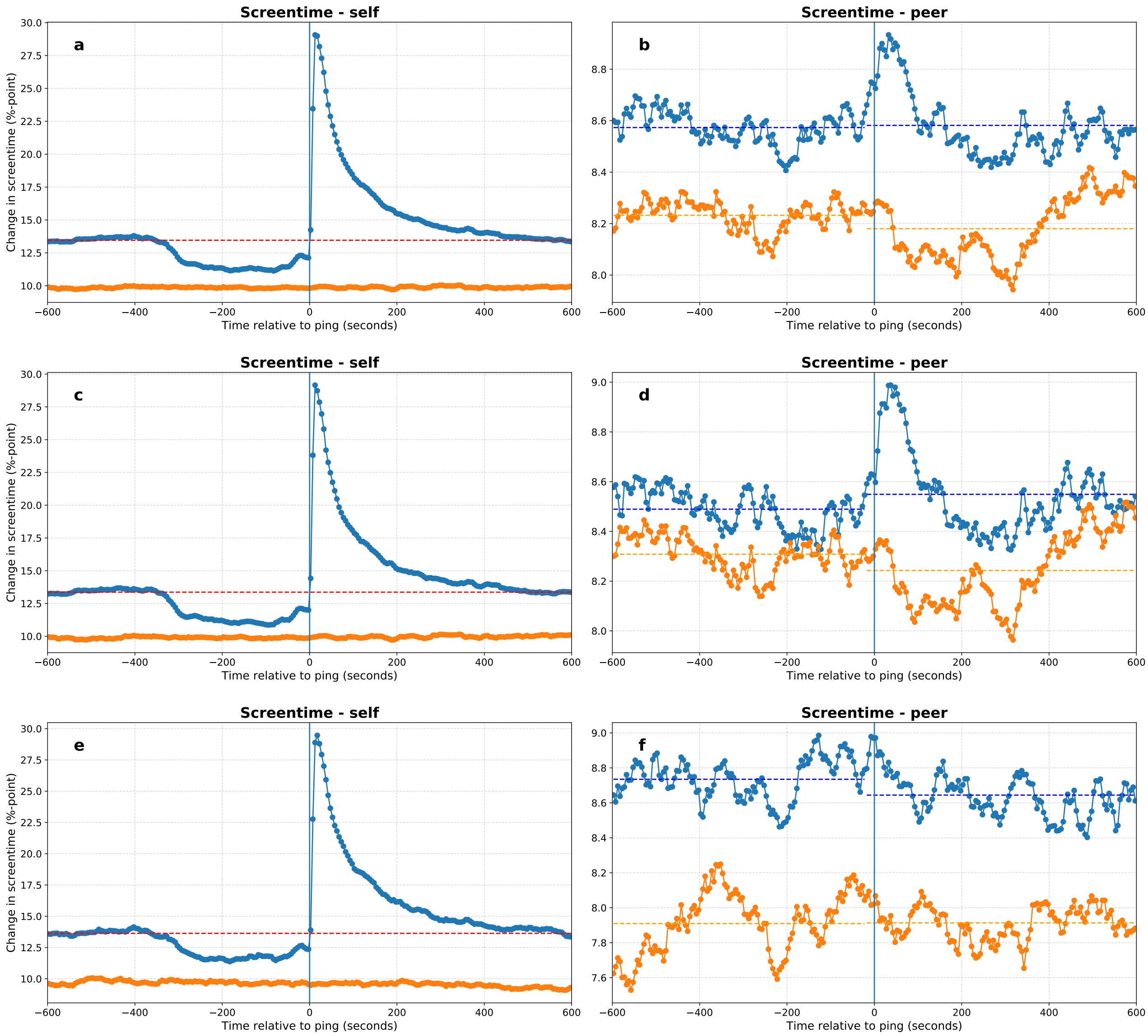

Figure 6: Average of mean raw screentime for each 5-seconds interval for recipients (left side) and peers (right side). Top, middle and bottom row show all observations, only related observations, and only non-related observations, respectively. Blue lines show treated observations, while orange lines show control observations. Dashed horizontal lines show show average before and after cue for treated (blue) and controls (orange).

B Displacement and timing of cue

Our effect measures rely on the exact timing for the arrival of a text message, i.e., the cue timestamp. However, each phone often tends to only approximately synchronize their clock, which in turn leads to temporal displacement in the cue timestamp.

We measure the distribution of temporal displacement between phones by matching calls and text messages recorded to be within the same 10-minute window. As we cannot inspect the content of the message and conversations, we assert that the calls and text messages recorded at the senders' and recipients' phones match by requiring that within the 10 minutes window, there is only a single match. This leaves us with 70,788 observations. From each of the temporal displacement measures, we subtract the median difference, which corresponds to the most common time to either connect in phone calls or for the text message to arrive. Figure 7 plots the estimated displacement. The plot shows that it is common for phones to have some displacement. 16% of the observations have more than 30 seconds displacement, and 9% of the observations have more than 60 seconds displacement.

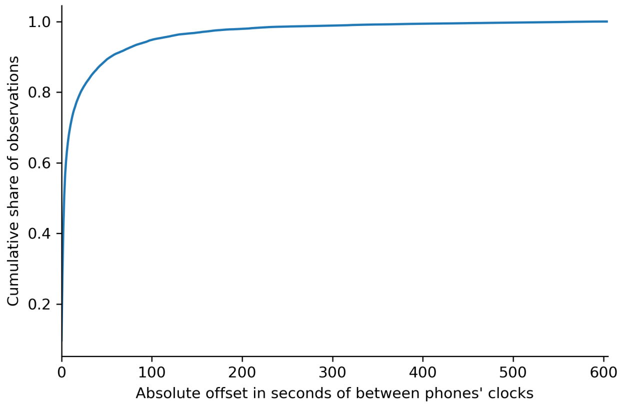

Figure 7: Distribution of temporal displacement between smartphones

To understand how these temporal measurement errors alter our effect estimates, we simulate what the screentime development would have been if the time to cue would be shifted according to the measured displacement. We compute the alternative screentime for the recipient under each of the shift measures and then take the mean at each point in time over these measures.

To isolate how the displacement affects the estimate, we begin under the assumptions that the pre-cue level is constant and equal to the level 10 minutes before. We estimate a fully dynamic fixed effects model [5, 9] in the form below:

$$S_{s,h} = \sum_{\substack{h=t_0 \\ h \neq -1}}^{t} \beta \mathbb{1}(T_{i,t} = h) + \mu_s + \epsilon_{st} \tag{2}$$

Equation 2 is estimated separately for recipients and peers. The variables uses the same notation and conceptual framework as Equation 1. However, the model does not rely on matching and thus one crucial difference is that fixed effects are at the situation level. Therefore, μ_s is an intercept for each social situation, which accounts for situation-specific characteristics that might affect smartphone use. We use robust standard errors clustered on the situation level [61].

Figure 8a demonstrates how displacement affects the estimates when the pre-cue screentime is held constant. The plot shows that after adjusting for displacement, a substantial part of the cue effect sets in on the recipient screentime use even before the arrival of the cue. Moreover, the effect in screentime use is lower in the immediate aftermath of the cue arrival, meaning that estimates are biased downwards.

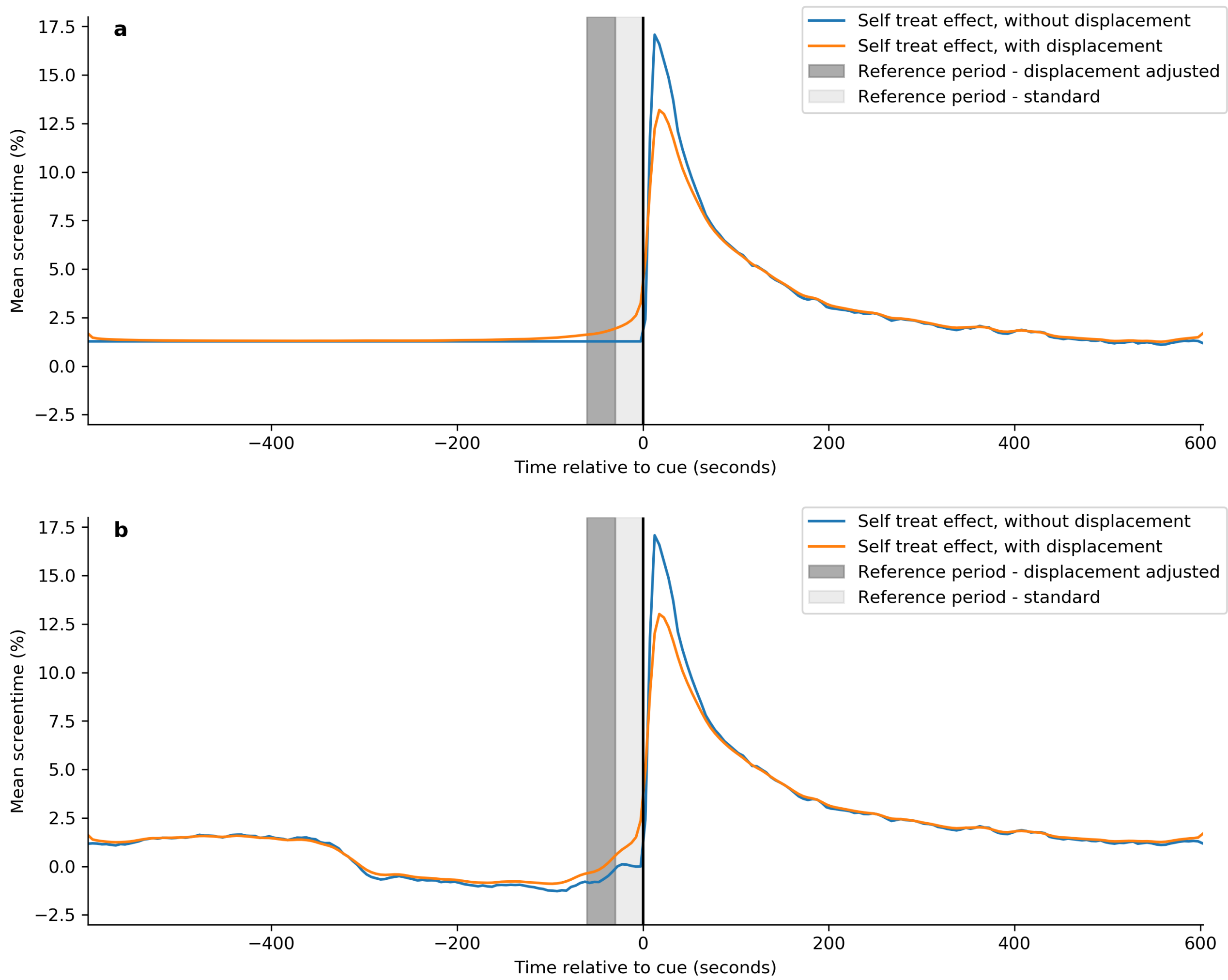

Figure 8: Estimated treatment effects of cue on recipient when correcting for displacement. The effects are obtained by simulating the development in screentime when displacement is sampled from the distribution of estimated displacement. Panel a) shows the screentime of the recipient around the cue when it's assumed that screentime prior to the cue was constant and equal to the initial level 600 seconds before. Panel b) shows the screentime of the recipient around the cue when using raw data on screentime prior to the cue.

We proceed with relaxing the assumption of constant pre-cue screentime use. Figure 8b shows the screentime use after adjusting for temporal displacement. Again, screentime before the cue arrival increases substantially. In particular, it is seen that the screentime after adjusting for displacement in the period 30-60 seconds before the cue arrival corresponds to the level 0-30 seconds before without displacement adjustment. This illustrates that the reference period should be 30-60 seconds prior to cue arrival as this corresponds to the unadjusted level of screentime use. Again, the smartphone use immediately after the cue is also substantially lower after adjusting for displacement.

C Treatment conditional on reaction

As previously stated, we might underestimate the effect of the recipient's screentime on the peer's screentime since the recipient will not always choose to look at the phone. To examine if this is actually the case, we limit the sample to only consist of situations where the recipient used the phone less than 15% (9 seconds) in the minute before cue and at least 80% (48 seconds) in the minute after cue.

We see in figure 9 **d** that the social contagion effect after the cue tops at around 1.5% points, which is three times the effect estimated in the unrestricted case. We see this as an indication that stronger treatment means a higher peer effect. However, the causality of this effect should be treated with care since we condition on screenuse after treatment.

The difference in peer's average screentime the first four minutes after treatment is 0.56%-points, corresponding to an average peer effect of 1.4 seconds.

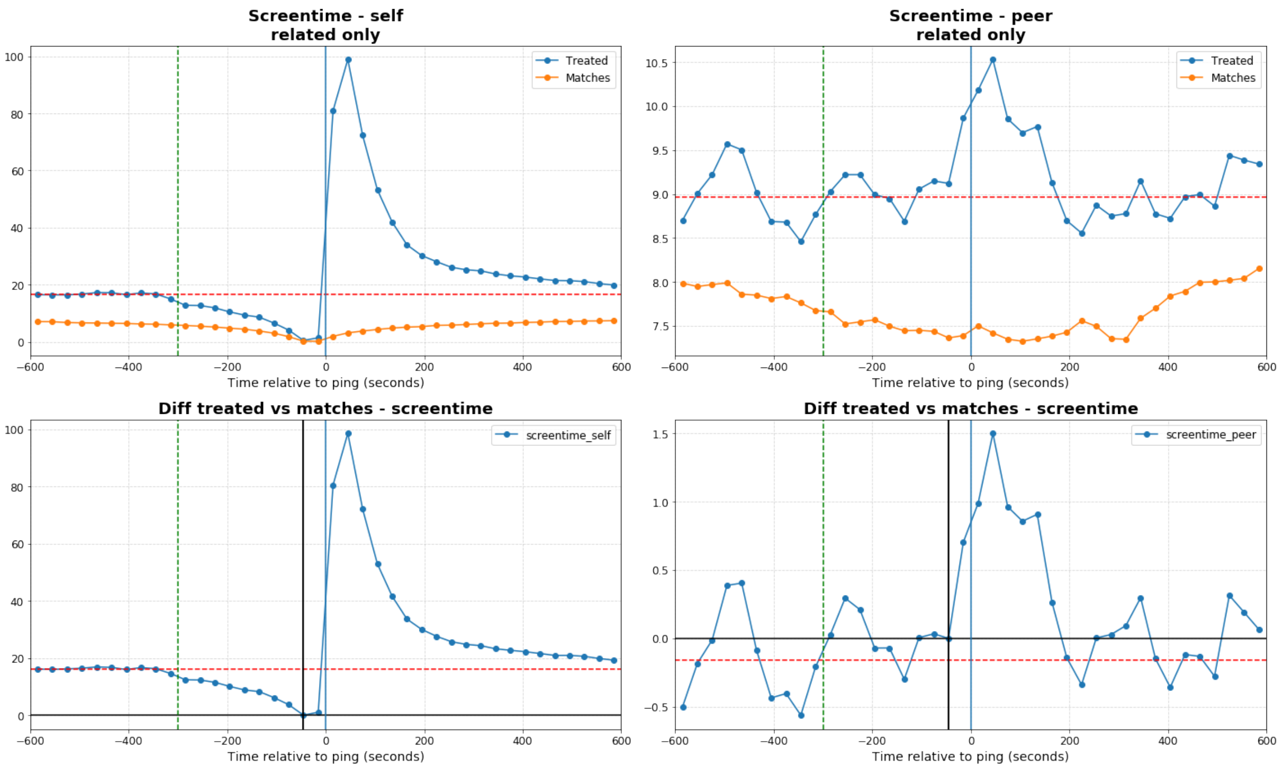

Figure 9: Restrictions: Average screentime 1 min before less than 15% (both treated and matched), average screentime after more than 80% (only for treated)

D The literature of smartphones impacts on humans

Smartphone's impact on individuals

This section summarizes the current literature on how smartphones impact individuals, and then in the next section how it impacts relations.

[60] review the literature on how smartphones affect cognition and outline evidence that smartphones affect our attention, memory, and patience. Central results regarding attention are [52] who shows that smartphone notifications can be distracting, even when the user does not respond to it, and [53] who show that the mere visibility lowers the performance in demanding cognitive tasks. Further, [34] have shown that the risk of making "resumption errors" - errors that arise in tasks that are resumed after an interruption - increases steeply when the interruption lasts more than 15 seconds, which is often the case in interruptions from exogenous smartphone cues.

Regarding memory, [50] show the "Google effect" on memory (sometimes called digital amnesia or transactive memory) which describes that we remember less because we can easily access information on our smartphone.

Finally, in regards to patience, there is evidence that smartphone use inhibits our ability to delay rewards. [59] shows that people who use their smartphone more have more preferences myopic in a waiting game and that this can be contributed to higher impulsivity. Further, [19] study a group of non-smartphone users, randomly hands out smartphones to a subgroup, and shows that this subgroup becomes more myopic in a waiting game, after receiving the smartphone.

Smartphone's impact on adolescents and young adults

The study of smartphone use in adolescents and young adults has received much attention - both from researchers and the media. Fears that smartphones are harmful to the youth have gotten significant media coverage [10, 54]. Further, research does indicate that smartphone use is correlated to adverse outcomes for young people. However, as we will discuss, these findings have to be interpreted carefully and with questions of causality and heterogeneous effect in mind.

[40] finds that smartphone use correlates negatively with mental well-being, but that marginal decrease is substantially higher with higher levels of screen use (more than 2 hours a week for weekdays) and that at lower levels (less than two hours for weekdays) marginal increase in

smartphone use might actually be associated with positive effects on mental well-being. They label the idea that there is an optimal sweet spot for smartphone use (where both higher and lower use of digital devices decrease mental health) the digital Goldilocks hypothesis. [38] find significant, but a small, negative association between smartphones and well-being, similarly [13] finds only a weak association between excessive screen use and depression. [17] raise questions about course and effect by showing that threats to social development and cognitive performance in the online world are being mirrored in the offline world.

Though smartphone use might not be harmful to all individuals, there are worries in the literature that psychologically vulnerable individuals, and individuals from weaker social backgrounds, are at higher risk of developing problematic smartphone use, which can exacerbate existing inequalities [37].

On the other side of the spectrum, there is also substantial evidence that smartphones can be used actively to improve mental health interventions targeted at reducing anxiety [15].

All in all, the literature on smartphones' effect on the youth has not yet reached a consensus. Within the field, there are calls for more large-scale social data sets and quasi-experimental studies that can access issues of causality [13, 17, 35, 38, 48].

Intimacy, close social relations, and trust

We now turn to look at the literature on how smartphones might affect our social relations.

When developing close and intimate social relations, two of the primary components are self-disclosure and (perceived) responsiveness [48]. Both require attention in social interactions. Self-disclosure is disclosing thoughts and feelings to another person, thereby deepening the relationship and strengthening trust. However, for a deeper social connection to happen, self-disclosure needs to be accompanied by responsiveness from the receiver. The person self-disclosing needs to feel that the listener conveys understanding, validation, and warmth [41]. Responsiveness is important in a wide range of relationship types such as romantic couples [11], leaders and subordinates [25], and physicians and patients [42]. Further, these processes facilitating closer relationship leads to better health and well-being [48].

Smartphones can be disruptive to social interactions. So much so that it has gotten it own term: Techonoference, which refers to how smartphone use may interfere with or intrude into everyday social interactions. (Related terms are phubbing - snubbing/ignoring other people by looking at your phones - and pphubbing - phubbing your partner) For example, [20] shows that a greater self-reported frequency of texting predicts lower relationship quality a year later, whereas low relationship quality does not predict future texting. Likewise, [45] finds that Pphubbing leads to relationship conflicts, which impact relationship satisfaction negatively and ultimately can lead to lower life satisfaction and depression.

Socially contagious mobile phones

[22] examines how mobile phones change the way we interact. He uses ethnographic methods to describe the social processes that start when someone in a social interaction receives a phone call and describe them as an (often subconscious) choreographed "dance." When the call is received, "[T]he non-using partner has to engage in symbolic behaviors that suggest valuable activity." When the phone user gets ready to end the conversation, "the non-participating partner mysteriously is able to resume focus on the mobile phone user, and begin engaging the user visually." Further, he describes how "the co-present partner, who had not been using his/her mobile phone, will often be prompted to begin using his/her own phone.", and that "Mobile phone use in public therefore seems to beget yet more public mobile phone use." Further, he points out that although mirroring in social situations is usually associated with companionship, it is not the case for mobile phones because people go from being present in the social interaction to being absent-present (as [18] calls it). Though Katz's study focuses on received calls, we believe that it illustrates that the social processes occurring, when social interactions are interrupted by a mobile phone, are both complex and latent.

Apart from [22] contagion in mobile phones has (to our knowledge) only been studied by [14]. In the observational study, they find evidence that smartphone use correlates between peers having lunch. However, smartphone contagion has not been studied in a large field experiment or and no causal evidence has been provided.

More broadly, social contagion has been shown by [6] who use weather conditions to causally show how peers across the US positively affect each other's exercise patterns. [33] shows how cashiers are more productive when they can be observed by high-productivity colleagues, compared to when they can be observed by low-productivity colleagues (though [55] have problems reproducing this finding in the lab).

Social contagion in network science

Social contagion is intensely studied within the field of network science. Models of social contagion study how phenomenons as news, gossip, and diseases spread through a social network (see [56] and [26] for a recent reviews). In the context of this literature, we zoom in on the dynamics of contagion from one node to another. Extending this to looking at propagation through the network would be interesting, but we leave this to further research. However, we do believe our results can be useful to network scientists, as it helps to understand the mechanisms of social contagion, which, e.g., [27] have called for.