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Privacy Choice during Crisis

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Abstract: Consumers' privacy choice between withholding and sharing personal data may change during crises. Crises not only alter personal considerations of benefits and costs of this choice, but also trigger societal considerations, such as use of shared data in crisis management. While the literature on privacy choice has focused on personal considerations, research on how this choice is influenced by broader circumstances remains sparse. We address this topic by leveraging newly available location big data and a global public health crisis as a natural shock. Analyzing 22 billion raw records of inter-temporal individual-level mobile location data across a wide spectrum of cities in the United States, we present first large-scale evidence that opt-out reduces during a crisis, and societal, beyond personal, considerations, might have influenced consumers' privacy choice.

1. Introduction

Consumers' privacy choice, between withholding and sharing personal data, bears significant implications to consumer well-being, firm data strategies, and government regulations. The literature has examined this choice as a personal cost-benefit trade-off, such as giving up privacy in exchange for map service (Acquisti et al. 2016). Nonetheless, human history is replete with crises, from natural disasters to social, economic, and public health crises. Crises influence the privacy choice, for instance, by elevating social solidarity and societal considerations, such as uses of shared personal data in crisis management (Douty 1972, Ferraro et al. 2005, DeWall and Baumeister 2007, Weinberger and Wallendorf 2012, Dunn et al. 2020, Chen et al. 2020). Such considerations have been under-explored in consumers' privacy choice. Our study, leveraging the latest granular big data, aims to address this gap.

For example, during the latest pandemic, while personal considerations, such as app usage, may have changed, societal considerations also entered the calculus of consumers' privacy choice. In particular, smartphone location data[1], despite their privacy concerns, have been publicized to help detect hot spots, predict epidemiological trends, plan healthcare capacities, and devise broader mitigation strategies (Grantz et al. 2020, Oliver et al. 2020)[2]. Reminiscent of the increased consumer acceptance post-9/11 to government surveillance[3], 58% (84%) of the U.S. adults have indicated willingness to share their location (health) data to help public officials flag hot spots during the pandemic[4]. Two thirds of the Americans, particularly those at higher health risks, younger, and more technologically savvy, are willing to install an app that helps reduce the viral spread and lockdown duration, even if the app collects their location and health data[5].

Despite theoretical and anecdotal indications, empirical investigations on consumers' privacy choice during crisis remain scant. *Will consumers reduce opt-out during a crisis when societal considerations escalate?* This investigation holds important implications to consumer well-being and firm strategies toward data infrastructure, ethical use of data, and consumer-facing communication. It also illuminates government regulations and public-private collaborations on data collection and data usage, particularly when crises or other societal needs for data emerge. Our study therefore explores this interesting and quintessential topic of theoretical importance and broad value to business and society. Specifically, leveraging a latest form of population-scale big data (mobile location data) and an external shock (global public health crisis), we examine:

(1) Have consumers reduced opt-out during the crisis?

(2) Is this reduction, if any, more pronounced for those with greater societal considerations?

To accomplish the above, we analyze 22 billion records of inter-temporal individual-level mobile location data from 20 U.S. cities. We first contrast the individual-level (and CBG-level) opt-out of location data sharing before versus after the crisis shock, to examine if consumers have changed their privacy choice, i.e., reduced opt-out. We then compare the magnitude of this change across consumers of varied levels of societal considerations, measured by their compliance with the public health policies and their individualism indices, while accounting for their core personal consideration of mobile app usage during the crisis. This allows us to infer whether societal, beyond personal, considerations play a role in any opt-out change during the crisis. We further explore additional psychographic (political ideology) and demographic (income, gender, race) heterogeneities.

In this process, we employ a multitude of methodologies, including geographic information system (GIS), machine learning, and spatial-temporal statistical analysis. We find that consumers have indeed reduced opt-out after the onset of the crisis. More importantly, the reduction is more pronounced among those with greater societal considerations, even after accounting for personal considerations. The reduction is also heterogeneous across psychographics and demographics. For example, the Democratic areas have experienced stronger opt-out declines.

In summary, our investigation broadens the growing literature on consumers' privacy choice from *personal* considerations to an added dimension of *societal* considerations (Goldfarb and Tucker 2012, Tucker 2013, Acquisti et al. 2016, Johnson et al. 2020, Macha et al. 2023). It offers initial large-scale empirical evidence that consumers have reduced opt-out during a crisis, and that the magnitude of this reduction is related to the extent of societal considerations. Relatedly, while the literature has accentuated the impact of consumers' privacy choice on *business outcomes*, such as revenues, innovation, advertising (Tucker 2013, Goh et al. 2015, Bleier et al. 2020, Johnson et al. 2020), crowdfunding (Burtch et al. 2015), personalization (Chellappa and Shivendu 2010, Lee et al. 2011), and competition (Lee et al. 2011), our research illustrates potential *societal implications* of consumers' privacy choice. Finally, this research showcases the value of the latest big location data to studying impactful business and societal topics.

The remainder of the manuscript is organized as follows. We will review the relevant literature in Section 2, introduce the data in Section 3, and models in Section 4. Then we will report the empirical findings in Section 5 and discuss the policy and managerial implications in Section 6.

2. Literature

Privacy choice. The public and private sectors' increased access to and use of granular consumer data have triggered widespread interests in consumers' privacy choice. This choice between privacy (i.e., withholding personal information) and divulgence (disclosing personal information or sharing personal data) has been framed as a personal cost-benefit trade-off (Acquisti et al. 2016, Wedel and Kannan 2016). The *costs*, primarily referring to privacy risks, may stem from misuse or theft of private financial or health records, or identification of a consumer's daily activities in the case of location data (Macha et al. 2023). The *benefits*, on the other hand, range from promotional coupons (Chellappa and Shivendu 2010) and reduced insurance premium (Soleymanian et al. 2019), to personalized services (Chellappa and Shivendu 2010) and rewards in social interactions (Jiang et al. 2013).

A variety of factors moderate consumers' willingness to share personal data, including (a) subjective factors, such as cognitive efforts devoted to a privacy choice (Dinev et al. 2015), perceived divulgence risks (Adjerid et al. 2016), anonymity of self (Jiang et al. 2013), or control of personal information (Xu et al. 2011, Tucker 2013); (b) demographics, such as age, wealth, technological sophistication, although the direction of these effects often varies with specific contexts (Goldfarb and Tucker 2012, Johnson et al. 2020); (c) externality, such as whether others are willing to divulge (Acquisti et al. 2012) or have registered with the do-not-call list (Goh et al. 2015); and (d) context or task related factors, such as descending or ascending intrusiveness of the information requested (Acquisti et al. 2012), framing of privacy options as "privacy setting" versus "app setting" (Adjerid et al. 2019), or hypothetical versus actual privacy choice (Adjerid et al. 2016).

Societal considerations during crises. Personal considerations when sharing data may change during a crisis. For instance, the public's perceived privacy costs when sharing data with authorities might decline due to increased uncertainty and need for guidance (Siegrist et al. 2005, Palen and Liu 2007, Lindell and Perry 2012). Also, perceived personal benefits might grow in exchange for valuable services during a crisis, such as medicine delivery or neighborhood risk alert (Acquisti and Grossklags 2005).[6] Meanwhile, societal considerations become more salient. On one hand, broader media coverage explicates uses of personal data in crisis management despite privacy concerns, such as location data to epidemiological forecasting. Crises also catalyze new social norms and behavioral expectations, such as data sharing, for collective well-being despite personal costs (Baumeister 1987, Cialdini et al. 1990, Triandis 1995, Hofstede 2001, Ellemers and Haslam 2012, Bian et al. 2022). On the other, the Social Identity Theory suggests that a crisis elevates social solidarity and prioritizes shared challenges (Tajfel et al. 1979, Turner and Killian 1987, Drury et al. 2009, Lee 2010, Jetten et al. 2012); and the Terror Management Theory indicates that heightened mortality salience during a crisis strengthens community and boosts donations (Douty 1972, Florian and Mikulincer 1997, Ferraro et al. 2005, DeWall and Baumeister 2007, Weinberger and Wallendorf 2012, Toubia and Stephen 2013, Pyszczynski et al. 2015, Dunn et al. 2020, Chen et al. 2020, Gershon et al. 2020).

Our contributions. The above review suggests that a crisis might add societal considerations to the privacy choice, such as societal values of shared data despite privacy costs. Such considerations could slant the choice of the consumers sharing data toward reduced opt-out. Nonetheless, empirical evidence of such an opt-out change, and its potential connection to societal considerations, remains sparse. Our research thus fills the void by examining this critical consumer choice as new considerations surface during a natural shock of a crisis. As a result, our exploration expands the literature on consumers' privacy choice from personal considerations to broader societal circumstances.

3. Data

We analyze four data sets: (1) individual-level mobile location data, to capture both the dependent variable – privacy choice (measured by opt-out of location data sharing), and independent variables – societal considerations (measured by compliance with public health policies) and personal considerations (measured by app usage); (2) individualism index from the Economics literature, as an alternative measure of societal considerations; (3) Census Block Group (CBG hereafter)-level demographics from the 2016 American Community Survey, to assess the demographic heterogeneity in the privacy choice; and (4) election data, to determine the psychographic heterogeneity (political ideology). Below we will describe the dependent and independent variables derived from these data.

3.1. Privacy Choice

A consumer's privacy choice in our context is measured by whether to opt out of location sharing. The location data are provided by a leading U.S. data aggregator that integrates location data from over 400 commonly used mobile apps in its app network. These apps have installed the aggregator's proprietary software development kit (SDK) to help minimize smartphone battery drainage while tracking locations.[7] The 32 categories of apps cover a wide range of an individual's daily life. The top five categories, social network, lifestyle, tools, shopping, and weather, account for an average of 94% (95%) of all app usage by an individual before (after) the pandemic began. There is no change in the set of mobile apps in the aggregator's app network during our sampling period. The names of the apps are not released to preserve confidentiality.

The data are tracked and aggregated in full compliance with privacy regulations, including the General Data Protection Regulation (GDPR) and California Consumer Privacy Act (CCPA). There are no changes in these privacy regulations, or the apps' and aggregator's privacy compliance during our sampling period. An individual may opt in by agreeing to both the app's and data aggregator's privacy agreements and turning on location tracking within the app's setting. The individual may also opt out any day by turning off location tracking with an easy switch on the app (then app by app if desired), on the aggregator's app or website for all apps in its app network, or on the phone's mobile operating system for all apps on the phone. While opt-out-then-in is conceptually feasible, it is not permitted by our definition of "opt-out", which refers to the complete disappearance from the data for the remainder of our sampling period. In fact, it is also rare in practice according to the aggregator's and app owners' back-end information.

The location data cover a quarter of the U.S. population across the Android and iOS operating systems; and are representative of the U.S. population based on the aggregator's detailed demographic analyses. Each individual is on average tracked every fifteen minutes and each data record represents a location visited by the individual, containing an anonymized and persistent ID common across all apps in the aggregator's app network for the same individual, timestamp, longitude, latitude of the location visited, speed, dwell time, and the app category that has captured this location record. The individual-level demographics are not included in the data to preserve confidentiality. An individual's home location is inferred based on the most frequent location 3-5AM over weekdays, and then linked to the corresponding CBG's demographics (Macha et al. 2023). Overall, the data offer granular, real-time, and inter-temporal observations of each individual's

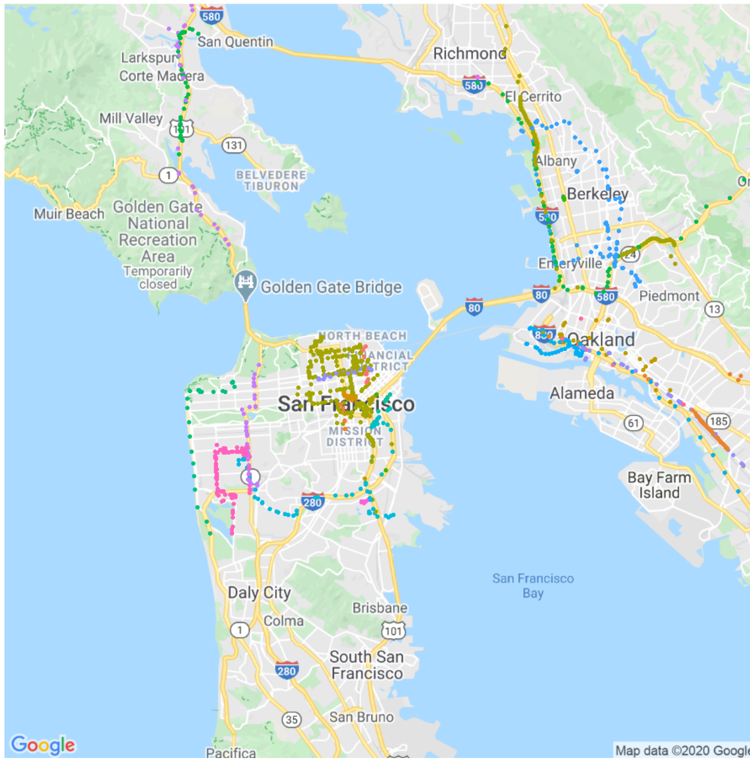


Figure 1 **Mobile Trajectories from 20 Randomly Sampled San Francisco Individuals**

locations. Figure 1 displays an example of one day's location data from 20 randomly sampled individuals visiting 2,318 unique locations in San Francisco.

We analyze 22 billion location records from January 1st to April 15th, 2020 across 20 U.S. cities from various geographical regions, including Baltimore (MD), Washington D.C., Boston (MA), San Francisco (CA), New Orleans (LA), New York City (NY), Seattle (WA), Pittsburgh (PA), Philadelphia (PA), Austin (TX), Phoenix (AZ), Arlington (TX), Oklahoma City (OK), Wichita (KS), Nashville (TN), Omaha (NE), Lexington (KY), Colorado Springs (CO), Virginia Beach (VA), and Jacksonville (FL). Also, the first 10 cities are the most liberal (blue) and remaining most conservative (red) (Tausanovitch and Warshaw 2014), allowing us to later examine the heterogeneity in the privacy choice across political ideology. For each city, we analyze an average of 1.1 billion location records containing 1.5 million unique locations from a random sample of 150,000 individuals, with 70 locations per person per day.

The location data are collected from those who have opted in[8]. Given opt-in, an individual's privacy choice on a specific day is either *OptIn* if the individual's location records continue to be present in the data, or *OptOut* if the records completely disappear from the data from this day onward until the end of the sampling period. That is, *OptOut* occurs when an individual opts out of all apps within the aggregator's app network or all apps on his/her phone. Therefore, *OptOut* is unlikely driven by uninstallations or reduced usage of a single or a few apps, particularly as we do not observe a decreasing trend in an individual's daily app usage, app categories, or number of location records before opt-out (Section 5.5).

The natural shock (*Shock*) is the U.S. declaration of the COVID-19 National Emergency on March 13, 2020, marking the onset of the pandemic and widespread awareness of the usage of location data in mitigating the pandemic.[9] We subsequently test city-specific lockdown dates, and also pseudo shock dates. All results remain consistent (Section 5.5). Below we will describe the variables related to potential mechanisms: four metrics of personal considerations (app usage) and two metrics of societal considerations (policy compliance and individualism).

Table 1 Variable Description

Variable Category	Level	Variable Name	Variable Description
Privacy Choice	Individual	OptOut (yes/no)	An indicator of whether an individual opted out of sharing location data that day.
	CBG	OptOutCount	Daily number of individuals who opted out of sharing location data.
Individuals in Sample	CBG	TotalActiveUsers	Daily number of individuals who have presently opted in to share location data.
	CBG	TotalNewUsers	Daily number of individuals who newly opted in that day.
Policy Compliance	CBG	NumContacts	Daily number of contacts in top 1% most visited locations.
	CBG	TravelDistance	Daily average distance across trips (km).
Health Risks	County	InfectionRate	Daily COVID-19 cases divided by population.
	County	DeathRate	Daily COVID-19 deaths divided by daily cases.
Demographics	CBG	Gender	Proportions of male and female populations.
	CBG	Income	Proportions of households with income <60K, 60-100K, 100-150K, 150-200K, 200K and above.
	CBG	Race	Proportions of White, Black, Asian, and Native Indian populations.
	CBG	PopulationLand	Population.
			Land (acre).
App Usage	Individual	TotalAppUsage	Daily duration of mobile app usage (min).
	Individual	Location-heavyAppUsage	Daily usage duration (min) of location-heavy app categories such as map and navigation.
	Individual	AppUsageCategory	Daily number of unique app categories used.
	Individual	AppUsageHHI	Herfindahl–Hirschman Index (HHI) of usage durations (min) across app categories.
Political ideology	City	Blue	Baltimore, DC, Boston, San Francisco, New Orleans, NYC, Seattle, Pittsburgh, Philadelphia, Austin.
		Red	Phoenix, Arlington, Oklahoma City, Wichita, Nashville, Omaha, Lexington, Colorado Spring, Virginia Beach, Jacksonville.
Shock	Country	Shock	On or after declaration of national emergency (March 13th, 2020).

3.2. Personal Considerations

To examine if app usage, the core personal consideration of sharing location data during the crisis, might be related to the *OptOut* change, we compute four daily app usage metrics: app usage duration in minutes across all app categories (*TotalAppUsage*), app usage duration in minutes across all location-heavy app categories such as maps (*Location-heavyAppUsage*), number of app categories used (*AppUsageCategory*), and Herfindahl-Hirschman Index (HHI) of app usage duration in minutes across all app categories (*AppUsageHHI*) (Table 1).

Table 2 Summary Statistics

Variable Category	Variable Name	Mean	Std. Dev.	Min	Max
Privacy Choice	OptOut (yes/no)	0.007	0.086	0	1
	OptOutCount	0.18	1.00	0	219
Individuals in Sample	TotalActiveUsers	19608	4939	3514	25000
	TotalNewUsers	0.21	1.76	0	433
Policy Compliance	NumContacts	2.29	10.1	0	787
	TravelDistance	8.53	12.34	0	983
Health Risk	InfectionRate (%)	0.04	0.12	0	1.02
	DeathRate (%)	0.01	0.03	0	0.36
Demographics	Gender (Male)	0.48	0.08	0.1	1
	Gender (Female)	0.51	0.08	0.06	1
	Income (<60K)	0.51	0.23	0	1
	Income (60-100K)	0.21	0.11	0	1
	Income (100-150K)	0.14	0.10	0	1
	Income (150-200K)	0.06	0.07	0	1
	Income (>200K)	0.07	0.11	0	1
	Race (White)	0.65	0.29	0	1
	Race (Black)	0.18	0.27	0	1
	Race (Asian)	0.08	0.12	0	1
	Race (Native Indian)	0.01	0.03	0	0.94
	Population	1420	799	3	15096
	Land (km^2)	3.13	39.57	0.0334	2482.7
App Usage	TotalAppUsage (hours)	4.48	8.85	0	23.86
	Location-HeavyAppUsage (hours)	4.14	8.74	0	23.68
	AppUsageCategory	0.267	0.452	0	4
	AppUsageHHI	0.237	0.424	0	1

Note: For all CBG-day-level variables, the number of observations is 16,333 (CBGs) × 106 (days) = 1,731,298. For all individual-day-level variables, the number of observations is 46,115 (sampled individuals) × 106 (days) = 4,888,190.

3.3. Societal Considerations

To examine whether the magnitude of the *OptOut* change varies by the extent of societal considerations, we measure societal considerations with two metrics: policy compliance and individualism index. Below we will describe each.

Policy Compliance. Social distancing and stay-at-home represent the principal non-pharmaceutical mitigation policies during the pandemic, resulting in dramatic changes in human

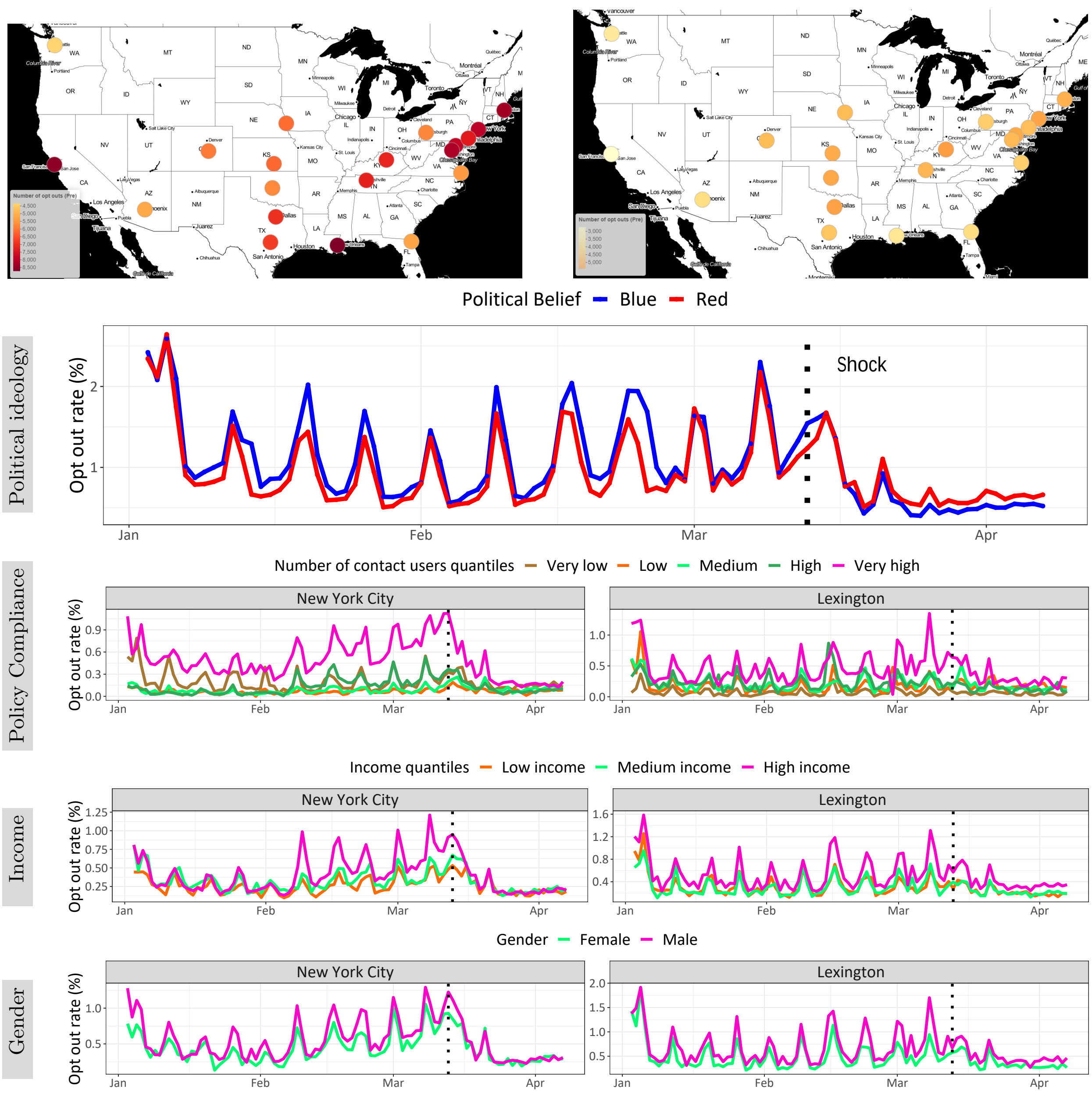


Figure 2 **Top: Monthly OptOutCount Pre- versus Post-shock (darker color = higher OptOutCount). Bottom: Daily Trend of Opt-out Rate by Political Ideology, Policy Compliance, Income, and Gender.**

mobility, such as daily number of social contacts, travel distance, and home duration (Bakker et al. 2020). While entailing great personal inconvenience, compliance with these policies leads to substantial health, economic, and societal benefits (Greenstone and Nigam 2020). Therefore, policy compliance by reducing human contacts, particularly at popular locations ("hot spots"), provides a great measure of an individual's societal concerns during the crisis. Specifically, we calculate an individual's, then (to further reduce data sparsity) CBG's, daily number of contacts (*NumContacts*). It is the number of co-locators within a 10-meter distance for more than 15 minutes at the top 1% most visited locations in a city (Benzell et al. 2020, Bakker et al. 2020). We also test alternative measures of $NumContacts$ by varying co-locating distance and duration, and alternative metrics of policy compliance, such as daily travel distance and home duration. All findings remain consistent.

Individualism. Individualism, a cultural, social, and psychological orientation, emphasizes the importance of personal achievement, self-reliance, and self-expression over collective interests (Baumeister 1987, Triandis 1995, Hofstede 2001, Bian et al. 2022). The Frontier Thesis (Turner 1994) suggests that the westward expanding frontier during the 18th and 19th centuries in the U.S. history has strongly influenced the American culture. Grounded on this thesis, Bazzi et al. (2020) propose a U.S. county-level individualism metric by the total frontier experience (TFE hereafter), i.e., the number of decades that each county spent on the frontier. A longer TFE translates into higher individualism. Individualism prizes self-reliance and personal effort, while against redistribution or government intervention. Higher individualism is linked to weaker societal considerations, such as charitable donations (Bian et al. 2022), civic duty, social distancing, or mask use during the pandemic (Bazzi et al. 2020, 2021). We hence employ this metric to capture varying societal considerations across CBGs.

3.4. Other Controls, Summary Statistics, and Model-free Evidence

We also consider an array of daily factors that might also influence the privacy choice, such as the daily number of presently opt-in individuals, daily number of newly opt-in individuals, and the daily health risk. Previous research shows that individuals with higher infection risks are more willing to install contact-tracing apps (http://webuse.org/covid/). Also, blue cities on average experienced higher infection rate and death rate than red cities (Appendix B). To further explore such psychographic and demographic heterogeneities, we incorporate the CBG-level key demographics (income, gender, race) and city-level political ideology (blue, red). Table 1 lists the key variables used in the subsequent analyses and Table 2 displays summary statistics. While the average daily opt-out rate per city is low (2%), over the entire sampling period, a sizable 1,685,353 out of 3,835,333 individuals (44%) across the 20 cities have opted out.

Before specifying the model, we first present some model-free evidence of the changing privacy choice. The top of Figure 2 reveals that each city's monthly $OptOutCount$ declines post-shock (with the daily trends in Appendix A). The bottom of Figure 2, using two cities as illustrations, also shows that the daily opt-out rate declines post-shock regardless of the political ideology, policy compliance, income, or gender. In addition, heterogeneities in this decline emerge. For instance, the decline is stronger among the blue cities (black line), despite a higher opt-out rate pre-shock[10], than the red cities (grey line). We also notice, albeit not the focus of our research, a weekly cycle of more opt-outs over weekends pre-shock, which becomes less prominent post-shock potentially due to the blurred boundary between weekends and weekdays during stay-at-home. Also, the decline is stronger among the more affluent ($200K+ income). Finally, the demographics of the 1,685,353 opt-out individuals are similar to those of the opt-in individuals, suggesting that the opt-outs are not driven by demographics. The demographics of both opt-out and opt-in individuals are also similar to those of the U.S. population, despite representing only 20 cities (Appendix M)[11].

4. Modeling

We enlist a series of panel models, at both the individual-day-level and CBG-day-level, to study how consumers' privacy choice (*OptOut*) might have changed during the crisis, and how this change varies across different levels of personal and societal considerations.

4.1. Main Effect

To examine the main effect of the crisis shock on an individual i's probability of *OptOut* (yes/no) on day t, we specify an individual-day-level Binary Logit Model:

$$Pr(OptOut_{it}) = \frac{\exp^{\overline{U_{it}}}}{1+\exp^{\overline{U_{it}}}}, \tag{1}$$

where

$$\overline{U_{it}} = \beta_1 Shock_t + \beta_2 Control_{it}. \tag{2}$$

Here $Shock_t$ is a dummy indicator, equal to 1 if day t is on or after the shock date. β_1 captures the main effect of the crisis on the privacy choice. $Control_{it}$ includes the daily health risk metrics, daily app usage metrics, weekly index, and day-of-the-week dummy (Table 1). To check robustness, we also estimate a Poisson model of the CBG-day-level *OptOutCount* using a similar set of covariates.

4.2. Personal Considerations

To check if the opt-out change varies with different levels of app usage, we specify an individual-day-level Binary Logit model:

$$Pr(OptOut_{it}) = \frac{\exp^{\overline{U_{it}}}}{1+\exp^{\overline{U_{it}}}}, \tag{3}$$

where

$$\overline{U_{it}} = \beta_1 Shock_t + \beta_2 Shock_t \times Personal_{it} + \beta_3 Personal_{it} + \beta_4 Control_{it}. \tag{4}$$

Here $Personal$ is an app usage metric described earlier: $TotalAppUsage$, $Location-heavyAppUsage$, $AppUsageCategory$, or $AppUsageHHI$. To check robustness, we also estimate a CBG-day-level Poisson model of *OptOutCount*, and find consistent results.

4.3. Societal Considerations

To examine if the opt-out change varies with different levels of societal considerations, we specify a CBG-day-level Poisson model:

$$\begin{aligned}\mathbb{E}(OptOutCount_{jt}) = \exp(&\alpha_j + \beta_1 Shock_t + \beta_2 Shock_t \times Societal_{jt} + \\ &\beta_3 Societal_{jt} + \beta_4 Controls_{jt}),\end{aligned} \tag{5}$$

where $OptOutCount_{jt}$ is the number of the opt-out individuals from CBG j on day t. α_j is the CBG fixed effect. $Societal_{jt}$ is the metric of societal considerations: either policy compliance or individualism. Hence, β_2 captures the effect of the varying societal considerations. To test robustness, we also estimate a CBG-day-level Negative Binomial model. All results remain consistent.

4.4. Additional Heterogeneities

Recent studies reveal a strong link between human behavior during a crisis and political ideology (as well as demographics) (Allcott et al. 2020, Fan et al. 2020, Barrios and Hochberg 2020, Coven and Gupta 2020, Ruiz-Euler et al. 2020, Wright et al. 2020, Chiou and Tucker 2020).We hence further explore such psychographic (political ideology) and demographic (income, gender, race) heterogeneities in consumers' privacy choice by estimating a series of CBG-day-level Poisson models:

$$\mathbb{E}(OptOutCount_{jt}) = \exp(\alpha_j + \beta_1 Shock_t + \beta_2 Shock_t \times D_j + \beta_3 D_j + \beta_4 Controls_{jt}), \tag{6}$$

where D_j contains CBG j's political ideology (percentage of Trump votes in the 2016 presidential election), or demographics (income, gender, race). As the location data do not contain the individual-level psychographics and demographics to preserve individual privacy, we estimate them at each individual's home CBG-level using the voting and U.S. Census data. β_2 captures the psychographic or demographic heterogeneities in any opt-out change post-shock. We also conduct robustness tests by estimating the CBG-day-level Negative Binomial models. The findings remain consistent.

5. Findings

In this section, we will report (1) the main effect: the opt-out declines during the crisis; (2) heterogeneous effect: the opt-out declines more among those with a greater inclination for societal considerations even after accounting for personal considerations of app usage; (3) additional heterogeneities: the opt-out declines more in areas with higher percentages of Democratic, affluent, and Asian populations; and (4) a series of robustness studies and discussions of potential alternative mechanisms.

Table 3 Main Effect on Opt-out

DV = *Individual OptOut* (Logit)	Main Effect (20 cities)
Shock	-0.044**** (0.012)
# Obs.	4,888,190
Controls	✓
* p <0.10, ** p <0.05, *** p <0.01, **** p <0.001.	

5.1. Main Effect

To estimate the main effect of the crisis on consumers' privacy choice, we estimate Equations (1) and (2) on a sample of 25,000 individuals per city to make the computation time more manageable. Table 3 reveals a significant decline in a consumer's likelihood of *OptOut* (-.047) even after controlling for the app usage.

We also vary the sample size and find consistent results. We further estimate the same model using only the individuals who have opted in since the start of the sampling period, hence teasing out the effect of those who opted in during the sampling period (Appendix K). We again find consistent results. A CBG-day-level Linear Probability Model (LPM, Appendix J) further supports the conclusion. These findings collectively suggest that consumers have reduced opt-out during the crisis even after considering their app usage patterns.

5.2. Personal Considerations

A potential mechanism underlying the opt-out decline is the increased personal benefits from the app usage during the crisis. Therefore, besides controlling for the daily app usage in the above main effect model (Equation 1 and 2), we also explicitly test if the reduced opt-out varies by heterogeneous levels of app usage (Equations 3 and 4) using each of the four app usage metrics: *TotalAppUsage*, *Location-heavyAppUsage*, *AppUsageCategory*, and *AppUsageHHI*.

Table 4 Heterogeneous Effect of App Usage on Opt-out

DV = Individual *OptOut* (Logit)	(1) Main Effect	(2) Interaction w/ Total_app_usage	(3) Interaction w/ Location_heavy_app_usage	(4) Interaction w/ App_usage_category	(5) Interaction w/ App_usage_hhi
Shock	-0.044****	-0.043****	-0.037***	-0.047****	-0.047****
	(0.012)	(0.006)	(0.006)	(0.006)	(0.006)
Total_app_usage		-3.130****			
		(0.073)			
Shock x Total_app_usage		1.887****			
		(0.081)			
Location_heavy_app_usage			-1.207****		
			(0.041)		
Shock x Location_heavy_app_usage			0.949****		
			(0.046)		
App_usage_category				-5.354****	
				(0.075)	
Shock x App_usage_category				0.459****	
				(0.088)	
App_usage_hhi					-5.119****
					(0.096)
Shock x App_usage_hhi					1.932****
					(0.107)
Other Controls	✓	✓	✓	✓	✓
# Obs.	4,888,190	4,888,190	4,888,190	4,888,190	4,888,190

*p<0.10; **p<0.05; ***p<0.01;****p<0.001.

Table 4 shows a consistent main effect of the *Shock* toward reduced opt-out across model specifications. Also, more app usage is indeed linked to lower opt-out pre-shock (-3.130, -1.207, -5.354, and -5.119 for the respective app usage metrics). Yet this connection is attenuated post-shock (1.887, 0.949, 0.459, and 1.932 respectively), suggesting a weakened role of personal considerations on consumers' privacy choice during the crisis. As we will show next, societal considerations also play an important role.

5.3. Societal Considerations

To further examine if the magnitude of the opt-out reduction is related to the extent of societal considerations (Equation (5), we test two alternative metrics of societal considerations below: policy compliance and individualism.

Policy compliance is a CBG-level $NumContacts$ at popular locations as described earlier, calculated on the original full sample of 150,000 individuals per city. Columns (1) - (3) of Table 5 contain the estimates across the 10 red cities, (4) - (6) across the 10 blue cities, and (7) - (9) across all 20 cities. The significantly negative coefficient of *Shock* across all columns show that consistent with the discovered main effect, the opt-out declines post-shock even after controlling for the app usage. More importantly, this decline is more pronounced among those with greater policy compliance (significantly positive coefficient of $Shock \times NumContacts$: 0.157 for red and 0.163 for blue cities), indicating a potential connection between reduced opt-out and societal considerations.

We also re-run the same model without controlling for the app usage (Appendix H). The consistent main effects with versus without app usage suggest that app usage does not erase the relationship between opt-out and policy compliance. We later perform a series of robustness studies, including further controlling for the opt-ins/outs of the adjacent CBGs to capture peer influence (Appendix D), re-estimating the same model city-by-city (Appendix G), estimating a Negative Binomial model, and operationalizing policy compliance with $TravelDistance$ and $\%HomeTime$. The results consistently support the association between opt-out and policy compliance.

Individualism is tested using three specifications of the Poisson Model (Equation 5) on the full sample of 150,000 individuals per city. Table 6 shows that while the opt-out declines across all CBGs (significantly negative coefficient of *Shock*), those with higher individualism opt out more than those with lower individualism (coefficient of $Shock \times Individualism = 0.013$, $p < 0.001$). We also conduct the same analysis using a Negative Binomial Model. The results consistently suggest that those with lower individualism or greater societal considerations reduce opt-out even more during the crisis.

Table 5 Heterogeneous Effect of Policy Compliance on Opt-out

DV = CBG *OptOutCount* (Poisson)	(1) Main Effect (10 Red Cities)	(2) w/ Policy Compliance (10 Red Cities)	(3) Interaction w/ Policy Compliance (10 Red Cities)	(4) Main Effect (10 Blue Cities)	(5) w/ Policy Compliance (10 Blue Cities)	(6) Interaction w/ Policy Compliance (10 Blue Cities)	(7) Main Effect (20 Cities)	(8) Interaction w/ Policy Compliance (20 Cities)	(9) Three-way Interaction (20 Cities)
Shock	-0.236****	-0.210****	-0.494****	-0.314****	-0.278****	-0.399***	-0.335****	-0.495****	-0.452****
	(0.018)	(0.017)	(0.025)	(0.016)	(0.016)	(0.016)	(0.012)	(0.015)	(0.017)
NumContacts		0.016**	-0.047****		-0.028****	-0.060****		-0.048****	-0.043****
		(0.007)	(0.007)		(0.007)	(0.007)		(0.005)	(0.007)
Shock × NumContacts			0.157****			0.163****		0.149****	0.137****
			(0.008)			(0.009)		(0.006)	(0.008)
Shock × Blue									-0.085****
									(0.015)
NumContacts X Blue									-0.006
									(0.010)
Shock × NumContacts X Blue									0.022*
									(0.011)
Total_app_usage	-0.136****	-0.152****	-0.153****	-0.112****	-0.117****	-0.117****	-0.121****	-0.130****	-0.130****
	(0.008)	(0.008)	(0.008)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Location_heavy_app_usage	-0.143****	-0.133****	-0.131****	-0.121	-0.113****	-0.114****	-0.128****	-0.118****	-0.119****
	(0.008)	(0.008)	(0.008)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
App_usage_category	10.01****	9.487****	9.433****	8.097****	7.627****	7.555****	8.741****	8.141****	8.119****
	(0.110)	(0.109)	(0.107)	(0.061)	(0.061)	(0.061)	(0.055)	(0.054)	(0.054)
App_usage_hhi	-1.284****	-0.986****	-0.928****	-0.681****	-0.458****	-0.442****	-0.782****	-0.524****	-0.383****
	(0.127)	(0.125)	(0.124)	(0.063)	(0.062)	(0.062)	(0.058)	(0.057)	(0.057)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
CBG FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
# Obs.	595,084	595,084	595,084	1,136,214	1,136,214	1,136,214	1,731,298	1,731,298	1,731,298

*p<0.10; **p<0.05; ***p<0.01;****p<0.001.

Table 6 Heterogeneous Effects of Individualism on Opt-out

DV = CBG *OptOutCount* (Poisson)	(1) Main Effect	(2) Interaction w/ Individualism
Shock	-0.335**** (0.012)	-0.403**** (0.015)
Shock × Individualism		0.013**** (0.001)
Controls	✓	✓
CBG FEs	✓	✓
# Obs.	1,731,298	1,731,298

*p<0.10, ** p<0.05, *** p<0.01, **** p<0.001.

5.4. Additional Heterogeneities

We explore additional psychographic (political ideology) and demographic (income, gender, race) heterogeneities in the main effect (Equation (6). Consistent with the model-free evidence (Figure 2), the *OptOutCount* has declined across all cities post-shock, while the blue cities display stronger declines than red cities. Figure 3 contrasts the main effects of the crisis across the 20 cities based on the CBG-day-level Poisson model (Equation 6). Overall, the *OptOutCount* has declined across all cities post-shock, while the blue cities on average display stronger declines than red cities.

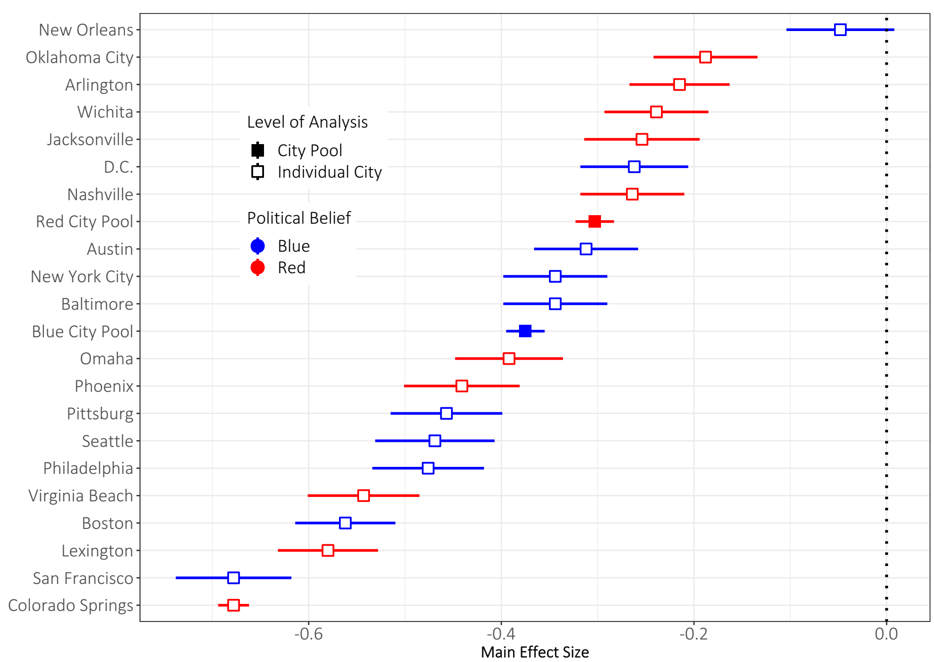


Figure 3 Main Effect on Opt-out across Political Ideology (DV = CBG *OptOutCount*, Poisson Model)

Also, all CBGs exhibit reduced opt-out after the onset of the crisis, particularly those with higher proportions of the most affluent (-0.908, $p < 0.001$), male (-0.922, $p < 0.01$), and Asian populations (-1.570, $p < 0.001$) (Appendix I).

In summary, our analyses present first large-scale empirical evidence that consumers have reduced opt-out during a crisis and the reduction is more pronounced among those with greater societal considerations after accounting for personal considerations.

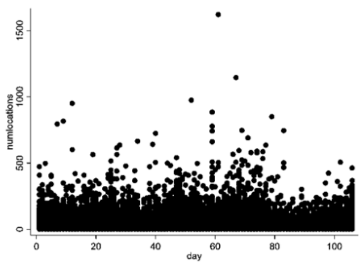
5.5. Robustness Studies

In addition to various alternative model specifications tested earlier, we also perform a series of robustness studies below to verify the findings.

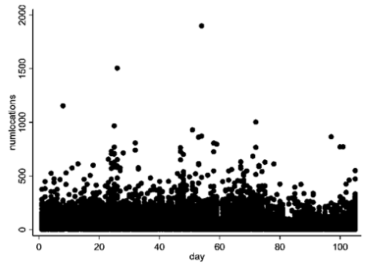
App usage immediately preceding opt-out. One may be curious if the reduced opt-out stems from any major changes in an individual's app usage in the days immediately preceding the opt-out. We hence compare the distributions of the usage of location-heavy apps across zero, one, two, three, and seven days prior to an individual's opt-out. Figure 4 shows no significant upward or downward trend. Moreover, the analysis of all apps' usage produces a consistent finding (Appendix E). We also conduct a Point-Biserial correlation analysis between an individual's *OptOut* (yes/no) and each of the four app usage metrics (*TotalAppUsage*, *Location-HeavyAppUsage*, *AppUsageCategory*, and *AppUsageHHI*) in the one, two, three, and seven days prior to an individual's opt-out. Nearly all correlations are insignificant, indicating that the reduced opt-out is unlikely attributable to the app usage immediately preceding the opt-out (Appendix E).

Time availability. One may also inquire if the reduced opt-out is attributable to consumers' increased time availability during the crisis when most stayed at home. Interestingly, more time available for consumers to read the privacy policies or media on location tracking, or more time to opt-out, would likely increase the opt-out. This is also supported by our earlier model-free evidence showing an increased opt-out over the weekends compared to weekdays pre-shock (Figure 2). Overall, the increased time availability is an untenable explanation of the observed opt-out decline.

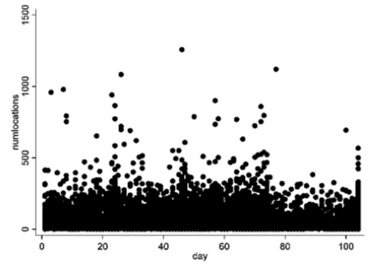
Alternative shock dates. We test whether the crisis indeed triggers a negative shock to the privacy choice, or there is simply a downward trend in the opt-out over time. In fact, the $Week$ index and $DayOfWeek$ dummy in the model have to a large extent helped control for such a time trend. Moreover, Figure 2 clearly shows that the prominent opt-out decline does not emerge until around the shock date. Nonetheless, we re-run the main analyses (Equations 1 and 2) using each of the 12 days in March immediately preceding the shock date, March 1st to March 12th, as an alternative shock date. The estimated effects over these 12 days are either insignificant or positive, as opposed to significantly negative (Appendix L illustrating the D. C. sample). Overall, we do



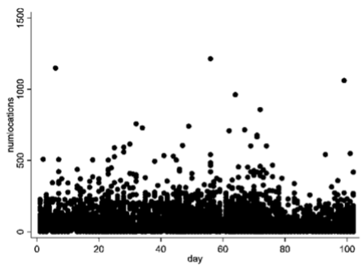
(a) Last Day of Observation



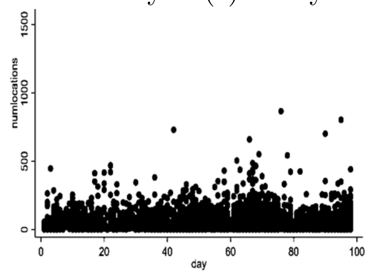
(b) 1 Day before Last Day



(c) 2 Days before Last Day



(d) 3 Days before Last Day



(e) 1 Week before Last Day

Figure 4 Distribution of Location Records from Location-heavy Apps for Opt-out Individuals in D.C.[12]
(x-axis = index of the day of opt-out; y-axis = # location records from location-heavy apps)

not find a significant opt-out decline under these hypothetical shock dates. We further test each of the 4 Fridays preceding the shock date as alternative shock dates: 1/17, 1/24, 2/14, and 2/28 (Appendix L). The same conclusion holds.

State-specific shock dates. We perform a CBG-day-level analysis for each city using the city-specific lockdown date as an alternative shock date (Appendix F). The results remain consistent.

In summary, all findings remain consistent across alternative metrics of societal considerations, alternative metrics of app usage, and a series of robustness studies, including pooled versus city-by-city analyses, alternative unit of analysis (individual-day-level versus CBG-day-level), alternative model specifications, alternative controls, falsification tests of shock dates, and national versus city-specific shock dates. These analyses collectively show a connection between the reduced opt-out during the crisis and societal, beyond personal, considerations.

6. Conclusions and Discussions

Key findings and contributions. Human history coexists with crises, which introduce broader considerations in consumer choice. A rich literature has examined consumers' privacy choice between sharing personal data and opting out as a personal cost-benefit trade-off. Nonetheless, research on privacy choice during a crisis when additional societal considerations arise remains limited. Our study explores this topic of theoretical and policy significance by leveraging the newly available location data and latest public health crisis as a natural shock, when location data become as a valuable tool to mitigate the crisis. Our analyses of 22 billion records of inter-temporal individual-level location data across 20 U.S. cities unveil two important and interesting findings corresponding to the two research questions. First, consumers have reduced opt-out during the crisis. Second, this reduction is more pronounced among those with greater societal, beyond personal, considerations. Our research hence extends the literature on privacy choice from focusing on personal considerations (and business outcomes) to additional societal considerations (and societal implications).

Policy and managerial implications. Our finding of reduced opt-out during crisis times offers valuable policy implications pertaining to privacy regulations. Policymakers may strategically communicate the societal value of the data during disastrous times. They may also consider fostering tighter collaborations between public and private sectors to establish effective frameworks for data sharing and data usage, as well as procedural transparency and accountability. Well-defined procedures may also be in place to ensure that data usage is confined to crisis mitigation and that individual privacy is protected.

Our findings also hold managerial implications for non-profit and for-profit organizations. In particular, organizations may adjust their offerings (e.g., adding location-aware services) and data infrastructure when anticipating consumers' changing privacy choice during a crisis. Firms may further accentuate mutual trust, which becomes more crucial during a crisis as consumers are more willing to engage with the organizations that they trust. Meanwhile, firms could streamline informed consent, granting consumers enhanced control over shared data to strike a balance between societal and personal interests. Most importantly, strategic firms develop comprehensive crisis preparedness plans that outline, for instance, how to adapt to potentially increased data sharing, ensure ethical and responsible use of data, and transparently communicate data usage with consumers.

Our findings further inform the heterogeneities in consumers' privacy choice, along dimensions such as policy compliance, individualism, personal benefits, political ideology, and demographics. Such heterogeneities importantly inform targeted implementations of personalized policy communication strategies toward diverse consumers.

In conclusion, our research offers valuable, under-explored insights into consumers' privacy choice during a crisis. Both policymakers and managers may effectively leverage these novel insights to make more informed decisions during crises, while accounting for consumers' personal and societal considerations.

Limitations and future research. Despite the valuable contributions, our research presents limitations and invites future research in this important and interesting domain. First, we recognize the boundary of our empirical study, such as regarding the exogeneity of the crisis shock, despite our tests on whether the shock can be predicted by earlier opt-outs. Second, while our larger-scale policy compliance and individualism indirectly measure societal considerations, future research may seek more direct measures to verify the findings. Future access to more granular data, such as specific app names, or individual-level app installations and opt-in/out timing, will enable further explorations of alternative explanations of our findings. Third, it would be interesting to study the longer-term effects, for instance, whether the opt-out would rebound after the crisis eases. Finally, future research may experiment with policies or methodologies that incentivize data sharing while preserving consumer privacy. Our study also invites more innovative thinking of privacy regulations that hold quintessential value to both consumer and societal well-being.

Notes

[1]Location data arise from a variety of sources, such as rideshare, fitbit, social media geo-tags, and Global Positioning System (GPS) tracking. Nonetheless, mobile apps supply a great proportion of consumer location data due to the wide adoptions of smartphones (https://mitpress.mit.edu/books/tap).

[2]https://www.washingtonpost.com/technology/2020/03/24/social-distancing-maps-cellphone-location/.
https://www.nytimes.com/interactive/2020/04/02/us/coronavirus-social-distancing.html.
https://www.cnn.com/2020/03/18/tech/us-government-location-data-coronavirus/index.html.
https://www.foxnews.com/tech/us-government-big-tech-smartphone-coronavirus-google-facebook.
https://www.foxnews.com/tech/taiwans-so-called-electronic-fence-monitor-for-those-quarantined-raises-privacy-concerns-report.

[3]"After 9/11, we gave up privacy for security. Will we make the same trade-off after COVID-19?" https://www.statnews.com/2020/04/08/coronavirus-will-we-give-up-privacy-for-security/.

[4]https://www.emarketer.com/content/consumers-are-more-willing-to-share-private-data-during-covid-19.

[5]https://blogs.scientificamerican.com/observations/will-americans-be-willing-to-install-covid-19-tracking-apps/.

[6]`https://clevertap.com/blog/q1-data-impact-of-covid-19/`.
`https://www.insiderintelligence.com/content/us-time-spent-with-mobile-2021`.

[7]Interested readers may refer to https://www.tamoco.com/blog/location-data-info-faq-guide/ for more information about the common industrial practice of mobile location tracking.

[8]The opt-in rate in North America around the time of the pandemic was reportedly 8% to 25% across various online information sources (e.g., https://www.airship.com/resources/benchmark-report/the-state-of-global-mobile-engagement-2020/; https://www.statista.com/statistics/1229170/location-opt-in-growth-rate-by-region-covid/).

[9]https://www.cnn.com/2020/03/10/health/coronavirus-contact-tracing/index.html;
https://www.cnn.com/2020/03/18/tech/us-government-location-data-coronavirus/index.html;
https://www.foxnews.com/tech/us-government-big-tech-smartphone-coronavirus-google-facebook;
https://www.foxnews.com/tech/taiwans-so-called-electronic-fence-monitor-for-those-quarantined-raises-privacy-concerns-report.

[10]This higher opt-out rate pre-shock in blue cities is consistent with the reports that Democrats are generally more concerned about privacy than Republicans (https://www.nytimes.com/2018/04/30/technology/privacy-concerns-politics.html)

[11]The U.S. Population features a female ratio = 0.504, White = 0.589 - 0.755, Asian = 0.063, Income < $60K = 0.45, Income > $200K = 0.10, according to https://www.census.gov/quickfacts/fact/table/US/LFE046221 and https://dqydj.com/2020-average-median-top-household-income-percentiles/.

[12]A similar analysis of the total app usage time shows consistent findings (Appendix E).

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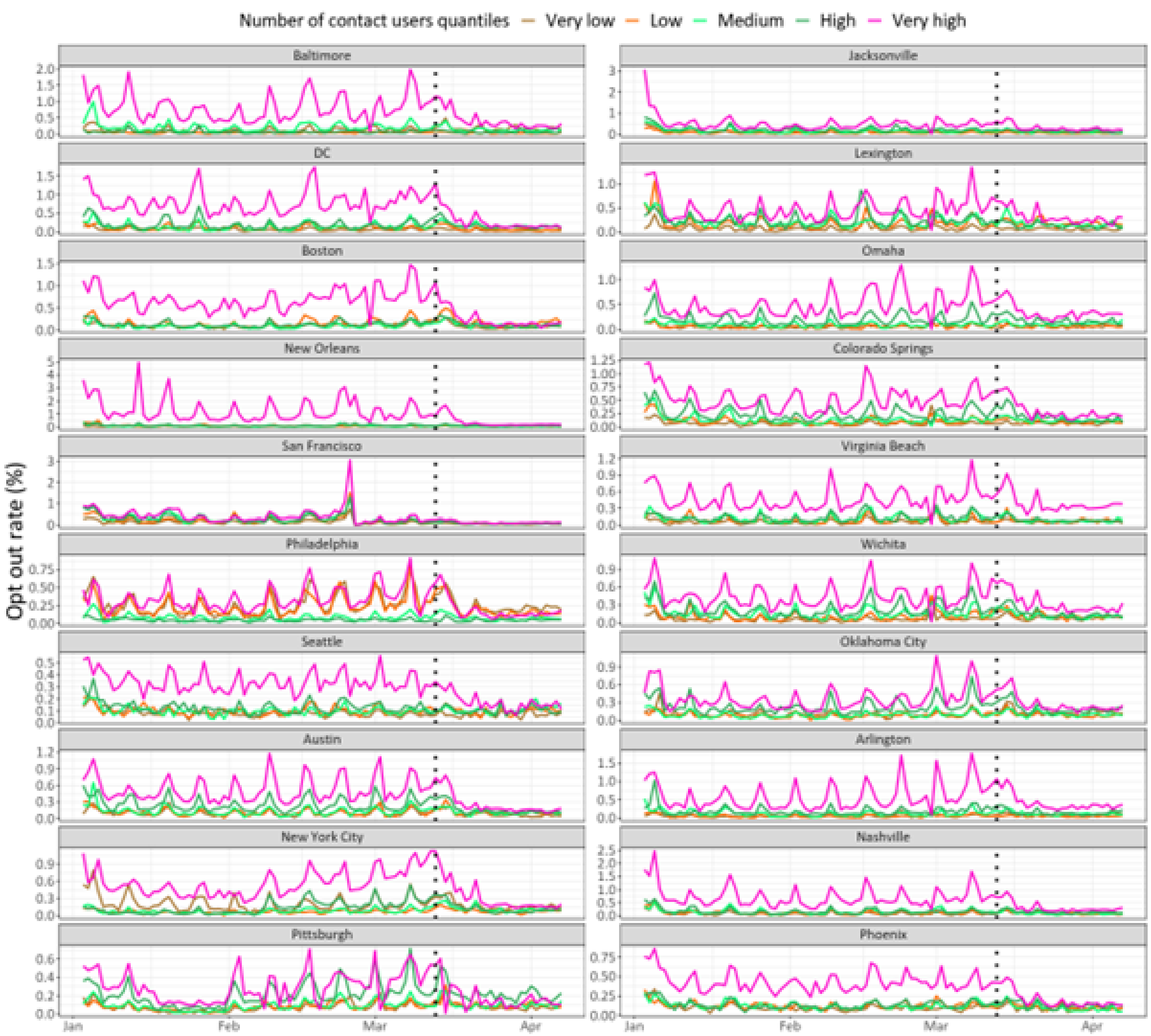
Appendix

Appendix A: City-by-City Results for Figure 2



Day Trend of City-level Opt-out Rate for Different *TotalContacts* Quantiles
(Left, Blue cities; Right, Red cities)

Day Trend of City-level Opt-out Rates for Different Income Quantiles
(Left, blue cities; Right, red cities; three quantiles – from highest to lowest income)

Day Trends of City-level Opt-out Rate for Males and Female
(Left, blue cities; Right, red cities)

Day Trend of City-level Opt-out Rate for Different Racial Diversities
(Left, blue cities; Right, red cities)

Appendix B: Infection Rate and Death Rate across Blue and Red Cities

Table B - COVID-19 Health Risks in Blue Cities versus Red Cities

	DV = Infection Rate	DV = Death Rate
Blue City	0.046****	0.011****
	(0.000)	(0.000)
R-squared	0.031	0.022
Observations	1,731,298	1,731,298

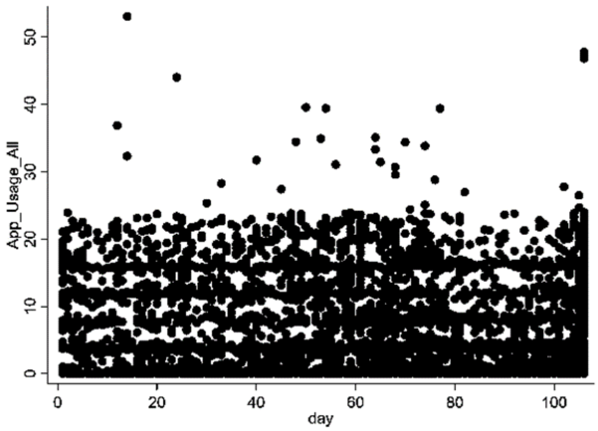
*p<0.10; **p<0.05; ***p<0.01;****p<0.001

Appendix D: Robustness Test with Controls for Spatially Adjacent Blocks

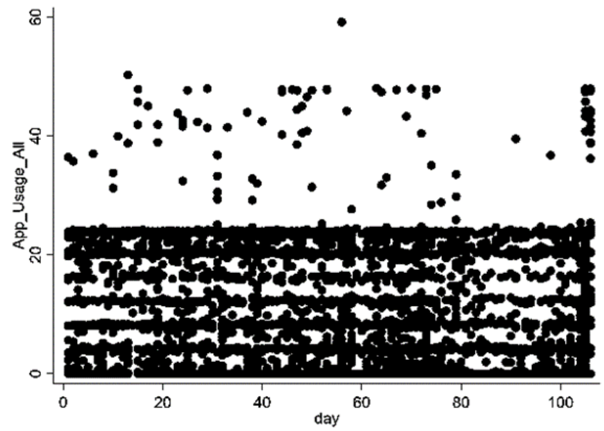
City = DC	(1)	(2)
	Main Effect	Interaction w/ Daily Contacts
DV = CBG *OptOutCount* (Poisson)		
Shock	-0.199****	-0.322****
	(0.028)	(0.030)
Shock X NumContacts		0.145****
		(0.012)
NumContacts	0.214****	0.173****
	(0.007)	(0.007)
Daily Travel Distance	0.298****	0.289****
	(0.011)	(0.011)
Daily Avg. Travel Speed	0.071****	0.072****
	(0.001)	(0.001)
Time Trend	0.015****	0.015****
	(0.001)	(0.001)
Control Variables		
Focal Block Population	Yes	Yes
Focal Block Land Area	Yes	Yes
Focal Block Population Income	Yes	Yes
Focal Block Population Gender	Yes	Yes
Focal Block Population Race	Yes	Yes
Focal Block Number of Existing Users	Yes	Yes
Focal Block Number of Opt-in Users	Yes	Yes
Focal Block Mobile App Usage	Yes	Yes
1st Closest Block Population	Yes	Yes
1st Closest Block Land Area	Yes	Yes
1st Closest Block Population Income	Yes	Yes
1st Closest Block Population Gender	Yes	Yes
1st Closest Block Population Race	Yes	Yes
1st Closest Block Number of Existing Users	Yes	Yes
1st Closest Block Number of Opt-in Users	Yes	Yes
1st Closest Block Mobile App Usage	Yes	Yes
2nd Closest Block Population	Yes	Yes
2nd Closest Block Land Area	Yes	Yes
2nd Closest Block Population Income	Yes	Yes
2nd Closest Block Population Gender	Yes	Yes
2nd Closest Block Population Race	Yes	Yes
2nd Closest Block Number of Existing Users	Yes	Yes
2nd Closest Block Number of Opt-in Users	Yes	Yes
2nd Closest Block Mobile App Usage	Yes	Yes
3rd Closest Block Population	Yes	Yes
3rd Closest Block Land Area	Yes	Yes
3rd Closest Block Population Income	Yes	Yes
3rd Closest Block Population Gender	Yes	Yes
3rd Closest Block Population Race	Yes	Yes
3rd Closest Block Number of Existing Users	Yes	Yes
3rd Closest Block Number of Opt-in Users	Yes	Yes
3rd Closest Block Mobile App Usage	Yes	Yes
Week Fixed Effect	Yes	Yes
Day of Week Fixed Effect	Yes	Yes
Log likelihood	-41420.74	-41352.1
Observations	84,270	84,270

*p<0.10; **p<0.05; ***p<0.01;****p<0.001

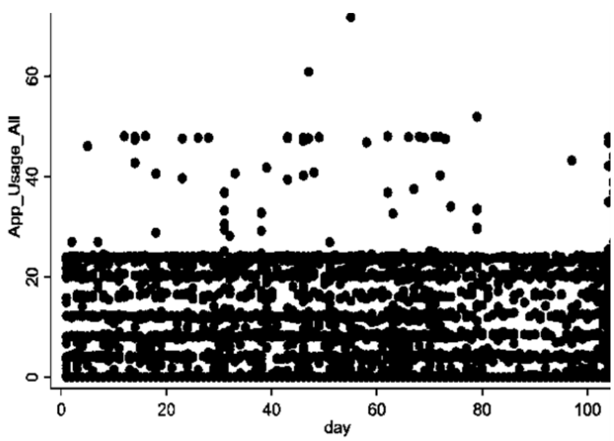
Appendix E: Additional Falsification Test



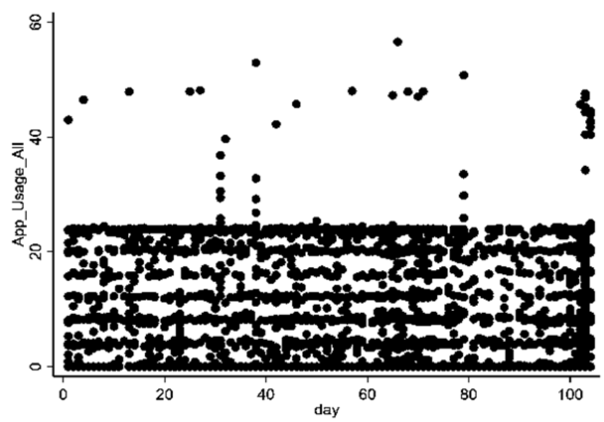
(a) Last Day of Observation



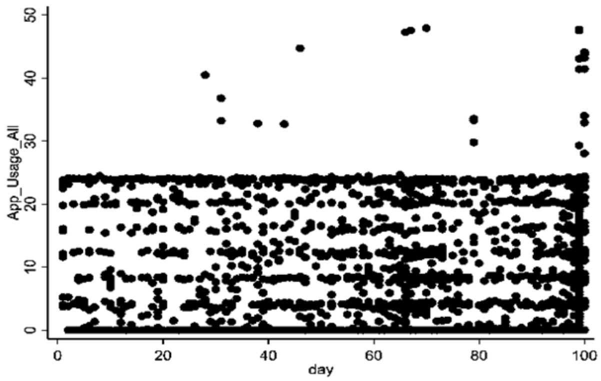
(b) 1 Day Before Last Day of Observation



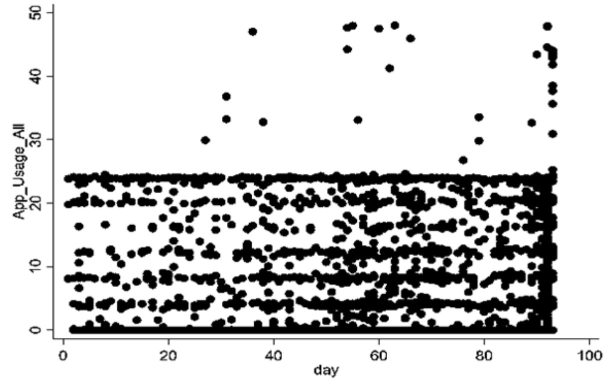
(c) 2 Days Before Last Day of Observation



(d) 3 Days Before Last Day of Observation



(e) 7 Days Before Last Day of Observation



(f) 14 Days Before Last Day of Observation

Distribution of *TotalAppUsage* for Each Opt-out Individuals on

(a) Zero; (b) One; (c) Two; (d) Three; (e) Seven; and (f) Fourteen Days Prior to Opt-out

Correlation between Opt-out and App Usage in Days Preceding Opt-out

	Lag 1 Day	**Lag 2 Days**	**Lag 3 Days**	**Lag 7 Days**
Opt-out and TotalAppUsage	0.0024 (0.7142)	-0.0109 (0.0929)	0.0064 (0.3237)	-0.0061 (0.3468)
Opt-out and Location-HeavyAppUsage	0.0015 (0.8143)	-0.0137* (0.0339)	0.0094 (0.1445)	-0.0050 (0.4366)
Opt-out and AppUsageCategory	0.0041 (0.5249)	-0.0112 (0.0844)	0.0052 (0.4187)	-0.0074 (0.2537)
Opt-out and Location-HeavyAppCategory	0.0024 (0.7142)	-0.0109 (0.0929)	0.0064 (0.3237)	-0.0061 (0.3468)

* = 5% significance level.

Appendix F: National Emergency versus City-specific Lockdowns as Shock

DV = CBG *OptOutCount* (Poisson)				
City	State	City-specific Lockdown Date	Main Effect (City-specific Lockdown)	Main Effect (National Emergency)
San Francisco	CA	19-Mar-20	-0.708**** (0.029)	-0.678**** (0.030)
New York City	NY	22-Mar-20	-0.828** (0.028)	-0.344**** (0.027)
New Orleans	LA	23-Mar-20	-0.489**** (0.032)	-0.048* (0.028)
Seattle	WA	23-Mar-20	0.106**** (0.031)	-0.469**** (0.031)
Boston	MA	24-Mar-20	-0.468**** (0.025)	-0.562**** (0.026)
Lexington	KY	26-Mar-20	-0.095**** (0.024)	-0.580**** (0.026)
Colorado Springs	CO	26-Mar-20	-0.015 (0.025)	-0.678**** (0.026)
Oklahoma City	OK	28-Mar-20	-0.001 (0.077)	-0.188**** (0.027)
Virginia Beach	VA	30-Mar-20	0.189**** (0.032)	-0.543**** (0.029)
Baltimore	MD	30-Mar-20	-0.271**** (0.026)	-0.337**** (0.027)
Wichita	KS	30-Mar-20	0.050 (0.031)	-0.239**** (0.027)
Nashville	TN	31-Mar-20	-0.147**** (0.030)	-0.264**** (0.027)
Phoenix	AZ	31-Mar-20	-0.002 (0.016)	-0.441**** (0.030)
D.C.	DC	1-Apr-20	-0.075*** (0.027)	-0.279**** (0.014)
Pittsburgh	PA	1-Apr-20	-0.001 (0.033)	-0.457**** (0.029)
Philadelphia	PA	1-Apr-20	-0.122**** (0.030)	-0.476**** (0.029)
Austin	TX	2-Apr-20	0.032 (0.033)	-0.312**** (0.027)
Arlington	TX	2-Apr-20	0.076*** (0.028)	-0.215**** (0.026)
Jacksonville	FL	3-Apr-20	0.044 (0.035)	-0.254**** (0.030)
Omaha	NE	n/a#	-	-0.392**** (0.028)
Control variables are the same as in Table 3				
*p<0.10; **p<0.05; ***p<0.01;****p<0.001				
# Nebraska never orders residents to stay home.				
Results are based on the main analyses using Poisson Model. We have also run the same analyses using Negative Binomial Model and the results remain highly consistent.				

We notice that the main effects are positive for Arlington and Virginia Beach, likely because the lockdown orders in those two states (TX and VA) were issued relatively late (4/2 and 3/30, 2020). We do not have enough daily observations to fully observe the post-shock trend, as 4/15/2020 is the last day of our sample. The main effect is also positive for Seattle, calling for future research.

Appendix G: City-by-City Results

Tables G - Heterogeneous Effect of Policy Compliance on Privacy Choice for each City (DV and model are the same as in Table 4)

1 - Boston

City = Boston DV = *Individual OptOut* (Logit)	(1) Main Effect	(2) Interaction w/ Daily Contacts
Shock	-0.562****	-0.615****
	(0.026)	(0.028)
Shock x NumContacts		0.063**** (0.012)
NumContacts	0.310****	0.289****
	(0.007)	(0.008)
Controls	Yes	Yes
Observations	97,308	97,308
*p<0.10; **p<0.05; ***p<0.01;****p<0.001		

2 - D.C.

City = D.c. DV = *Individual OptOut* (Logit)	(1) Main Effect	(2) Interaction w/ Daily Contacts
Shock	-0.262****	-0.416****
	(0.028)	(0.029)
Shock x NumContacts		0.219**** (0.012)
NumContacts	0.265****	0.206****
	(0.006)	(0.007)
Controls	Yes	Yes
Observations	84,270	84,270
*p<0.10; **p<0.05; ***p<0.01;****p<0.001		

3 - Baltimore

City = Baltimore DV = *Individual OptOut* (Logit)	(1) Main Effect	(2) Interaction w/ Daily Contacts
Shock	-0.337****	-0.520****
	(0.027)	(0.029)
Shock x NumContacts		0.248**** (0.015)
NumContacts	0.257****	0.169****
	(0.008)	(0.010)
Controls	Yes	Yes
Observations	71,126	71,126
*p<0.10; **p<0.05; ***p<0.01;****p<0.001		

4 - Lexington

City = Lexington DV = *Individual OptOut* (Logit)	(1) Main Effect	(2) Interaction w/ Daily Contacts
Shock	-0.580****	-0.936****
	(0.026)	(0.031)
Shock x NumContacts		0.203****
		(0.009)
NumContacts	0.259****	0.153****
	(0.006)	(0.007)
Controls	Yes	Yes
Observations	26,500	26,500
*p<0.10; **p<0.05; ***p<0.01;****p<0.001		

5 - Colorado Spring

City = Colorado Spring DV = *Individual OptOut* (Logit)	(1) Main Effect	(2) Interaction w/ Daily Contacts
Shock	-0.678****	0.046
	(0.026)	(0.038)
Shock x NumContacts		-0.216****
		(0.008)
NumContacts	0.192****	0.319****
	(0.005)	(0.007)
Controls	Yes	Yes
Observations	33,496	33,496
*p<0.10; **p<0.05; ***p<0.01;****p<0.001		

6 - Virginia Beach

City = Virginia Beach DV = *Individual OptOut* (Logit)	(1) Main Effect	(2) Interaction w/ Daily Contacts
Shock	-0.491****	-0.887****
	(0.029)	(0.039)
Shock x NumContacts		0.127****
		(0.008)
NumContacts	0.391****	0.320****
	(0.006)	(0.007)
Controls	Yes	Yes
Observations	30,422	30,422
*p<0.10; **p<0.05; ***p<0.01;****p<0.001		

7 - San Francisco

City = San Francisco DV = *Individual OptOut* (Logit)	(1) Main Effect	(2) Interaction w/ Daily Contacts
Shock	-0.678****	-0.673****
	(0.030)	(0.030)
Shock x NumContacts		-0.138*
		(0.083)
NumContacts	0.313****	0.322****
	(0.020)	(0.021)
Controls	Yes	Yes
Observations	132,924	132,924
*p<0.10; **p<0.05; ***p<0.01;****p<0.001		

8 - Jacksonville

City = Jacksonville DV = *Individual OptOut* (Logit)	(1) Main Effect	(2) Interaction w/ Daily Contacts
Shock	-0.195****	-0.556****
	(0.029)	(0.035)
Shock x NumContacts		0.225****
		(0.011)
NumContacts	0.318****	0.225****
	(0.007)	(0.008)
Controls	Yes	Yes
Observations	60,526	60,526
*p<0.10; **p<0.05; ***p<0.01;****p<0.001		

9 - New Orleans

City = New Orleans DV = *Individual OptOut* (Logit)	(1) Main Effect	(2) Interaction w/ Daily Contacts
Shock	-0.027	-0.409****
	(0.028)	(0.034)
Shock x NumContacts		0.196****
		(0.010)
NumContacts	0.545****	0.489****
	(0.007)	(0.008)
Controls	Yes	Yes
Observations	45,156	45,156
*p<0.10; **p<0.05; ***p<0.01;****p<0.001		

10 - Omaha

City = Omaha DV = *Individual OptOut* (Logit)	(1) Main Effect	(2) Interaction w/ Daily Contacts
Shock	-0.392****	-0.628****
	(0.028)	(0.035)
Shock x NumContacts		0.101****
		(0.009)
NumContacts	0.335****	0.283****
	(0.005)	(0.007)
Controls	Yes	Yes
Observations	48,972	48,972
*p<0.10; **p<0.05; ***p<0.01;****p<0.001		

11 - NYC

City = NYC DV = *Individual OptOut* (Logit)	(1) Main Effect (Poisson)	(2) Interaction w/ Daily Contacts (Poisson)
Shock	-0.344****	-0.493****
	(0.027)	(0.028)
Shock x NumContacts		0.305****
		(0.015)
NumContacts	0.373****	0.312****
	(0.008)	(0.008)
Controls	Yes	Yes
Observations	291,394	291,394
*p<0.10; **p<0.05; ***p<0.01;****p<0.001		

12 - Pittsburgh

City = Pittsburgh DV = *Individual OptOut* (Logit)	(1) Main Effect (Poisson)	(2) Interaction w/ Daily Contacts (Poisson)
Shock	-0.457****	-0.576****
	(0.029)	(0.031)
Shock x NumContacts		0.151****
		(0.014)
NumContacts	0.300****	0.241****
	(0.007)	(0.009)
Controls	Yes	Yes
Observations	157,516	157,516
*p<0.10; **p<0.05; ***p<0.01;****p<0.001		

13 - Oklahoma City

City = Oklahoma City DV = *Individual OptOut* (Logit)	(1) Main Effect (Poisson)	(2) Interaction w/ Daily Contacts (Poisson)
Shock	-0.188****	-0.365****
	(0.027)	(0.030)
Shock x NumContacts		0.153****
		(0.011)
NumContacts	0.262****	0.193****
	(0.006)	(0.008)
Controls	Yes	Yes
Observations	82,256	82,256
*p<0.10; **p<0.05; ***p<0.01;****p<0.001		

14 - Philadelphia

City = Philadelphia DV = *Individual OptOut* (Logit)	(1) Main Effect (Poisson)	(2) Interaction w/ Daily Contacts (Poisson)
Shock	-0.476****	-0.500****
	(0.029)	(0.029)
Shock x NumContacts		0.141****
		(0.021)
NumContacts	0.240****	0.206****
	(0.010)	(0.011)
Controls	Yes	Yes
Observations	222,918	222,918
*p<0.10; **p<0.05; ***p<0.01;****p<0.001		

15 - Austin

City = Austin DV = *Individual OptOut* (Logit)	(1) Main Effect (Poisson)	(2) Interaction w/ Daily Contacts (Poisson)
Shock	-0.312****	-0.542****
	(0.027)	(0.031)
Shock x NumContacts		0.172****
		(0.011)
NumContacts	0.267****	0.202****
	(0.006)	(0.008)
Controls	Yes	Yes
Observations	65,190	65,190
*p<0.10; **p<0.05; ***p<0.01;****p<0.001		

16 - Seattle

City = Seattle DV = *Individual OptOut* (Logit)	(1) Main Effect (Poisson)	(2) Interaction w/ Daily Contacts (Poisson)
Shock	-0.469****	-0.494****
	(0.031)	(0.033)
Shock x NumContacts		0.034****
		(0.014)
NumContacts	0.268****	0.254****
	(0.008)	(0.009)
Controls	Yes	Yes
Observations	297,542	297,542
*p<0.10; **p<0.05; ***p<0.01;****p<0.001		

17 - Arlington

City = Arlington DV = *Individual OptOut* (Logit)	(1) Main Effect (Poisson)	(2) Interaction w/ Daily Contacts (Poisson)
Shock	-0.215****	-0.799****
	(0.026)	(0.033)
Shock x NumContacts		0.250****
		(0.010)
NumContacts	0.386****	0.258****
	(0.006)	(0.008)
Controls	Yes	Yes
Observations	27,772	27,772
*p<0.10; **p<0.05; ***p<0.01;****p<0.001		

18 - Phoenix

City = Phoenix DV = *Individual OptOut* (Logit)	(1) Main Effect (Poisson)	(2) Interaction w/ Daily Contacts (Poisson)
Shock	-0.441****	-0.493****
	(0.030)	(0.033)
Shock x NumContacts		0.077****
		(0.015)
NumContacts	0.245****	0.218****
	(0.008)	(0.010)
Controls	Yes	Yes
Observations	264,364	264,364
*p<0.10; **p<0.05; ***p<0.01;****p<0.001		

19 - Nashville

City = Nashville DV = *Individual OptOut* (Logit)	(1) Main Effect (Poisson)	(2) Interaction w/ Daily Contacts (Poisson)
Shock	-0.264****	-0.406****
	(0.027)	(0.029)
Shock x NumContacts		0.203****
		(0.014)
NumContacts	0.279****	0.222****
	(0.007)	(0.009)
Controls	Yes	Yes
Observations	58,512	58,512
*p<0.10; **p<0.05; ***p<0.01;****p<0.001		

20 - Wichita

City = Wichita DV = *Individual OptOut* (Logit)	(1) Main Effect (Poisson)	(2) Interaction w/ Daily Contacts (Poisson)
Shock	-0.239****	-0.474****
	(0.027)	(0.039)
Shock x NumContacts		0.076****
		(0.009)
NumContacts	0.252****	0.214****
	(0.006)	(0.007)
Controls	Yes	Yes
Observations	33,072	33,072
*p<0.10; **p<0.05; ***p<0.01;****p<0.001		

Appendix H: Heterogeneous Effect of Policy Compliance on Privacy Choice (Without App Usage Controls)

Table H - Heterogeneous Effect of Policy Compliance on Privacy Choice (Without App Usage Controls)

DV = CBG *OptOutCount* (Poisson)	(1) Main Effect (10 Red Cities)	(2) w/ Policy Compliance (10 Red Cities)	(3) Interaction w/ Policy Compliance (10 Red Cities)	(4) Main Effect (10 Blue Cities)	(5) w/ Policy Compliance (10 Blue Cities)	(6) Interaction w/ Policy Compliance (10 Blue Cities)	(7) Main Effect (20 Cities)	(8) Interaction w/ Policy Compliance (20 Cities)	(9) Three-way Interaction (20 Cities)
Shock	-0.339****	-0.289****	-0.62****	-0.499****	-0.427****	-0.576***	-0.477****	-0.631****	-0.471****
	(0.019)	(0.018)	(0.025)	(0.017)	(0.016)	(0.017)	(0.012)	(0.015)	(0.017)
NumContacts		0.064****	0.003		0.027****	-0.016**		-0.009****	0.001****
		(0.007)	(0.007)		(0.007)	(0.007)		(0.005)	(0.007)
Shock X NumContacts			0.154****			0.216****		0.178****	0.133****
			(0.008)			(0.008)		(0.006)	(0.008)
Shock X Blue									-0.301****
									(0.015)
NumContacts X Blue									0.003
									(0.011)
Shock X NumContacts X Blue									0.082****
									(0.012)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
CBG FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
# Obs.	595,084	595,084	595,084	1,136,214	1,136,214	1,136,214	1,731,298	1,731,298	1,731,298

*p<0.10; **p<0.05; ***p<0.01;****p<0.001

Appendix I: Additional Heterogeneity We explore the additional heterogeneous effects of the psychographics (political ideology) and demographics (income, gender, race) (Equation (6). As discussed, political ideology impacts the Americans' attitude toward institutional surveillance: with Republicans (Democrats) displaying a warmer (cooler) response[13]. Also, lower- versus higher-income populations might differ, for instance, in their abilities to protect personal information[14].

Demographics. Table I presents the heterogeneous effects of demographics across the 20 cities. We estimate these effects for each demographic variable separately for ease of interpretation. Additional city-by-city analyses also produce consistent results. Overall, the significant and negative effect of the crisis (*Shock*) is consistent with the earlier model-free evidence and the discovered main effect of the crisis: individuals irrespective of demographic heterogeneities have reduced opt-out after the crisis began. This effect is particularly strong (negative $Shock \times Demographics$) among the CBGs with higher proportions of the most affluent (Income >200k), least affluent(Income <60k), and Asian populations. [15]

Table I - Heterogeneous Effect of Demographics on Opt-out

DV = CBG *OptOutCount* (Poisson)	(1) Main Effect	(2) Interaction w/ Income	(3) Interaction w/ Gender	(4) Interaction w/ Race	(5) Interaction w/ Pooled
Shock	-0.326**** (0.011)	-0.530**** (0.021)	-0.922*** (0.044)	-0.251*** (0.022)	-0.941*** (0.074)
Shock × Income 60-100K		0.796**** (0.066)			0.496*** (0.088)
Shock × Income 100-150K		0.400*** (0.068)			-0.048 (0.087)
Shock × Income 150-200K		0.369*** (0.110)			0.297* (0.136)
Shock × Income >200K		-0.908**** (0.074)			-0.361*** (0.099)
Shock × Female			1.175*** (0.082)		1.176*** (0.123)
Shock × Race Black				-0.159*** (0.035)	-0.195*** (0.041)
Shock × Race Asian				-1.570*** (0.095)	-1.457*** (0.094)
Shock × Race Native				0.346* (0.148)	0.454** (0.156)
Shock × Race Other				0.476* (0.222)	0.376 (0.223)
Controls	✓	✓	✓	✓	✓
CBG FEs	✓	✓	✓	✓	✓
Log likelihood	-553647.35	-552826.27	-553429.17	-552691.92	-200093.99
# Obs.	1,731,298	1,731,298	1,731,298	1,731,298	1,731,298

* p <0.10, ** p <0.05, *** p <0.01, **** p <0.001.
Controls are same as those in Table 5.

Appendix J: Alternative Model Specifications

Table J - Main Effect Using CBG-level Linear Probability Model

	Main Effect
Shock	-0.090****
	(0.002)
# Obs.	1,731,298
Controls	✓
CBG FEs	✓
*p<0.10; **p<0.05; ***p<0.01;****p<0.001	

Appendix K: Main Effect Using Only Individuals Who Opted in Since Jan. 1

DV = *Individual OptOut* (Logit)	Effect (All 20 Cities)
Shock	-0.040*** (0.014)
# Obs.	408,557
Controls	✓
*p<0.10; **p<0.05; ***p<0.01;****p<0.001	

Appendix L: Falsification Test: Alternative shock Dates

Falsification Test: Alternative Shock Dates

DV = CBG *OptOutCount* (Poisson)	Shock Jan. 17	Shock Jan. 24	Shock Feb. 14	Shock Feb. 28
Shock	0.069* (-0.040)	0.051 (-0.033)	-0.006 (-0.026)	0.038 (-0.024)
Controls	✓	✓	✓	✓
Log likelihood	-48213.46	-48213.73	-48214.89	-48213.72
# Obs.	84,270	84,270	84,270	84,270

* p < 0.10, ** p < 0.05, *** p < 0.01, **** p < 0.001.
Controls are same as those in Table 5.

Falsification Test: Alternative Shock Dates (Two Weeks Pre-Shock, D. C. Sample)

DV = *Individual OptOut* (Logit)	Mar. 1	Mar. 2	Mar. 3	Mar. 4	Mar. 5	Mar. 6
Shock	-0.010 (0.014)	0.008 (0.013)	0.015 (0.013)	0.025 (0.013)	0.035*** (0.014)	0.037*** (0.014)
Log likelihood	-669224.3	-669224.6	-669223.3	-669220.2	-669215.7	-669214.7
Controls	✓	✓	✓	✓	✓	✓
Individual FEs	✓	✓	✓	✓	✓	✓
# Obs.	1,395,904	1,395,904	1,395,904	1,395,904	1,395,904	1,395,904

* p < 0.10, ** p < 0.05, *** p < 0.01, **** p < 0.001.

DV = *Individual OptOut* (Logit)	Mar. 7	Mar. 8	Mar. 9	Mar. 10	Mar. 11	Mar. 12
Shock	0.044*** (0.014)	0.042*** (0.014)	0.039*** (0.014)	0.027 (0.014)	0.013 (0.015)	0.001 (0.015)
Log likelihood	-669211.1	-669212.8	-669215.4	-669220.8	-669224.2	-669225.1
Controls	✓	✓	✓	✓	✓	✓
Individual FEs	✓	✓	✓	✓	✓	✓
# Obs.	1,395,904	1,395,904	1,395,904	1,395,904	1,395,904	1,395,904

* p < 0.10, ** p < 0.05, *** p < 0.01, **** p < 0.001.

Appendix M: Demographics of Opt-in and Opt-out Users

	Opt-out users' mean	Opt-in users' mean	Opt-out users' mean before March 13th
Gender (Female)	0.489	0.503	0.485
Income (<60K)	0.486	0.481	0.482
Income (60-100K)	0.215	0.231	0.211
Income (100-150K)	0.143	0.155	0.142
Income (150-200K)	0.063	0.062	0.064
Income (>200K)	0.069	0.062	0.073
Race (White)	0.68	0.714	0.674
Race (Black)	0.15	0.136	0.149
Race (Asian)	0.07	0.062	0.075
Race (Native Indian)	0.008	0.009	0.007

Online Appendix

Self-reported societal considerations. The third metric of societal considerations is the individuals' self-reported tendency for societal considerations, collected from a survey among 879 qualified Amazon MTurkers. We acknowledge that the survey-based dataset may not be representative of the whole population and therefore can only provide partial evidence to support the role of prosocial tendencies in reducing opt-outs. Therefore, we do not claim that this survey provides undoubted evidence. Instead, the survey serves to support the main dataset by ruling out alternative explanations, such as time availability, or reduced privacy concerns due to stay-at-home or decreased travel.

This survey examines how individuals' attitude and behavior toward location data sharing have changed since the crisis commenced, and how these changes are related to their self-reported tendency for societal considerations. The survey comprises questions on smartphone usage, awareness of the use of location data to curb the pandemic, societal considerations during the pandemic and in broader contexts, and demographics (details in Online Appendix A). The summary statistics in Online Appendix B reveal that most respondents are aware of the tracking of location data (74.4%) and use of location data to curb the pandemic (81.6%); 48.4% acknowledge that they have become more willing to share location data to help combat the pandemic; 55.1% agree that people need to share location data to help combat the pandemic; a majority agrees that people should wear masks (87.2%), social distance (86.9%), and stay at home (83.6%) during the pandemic; and 36.6% agree that they opted out, changing the location setting from on to off, compared to 50.3% who disagree. These results corroborate with our earlier finding that individuals have opted out less, sharing more location data post-treatment.

We link the opt-out (ordinal *location.on.off*) to each respondent's self-reported societal considerations using both the Ordinal Logit and Ordinary Least Square (OLS) regressions, while controlling for the demographics. The results are consistent. Online Appendix C reveals that those with greater societal considerations, believing in the need to share location data to curb the pandemic (*share.location.prosocial*), wear masks (*wear.masks*), or social distance (*social.distancing*), are significantly less likely to opt out. To explore potential alternative mechanisms, we further link the opt-out (*location.on.off*) to a number of surveyed factors not readily observed in the location data, again using both the Ordinal Logit and OLS regressions. Both produce consistent results (Online Appendix D). We find that those reading privacy policies more carefully (*read.privacy.policies*) are more likely to opt out. The opt-out choice is unrelated to the reduced privacy concern due to increased stay-at-home (*share.location.home*), but more related to individuals' willingness to share location data to help combat the pandemic (*share.location.pandemic*). Overall, these results consistently support the earlier finding that individuals with greater societal considerations opt-out less during the pandemic. Moreover, our subsequent robustness check confirms a significant association between individuals' societal considerations during the pandemic and such considerations across broader contexts, such as helping others, caring about social issues, or donating to charities (Online Appendix E).

Specifically, 40.9% (45.3%) of the respondents donate to charities (social causes); 72.6% (80.8%) agree that they deeply care about social issues (often help others). We average these responses into one variable (prosocial) and gauge associations with pro-social behavior and belief during the pandemic.

Online Appendix A: Survey

EmbeddedData
Random ID = ${rand://int/10000:99999}

Block: Consent Form (6 Questions)
Standard: Behavioral Questions (3 Questions)
Standard: Install (3 Questions)
Standard: Uninstall (3 Questions)
Standard: Off to On (3 Questions)
Standard: On to off (3 Questions)
Standard: General Perception (2 Questions)
Standard: Pro Social (2 Questions) Standard:
Tech Savviness (1 Question) Standard:
Demographics (8 Questions) Standard: Block
4 (1 Question)
Block: (0 Questions)

Start of Block: Consent Form

We are university researchers interested in how your attitude and behavior regarding smartphone location data sharing might have changed since the onset of the COVID-19 pandemic, particularly in the first few months of the pandemic. Thank you for your participation.

---

*

I am aged 18 or older

- Yes (1)
- No (2)

---

*

I am a fluent English speaker

- Yes (1)
- No (2)

*

I am a smartphone user

- ○ Yes (1)
- ○ No (2)

*

I have read and understood the information above

- ○ Yes (1)
- ○ No (2)

*

Are you aware that public authorities across the world are using smart phone data to curb the growth of the pandemic? (Examples : Contact tracing, tracking pandemic spread, opening/re-opening commercial spaces based on mobility)

- ○ Yes (1)
- ○ No (2)

End of Block: Consent Form

Break

Start of Block: Behavioral Questions

Please rate each of the following statements from 1 = strongly disagree to 5 = strongly agree.

Over the **first few months** of the COVID-19 pandemic

	Strongly disagree (6)	Somewhat disagree (7)	Neither agree nor disagree (8)	Somewhat agree (9)	Strongly agree (10)
I have used my smartphone more heavily compared to before the pandemic. (1)	○	○	○	○	○
I have installed more apps on my smartphone compared to before the pandemic. (2)	○	○	○	○	○
I have used those smartphone apps that require my locations more heavily compared to before the pandemic. (10)	○	○	○	○	○
I have become more aware that my smartphone collects my location data. (4)	○	○	○	○	○

I have become more aware that location data are used to combat the pandemic. (Examples: Contact tracing, tracking pandemic spread, opening/re-opening commercial spaces based on mobility) (11)	○	○	○	○	○

Page Break

Over the **first few months** of the pandemic

	Strongly disagree (32)	Somewhat disagree (33)	Neither agree nor disagree (34)	Somewhat agree (35)	Strongly agree (36)
I have spent more time or become more careful reading the privacy policies before granting smartphone apps permission to collect my location data. (1)	○	○	○	○	○
I have become more willing to grant mobile apps permission to collect my location data, because I believe sharing location data can help combat the pandemic. (5)	○	○	○	○	○
I have become more willing to grant mobile apps permission to collect my location data, because I stayed home most of the time and did not care about my	○	○	○	○	○

location data being collected as much. (2)	

End of Block: Behavioral Questions

Start of Block: Install

During the pandemic,

	Strongly disagree (18)	Somewhat disagree (19)	Neither agree nor disagree (20)	Somewhat agree (21)	Strongly agree (22)
I have installed new apps that require location sharing. (1)	○	○	○	○	○

If so, for what application categories (Example : Games, Music, Online delivery). Enter NA if not applicable.

____

Provide a short reason (optional)

____

End of Block: Install

Start of Block: Uninstall

During the pandemic,

	Strongly disagree (20)	Somewhat disagree (21)	Neither agree nor disagree (22)	Somewhat agree (23)	Strongly agree (24)
I have uninstalled apps that required location sharing. (1)	○	○	○	○	○

If so, for what application categories (Example : Games, Music, Online delivery). Enter NA if not applicable.

____

Provide a short reason (optional)

____

End of Block: Uninstall

Start of Block: Off to On

During the pandemic,

	Strongly disagree (20)	Somewhat disagree (21)	Neither agree nor disagree (22)	Somewhat agree (23)	Strongly agree (24)
I have switched “location data sharing” from “Off” to “On” at least once for at least one mobile app on my phone. (1)	○	○	○	○	○

If so, for what application categories (Example : Games, Music, Online delivery). Enter NA if not applicable.

____

Provide a short reason (optional)

____

End of Block: Off to On

Start of Block: On to off

During the pandemic,

	Strongly disagree (20)	Somewhat disagree (21)	Neither agree nor disagree (22)	Somewhat agree (23)	Strongly agree (24)
I have switched “location data sharing” from “On” to “Off” at least once for at least one mobile app on my phone. (1)	○	○	○	○	○

If so, for what application categories (Example : Games, Music, Online delivery). Enter NA if not applicable.

____

Provide a short reason (optional)

____

End of Block: On to off

Start of Block: General Perception

Please rate each of the following statements from 1 = strongly disagree to 5 = strongly agree.

During a pandemic,

	Strongly disagree (6)	Somewhat disagree (7)	Neither agree nor disagree (8)	Somewhat agree (9)	Strongly agree (10)
People need to share their private information (such as their locations) if it contributes to the greater good of the public. (1)	○	○	○	○	○
People need to protect themselves and others by wearing masks during the pandemic. (2)	○	○	○	○	○
People need to protect themselves and others by practicing social distancing during the pandemic. (3)	○	○	○	○	○
People need to protect themselves and others by staying at home more often during the pandemic. (4)	○	○	○	○	○
Please go ahead and select Somewhat agree for this question (5)	○	○	○	○	○

End of Block: General Perception

Start of Block: Pro Social

Please rate your preference levels for the activities listed below.

	Do not prefer (28)	Prefer slightly (29)	Prefer a moderate amount (30)	Prefer a lot (31)	Prefer a great deal (32)
Donation to charities (1)	○	○	○	○	○
Donation to social causes (2)	○	○	○	○	○

Please rate each of the following statements from 1 = strongly disagree to 5 = strongly agree.

	Strongly disagree (9)	Somewhat disagree (10)	Neither agree nor disagree (11)	Somewhat agree (12)	Strongly agree (13)
I often help others (1)	○	○	○	○	○
I deeply care about social issues (2)	○	○	○	○	○

End of Block: Pro Social

Start of Block: Tech Savviness

Please rate your knowledge levels for the activities listed below

	Extremely knowledgeable (16)	Very knowledgeable (17)	Moderately knowledgeable (18)	Slightly knowledgeable (19)	Not knowledgeable at all (20)
Opting out of location sharing on my smart phone (1)	○	○	○	○	○
Clearing cookies on my browser and smart devices (2)	○	○	○	○	○

End of Block: Tech Savviness

Start of Block: Demographics

Your gender

○ Male (1)

○ Female (2)

○ Non-binary / third gender (3)

○ Prefer not to say (4)

○ Other, please enter (5) ____

Your age

- 18 - 24 (1)
- 25 - 34 (2)
- 35 - 44 (3)
- 45 - 54 (4)
- 55 - 64 (5)
- 65 - 74 (6)
- 75 - 84 (7)
- 85 or older (8)

Your ethnicity

- White (8)
- Black or African American (9)
- American Indian or Alaska Native (10)
- Asian (11)
- Native Hawaiian or Pacific Islander (12)
- Hispanic (14)
- Other (13)

In which state do you currently reside?

____

What's the highest level of education that you have received?

- ○ Less than high school (1)
- ○ High school graduate (2)
- ○ Some college (3)
- ○ 2 year degree (4)
- ○ 4 year degree (5)
- ○ Professional degree (6)
- ○ Doctorate (7)

What is your annual household income before tax?

- ○ Less than $10,000 (1)
- ○ $10,000 - $19,999 (2)
- ○ $20,000 - $29,999 (3)
- ○ $30,000 - $39,999 (4)
- ○ $40,000 - $49,999 (5)
- ○ $50,000 - $59,999 (6)
- ○ $60,000 - $69,999 (7)
- ○ $70,000 - $79,999 (8)
- ○ $80,000 - $89,999 (9)
- ○ $90,000 - $99,999 (10)
- ○ $100,000 - $149,999 (11)
- ○ More than $150,000 (12)

What type of smartphone do you have?

- ○ Android (1)
- ○ Apple (2)
- ○ Others, please specify (3) ____

Are you an essential worker during the pandemic (i.e., workers who conduct operations and services that are essential for critical infrastructure operations, e.g., healthcare, food service, public transportation)

○ Yes (1)

○ No (2)

End of Block: Demographics

Start of Block: Block 4

Here is your Random ID for completion of the survey text : ${e://Field/Random%20ID}

Copy this value to paste it into MTurk.

When you have copied this ID, please click next to submit your survey.

Thanks for your participation!

End of Block: Block

Variable	**Survey Question**	**Strongly Or Somewhat Agree**	**Neither Agree Nor Disagree**	**Somewhat Or Strongly Disagree**
Mobile Usage	Used mobile more heavily during pandemic	71.5	14.2	14.3
	Installed more mobile applications during pandemic	57.7	12.9	29.4
	Used apps that require locations more heavily	52.7	18.3	29
Awareness	Location data being used to curb the growth of pandemic	81.6	10.0	8.4
	Smartphones collect location data	74.4	15.4	10.2
Behavior toward Societal Considerations	They are more willing to share location data to help combat pandemic (share.location.pandemic)	48.4	20.8	30.8
Tendency for societal considerations	People need to share location data to help combat the pandemic (share.location.prosocial)	55.1	19.6	25.3
	People need to wear masks (wear.masks)	87.2	8.3	4.5
	People need to social distance (social.distancing)	86.9	8.3	4.8
	People need to stay at home (stay.at.home)	83.6	11.0	5.4
Location Data Sharing	Changed location settings from ON to OFF (location.on.off)	36.6	13.1	50.3

Online Appendix B: Survey Summary Statistics (% of 879 respondents)

Online Appendix C: Heterogeneous Treatment Effect of Self-reported Societal Considerations on Privacy Choice

DV = location.on.off (OLS)	(1)	(2)	(3)	(4)
social.distancing	-0.189^{***}	-0.280^{***}	-0.246^{***}	-0.252^{***}
	(0.059)	(0.083)	(0.091)	(0.091)
wear.masks		0.127	0.154^{*}	0.169^{*}
		(0.082)	(0.087)	(0.087)
stay.at.home			-0.072	-0.051
			(0.079)	(0.080)
share.location.prosocial				-0.085^{**}
				(0.043)
Controls	✓	✓	✓	✓
# Obs.	879	879	879	879
R^2	0.094	0.097	0.098	0.102
Adjusted R^2	0.057	0.058	0.058	0.061
Residual Std. Error	1.469 (df = 843)	1.467 (df = 842)	1.468 (df = 841)	1.465 (df = 840)
F Statistic	2.502^{***} (df = 35; 843)	2.504^{***} (df = 36; 842)	2.458^{***} (df = 37; 841)	2.507^{***} (df = 38; 840)

*p<0.1; **p<0.05; ***p<0.01.
Controls include age, gender, ethnicity, education, income, and whether essential worker.

Online Appendix D: Impact of Alternative Factors on Privacy Choice

DV = location.on.off (OLS)	(1)	(2)	(3)
read.privacy.policies	0.171***	0.186***	0.190***
	(0.044)	(0.045)	(0.045)
share.location.home		−0.065	0.010
		(0.042)	(0.059)
share.location.pandemic			−0.105*
			(0.058)
Controls:	✓	✓	✓
# Obs.	879	879	879
R^2	0.099	0.102	0.105
Adjusted R^2	0.062	0.064	0.066
Residual Std. Error	1.464 (df = 843)	1.463 (df = 842)	1.461 (df = 841)
F Statistic	2.658*** (df = 35; 843)	2.655*** (df = 36; 842)	2.678*** (df = 37; 841)

*p<0.1; **p<0.05; ***p<0.01.
Controls include age, gender, ethnicity, education, income, and whether essential worker.

Online Appendix E: Robustness Checks for the Survey Results

	(1)	(2)	(3)	(4)	(5)
social.distancing	0.167***	0.042	-0.043	-0.019	-0.019
	(0.031)	(0.042)	(0.046)	(0.043)	(0.043)
wear.masks		0.176***	0.108**	0.081*	0.075*
		(0.042)	(0.044)	(0.042)	(0.042)
stay.at.home			0.179***	0.132***	0.125***
			(0.040)	(0.038)	(0.038)
share.location.pandemic				0.207***	0.178***
				(0.020)	(0.024)
share.location.prosocial					0.054**
					(0.024)
Controls (Same as above)	✓	✓	✓	✓	✓
Observations	876	876	876	876	876
R^2	0.168	0.185	0.204	0.295	0.299
Adjusted R^2	0.133	0.150	0.169	0.263	0.267
Residual Std. Error	0.762	0.754	0.746	0.702	0.701
	(df = 840)	(df = 839)	(df = 838)	(df = 837)	(df = 836)
F Statistic	4.842***	5.287***	5.796***	9.220***	9.154***
	(df = 35; 840)	(df = 36; 839)	(df = 37; 838)	(df = 38; 837)	(df = 39; 836)

*p<0.10; **p<0.05; ***p<0.01