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Do People Around the World Care Where Their Data Are Stored?

Jeffrey Prince and Scott Wallsten

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Abstract

Using carefully designed discrete choice surveys, we measure how much individuals care whether their data are stored domestically, i.e., the premium people place on limiting the sharing of their data to their home country compared to elsewhere. We conduct this measure across countries (United States, United Kingdom, South Korea, Japan, Italy, India, and France) and data types (home address and phone number, personal information on finances, biometrics, health status, location, networks, communications, and music preferences). We find only modest evidence of added value resulting from data localization; to the extent that there is added value from localization, it appears to largely come for data types where privacy (i.e., full restrictions on data sharing) is already of high value: financial (account balance) and biometric (facial image) data, and home address and phone number. We also find that, for the U.S., U.K., Italy, India and France, there is no evidence that excluding China and Russia when allowing for international data sharing impacts data localization premium. Interestingly, for Japan and South Korea, we find evidence of a preference *against* excluding China and Russia if data are to be shared internationally. We discuss privacy policy implications.

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1. Introduction

As data becomes increasingly valuable (Economist, 2017), policymakers have debated how to oversee data privacy. A compelling dimension of this debate concerns data localization mandates, i.e., measures that require certain types of data to be stored in its country of origin. Rules can involve preventing information from being sent outside the country, storing a local copy of data, imposing taxes on data exports, or requiring subjects' consent before moving the data to another country (Chander and Le, 2015).

A number of countries have either enacted (e.g., Kazakhstan, Russia, China, Vietnam), or considered enacting (e.g., France, United States), data localization laws. The European Union (EU), through its General Data Protection Regulation (GDPR) also imposes a form of data localization, placing restrictions on exporting data outside the EU. McKinsey (2022) estimated that about 75 percent of all countries had some type of data localization rules.¹ However, citing concerns about impacts on trade and firm efficiency (among others), various trade partnerships have tried to restrict data localization laws.²

Data localization laws can significantly impact the business practices of data intensive firms such as Apple, Google, Microsoft, and others (Miller, 2014; Gurman & Popina, 2019). However, the impact of such laws can extend to a wide range of firms and sectors (Castro & McQuinn, 2015). The challenges in regulating data flows highlight the deep relationship between Internet regulation and trade laws. As Tim Wu noted in 2006, World Trade Organization (WTO) members will have to balance domestic regulation with barriers to trade when deciding how

¹ <https://www.mckinsey.com/capabilities/risk-and-resilience/our-insights/localization-of-data-privacy-regulations-creates-competitive-opportunities>

² <https://www.csis.org/analysis/whose-rules-quest-digital-standards>

much control of the Internet to exert (Wu, 2006). Data localization laws are clearly Internet regulatory decisions that face such a balancing act.

Prevalent factors cited when determining whether, and to what extent, to enact data localization laws include privacy concerns, international trust, and protectionism (discussed further in Section 2). All of these factors have real positive or negative economic value. Some may be large, and some may be so small as to be irrelevant; virtually all are difficult to quantify. For example, privacy concerns encompass aversion, if any, among the citizenry to collecting, processing, and/or storing data outside of the country. However, to our knowledge, no studies have measured the extent of such an aversion or even empirically established that it exists. Put another way, while privacy concerns are often cited as a basis for enacting data localization laws, no empirical evidence demonstrates or measures the size of such concerns and thus the potential welfare benefits such laws may generate along this dimension.

Understanding whether and how much people value data localization is an important element in analyzing any proposed data localization policies, as these values are a key component of policy benefits. As we discuss in Section 2, these benefits, if they exist, should be coupled with other policy benefits and weighed against associated costs to ensure that proposed rules do not cost more than citizens would themselves want imposed.

If citizens' valuation of data localization for various data differs across countries or regions, then acceptable rules and regulations may similarly differ across regions and across data types. At a high level, if, for example, we were to discover that Indians value localization of certain data elements more than Americans, then localization laws tailored to those data elements might yield net benefits in India but not the U.S. If the data element in question is payment

system data, such a difference could rationalize India’s current localization laws for payment system data and the lack of such laws in the U.S.

In this paper, we estimate people’s relative valuations of data privacy across different levels of data localization and we assess how these valuations vary across countries, data types, and platforms. To measure and compare how much citizens value the localization of different types of data, we employed a battery of discrete-choice surveys—a trusted approach demonstrated to be more reliable than open-ended surveys. This approach is especially relevant for various types of data privacy valuation including localization, given it closely mimics the types of choices individuals can make in real markets for personal data³ and policy proposals that would have firms pay consumers for data.⁴

We constructed five different survey structures, one each centered on the respondent’s smartphone, financial institution, healthcare app, smart home device, and social media. Across the five survey structures and for a range of data types, we measure the relative value of full privacy (no data sharing) versus sharing only domestically (localization), sharing domestically and internationally (no localization), and sharing domestically and internationally excluding China and Russia (no localization but with limits). The data types we consider include home address, phone number, income, financial activity, health status and activity, biometrics, music preferences, location, networks, and communications. We administered each of these five different surveys across seven different countries: the United States, the United Kingdom, South Korea, Japan, Italy, India, and France.

³ For example, at the end of 2020, Amazon launched a program in which it would pay consumers to share information about non-Amazon purchases (<https://techcrunch.com/2020/10/20/amazon-launches-a-program-to-pay-consumers-for-their-data-on-non-amazon-purchases/>).

⁴ California and other states have proposed requiring such payments (<https://www.cnet.com/news/california-wants-silicon-valley-to-pay-you-a-data-dividend/>).

For each platform/data type/country combination, we calculate a data localization premium, which is the percentage increase in willingness-to-accept for citizens to be willing to have their data shared outside of their home country, as opposed to being shared only domestically. More specifically, the premium is the ratio in utility when the data type is shared internationally to utility when sharing of the data type is limited to only the home country. In essence, the data localization premium is

We find little evidence that people in any of the countries we survey value data localization. For only 22 out of 175 platform/data type/country combinations was the data localization premium statistically different from zero. To the extent that those 22 are indicative of added value from localization, it appears to largely come for data types where privacy is already of relatively high value: financial and biometric data, and home address and phone number. In addition, we find that, for the U.S., U.K., Italy, India and France, there is no evidence that excluding China and Russia when allowing for international data sharing impacts the measured data localization premium. Interestingly and in contrast, for Japan and South Korea, we find evidence of a preference *against* excluding China and Russia if data are to be shared internationally.

These findings have several implications. First, they suggest that the use of privacy concerns as motivation for data localization laws may be overstated, although there may be some gross welfare gains for some types of data. Our findings also indicate that if international sharing is allowed, consumers place little value on restricting their data from prominent authoritarian countries such as China and Russia, at least for a number of highly populated countries. Our findings for Japan and South Korea identify circumstances where citizens may have a preference

against international restrictions, possibly indicative of a belief that restricting data access to a major trading partner could come at a cost.

Overall, we do not argue that these results, per se, show net costs of data localization requirements. Our analysis does not include other factors, like national security. However, when considering such laws, policymakers should take into account that consumers do not appear to place any value on imposing constraints on international data sharing. Consequently, our findings suggest that welfare justifications for data localization laws should not solely rely on assumed preferences of citizenry for such restrictions.

2. Consequences of Data Localization

Data localization laws could, in principle, improve or worsen consumer welfare. Hence, making an optimal decision in terms of welfare requires weighing the estimated magnitude of countervailing effects.

In the literature, consequences of data localization generally fit somewhere in the civil liberties, government functioning, and economic paradigm described by Bailey and Parsheera (2018). All can be argued to contribute to welfare in some way, but whether the net direction is positive or negative is debatable. Data localization consequences concerning civil liberties include the right to privacy, protection from government surveillance, and freedom of speech and expression. Some argue that data localization laws protect citizens' online privacy (Bauer et al., 2014), but this presumes an effective data protection regime. Further, data localization laws may protect from foreign surveillance, but might also facilitate surveillance by domestic government

(Bailey and Parsheera, 2018).⁵ Lastly, data localization laws could infringe on individual rights, limiting their autonomy, free speech, and right to carry on business and trade with respect to their personal information.

Data localization consequences concerning government function generally pertain to data access necessary for law enforcement, regulatory functions, and protecting national security (Bailey and Parsheera, 2018). The economic consequences of data localization include promoting domestic firms. However, such promotion is a form of protectionism and can come at the cost of gains from trade, ultimately hurting overall welfare in the domestic economy. Data localization can also reduce efficiency for global firms, restricting their ability to optimize where they house data and how they use it.

This paper contributes to our understanding of a key element of the civil liberties effects of data localization, namely the value citizens place on any perceived privacy protection that comes with mandating data stay local. How much consumers value data localization, if at all, is a fundamental element of the welfare implications of data localization laws; consequently, a clearer understanding of this metric could be a crucial factor in determining the optimal extent, if any, of such laws from a welfare point of view.

3. Survey Design

The surveys we construct measure individuals' relative valuations of various forms of data privacy, depending on the level of localization for those data. To estimate these relative

⁵ Hill (2014) suggests that a major impetus behind consideration of data localization laws internationally over the past decade was concern about U.S. surveillance after revelations by Edward Snowden about practices by the U.S. National Security Agency.

valuations, we collect and analyze data from five separate surveys that employ repeated discrete choice experiments (DCEs). The five surveys pertain to respondents' financial institution, healthcare app, smart home device, smartphone, and social media. Because we are interested in comparing results across countries, the survey had to be in five languages given our country choices: English, French, Italian, Japanese, and Korean. We designed the survey in English, paid to have it translated into each language, and then had native speakers review the translations and compare to the English to ensure not just proper translation but also that the same meanings and information were conveyed to the respondent.

Prior work has shown that DCEs mitigate the reporting inaccuracy of stated-preference data (Carare et al. 2015). Even if hypothetical bias may potentially overestimate demand, the estimation for changes in feature levels is statistically unbiased, at least for willingness-to-pay (WTP) estimates (Ding et al. 2005; Miller et al. 2011). A reliable DCE method, however, requires a careful design to cause respondents to answer truthfully, as if they are making a choice in the real market (Ben-Akiva et al. 2016). We thus structure the survey in three parts. We first collect relevant demographic information in order to conduct comparative analyses and to ensure a representative sample. Demographics we collect include sex, age, proximity to a city, and household income.

Second, we provide respondents descriptions for each of the relevant features about which we will inquire in the third part of the survey. We carefully vetted these descriptions through several focus groups.⁶

⁶ We ran a number of pretests online using expert services of the firm GBK.

The final part of the survey consists of repeated choice experiments. Here, we mimic a real market choice situation while exogenously varying our variables of interest – particularly, payments, exposure to targeted ads (in our social media survey), and the types of data the user shares along with the level of localization when sharing. In the DCEs, individuals make a series of choices over hypothetical alternatives, defined by a set of attributes. Since our primary goal is to estimate how individuals value localization for various data types, the core attributes are various measures of data privacy and corresponding localization. We provide the descriptions and levels for each survey in Tables 1a-1e.

Table 1a: Attributes, Descriptions, and Levels for Finance Survey

Attributes	Description	Levels
Sharing of your home address with third parties	The extent to which the bank can use and distribute your home address to Third Parties	No Sharing Shares with Domestic Third Parties Only Shares with Domestic and International Third Parties Shares with Domestic and International Third Parties Except China and Russia
Sharing of your phone number with third parties	The extent to which the bank can use and distribute your phone number to Third Parties	
Sharing of your balance with third parties	The extent to which the bank can use and distribute your balance information to Third Parties	
Sharing of cash withdrawals with third parties	The extent to which the bank can use and distribute information about the frequency and amounts of your cash withdrawals to Third Parties	
Sharing of your income with third parties	The extent to which the bank can use and distribute your income information to Third Parties	
Monthly Payment	The amount you would receive in monthly payments from your bank	Fra: €0,€0.25,€0.50,...,€4.00,€4.25 Ita.: €0,€0.25,€0.50,...,€4.00,€4.25 Ind.: ₹0, ₹6, ₹12,..., ₹96, ₹102 Jap.: ¥0,¥25,¥50,...,¥400,¥425 S.Ko.: ₩0,₩225,₩450,...,₩3,600, ₩3,825 U.K.: £0,£0.20,£0.40,...,£3.20,£3.40 U.S.: \$0,\$0.25,\$0.50,...,\$4.00,\$4.25

Table 1b: Attributes, Descriptions, and Levels for Healthcare App Survey

Attributes	Description	Levels
Sharing of your home address with third parties	The extent to which the healthcare app can use and distribute your home address to Third Parties	<p>No Sharing</p> <p>Shares with Domestic Third Parties Only</p> <p>Shares with Domestic and International Third Parties</p> <p>Shares with Domestic and International Third Parties Except China and Russia</p>
Sharing of your phone number with third parties	The extent to which the healthcare app can use and distribute your phone number to Third Parties	
Sharing of your physical health status with third parties	The extent to which the healthcare app can use and distribute information about your physical health status to Third Parties	
Sharing of your mental health status with third parties	The extent to which the healthcare app can use and distribute information about your mental health status to Third Parties	
Sharing of information about healthcare services provided to you with third parties	The extent to which the healthcare app can use and distribute information about healthcare services provided to you to Third Parties	
Sharing of your Covid-19 vaccination status with third parties	The extent to which the healthcare app can use and distribute your Covid-19 vaccination status to Third Parties	
Monthly Payment	The amount you would receive in monthly payments from your healthcare app	<p>Fra: €0,€0.25,€0.50,...,€4.00,€4.25</p> <p>Ita.: €0,€0.25,€0.50,...,€4.00,€4.25</p> <p>Ind.: ₹0, ₹6, ₹12,..., ₹96, ₹102</p> <p>Jap.: ¥0,¥25,¥50,...,¥400,¥425</p> <p>S.Ko.: ₩0,₩225,₩450,...,₩3,600, ₩3,825</p> <p>U.K.: £0,£0.20,£0.40,...,£3.20,£3.40</p> <p>U.S.: \$0,\$0.25,\$0.50,...,\$4.00,\$4.25</p>

Table 1c: Attributes, Descriptions, and Levels for Home Smart Device Survey

Attributes	Description	Levels
Sharing of your home address with third parties	The extent to which the home smart device can use and distribute your home address to Third Parties	
Sharing of your phone number with third parties	The extent to which the home smart device can use and distribute your phone number to Third Parties	
Sharing of your voiceprint with third parties	A voiceprint is the data required for a computer to identify your voice as yours. For example, Alexa on an Amazon Echo can use this information to identify you as the speaker. The extent to which the home smart device can use and distribute your voiceprint information to Third Parties	
Sharing of your music preferences with third parties	The extent to which the healthcare app can use and distribute your music preferences to Third Parties	
Monthly Payment	The amount you would receive in monthly payments from the manufacturer of your home smart device	

Table 1d: Attributes, Descriptions, and Levels for Smartphone Survey

Attributes	Description	Levels
Sharing of your phone number with third parties	The extent to which the smartphone allows apps to use and distribute your phone number to Third Parties	No Sharing Shares with Domestic Third Parties Only Shares with Domestic and International Third Parties Shares with Domestic and International Third Parties Except China and Russia
Sharing of your fingerprint with third parties	The extent to which the smartphone allows apps to use and distribute your fingerprint information to Third Parties	
Sharing of your location with third parties	The extent to which the smartphone allows apps to use and distribute your location information to Third Parties	
Sharing of your facial image with third parties	The extent to which the smartphone allows apps to use and distribute your facial image information to Third Parties	
Sends you advertisements	The smartphone allows apps to send you advertisements tailored to your interests (sometimes called “targeted advertisements”)	Yes No
Monthly Payment	The amount you would receive in monthly payments from the manufacturer of your smartphone	Fra: €0,€0.25,€0.50,...,€4.00,€4.25 Ita.: €0,€0.25,€0.50,...,€4.00,€4.25 Ind.: ₹0, ₹6, ₹12,..., ₹96, ₹102 Jap.: ¥0,¥25,¥50,...,¥400,¥425 S.Ko.: ₩0,₩225,₩450,...,₩3,600, ₩3,825 U.K.: £0,£0.20,£0.40,...,£3.20,£3.40 U.S.: \$0,\$0.25,\$0.50,...,\$4.00,\$4.25

Table 1e: Attributes, Descriptions, and Levels for Social Media Survey

Attributes	Description	Levels
Sharing of your home address with third parties	The extent to which the social media company can use and distribute your home address to Third Parties	No Sharing Shares with Domestic Third Parties Only Shares with Domestic and International Third Parties Shares with Domestic and International Third Parties Except China and Russia
Sharing of your phone number with third parties	The extent to which the social media company can use and distribute your phone number to Third Parties	
Sharing of your posts with third parties	The extent to which the social media company can use and distribute information from your social media posts to Third Parties	
Sharing of information about your network of friends with third parties	The extent to which the social media company can use and distribute your information about your friend network to Third Parties	
Sharing of your contact list with third parties	The extent to which the social media company can use and distribute your contact list from your smartphone to Third Parties	
Inserts targeted ads in your social media feed	The social media company allows advertisers to target you based on what the social media company knows but does not share that information with the advertiser	Yes No
Monthly Payment	The amount you would receive in monthly payments from the social media company	Fra: €0,€0.25,€0.50,...,€4.00,€4.25 Ita.: €0,€0.25,€0.50,...,€4.00,€4.25 Ind.: ₹0, ₹6, ₹12,..., ₹96, ₹102 Jap.: ¥0,¥25,¥50,...,¥400,¥425 S.Ko.: ₩0,₩225,₩450,...,₩3,600, ₩3,825 U.K.: £0,£0.20,£0.40,...,£3.20,£3.40 U.S.: \$0,\$0.25,\$0.50,...,\$4.00,\$4.25

In principle, we could include other common attributes for each survey. However, our surveys are not designed to elicit choices over the products and services themselves (e.g., choices over different smartphones or checking accounts). Rather, for a given product or service, respondents make choices about corresponding privacy packages. Such choices are not inconsistent with actual market decisions. For example, Amazon offers to pay consumers for data about non-Amazon purchases, so markets for privacy already exist.⁷ We also note that the specific types of privacy we consider were generally motivated by existing policies, such as the General Data Protection Regulation (GDPR) and California Consumer Privacy Act (CCPA).

Each respondent is presented with ten different choice questions, a common volume for such surveys at this level of complexity (Johnson & Orme, 1996). In addition, to mitigate endogeneity concerns, we explicitly state that any omitted feature should be assumed to be identical across all alternatives. In other words, any omitted attributes are controlled for, i.e., held fixed, when making the comparison. We provide the content of each survey (the U.S. version – UK and India are also in English with minor alterations) in an online appendix, including an example choice question.⁸

We conclude this subsection with a brief description of our process for arriving at an optimal design, i.e., the construction of the levels for each attribute presented to each respondent for each choice. For a statistically optimal design, we rely on D-optimality (Zwerina et al. 2010), which we implement in the statistical software program SAS. We use a fractional factorial design to capture the main effects.⁹ The chosen design generates 80 choice questions for all five

⁷ <https://panel.amazon.com/>

⁸ Translated versions in French, Italian, Japanese, and Korean are available upon request.

⁹ We use SAS %mktruns and %mktex to produce candidate runs given our target sample size. We avoid dominated alternatives (i.e. better privacy and higher payment) by using the SAS %macro. We then evaluate and select the design by using SAS %choiceff.

surveys. We grouped the choice questions into sets of ten (which we call versions), with four alternatives for all five surveys. We randomly vary the alternatives for each choice, and randomly distribute the versions across respondents.

4. Data

Our data come from Dynata's standing Internet panel across seven countries: United States, United Kingdom, South Korea, Japan, Italy, India, and France. We requested 325 completed surveys per type (smartphone, etc.), per country. Hence, our total number of requested completed surveys is $5 \text{ platform types} * 7 \text{ countries} * 325 \text{ completes per country} = 11,375$. Dynata makes sure that the target sample sizes are satisfied. In our analyses, we also weight observations according to the most recent census estimates of each country for both age and sex.¹⁰

A qualified response requires the household respondent to be at least 18 years old. For the finance, healthcare app, and smartphone surveys, respondents were required to own a smartphone. For the home smart device survey, respondents were required to own a home smart device, and for the social media survey, respondents were required to have a social media account. In all five surveys, the respondent must have been the primary decision-maker for the relevant product or service if they already had it.

Tables AA1-AA7 in Appendix A contain demographic distributions for each country, broken down by the five survey types.

¹⁰ We note that none of our qualitative findings depend on this weighting, and the quantitative findings only change minimally, suggesting any selection in terms of who completes the surveys in each country is unlikely to be driving our main results.

5. Econometric Methods

To estimate values for privacy, we use a conditional logistic regression model (McFadden 1974; Greene 2012) to estimate utility parameters and ultimately calculate valuations for data localization.

Let \mathbf{x}_{ijk} be a vector of attributes for alternative j in choice question k that individual i faces. A linear random utility model can be written as:

$$u_{ijk} = \mathbf{x}'_{ijk}\boldsymbol{\beta} + \varepsilon_{ijk} \quad (1)$$

We interpret the errors (ε_{ijk}) as individual idiosyncratic preference and assume that it is independently and identically distributed with type I extreme value distributions. With this assumption, the probability for individual i to choose alternative j among, say, four alternatives in question k is then:

$$\text{Prob}(Y_{ik} = j) = \frac{\exp(\mathbf{x}'_{ijk}\boldsymbol{\beta})}{\sum_{n=1}^4 \exp(\mathbf{x}'_{ink}\boldsymbol{\beta})} \quad (2)$$

Since we observe individual choices in each question, we are able to generate the likelihood function based on these probabilities. We then optimize the likelihood function with respect to $\boldsymbol{\beta}$ and obtain the estimated utility parameters for each attribute, clustering our errors on individuals.

Our calculations for the value of data localization rely on $\boldsymbol{\beta}$. In our case, besides payment, the attributes consist of combinations of the privacy and level of localization of personal data whose values we intend to compare. For illustration, consider our survey focusing on smartphones. In this survey, we partition \mathbf{x}'_{ijk} into:

$[Payment_{ijk}, PhoneDom_{ijk}, PhoneDomIntNCR_{ijk}, PhoneDomInt_{ijk}, FingerDom_{ijk},$
 $FingerDomIntNCR_{ijk}, FingerDomInt_{ijk}, LocationDom_{ijk}, LocationDomIntNCR_{ijk},$
 $LocationDomInt_{ijk}, FacialDom_{ijk}, FacialDomIntNCR_{ijk}, FacialDomInt_{ijk}, Ads_{ijk}]$

In this formulation, all variables, except payment, are dummy variables equal to 1 if the corresponding data are shared as indicated and 0 otherwise. Here, a suffix of Dom implies sharing domestically only, a suffix of DomIntNCR implies sharing domestically and internationally except China and Russia, and a suffix of DomInt implies sharing domestically and internationally with no country restrictions. The corresponding β' is:

$[\beta_P, \beta_{PD}, \beta_{PDInCR}, \beta_{PDI}, \beta_{FD}, \beta_{FDInCR}, \beta_{FDI}, \beta_{LD}, \beta_{LDInCR}, \beta_{LDI}, \beta_{FaD}, \beta_{FaDInCR}, \beta_{FaDI}, \beta_{Ads}]$

Using this formulation, we calculate two “data localization premiums” using the following formulas (illustrated for fingerprint data):

$$DLP_{All}(fingerprint) = \frac{\beta_{FDI}}{\beta_{FD}} - 1 \quad (3)$$

$$DLP_{noCR}(fingerprint) = \frac{\beta_{FDInCR}}{\beta_{FD}} - 1 \quad (4)$$

The above two formulas produce the percentage premium in payment (above what would be required to share only domestically) that an individual would require to share fingerprint data internationally, with no restrictions and restricting China and Russia, respectively. We estimate the variance of our data localization premiums by using a linear transformation of the variance-covariance matrix of β , also known as the delta method.

A key merit of using a survey is the ability to generate sufficient variation in our variables of interest and cleanly identify the underlying parameters. The use of a hypothetical

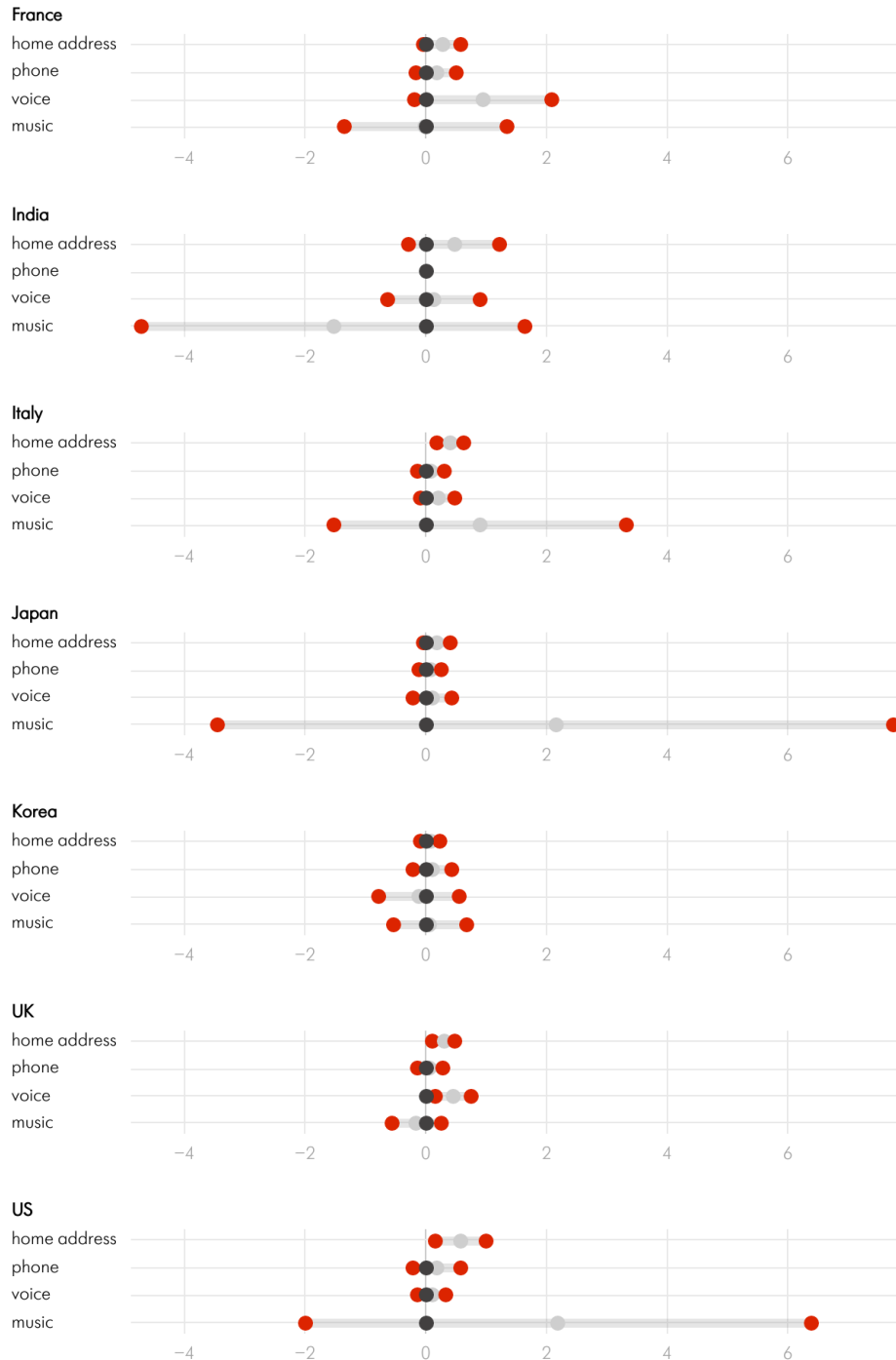
environment, however, may also induce unrealistic responses that generate bias. To minimize this possibility, we carefully designed our survey to elicit respondents' preferences and mimic the real market situation with respect to payments for data access. However, we are not actually collecting the private information we ask about (e.g., location data), nor are we providing an actual payment in return.

6. Results

For all five surveys across all seven countries, Tables AB1-AB5 contain our parameter estimates, which we use to attain our data localization premiums, as described in Section 5. Our main findings are in Figures 1a-1e. Figures 1a-1e present point estimates and confidence intervals for our data localization premium estimates from equation (3) (where no localization means sharing with any country, including China and Russia) for all platform/data type/country combinations, which are the premiums respondents place on keeping data local versus sharing it internationally without restriction.

Figure 1a: Home Smart Device

95% Confidence Interval Shown Around Point Estimate.
Zero shown in black except where it is outside of CI.



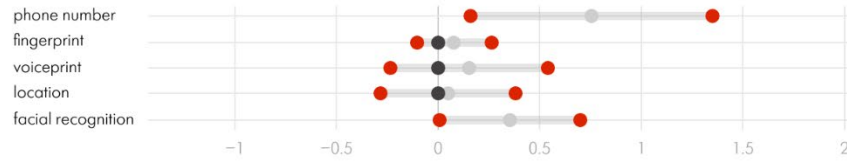
India phone excluded because confidence interval is $(-18, 13)$, which changes the scale in a way that makes the other estimates unreadable.



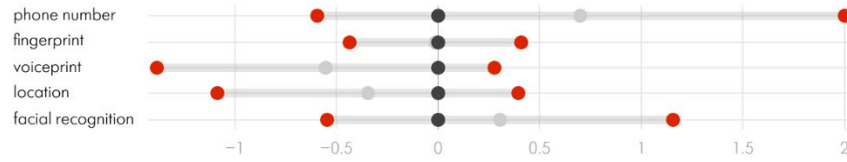
Figure 1b: Smartphone

95% Confidence Interval Shown Around Point Estimate.
Zero shown in black except where it is outside of CI.

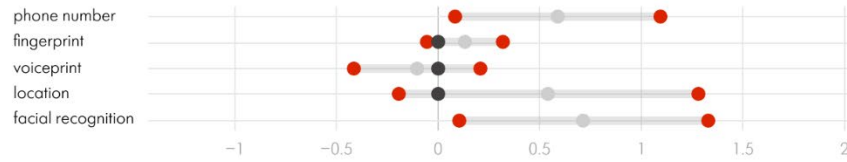
France



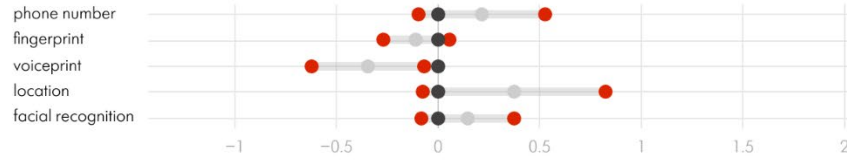
India



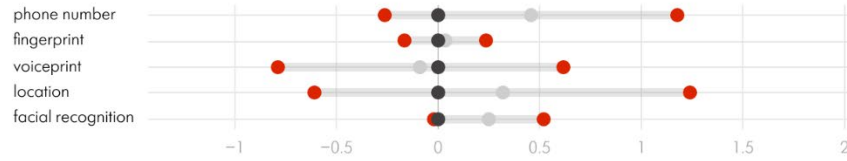
Italy



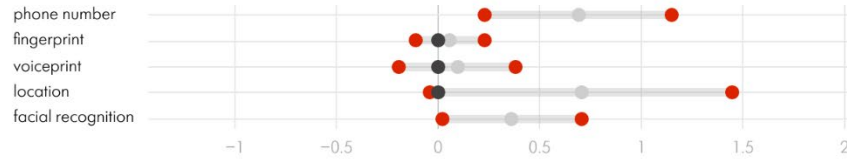
Japan



Korea



UK



US

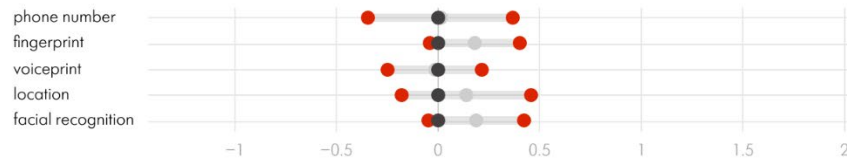
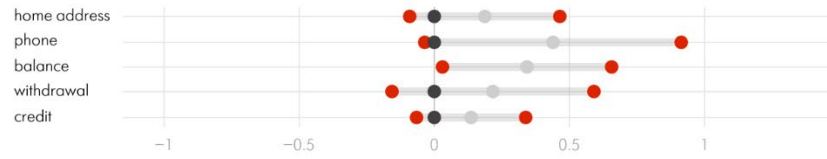


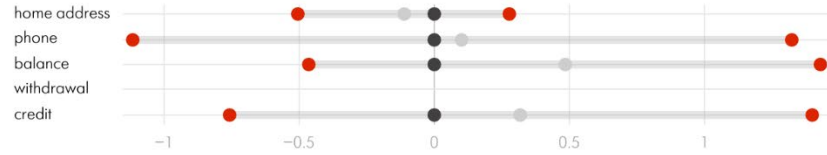
Figure 1c: Finance

95% Confidence Interval Shown Around Point Estimate.
Zero shown in black except where it is outside of CI.

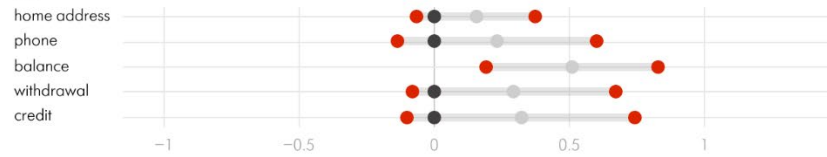
France



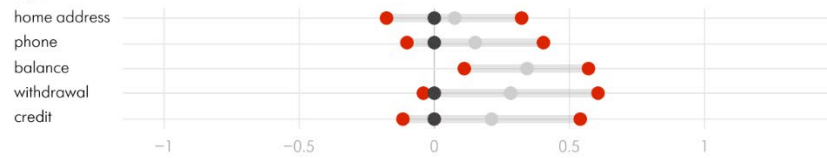
India



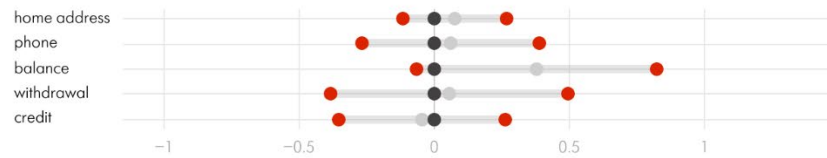
Italy



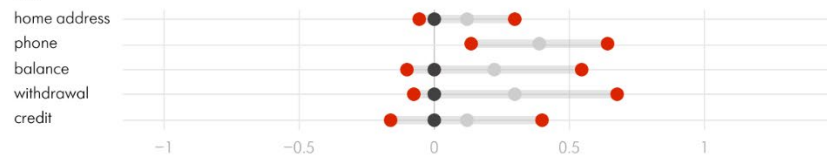
Japan



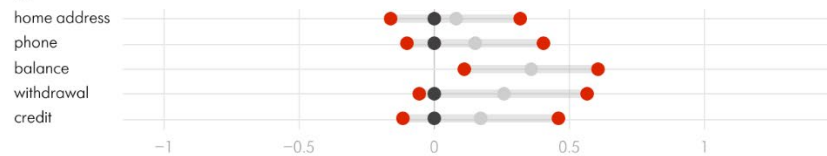
Korea



UK



US

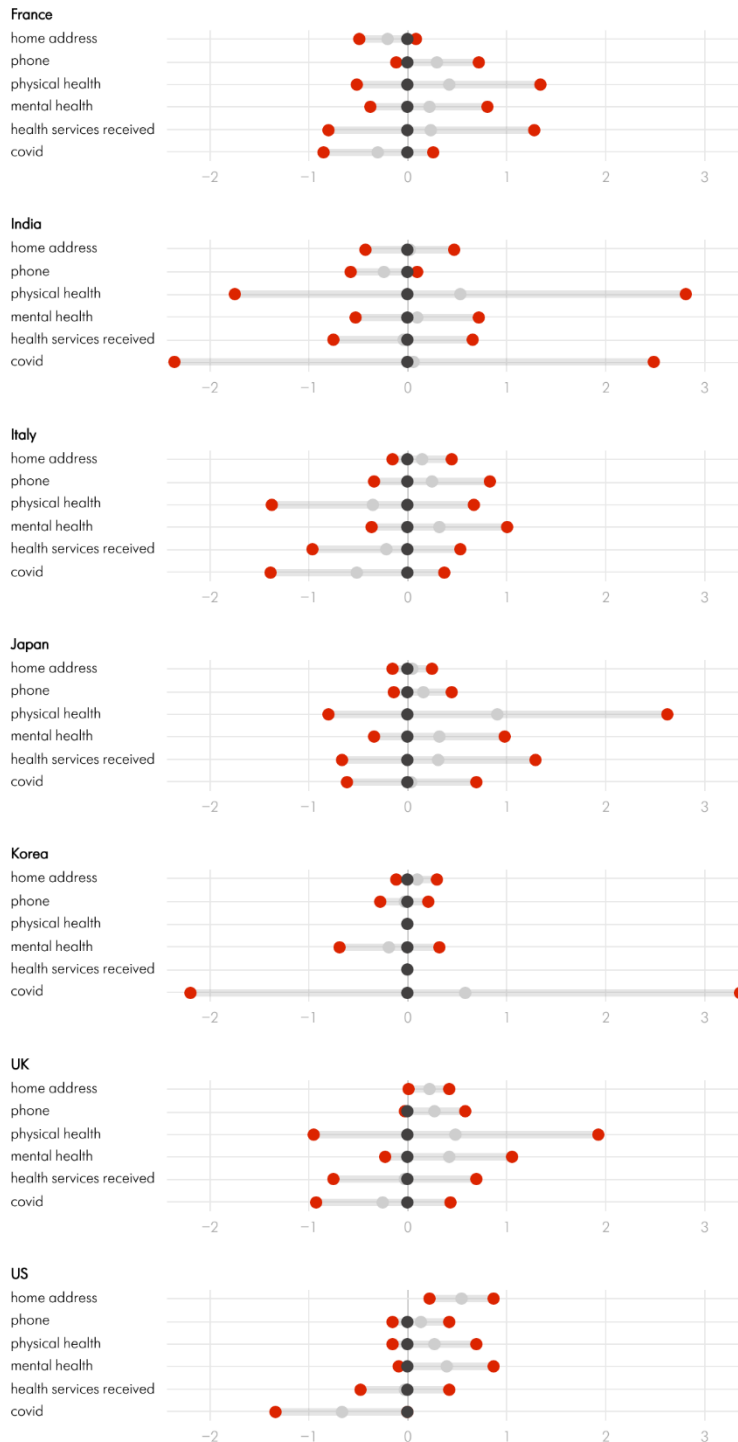


India withdrawal excluded because its confidence interval is $(-37, 26)$, which changes the scale in a way that makes the other estimates unreadable.



Figure 1d: Health App

95% Confidence Interval Shown Around Point Estimate.
 Zero shown in black except where it is outside of CI.



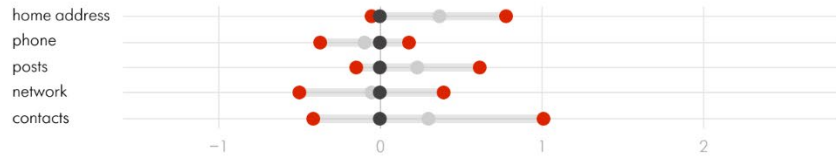
Korea physical health and health services received excluded because confidence intervals are [-112, 126] and [-6, 10], which changes the scale in a way that makes the other estimates unreadable.



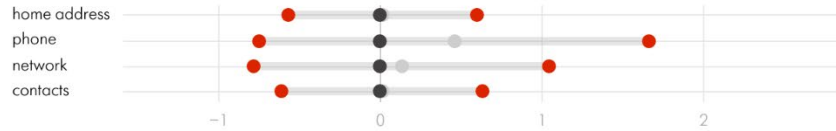
Figure 1e: Social Media

95% Confidence Interval Shown Around Point Estimate.
Zero shown in black except where it is outside of CI.

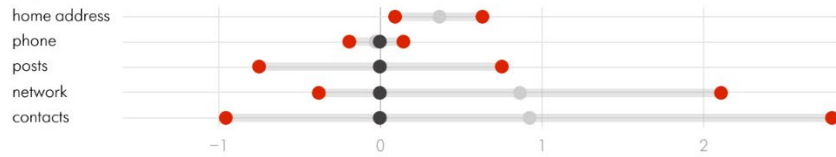
France



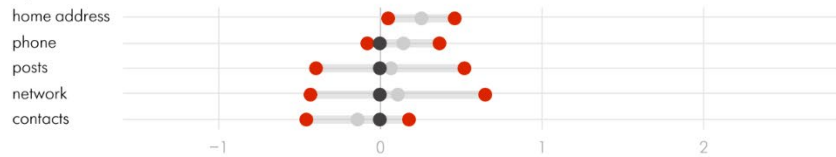
India



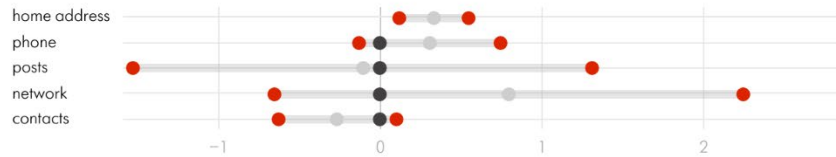
Italy



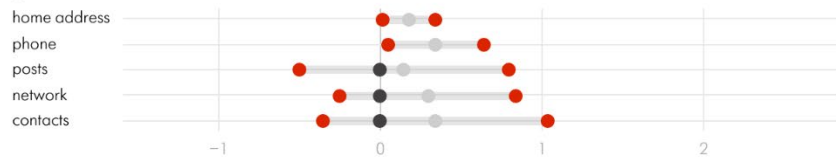
Japan



Korea



UK



US



India posts excluded because confidence interval is (-4.5, 1.5), which changes the scale in a way that makes the other estimates more difficult to read.

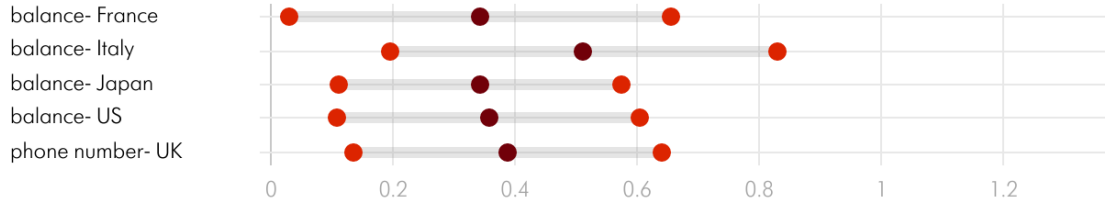


In Figure 2, we collect all of the statistically significant estimates from Figures 1a-1e. In this figure, it is evident that there are a just handful of data types for which we find any notable data localization premium: bank balance, facial recognition, home address, and phone number, all with multiple instances, and voiceprint, with one instance. Revisiting Tables AB1-AB5, we note that these are generally the data types for which we find the greatest disutility from any sharing (including domestically). Put another way, the data types for which we find a data localization premium are also the data types for which citizens find the most value in having no sharing of any kind.

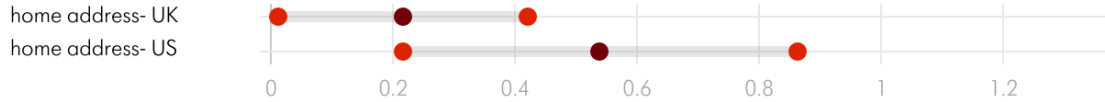
Figure 2: Statistically Significant Coefficient Estimates

95% Confidence Interval Shown Around Point Estimate.

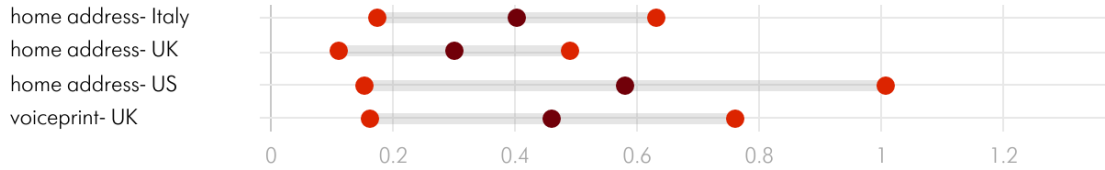
finance



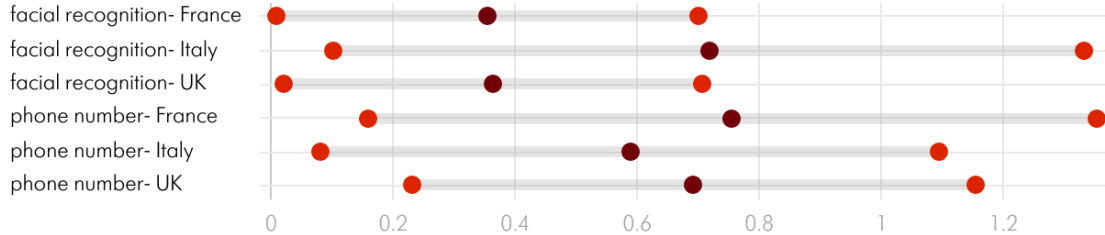
health



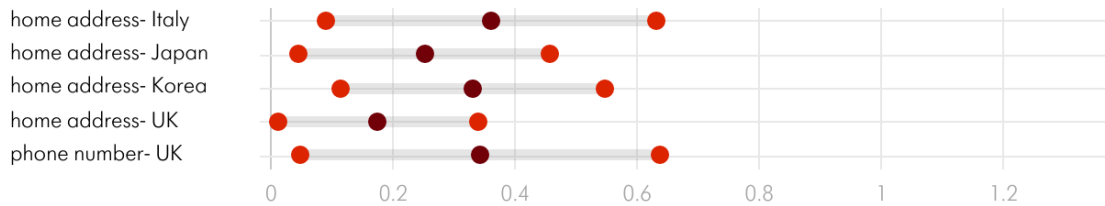
home



smartphone

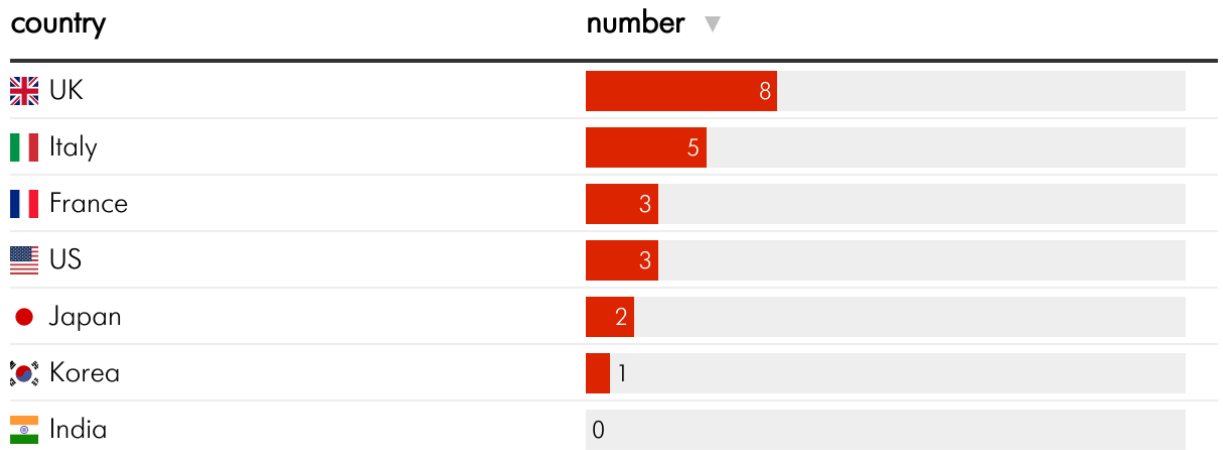


social media



Additionally, meta-analysis of the data in Figure 3 shows that people in the UK care about the largest number of data types, with 8 out of 25 types being statistically significant, followed by Italy with 5, France and the US with 3, Japan with 2, Korea with 1, and India with none.

Figure 3: Number of Survey-Information Types Out of 25 That Were Statistically Significant



Last, in Table 2, we assess whether citizens have any difference in their preferences concerning data localization when the two most prominent authoritarian countries, China and Russia, are excluded from international data sharing. To make this comparison, we test for any difference in data localization premium when China and Russia are included versus excluded when there is international data sharing. Referring back to Section 5, we test for a difference between the data localization measure from equation (3) and the data localization measure from equation (4)¹¹. In Table 2, an entry of “Neg” means that there is a greater data localization

¹¹ Note that simple arithmetic implies that this test is essentially a test for any difference between β_{FDI} and β_{FDInCR} for our example concerning fingerprint.

premium when China and Russia are excluded when there is international sharing, and an entry of “Pos” means that there is a data localization premium when China and Russia are included when there is international sharing. Put another way, “Neg” implies a preference to have China and Russia included if there is international data sharing, and “Pos” implies a preference to have China and Russia excluded if there is international data sharing.

Table 2: Change in Localization Premium when adding China and Russia to non-localized access¹²

Platform	Data Type	U.S.	U.K.	Korea	Japan	Italy	India	France
Finance	Home Address	Neg	Neg	Neg	Neg	Neg	Neg***	Neg
	Phone Number	Pos	Pos	Neg*	Pos	Pos	Neg	Neg
	Balance	Neg	Neg	Neg**	Neg	Pos	Neg	Neg
	Withdrawals	Pos	Neg***	Neg***	Pos	Neg	Neg**	Neg
	Income	Neg	Neg*	Neg***	Neg*	Neg	Neg	Neg
Healthcare								
	Home Address	Pos***	Neg	Neg	Neg**	Neg	Pos	Neg***
	Phone Number	Neg	Neg*	Neg	Neg	Neg	Pos	Pos
	Physical Health	Neg	Neg	Neg	Pos	Neg	Pos	Pos
	Mental Health	Pos	Neg**	Neg	Neg	Neg	Pos	Pos
	Health Services	Neg	Neg	Neg	Neg	Neg	Neg	Neg
	Covid-19 Vax	Neg	Neg	Neg*	Neg	Neg	Pos	Neg
Home Device	Home Address	Pos	Pos*	Neg***	Neg*	Pos*	Pos	Neg
	Phone Number	Neg	Pos	Pos	Neg	Neg	Neg	Neg**
	Voiceprint	Pos	Pos	Neg	Neg	Neg	Pos	Pos
	Music Prefs	Pos	Neg	Neg	Neg	Pos	Pos	Neg
Smartphone	Phone Number	Neg*	Pos	Neg*	Neg	Pos**	Neg	Pos
	Fingerprint	Neg	Neg	Pos	Neg***	Pos	Neg	Neg
	Voiceprint	Pos	Neg	Neg**	Neg***	Neg	Neg	Neg

¹² *** significant at 1%, ** significant at 5%, * significant at 10%

	Location	Neg	Pos	Pos	Pos**	Pos**	Neg*	Neg
	Facial Image	Neg	Neg	Neg	Neg	Pos	Neg	Neg
Social Media	Home Address	Pos**	Neg	Pos**	Neg**	Pos	Neg	Pos
	Phone Number	Pos	Neg	Neg**	Neg	Neg	Neg	Neg
	Posts	Neg	Neg	Neg	Neg	Neg	Neg	Neg
	Network	Neg	Neg	Neg	Neg**	Neg	Neg	Neg
	Contacts	Neg	Pos	Neg	Neg	Pos	Pos	Pos**

In Table 2 we see, for the U.S., U.K., Italy, India and France, no evidence that excluding China and Russia when allowing for international data sharing impacts the measured data localization premium. While 17 out of 125 results are statistically significant results for that collection of countries, that share is not inconsistent with what we'd expect to find by chance if all the true population differences were zero.¹³ In contrast, for Japan and South Korea, we have 17 out of 50 estimates statistically significant at the 10% level, which is more than one would expect by chance if no differences truly existed. Notably all but one are negative, indicating a preference *against* excluding China and Russia if data are to be shared internationally.

7. Discussion and Conclusions

Using carefully designed conjoint surveys, we find that citizens for seven highly populated countries (U.S., U.K., South Korea, Japan, Italy, India, and France) place little to no value in data localization requirements. We also find that, for five of these countries (U.S., U.K., Italy, India, France), there is no preference to exclude China and Russia when data are shared internationally,

¹³ The odds of finding at least 17 results out of 125 to be statistically significant at the 10% level when the true parameters are all zero is 12%, using the formula for a binomial distribution with success probability of 0.10 and 125 trials.

and for South Korea and Japan, there appears to be a substantial preference against excluding China and Russia when data are shared internationally.

Our findings have several implications. First, they suggest that the use of privacy concerns as motivation for data localization laws may be overstated, although there may be some gross welfare gains for some types of data. Our findings also indicate that if international sharing is allowed, restricting prominent authoritarian countries such as China and Russia appears to have little impact on consumer value, at least for a number of highly populated countries. Our findings for Japan and South Korea identify circumstances where citizens may have a preference against international restrictions. China, Japan, and South Korea comprise a significant economic bloc, so this finding could indicate a believe by Japanese and South Korean citizens that restricting data access to a major trading partner could come at a cost.

Overall, we do not claim these results necessarily imply net costs of data localization requirements, as there may be other welfare-enhancing benefits, such as national security. However, our findings do provide a counterweight to any claim that citizens find value from imposing constraints on international data sharing. To the contrary, if anything, our findings highlight that citizens may be mindful of downsides of restricting access from trading partners. Consequently, a notable takeaway from our analyses is that welfare justifications for data localization laws should not solely rely on assumed preferences of citizenry for such restrictions.

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Appendix A

Demographic Summary Stats (Percentages for Each Demographic Category)

Table AA1: U.S. Respondents

		Finance	Health	Home	Smart	Social
Sex	Male	48.62	42.46	54.46	51.38	47.69
	Female	51.38	57.23	45.54	48.62	52.31
Age	18-24	8.62	12.62	12.00	10.46	7.08
	25-34	12.31	12.00	16.62	13.85	13.23
	35-44	17.85	17.85	22.77	19.38	22.46
	45-54	16.00	11.69	13.85	17.85	15.38
	55-64	17.85	12.00	13.85	18.77	18.15
	65+	27.38	33.85	20.92	19.69	23.69
Annual_Income	< \$15K	8.00	6.15	9.23	8.62	9.54
	\$15-25K	8.62	9.85	5.54	9.23	7.38
	\$25-50K	17.23	14.46	16.00	12.92	12.62
	\$50-75K	10.46	14.46	11.08	13.85	14.77
	\$75-100K	14.15	11.69	10.77	10.77	11.08
	\$100-150K	11.38	15.69	17.54	15.38	14.46
	\$150-200K	8.92	8.92	7.08	7.08	9.23
	\$200-250K	7.38	6.15	8.31	6.46	6.77
	\$250-500K	5.54	4.92	5.23	6.77	7.38
	\$500-1000K	1.23	0.62	1.85	3.08	0.92
	> \$1000K	1.54	0.92	1.85	0.92	0.92
	No Ans. or NoA	5.54	6.15	5.54	4.92	4.92
Urban_Rural	In a City	38.77	47.08	49.23	43.08	44.31
	Near a City	48.92	43.69	40.62	43.69	42.46
	Far from a City	12.31	9.23	10.15	13.23	13.23

Table AA2: U.K. Respondents

		Finance	Health	Home	Smart	Social
Sex	Male	48.31	41.23	43.08	45.85	36.00
	Female	51.38	58.46	56.92	54.15	64.00
Age	18-24	6.15	11.69	12.00	5.23	11.08
	25-34	17.54	23.69	23.69	12.92	24.92
	35-44	20.31	18.15	25.85	17.54	27.69
	45-54	21.23	21.54	17.54	16.62	16.00
	55-64	18.46	16.31	12.62	23.08	10.77
	65+	16.31	8.62	8.31	24.62	9.54
Annual Income	< \$15K	12.92	9.85	3.69	10.15	8.92
	\$15-25K	14.77	16.92	15.38	18.46	14.15
	\$25-50K	38.77	32.31	36.62	35.08	38.46
	\$50-75K	17.23	20.00	24.92	18.46	21.85
	\$75-100K	7.69	10.15	11.69	8.62	9.54
	\$100-150K	3.38	6.77	2.77	2.77	4.00
	\$150-200K	0.62	0.62	0.62	0.92	0.31
	\$200-250K	1.23	0.92	0.62	0.92	0.62
	\$250-500K	0.00	0.31	0.31	0.00	0.00
	\$500-1000K	3.38	2.15	3.38	4.62	2.15
	> \$1000K	12.92	9.85	3.69	10.15	8.92
Urban Rural	In a City	32.00	37.85	34.15	33.85	37.54
	Near a City	48.31	50.77	47.69	44.31	46.15
	Far from a City	19.69	11.38	18.15	21.85	16.31

Table AA3: Korea Respondents

		Finance	Health	Home	Smart	Social
Sex	Male	53.85	56.31	53.85	53.54	55.38
	Female	45.54	42.46	45.85	44.92	44.31
Age	18-24	4.92	8.62	5.85	9.54	5.54
	25-34	20.92	23.69	20.62	25.85	21.23
	35-44	30.15	32.00	42.15	24.62	33.85
	45-54	29.54	23.38	20.00	22.15	27.38
	55-64	10.77	10.46	8.62	12.92	9.85
	65+	3.69	1.85	2.77	4.92	2.15
Annual Income	No Ans. or NoA	100.00	100.00	100.00	100.00	100.00
Urban_Rural	In a City	84.92	91.08	86.46	87.38	87.69
	Near a City	11.38	8.31	12.31	10.46	9.54
	Far from a City	3.69	0.62	1.23	2.15	2.77

Table AA4: Japan Respondents

		Finance	Health	Home	Smart	Social
Sex	Male	48.62	73.23	72.92	51.38	64.31
	Female	51.38	26.15	26.77	48.62	34.77
Age	18-24	8.62	3.69	1.85	10.46	4.92
	25-34	12.31	6.77	9.85	13.85	12.62
	35-44	17.85	15.69	20.31	19.38	26.77
	45-54	16.00	32.31	28.62	17.85	26.46
	55-64	17.85	24.31	24.31	18.77	20.31
	65+	27.38	17.23	15.08	19.69	8.92
Annual Income	< \$15K	8.00	6.15	5.54	8.62	7.69
	\$15-25K	8.62	6.46	2.77	9.23	5.54
	\$25-50K	17.23	8.31	5.85	12.92	11.69
	\$50-75K	10.46	11.38	10.77	13.85	11.38
	\$75-100K	14.15	8.31	8.00	10.77	11.08
	\$100-150K	11.38	10.77	9.54	15.38	11.38
	\$150-200K	8.92	8.31	9.85	7.08	7.69
	\$200-250K	7.38	6.15	12.00	6.46	6.15
	\$250-500K	5.54	9.23	8.92	6.77	7.08
	\$500-1000K	1.23	15.08	15.69	3.08	9.85
	> \$1000K	1.54	7.08	9.54	0.92	8.62
	No Ans. or NoA	5.54	2.77	1.54	4.92	1.85
Urban Rural	In a City	38.77	37.23	41.85	43.08	38.15
	Near a City	48.92	37.85	39.69	43.69	40.62
	Far from a City	12.31	24.92	18.46	13.23	21.23

Table AA5: Italy Respondents

		Finance	Health	Home	Smart	Social
Sex	Male	49.23	48.92	52.62	50.77	48.31
	Female	50.77	51.08	47.08	48.92	51.69
Age	18-24	2.46	6.46	7.08	5.85	4.00
	25-34	15.08	19.38	20.00	15.69	20.00
	35-44	22.77	27.08	27.38	24.00	25.85
	45-54	29.85	27.38	23.08	25.23	24.00
	55-64	18.46	13.85	14.15	19.38	18.15
	65+	11.38	5.85	8.31	9.85	8.00
Annual Income	< \$15K	12.92	8.31	6.46	9.54	15.08
	\$15-25K	18.46	15.38	21.54	20.62	23.08
	\$25-50K	38.77	0.62	41.85	41.85	27.69
	\$50-75K	14.46	0.62	15.08	11.38	14.46
	\$75-100K	2.77	9.85	5.85	4.31	5.85
	\$100-150K	2.77	2.77	0.92	2.46	5.23
	\$150-200K	0.31	0.31	0.92	0.31	0.92
	\$200-250K	0.00	0.00	1.23	0.00	0.00
	\$250-500K	0.31	43.08	0.62	0.31	0.31
	\$500-1000K	0.31	12.31	0.00	0.31	0.62
	> \$1000K	0.62	0.92	0.00	0.31	0.31
	No Ans. or NoA	8.31	5.85	5.54	8.62	6.46
Urban Rural	In a City	57.85	63.69	62.77	57.23	59.69
	Near a City	26.15	25.54	28.62	28.31	28.92
	Far from a City	16.00	10.77	8.62	14.46	11.38

Table AA6: India Respondents

		Fianace	Health	Home	Smart	Social
Sex	Male	61.23	60.92	53.54	52.31	56.92
	Female	38.77	38.77	46.15	47.69	43.08
Age	18-24	24.31	20.62	22.15	24.92	19.38
	25-34	37.23	44.31	46.77	44.31	43.08
	35-44	26.77	25.85	23.08	21.85	30.77
	45-54	8.31	6.77	6.77	6.15	5.54
	55-64	2.15	1.85	1.23	2.46	1.23
	65+	1.23	0.62		0.31	
Annual_Income	< \$15K	26.15	19.08	19.38	27.69	20.62
	\$15-25K	22.46	26.46	30.46	25.85	30.77
	\$25-50K	26.15	27.38	25.54	24.31	23.08
	\$50-75K	15.38	13.54	12.92	8.62	12.92
	\$75-100K	7.08	8.31	8.62	7.08	7.38
	\$100-150K	0.31	0.92	1.85	1.54	1.54
	\$150-200K	1.85	2.77	0.62	2.46	1.54
	\$200-250K	0.62	1.54	0.62	2.46	2.15
Urban_Rural	In a City	84.92	88.31	88.92	90.46	86.77
	Near a City	13.85	10.77	10.15	8.00	10.77
	Far from a City	1.23	0.92	0.92	1.54	2.46

Table AA7: France Respondents

		Finance	Health	Home	Smart	Social
Sex	Male	49.85	48.00	61.23	50.77	50.46
	Female	50.15	52.00	38.77	49.23	49.23
Age	18-24	6.77	14.77	12.00	5.54	8.92
	25-34	13.85	25.54	18.46	13.54	15.38
	35-44	15.08	26.15	20.92	13.85	27.38
	45-54	26.15	13.54	21.85	25.85	20.62
	55-64	22.77	11.69	15.69	23.69	17.54
	65+	15.38	8.31	11.08	17.54	10.15
Annual_Income	< \$15K	8.92	13.85	8.92	10.77	11.69
	\$15-25K	32.31	29.54	24.92	24.62	28.62
	\$25-50K	21.85	26.46	35.08	27.69	28.00
	\$50-75K	14.77	14.46	13.85	18.77	19.69
	\$75-100K	8.92	7.08	9.23	9.23	5.54
	\$100-150K	8.00	4.92	4.31	4.31	4.31
	\$150-200K	5.23	3.69	3.69	4.62	2.15
Urban_Rural	In a City	55.69	64.00	61.54	56.92	55.69
	Near a City	31.08	28.92	30.77	28.00	28.31
	Far from a City	13.23	7.08	7.69	15.08	16.00

Appendix B
Parameter Estimates

Table AB1: Parameter Estimation Results for Finance Survey¹⁴

		U.S.	U.K.	Korea	Japan	Italy	India	France
Home Address	Domestic only	-0.480	-0.600*** (0.064)	-0.558*** (0.067)	-0.471*** (0.064)	-0.502*** (0.063)	-0.237*** (0.056)	-0.372*** (0.060)
	Domestic & international, not China, Rus.	0.063	-0.711*** (0.067)	-0.692*** (0.072)	-0.547*** (0.067)	-0.596*** (0.066)	-0.400*** (0.057)	-0.557*** (0.067)
	Domestic & international	-0.517*** (0.068)	-0.677*** (0.069)	-0.603*** (0.065)	-0.517*** (0.068)	-0.593*** (0.062)	-0.221*** (0.057)	-0.457*** (0.060)
Phone Number	Domestic only	-0.492*** (0.066)	-0.508*** (0.063)	-0.349*** (0.067)	-0.492*** (0.066)	-0.331*** (0.063)	-0.073 (0.056)	-0.286*** (0.064)
	Domestic & international, not China, Rus.	-0.559*** (0.067)	-0.643*** (0.066)	-0.501*** (0.069)	-0.559*** (0.067)	-0.395*** (0.060)	-0.149** (0.051)	-0.455*** (0.067)
	Domestic & international	-0.557*** (0.068)	-0.713*** (0.069)	-0.389*** (0.067)	-0.557*** (0.068)	-0.413*** (0.063)	-0.100 (0.057)	-0.419*** (0.065)
Balance	Domestic only	-0.516*** (0.065)	-0.352*** (0.061)	-0.298*** (0.054)	-0.516*** (0.065)	-0.456*** (0.064)	-0.150** (0.056)	-0.411*** (0.063)
	Domestic & international, not China, Rus.	-0.758*** (0.069)	-0.492*** (0.065)	-0.558*** (0.062)	-0.758*** (0.069)	-0.605*** (0.067)	-0.212*** (0.056)	-0.579*** (0.066)
	Domestic & international	-0.700*** (0.068)	-0.436*** (0.060)	-0.408*** (0.059)	-0.700*** (0.068)	-0.694*** (0.066)	-0.211*** (0.058)	-0.549*** (0.065)
Withdrawals	Domestic only	-0.371*** (0.059)	-0.309*** (0.055)	-0.238*** (0.059)	-0.371*** (0.059)	-0.285*** (0.055)	-0.014 (0.052)	-0.294*** (0.055)
	Domestic & international, not China, Rus.	-0.431*** (0.065)	-0.543*** (0.063)	-0.388*** (0.067)	-0.431*** (0.065)	-0.406*** (0.059)	-0.193*** (0.053)	-0.444*** (0.060)
	Domestic & international	-0.460*** (0.065)	-0.399*** (0.060)	-0.253*** (0.062)	-0.460*** (0.065)	-0.355*** (0.059)	-0.090 (0.051)	-0.388*** (0.059)
Income	Domestic only	-0.443*** (0.066)	-0.385*** (0.068)	-0.338*** (0.063)	-0.443*** (0.066)	-0.314*** (0.070)	-0.131* (0.063)	-0.540*** (0.069)
	Domestic & international, not China, Rus.	-0.509*** (0.067)	-0.528*** (0.067)	-0.494*** (0.066)	-0.592*** (0.069)	-0.475*** (0.070)	-0.187** (0.059)	-0.665*** (0.066)
	Domestic & international	-0.592*** (0.069)	-0.446*** (0.064)	-0.320*** (0.058)	-0.509*** (0.067)	-0.398*** (0.065)	-0.166** (0.058)	-0.617*** (0.062)
Payment		0.100** (0.031)	0.091** (0.033)	0.123*** (0.031)	0.100** (0.031)	0.136*** (0.034)	0.180*** (0.031)	0.052 (0.032)
Obs.		13,000	13,000	13,000	13,000	13,000	13,000	13,000

¹⁴ T-stats in parentheses. + is significant at 10% level. * is significant at 5% level. ** is significant at 1% level.

Table AB2: Parameter Estimation Results for Healthcare Survey¹⁵

		U.S.	U.K.	Korea	Japan	Italy	India	France
Home Address	Domestic only	-0.429*** (0.064)	-0.642*** (0.070)	-0.599*** (0.073)	-0.611*** (0.072)	-0.407*** (0.063)	-0.241*** (0.061)	-0.333*** (0.061)
	Domestic & international, not China, Rus.	-0.512*** (0.065)	-0.815*** (0.077)	-0.687*** (0.074)	-0.842*** (0.077)	-0.478*** (0.066)	-0.242*** (0.062)	-0.450*** (0.065)
	Domestic & international	-0.672*** (0.067)	-0.782*** (0.072)	-0.650*** (0.070)	-0.669*** (0.069)	-0.468*** (0.062)	-0.265*** (0.061)	-0.256*** (0.058)
Phone Number	Domestic only	-0.368*** (0.066)	-0.439*** (0.067)	-0.447*** (0.065)	-0.448*** (0.069)	-0.249*** (0.064)	-0.272*** (0.060)	-0.350*** (0.061)
	Domestic & international, not China, Rus.	-0.497*** (0.066)	-0.650*** (0.072)	-0.488*** (0.065)	-0.557*** (0.073)	-0.350*** (0.062)	-0.167** (0.059)	-0.378*** (0.060)
	Domestic & international	-0.434*** (0.070)	-0.536*** (0.072)	-0.463*** (0.064)	-0.517*** (0.071)	-0.275*** (0.066)	-0.213*** (0.062)	-0.429*** (0.066)
Physical Health	Domestic only	-0.284*** (0.051)	-0.103 (0.057)	-0.015 (0.051)	-0.093 (0.054)	-0.086 (0.051)	(0.043) (0.050)	-0.139* (0.054)
	Domestic & international, not China, Rus.	-0.396*** (0.061)	-0.168** (0.055)	-0.063 (0.053)	-0.141* (0.059)	-0.123* (0.055)	(0.066) (0.052)	-0.182** (0.058)
	Domestic & international	-0.339*** (0.057)	-0.151** (0.055)	-0.036 (0.048)	-0.174** (0.055)	-0.039 (0.050)	(0.089) (0.051)	-0.184*** (0.054)
Mental Health	Domestic only	-0.252*** (0.059)	-0.193*** (0.057)	-0.190*** (0.056)	-0.190** (0.059)	-0.186** (0.057)	-0.157** (0.055)	-0.161** (0.059)
	Domestic & international, not China, Rus.	-0.342*** (0.058)	-0.365*** (0.060)	-0.234*** (0.054)	-0.303*** (0.055)	-0.248*** (0.052)	-0.155** (0.059)	-0.187*** (0.056)
	Domestic & international	-0.332*** (0.062)	-0.275*** (0.062)	-0.163** (0.055)	-0.273*** (0.059)	-0.227*** (0.054)	-0.156** (0.058)	-0.207*** (0.059)
Health Services	Domestic only	-0.268*** (0.055)	-0.171** (0.058)	-0.046 (0.055)	-0.152** (0.054)	-0.132** (0.051)	-0.168** (0.053)	-0.138* (0.055)
	Domestic & international, not China, Rus.	-0.289*** (0.058)	-0.172** (0.058)	-0.169** (0.060)	-0.255*** (0.061)	-0.110* (0.048)	-0.154** (0.055)	-0.180** (0.056)
	Domestic & international	-0.247*** (0.060)	-0.153** (0.055)	-0.119* (0.053)	-0.170** (0.054)	-0.088 (0.052)	-0.113* (0.055)	-0.136* (0.055)
Covid-19 Vaccination	Domestic only	-0.155** (0.058)	-0.167** (0.055)	-0.049 (0.050)	-0.174*** (0.052)	-0.125* (0.059)	-0.045 (0.057)	-0.156** (0.056)
	Domestic & international, not China, Rus.	-0.129* (0.056)	-0.170** (0.056)	-0.195*** (0.057)	-0.200*** (0.055)	-0.137* (0.056)	-0.025 (0.054)	-0.175** (0.056)
	Domestic & international	-0.034 (0.054)	-0.129* (0.055)	-0.079 (0.053)	-0.174*** (0.049)	-0.060 (0.058)	-0.034 (0.055)	-0.116* (0.057)
Payment		0.197*** (0.033)	0.216*** (0.034)	0.112*** (0.033)	0.064 (0.034)	0.195*** (0.036)	0.229*** (0.030)	0.093** (0.034)
Obs.		13,000	13,000	13,000	13,000	13,000	13,000	13,000

¹⁵ T-stats in parentheses. + is significant at 10% level. * is significant at 5% level. ** is significant at 1% level.

Table AB3: Parameter Estimation Results for Home Device Survey¹⁶

		U.S.	U.K.	Korea	Japan	Italy	India	France
Home Address	Domestic only	-0.359*** (0.064)	-0.713*** (0.071)	-0.738*** (0.072)	-0.596*** (0.071)	-0.602*** (0.067)	-0.185** (0.063)	-0.368*** (0.060)
	Domestic & international, not China, Rus.	-0.470*** (0.065)	-0.815*** (0.074)	-1.006*** (0.082)	-0.790*** (0.077)	-0.687*** (0.073)	-0.221*** (0.065)	-0.474*** (0.065)
	Domestic & international	-0.562*** (0.065)	-0.915*** (0.073)	-0.797*** (0.073)	-0.687*** (0.069)	-0.811*** (0.074)	-0.265*** (0.065)	-0.447*** (0.063)
Phone Number	Domestic only	-0.259*** (0.063)	-0.554*** (0.070)	-0.330*** (0.066)	-0.606*** (0.066)	-0.457*** (0.066)	0.019 (0.059)	-0.291*** (0.069)
	Domestic & international, not China, Rus.	-0.375*** (0.067)	-0.514*** (0.073)	-0.363*** (0.074)	-0.680*** (0.076)	-0.554*** (0.076)	-0.096 (0.065)	-0.455*** (0.073)
	Domestic & international	-0.320*** (0.067)	-0.579*** (0.072)	-0.382*** (0.063)	-0.650*** (0.067)	-0.470*** (0.071)	-0.043 (0.058)	-0.352*** (0.068)
Voiceprint	Domestic only	-0.502*** (0.066)	-0.492*** (0.065)	-0.182** (0.056)	-0.429*** (0.068)	-0.426*** (0.068)	-0.128* (0.061)	-0.164** (0.059)
	Domestic & international, not China, Rus.	-0.497*** (0.070)	-0.693*** (0.071)	-0.202*** (0.060)	-0.535*** (0.071)	-0.508*** (0.069)	-0.118 (0.062)	-0.341*** (0.062)
	Domestic & international	-0.530*** (0.071)	-0.707*** (0.066)	-0.154** (0.054)	-0.467*** (0.066)	-0.500*** (0.070)	-0.176** (0.062)	-0.331*** (0.063)
Music Prefs	Domestic only	-0.073 (0.057)	-0.259*** (0.058)	-0.175** (0.056)	-0.098 (0.055)	-0.116* (0.058)	0.037 (0.057)	-0.116* (0.058)
	Domestic & international, not China, Rus.	-0.176** (0.054)	-0.232*** (0.056)	-0.224*** (0.058)	-0.282*** (0.057)	-0.116 (0.060)	0.040 (0.057)	-0.134* (0.054)
	Domestic & international	-0.238*** (0.059)	-0.217*** (0.057)	-0.192*** (0.051)	-0.222*** (0.052)	-0.145** (0.056)	-0.006 (0.055)	-0.062 (0.055)
Payment		0.194*** (0.031)	0.182*** (0.030)	-0.020 (0.028)	-0.092** (0.033)	0.186*** (0.032)	0.222*** (0.029)	0.094** (0.031)
Obs.		13,000	13,000	13,000	13,000	13,000	13,000	13,000

¹⁶ T-stats in parentheses. + is significant at 10% level. * is significant at 5% level. ** is significant at 1% level.

Table AB4: Parameter Estimation Results for Smartphone Survey¹⁷

		U.S.	U.K.	Korea	Japan	Italy	India	France
Phone Number	Domestic only	-0.303*** (0.057)	-0.303*** (0.057)	-0.160** (0.055)	-0.303*** (0.057)	-0.252*** (0.055)	-0.113* (0.054)	-0.264*** (0.059)
	Domestic & international, not China, Rus.	-0.412*** (0.062)	-0.412*** (0.062)	-0.364*** (0.063)	-0.412*** (0.062)	-0.313*** (0.059)	-0.229*** (0.059)	-0.454*** (0.065)
	Domestic & international	-0.320*** (0.060)	-0.320*** (0.060)	-0.260*** (0.059)	-0.320*** (0.060)	-0.441*** (0.062)	-0.161** (0.061)	-0.477*** (0.060)
Fingerprint	Domestic only	-0.516*** (0.068)	-0.516*** (0.068)	-0.491*** (0.068)	-0.516*** (0.068)	-0.581*** (0.069)	-0.240*** (0.064)	-0.603*** (0.069)
	Domestic & international, not China, Rus.	-0.516*** (0.068)	-0.627*** (0.071)	-0.462*** (0.075)	-0.627*** (0.071)	-0.638*** (0.073)	-0.290*** (0.066)	-0.680*** (0.072)
	Domestic & international	-0.617*** (0.068)	-0.617*** (0.068)	-0.529*** (0.074)	-0.617*** (0.068)	-0.672*** (0.075)	-0.258*** (0.066)	-0.617*** (0.072)
Voiceprint	Domestic only	-0.505*** (0.055)	-0.505*** (0.055)	-0.152** (0.052)	-0.505*** (0.055)	-0.345*** (0.056)	-0.127* (0.057)	-0.305*** (0.057)
	Domestic & international, not China, Rus.	-0.443*** (0.055)	-0.443*** (0.055)	-0.253*** (0.055)	-0.443*** (0.055)	-0.323*** (0.057)	-0.059 (0.056)	-0.362*** (0.059)
	Domestic & international	-0.500*** (0.060)	-0.500*** (0.060)	-0.128* (0.050)	-0.500*** (0.060)	-0.313*** (0.057)	-0.058 (0.058)	-0.375*** (0.058)
Location	Domestic only	-0.330*** (0.052)	-0.330*** (0.052)	-0.164** (0.054)	-0.330*** (0.052)	-0.185** (0.058)	-0.097* (0.049)	-0.321*** (0.054)
	Domestic & international, not China, Rus.	-0.402*** (0.060)	-0.402*** (0.060)	-0.162** (0.057)	-0.402*** (0.060)	-0.189** (0.058)	-0.164** (0.050)	-0.405*** (0.060)
	Domestic & international	-0.380*** (0.062)	-0.380*** (0.062)	-0.204*** (0.049)	-0.380*** (0.062)	-0.295*** (0.061)	-0.072 (0.049)	-0.339*** (0.055)
Facial Image	Domestic only	-0.501*** (0.063)	-0.501*** (0.063)	-0.431*** (0.064)	-0.501*** (0.063)	-0.253*** (0.061)	-0.139* (0.056)	-0.362*** (0.057)
	Domestic & international, not China, Rus.	-0.625*** (0.064)	-0.625*** (0.064)	-0.584*** (0.067)	-0.625*** (0.064)	-0.388*** (0.061)	-0.220*** (0.057)	-0.532*** (0.064)
	Domestic & international	-0.595*** (0.060)	-0.595*** (0.060)	-0.552*** (0.064)	-0.595*** (0.060)	-0.441*** (0.060)	-0.173** (0.055)	-0.501*** (0.058)
Ads		0.026 (0.044)	0.026 (0.044)	-0.008 (0.038)	0.026 (0.044)	-0.008 (0.041)	-0.003 (0.040)	0.097* (0.043)
Payment		0.115*** (0.032)	0.115*** (0.032)	0.078* (0.032)	0.115*** (0.032)	0.189*** (0.034)	0.209*** (0.031)	0.100** (0.033)
Obs.		13,000	13,000	13,000	13,000	13,000	13,000	13,000

¹⁷ T-stats in parentheses. + is significant at 10% level. * is significant at 5% level. ** is significant at 1% level.

Table AB5: Parameter Estimation Results for Social Media Survey¹⁸

		U.S.	U.K.	Korea	Japan	Italy	India	France
Home Address	Domestic only	-0.643*** (0.069)	-0.751*** (0.072)	-0.591*** (0.074)	-0.623*** (0.068)	-0.486*** (0.072)	-0.163* (0.063)	-0.273*** (0.063)
	Domestic & international, not China, Rus.	-0.616*** (0.072)	-0.900*** (0.080)	-0.656*** (0.078)	-0.900*** (0.077)	-0.630*** (0.079)	-0.200** (0.068)	-0.321*** (0.068)
	Domestic & international	-0.736*** (0.073)	-0.875*** (0.075)	-0.777*** (0.077)	-0.786*** (0.071)	-0.663*** (0.073)	-0.200** (0.063)	-0.386*** (0.062)
Phone Number	Domestic only	-0.467*** (0.065)	-0.407*** (0.065)	-0.279*** (0.065)	-0.530*** (0.067)	-0.609*** (0.070)	-0.139* (0.062)	-0.367*** (0.063)
	Domestic & international, not China, Rus.	-0.493*** (0.066)	-0.584*** (0.066)	-0.477*** (0.072)	-0.646*** (0.072)	-0.605*** (0.073)	-0.190** (0.062)	-0.427*** (0.063)
	Domestic & international	-0.551*** (0.068)	-0.551*** (0.068)	-0.359*** (0.066)	-0.584*** (0.070)	-0.576*** (0.072)	-0.186** (0.065)	-0.350*** (0.061)
Posts	Domestic only	-0.240*** (0.055)	-0.177** (0.056)	-0.067 (0.049)	-0.174** (0.056)	-0.115* (0.051)	-0.076 (0.056)	-0.337*** (0.065)
	Domestic & international, not China, Rus.	-0.306*** (0.058)	-0.219*** (0.062)	-0.093 (0.052)	-0.279*** (0.060)	-0.155** (0.049)	-0.046 (0.054)	-0.388*** (0.067)
	Domestic & international	-0.303*** (0.056)	-0.197** (0.060)	-0.059 (0.048)	-0.187** (0.057)	-0.134** (0.049)	-0.025 (0.055)	-0.376*** (0.065)
Network	Domestic only	-0.265*** (0.049)	-0.197*** (0.053)	-0.078 (0.050)	-0.208*** (0.053)	-0.133** (0.051)	-0.100 (0.052)	-0.218*** (0.050)
	Domestic & international, not China, Rus.	-0.375*** (0.056)	-0.285*** (0.060)	-0.276*** (0.059)	-0.364*** (0.060)	-0.285*** (0.057)	-0.114* (0.056)	-0.224*** (0.054)
	Domestic & international	-0.327*** (0.053)	-0.255*** (0.056)	-0.166** (0.051)	-0.231*** (0.053)	-0.237*** (0.048)	-0.136** (0.049)	-0.220*** (0.048)
Contacts	Domestic only	-0.310*** (0.061)	-0.209*** (0.057)	-0.305*** (0.055)	-0.331*** (0.061)	-0.096 (0.052)	-0.150** (0.057)	-0.200*** (0.057)
	Domestic & international, not China, Rus.	-0.401*** (0.061)	-0.237*** (0.056)	-0.329*** (0.055)	-0.354*** (0.061)	-0.132** (0.049)	-0.102 (0.058)	-0.141** (0.052)
	Domestic & international	-0.370*** (0.064)	-0.266*** (0.061)	-0.210*** (0.057)	-0.295*** (0.062)	-0.181** (0.058)	-0.171** (0.061)	-0.258*** (0.062)
Ads		0.126** (0.040)	0.117** (0.039)	0.025 (0.039)	0.044 (0.042)	0.139*** (0.040)	-0.010 (0.040)	-0.007 (0.039)
Payment		0.158*** (0.031)	0.152*** (0.031)	0.123*** (0.034)	-0.035 (0.031)	0.320*** (0.037)	0.357*** (0.031)	0.062 (0.033)
Obs.		13,000	13,000	13,000	13,000	13,000	13,000	13,000

¹⁸ T-stats in parentheses. + is significant at 10% level. * is significant at 5% level. ** is significant at 1% level.