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https://pubsonline.informs.org/journal/mnsc

MANAGEMENT SCIENCE
Articles in Advance, pp. 1–16
ISSN 0025-1909 (print), ISSN 1526-5501 (online)

The Value of Personal Data in Internet Commerce: A High-Stakes Field Experiment on Data Regulation Policy

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Received: June 19, 2020
Revised: January 14, 2021; June 2, 2021
Accepted: June 23, 2021
Published Online in Articles in Advance: June 8, 2023

https://doi.org/10.1287/mnsc.2023.4828

Abstract. Personal data have become a key input in internet commerce, facilitating the matching between millions of customers and merchants. Recent data regulations in China, Europe, and the United States restrict internet platforms' ability to collect and use personal data for personalized recommendation and may fundamentally impact internet commerce. In collaboration with the largest e-commerce platform in China, we conduct a large-scale field experiment to measure the potential impact of data regulation policy and to understand the value of personal data in internet commerce. For a random subset of 555,800 customers on the Alibaba platform, we simulate the regulation by banning the use of personal data in the home page recommendation algorithm and record the matching process and outcomes between these customers and merchants. Compared with the control group with personal data, we observe a significantly higher concentration in the algorithmic recommendation of products in the treatment group and a very sharp decrease in the matching outcomes as measured by both customer engagement (click-through rate and product browsing) and market transaction (sales volume and amount). The negative effect is disproportionate and more pronounced for niche merchants and customers who would benefit more from e-commerce. We discuss the potential economic impact of data regulation on internet commerce as well as the role of personal data in generating value and fostering long-tail innovations.

History: Accepted by Chris Forman, information system.
Funding: Z. Yuan wants to acknowledge financial support from NSFC [Grants 72203202, 72192803 and 72141305].
Supplemental Material: The data files and online appendix are available at https://doi.org/10.1287/mnsc.2023.4828.

Keywords: field experiments • personal data • e-commerce • privacy • data regulation

1. Introduction

Personal data have become a key input in the digital economy (Goldfarb and Tucker 2019), facilitating the matching between customers and merchants, enabling the personalized distribution of content and service, and stimulating innovations across a range of sectors, such as advertising, health, and finance. Despite the value, there are significant concerns and discussions on the privacy and proper use of personal data (Goldfarb and Tucker 2012b; Acquisti et al. 2015, 2016; Federal Trade Commission 2016). To address the concerns, countries and regions have enacted or proposed various types of data regulation policy, including the General Data Protection Regulation (GDPR) in Europe and the Consumer Privacy Act in California and a range of other states in the United States. China was in the process of adopting a comprehensive data regulation law "Data Security Administrative Measure" in 2020, and the impact might be on par with GDPR in Europe and would affect all internet platforms and the entire digital economy that relies on personal data. An emerging stream of research has discussed the issue of privacy regulation and its potential effect on online advertising (Goldfarb and Tucker 2011c), web traffic (Goldberg et al. 2019), innovation (Jia et al. 2021), and healthcare (Adjerid et al. 2016). However, little is known about the economic impact of the data regulation on internet commerce. Despite its enormous market size (hundreds of billions of transactions on e-commerce platforms in both the United States and China) and central role in the digital economy (Brynjolfsson and Smith 2000, Forman et al. 2009, Einav et al. 2014, Dolfen et al.

2023), no systematic study has been conducted to measure the impact of data regulation on e-commerce, and relatively little insight has been derived on how personal data would create value in this area. When designing the regulation on personal data, policy makers and the public still face a dearth of empirical evidence and thus, may have challenges to balance the considerations on data value and data privacy when making decisions.

Recognizing the empirical vacuum and the urgency of data regulation policy in China, Europe, and the United States, our study examines the economic impact of data regulation on internet commerce by simulating the ban of personal data on Alibaba e-commerce platform through a large-scale randomized field experiment. The restriction of personal data collection, data retention, and data use has been widely discussed in policy in China, Europe, and the United States. For instance, in the draft of China's "Administrative Measure" issued in the summer of 2019, all three types of regulation are strictly emphasized: on data collection (requiring explicit consent from all customers), on data retention (saving customers' historical data only for a certain period), and on data use (offering an explicit opt-in/opt-out option and a clear legend/notification for any personalized service).[1] See Online Appendix A for detailed discussions on the terms of the very strict data regulation in the legislation process in China. All three types of policy, to the extreme, can converge to the ban of personal data. In the worst case, personal data could not be collected, stored, and used for a significant portion of customers, equivalent to the ban on them. In fact, the Ministry of Industry and Information Technology has already tested the water; it regulated 8,000+ apps in November of 2019 (including major platforms, like Alibaba, JD.com, Tencent, and Xiao Mi) for a short period of time and enforced a policy similar to the scenario of our experiment.[2] Our experiment mimics the most stringent policy and also serves as a benchmark that evaluates the impact of each type of policy from the extreme. It is crucial to understand how such regulation may affect overall market transaction and various merchants and customers in internet commerce.

Specifically, we collaborate with the Alibaba e-commerce platform to implement the large-scale randomized field experiment involving 555,800 customers who open the Alibaba app and are exposed to the home page recommendation. About half of those users are randomly assigned to the treatment group; any of their personal data (e.g., demographics, past click and purchase behaviors) would not be used in the product recommendation on the home page, whereas the remaining half in the control group will experience the normal product recommendation powered by the same algorithm but using their personal data. The stake of the experiment is high as home page recommendation is the most important way for customers to find products on Alibaba, and they on average spend a lot of time browsing and interacting with over 100 recommended products there. The e-commerce platform heavily relies on the home page recommendations to match hundreds of millions of users with millions of merchants on the platform. In collaboration with Alibaba, we implement the experiment and collect very granular data on the matching process and outcomes for each customer in the experiment.

The experiment findings shed light on the impact of personal data regulation. Compared with the recommendation in the control group using personal data, we observe in the treatment group that there is a significantly higher concentration in product recommendation and a significant decrease in the "match" between the recommended products and customers' preference as revealed from their past behaviors. More importantly, the recommendations without personal data result in a very sharp drop in the matching outcomes as measured by both customer engagement and market transaction. After the experiment starts, we observe an immediate drop in customers' click-through rate (CTR) on the recommended products by 75%. Even worse, customers start to disengage with e-commerce and reduce their browsing on the home page by 33% as measured by product views (PVs). Combining the two effects, we see a sharp drop of 81% in customer purchase (gross merchandise volume (GMV)) facilitated by home page recommendations. Such a drop cannot be compensated for by customers' active search (we observe a 7% increase in customer search queries in the treatment group) and represents a net loss in internet commerce. We further examine the heterogeneity and find that the negative effect on PV and transactions is disproportionate on various types of merchants and customers. On the merchant side, the decrease is larger for smaller merchants and merchants at a lower rating tier as well as on long-tail items. On the customer side, the negative effect is disproportionate and more pronounced for customers who are newer and with less purchase power, female, and from developing regions (i.e., customers who would benefit most from e-commerce). We then explore the mechanisms underlying the impact of personal data regulation using individual-level data on product recommendations and users' past behaviors.

Overall, our experiment provides clean empirical evidence on the potential consequences of data regulation. The economic implication on internet commerce is significant; the Alibaba platform alone facilitated U.S. $768 billion of transactions/GMV in 2018 and created over 40 million jobs across 10 million merchants.[3] If the data regulation and the subsequent impact are scaled up, we may observe a significant decrease in market transaction and customer engagement on e-commerce platforms, which might lead to a decline of digital economy and significantly affect e-commerce-related entrepreneurship and employment.[4] In addition, the impact from data regulation will not be borne equally by all and will hurt those small and niche merchants who would benefit more from internet commerce. Thus, the regulation regime would not only affect the market size of internet commerce but also bias its development and the innovations in the ecosystem in certain directions (Goldfarb and Tucker 2012a). From the field experiment, policy makers may understand the potential economic impact and qualitative pattern of data regulation on various participants in e-commerce and make an informed decision by balancing the data privacy and data value. Ideally, personal data can be processed and protected to enhance customer privacy while still being used in some way to facilitate the matching between products/merchants and customers, therefore reducing market inequality and fostering long-tail innovations (e.g., through new design of informed consent and differential privacy). Digital platforms can also prepare in advance by designing alternative matching mechanisms and search tools to protect vulnerable merchants and customers. The experiment sheds light on the value of personal data in e-commerce and shows how it would help improve the "match" between products and customers, thus boosting market transactions and benefiting long-tail sales and innovations.

2. Related Literature

Our study builds on and contributes to several streams of literature in information systems, marketing, and economics. First, a stream of research has investigated the economic impact of data regulation policy, with a focus of GDPR and other privacy policies. Goldfarb and Tucker (2011c) shows that the European Union (EU) data regulation directive that restricted various aspects of personal data tracking led to a substantial decline in the effectiveness of online advertising and had an asymmetric impact on certain websites and ads. Goldberg et al. (2019) show that GDPR may result in about a 10% fall of recorded page views and revenues of online sites for EU users. Godinho de Matos and Adjerid (2022) studied the effectiveness of different GDPR consent campaigns in obtaining customer consent as well as the subsequent impact on the outcomes of targeted marketing.[5] Our study extends the stream of research in three ways. First, we study the economic impact of data regulation on *internet commerce*, which is an important sector in the digital economy and worth a new investigation. Unlike target advertising (Goldfarb and Tucker 2011b, Tucker 2012, Goldfarb 2014, Zhang et al. 2019), in internet commerce customers are actively gathering information (i.e., *strong shopping intent*) using a central matching interface (e.g., a list of recommendations with *many products*), and the search cost is relatively low with the help of an explicit recommendation algorithm.[6] Such differences in customer intent, matching process, and search environment may lead to a difference in the value of personal data in e-commerce, thus requiring a separate measure. Moreover, beyond the heterogeneous impact among customers, imposing data regulation in e-commerce may also lead to a disproportional impact on certain merchants, and thus, it can change market structure and exacerbate inequality (Campbell et al. 2015). Second, most of the previous studies treat data regulation as an event and leverage its timing for econometric identification (usually with the difference-in-difference method); our study is among the first to design a randomized field experiment to simulate the regulation policy itself and identify the causal effect of data regulation. The experiment provides the exogenous variations in the policy and allows us to understand its overall impact on various merchants and customers in the e-commerce. Third, the data regulation in China is urgent (a discussion is in Online Appendix A) and may have a profound impact on the digital economy in China. We collaborate with the largest internet commerce platform in China and conduct the first experiment to examine its potential impact. The empirical evidence has already been presented to policy makers and industry leaders and may help inform the design of the first data regulation law in China.

In parallel, a closely related stream of research has studied the value of personal data, which is the flip side of data regulation. Data tracking technology has facilitated the collection and use of customers' personal data.[7] Additionally, most research conducted in the area is focused on personalized pricing (Chen and Iyer 2002, Fudenberg and Miguel Villas-Boas 2007, Zhang 2011, Shin and Yu 2021), advertising/targeting (Goldfarb and Tucker 2011a, c; Tucker 2012; Luo et al. 2014; Aziz and Telang 2016; Ascarza 2018; Zhang et al. 2019; Marotta et al. 2022), news curation (Claussen et al. 2019), and search (Yoganarasimhan 2020). Yoganarasimhan (2020) shows that the returns to search personalization are concavely increasing with the length of user history data and finds that personalization based on short-term history or "within-session" behavior data is less valuable than long-term or "across-session" data. Claussen et al. (2019) and Rafieian and Yoganarasimhan (2021) examine the value of personalized targeting using different volumes or types of data and show the sources of gains in the performance. However, to date, relatively little research has studied the value of personal data in *e-commerce* (Goldfarb and Tucker 2019). There are key differences between internet commerce and other sectors of the digital economy (e.g., target advertising, fintech, and consumer borrowing), which may affect the value of personal data, and thus, they are worth separate investigations.[8]

Third, our study is related to a growing stream of literature on internet commerce; e-commerce represents a rapidly growing share of consumer spending in the United States and China. Dolfen et al. (2019) estimates that e-commerce spending in the United States reached

8% of consumption by 2017, yielding consumers the equivalent of a 1% permanent boost to their consumption or over $1,000 per household. A large stream of literature has focused on the adoption and growth of internet commerce (Forman et al. 2009, Einav et al. 2014, Chu and Manchanda 2016, Xu et al. 2016) as well as the comparison of internet retailers with traditional retailers (Brynjolfsson and Smith 2000, Smith and Brynjolfsson 2001) and the economic implications of e-commerce on market outcomes, such as transaction or listing price, product variety, market concentration, and international trade (Bakos 1997; Brynjolfsson et al. 2003, 2011, 2019; Overby and Forman 2015). Recent studies have also investigated the role of reputation systems (Forman et al. 2008, Hui et al. 2016, Gu and Zhu 2021), recommender systems (Fleder and Hosanagar 2009, Oestreicher-Singer and Sundararajan 2012, Hosanagar et al. 2014, Kumar and Hosanagar 2019, Lee and Hosanagar 2019), and search technology in the matching process (Ghose et al. 2012, 2014, 2019a, b; Dinerstein et al. 2018).[9] However, to date, relatively little research has systematically studied the value of personal data in e-commerce. Our experiment addresses the gap and helps extend the literature in two ways: (1) by isolating the role of personal data in sustaining internet commerce and driving the market outcomes and 2) by shedding light on the potential consequences if such personal data could not be used because of regulation.

Finally, from a mechanism perspective, our paper also relates to a recent stream of literature on search cost. Search cost would occur when customers are actively looking for information (Ghose et al. 2014, Honka 2014). Previous literature has studied the consequence of reduced search cost in internet commerce (Bakos 2001, Ellison and Ellison 2005, Forman et al. 2009), especially how such reduced search cost would affect product price (Varian 1980, Ellison and Ellison 2009, Dinerstein et al. 2018), quality (Lynch and Ariely 2000), and market structure (Brynjolfsson and Smith 2000, Bar-Isaac et al. 2012). A recent paper also applies analytical models to investigate the impact of search accuracy or market equilibrium (Shin and Yu 2021). Our study is not examining the search cost advantage of e-commerce but focuses on how the ban of personal data might vary such search costs within internet commerce and erode its competitive advantage. In addition, we also examine the impact of data regulation on search cost for different types of merchants and customers, as low search cost might be especially crucial for niche merchants in the long tail (Yang 2013) and for certain types of customers. Finally, we also derive interesting findings on the effect of increased search cost (because of a worse match from algorithmic recommendation) on customers' active search behavior, which provided a new angle to understand the substitution between recommendation and search (Fong 2016, Fong et al. 2019).

3. Research Context

We collaborate with the Alibaba e-commerce platform (Taobao mobile app) and conduct a large-scale randomized experiment to simulate the ban of personal data on the platform and to understand the impact of personal data regulation on the customers, merchants, and market outcomes in internet commerce. Alibaba has over 10 million sellers and 650 million buyers as well as over 2 billion product listings. Each day, there are tens of millions of transactions and U.S. $1.85 billion of GMV. As of 2018, Taobao accounts for 70% of the market share of e-commerce in China, which accounts for 18% of retail sales in the Chinese economy.[10] With its status, Alibaba can essentially represent internet commerce in both size and variety.

Given the millions of merchants and the large variety of products, the Alibaba platform matches its offerings with hundreds of millions of customers through personalized recommendations (Adomavicius and Tuzhilin 2005). We focus on the home page recommendations on e-commerce platforms, which are the most important personalized recommendation modules on the platform and are designed to reduce search cost and facilitate matching of customers and merchants. When opening the Alibaba app, customers will immediately receive a list of recommended products on the home page based on their personal data, with information of the products/merchants (Figure B1 in the online appendix). Customers can keep browsing the recommended products by scrolling through the (endless) product feed on the mobile screen. They can also click on any of recommended products for further browsing and make a purchase. An average customer spends a good amount of time browsing about 100 recommended products on the home page. The home page recommendation is purely controlled by an algorithm and does not support any sponsored listing. It incorporates personal data as well as product data and merchant data. Given the high stakes of the experiment, we were focusing on varying the data under the collaborative filtering (CF) algorithm adopted on the Alibaba e-commerce platform.[11] CF is a standard algorithm deployed in most recommender systems in e-commerce and other industries (Sarwar et al. 2001, Linden et al. 2003), and it has been thoroughly discussed in the previous Information Systems literature on recommender systems (Fleder and Hosanagar 2009, Adamopoulos and Tuzhilin 2013, Hosanagar et al. 2014, Lee and Hosanagar 2019).

A customer's online shopping process could benefit from personalized recommendations in several ways. First, the recommendation could help reduce the search cost and make it easier for customers to shop. The algorithm may help users discover items that are well aligned with their interest (as revealed from past clicks and purchases). Second, recommendation might encourage the customers to stay longer and engage more with the platform. Besides recommendation, the main alternative for customers to find products is active search. They can directly search on the search bar (our experiment did not ban the use of personal data in the search algorithm). We will examine the effect of data regulation on the alternative way of information gathering—customers' active search.

4. Experiment Design and Data

We conduct the experiment on a regular day in the summer of 2019 with no major promotions or campaigns. During the experiment period, a random subset of users who open the app and are exposed to the home page recommendation is assigned into our experiment. We then randomly split the subjects into control and treatment groups. We use the same algorithm to produce the recommendations across control and treatment groups but vary the use of personal data in the algorithm. Specifically, the input in the algorithm for the control group includes the merchant data, the product data, and the personal data (basic information, such as demographics, and behavior information, such as past browsing, click, and purchase). In the treatment group, the use of personal data is banned; thus, only product data and merchant data are incorporated in the algorithm. The goal of the algorithm is the same as the mission of the platform: to maximize the matching probability. The treatment group essentially simulates the extreme condition of internet commerce under the data regulation.

The field experiment uses about 2% of Alibaba home page traffic.[12] Because of the high stakes involved, it is scheduled for about seven hours. The randomized experiment allows us to create a large and exogenous shock in the recommended matching between customers and merchants. We record the matching process and outcomes at an individual level. We closely follow the schedule of the experiment and turn the personal data back after the experiment ends.

In total, there are 555,800 customers in our experiment who have been exposed to home page recommendations (more details are in Online Appendix B). For every customer, we record information, including the unique hashed identifier of the customers, the assigned test group, the recommended products and merchants they have browsed, and their clicks and purchases during the experiments as well as their demographics, registration date, and all historical purchases and clicks. For each purchase, we record detailed information, including the purchased product(s), the merchant, and the revenue and profits from the purchase as well as the time stamp. For each click, we record similar information. We further augment the data set with rich product characteristics (category, brand), merchant characteristics (annual revenue, rating tier), and user characteristics (demographics). The resulting data set enables us to analyze the effect of different interventions at an aggregate level as well as at a more granular level.

Besides the exogeneous variations created by randomization, there are several strengths in our data. First, we record the detailed product recommendations that each customer has browsed. Thus, we can characterize the changes in the recommended product at both a test group level as well as an individual level. Second, we collect the detailed behavior data for each user, including historical clicks and purchases. Thus, we can infer the preference of each customer and characterize the match between product recommendations and her or his preference. Third, we collect customers behaviors beyond the home page; therefore, we could understand customers' information gathering through active search (i.e., the indirect impact of data regulation).

We provide the variable definitions and descriptive statistics in Tables 1 and 2. We also conduct a randomization check on customer demographics and past behaviors and find no significant difference across customers in the control and treatment groups (Table 2), indicating that the experiment randomization is at work.

5. Experiment Results

5.1. Impact on the Product Recommendations

We first examine the differences in product recommendation when the usage of personal data is allowed (C) and banned (T). We draw the distribution of the number of PVs across items in the control and treatment groups (Figure 1) and find that once the personal data are turned off, there is a significant increase in the concentration of product recommendations. First, in the control group, the recommendations are evenly spread over a long tail (over 4 million items), and even the most exposed items only receive hundreds of exposures. The top 1,000 items account for only ~4% of all PVs in the home page recommendations. In contrast, the recommendations in the treatment group are concentrated on a smaller number of items; the most recommended items receive over 30,000 exposures, and the top 1,000 items account for almost 90% of all product views in the home page recommendations (with Gini index of ~0.97). Cumulative distribution in Figure 2 also contrasts the even distribution in control versus sharp concentration in the treatment. Moreover, such concentration leads to a significant reduction in the variety of items in the recommendation (from 4 million to 280,000) and a systematic redistribution of recommended products across merchants (favoring larger merchants and top items as we will discuss later). Without personal data, the platforms cannot identify the type of each customer and at best, can only recommend mainstream products that match the preference of an average customer with the largest likelihood (Bakos 1997). Such a lack of

Table 1. Variable Definition

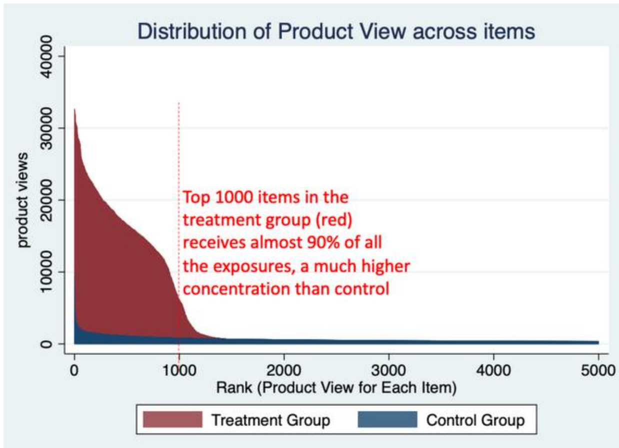
	Definition
Test group	
No Data	Treatment group dummy (for treatment group: "no data" = 1)
Outcome variable	
PV	Number of product views during experiment period
Click	Number of product clicks during experiment period
Pay_cnt	Number of product purchases during experiment period
GMV	Gross merchandise volume: amount of purchases during experiment
CTR	Click-through rate: defined as (click/PV)
Customer characteristics	
Female	Female dummy
Age tier	Tier of age: 1 for below 25, 2 for 25–35, 3 for 35–45, 4 for 45–55, 5 for 55–65, 6 for above 65
City Tier	Tier of city size: 1 for largest cities, such as Beijing and Shanghai; 2 for second-tier cities, such as Hangzhou and Nanjing; 6 for smallest cities
Purchase Tier	Tier of customer purchase power, which is defined and used by Alibaba platform based on the historical purchase behaviors of each customer. There are 5 tiers in total (tiers 1–5). A higher tier indicates more purchase power as inferred from past transactions.
Number of Registered Years	Number of registered years on the e-commerce platforms
Number of Login Days in 30 days	Number of login days in the past 30 days
Clicks in the past 30 days	Number of clicks in the past 30 days
Purchases in the past 30 days	GMV in the past 30 days

Table 2. Description Statistics of Outcome Variables and the Customer Characteristics and Randomization Check Using Customer Characteristics

	Mean and standard error	Control n = 280,427	Treat n = 275,373	p-value (C = T)
Outcome variables				
PV	Mean	116.94	77.91	<0.001
	Standard error	0.396	0.234	
Click	Mean	5.284	0.869	<0.001
	Standard error	0.018	0.0039	
Pay_cnt	Mean	0.022	0.003	<0.001
	Standard error	0.00034	0.00011	
GMV	Mean	1.363	0.258	<0.001
	Standard error	0.046	0.020	
Customers characteristics				
Female	Mean	0.690	0.691	0.435
	Standard error	0.001	0.001	
Age tier	Mean	2.167	2.167	0.800
	Standard error	0.0019	0.0019	
City Tier	Mean	3.673	3.665	0.080
	Standard error	0.035	0.035	
Purchase Tier	Mean	2.260	2.263	0.274
	Standard error	0.002	0.002	
Number of Registered Years	Mean	5.227	5.240	0.125
	Standard error	0.006	0.006	
Number of Login Days in 30 days	Mean	24.988	25.019	0.065
	Standard error	0.012	0.012	
Clicks in the past 30 days	Mean	543.58	544.54	0.557
	Standard error	1.143	1.161	
Purchases in the past 30 days	Mean	14.924	14.937	0.810
	Standard error	0.042	0.036	

Note. Variable definitions are in Table 1.

Figure 1. (Color online) Distribution of Product Views on Items (Control and Treatment Groups)



Notes. We draw the distribution of the number of product views for each item in the control and treatment groups (we only show the top 5,000 items in the control and treatment groups). The figure shows that once the personal data are turned off, there is a significant increase in the concentration of the product recommendation. In the control group, the recommendations are widely spread out across a long tail (over 4 million items), and even the most exposed items only receive hundreds of exposures. The top 1,000 items account for only 4% of all exposures in the recommendations. In contrast, the recommendations in the treatment group are concentrated on a smaller number of items, and the most recommended items receive over 30,000 exposures. The top 1,000 items account for almost 90% of all product views in the home page recommendations (with Gini index of ~0.97).

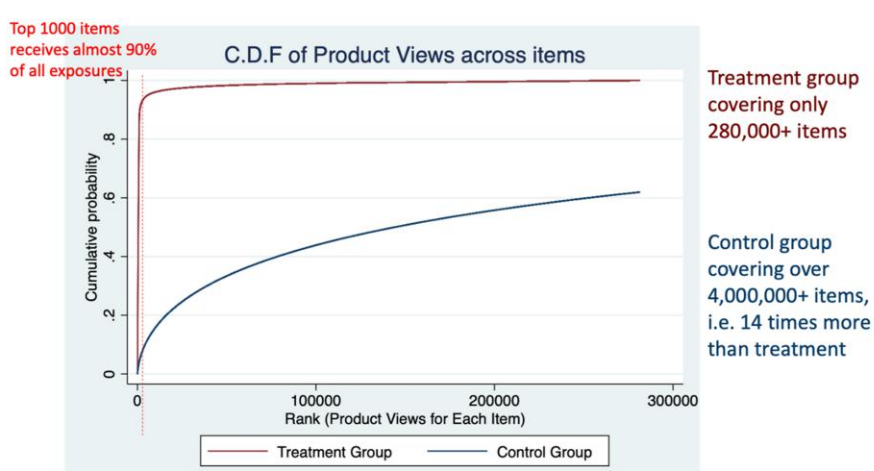
personal data leads to a concentration of recommendations on a relatively small subset of products. It is important to emphasize that the objective of the e-commerce platform remains the same (maximize match probability), but when lacking information about customers, recommendation patterns automatically change when fulfilling the goal. The qualitative pattern of such distribution change of recommendations is aligned with theoretical predictions (Hoteling model) and likely to be general and independent of the specifics of the algorithm.

5.2. Impact on Matching Outcomes (Click-Through Rate, Browsing, and Purchase) and on Consumption Diversity

We track customer CTR on the recommended products and see a sharp drop in CTR (by 75.3%) immediately after the experiment starts (Table 3).[13] The decrease is likely to be driven by less relevant recommendations because of the ban of personal data (more in Section 5.5). Even worse, we also see an immediate drop in customers' browsing of recommended products (PVs) by 33.6%: a significant decrease in customers' interest in engaging with the e-commerce platform. Combining the two effects on click-through and engagement, there is a dramatic decrease in the customer transaction (by 81.1%) facilitated by the home page recommendation. The same pattern holds for alternative measures, such as the number of unique transactions (a decrease of ~86%). The magnitude of decrease is highly significant for the e-commerce platform if the regulation is scaled up to the entire platform (more discussions are in Section 6). We further perform regression analyses using alternative model specifications and alternative outcomes. The results are consistent across different models and outcomes with and without control variables (see Table C1 in Online Appendix C for details).

Besides the matching outcomes, we also examine the effect of turning off personal data on customers' consumption diversity and concentration at an aggregate level and at an individual level. We find that when personal data are turned off, consumption diversity will

Figure 2. (Color online) Cumulative Distribution of Product Views Across Items in the Control and Treatment Groups



Notes. We draw the cumulative distribution of product views across items in the control and treatment groups (normalized cumulative probability to one; we only show the top 281,131 items as the treatment group only covers 281,131 items). The concentration pattern in Figure 1 can also be clearly seen here. It also leads to a significant reduction in the variety of items in the recommendations (from about 4 million to 281,131). C.D.F. is the shorthand for Cumulative distribution function.

Table 3. Main Effect of Turning off Personal Data on Key Outcomes

Outcome	(1) PV	(2) PV	(3) Click	(4) Click	(5) GMV	(6) GMV
No Data	−39.03***	−39.08***	−4.416***	−4.418***	−1.106***	−1.105***
	(0.462)	(0.460)	(0.019)	(0.019)	(0.050)	(0.050)
Constant	116.9***	108.5***	5.284***	4.121***	1.363***	0.593
	(0.325)	(35.77)	(0.0133)	(1.464)	(0.035)	(3.899)
With control (customer characteristics)	No	Yes	No	Yes	No	Yes
R^2	0.013	0.020	0.090	0.096	0.001	0.001
Observations	555,800	555,800	555,800	555,800	555,800	555,800

Notes. Standard errors are in parentheses. GMV indicates the transaction volume in RMB.
$^{***}p < 0.01$.

decrease at both levels. In addition, consumption concentration, as measured by the Gini coefficient at an aggregate level, is significantly increased in customers' browsing, clicks, and purchases. The findings complement previous studies on the recommender system (Fleder and Hosanagar 2009, Hosanagar et al. 2014) and are aligned with the changes in the product recommendations as documented in Section 5.1. See the detailed analyses and discussions in Online Appendix E and the literature review.

5.3. Impact on Different Types of Merchants and Items

We further examine the effect of banning personal data on various types of merchants and items. In Table 4, we report the effect on different types of merchants using both the number of product views they have received (PV) and their sales (GMV). There are two major measures of merchants used by Alibaba: annual revenue and rating tier. We categorize the merchants on the Alibaba platform using these two indicators. First, following the tradition of the Alibaba e-commerce platform and that of the Chinese merchant tax system, we group merchants into big and small sellers based on their annual revenue in the past 12 months (July 2018 to June 2019). We consider the merchants with annual revenue less than 1.2 million RMB (the official currency of the People's Republic of China) as small sellers ("small-scale tax payer" in the Chinese merchant tax system) and those with more than 1.2 million RMB as big sellers. Second, we group merchants based on Alibaba's seller rating tier system (Online Appendix B). Seller rating is given by Alibaba customers after each order and prominently displayed as the reputation of the merchant. The rating tier is largely determined by the total number of sales of the seller and thus, favors the incumbents (Fan et al. 2016). The "hearts" tier indicates fewer cumulative ratings, whereas "diamonds," "crown," and "golden crown" tiers indicate more cumulative ratings. For each of the two dimensions, we also examine the treatment effects on different merchants using alternative cutoffs of the seller groups (e.g., 5 million GMV as the cutoff for small versus big merchants and "heart" and "diamond" as the cutoffs for rating tiers). The results are robust

Table 4. Heterogeneity of the Treatment Effect on Different Types of Merchants Based on Seller Size and Rating Tier

Outcome	(1) PV on Small seller	(2) PV on Big seller	(3) PV on Low tier	(4) PV on High tier	(5) GMV on Small seller	(6) GMV on Big seller	(7) GMV on Low tier	(8) GMV on High tier
No Data	−14.71***	−22.45***	−1.129***	−36.08***	−0.253***	−0.853***	−0.013***	−1.093***
	(0.11)	(0.34)	(0.0055)	(0.44)	(0.017)	(0.047)	(0.0037)	(0.050)
Constant	27.26***	82.25***	1.221***	108.3***	0.280***	1.083***	0.0133***	1.349***
	(0.08)	(0.24)	(0.0039)	(0.31)	(0.012)	(0.033)	(0.0026)	(0.035)
% Change	−54%	−27%	−92%	−33%	−90%	−79%	−96%	−81%
Observations	555,800	555,800	555,800	555,800	555,800	555,800	555,800	555,800
R^2	0.031	0.008	0.071	0.012	0.001	0.001	0.000	0.001

Notes. GMV indicates the transaction volume in RMB. In accordance with Alibaba platform rules and the China merchant tax system, we define those with less than 1.2 million RMB GMV as small sellers and those with more than 1.2 million RMB GMV as big sellers. In accordance with Alibaba platform rules, we define merchants in the "hearts" tier as the low rating tier and merchants in the "diamonds," "crown," and "golden crown" as the high rating tier. Merchants in the high rating tier have a significantly higher number of cumulative ratings. The results and patterns are robust under alternative definitions and cutoff points. See Online Appendix C.
$^{***}p < 0.01$.

with the same pattern (Online Appendix C). As shown in Table 4, the negative impact of turning off personal data on product views and sales is larger for smaller sellers and sellers at a low rating tier (in relative measure, percentage). For instance, the ban of personal data negatively affects the PV of small sellers by 54% as compared with the 27% decrease for the big sellers.[14] A large number of those small sellers do not receive any product exposure after the policy change (i.e., PV decreases to zero). Similarly, the decrease in sales is also larger for small sellers, with many small sellers not getting any revenue during the experiment. Second, sellers with a lower rating tier (i.e., with fewer cumulative ratings) suffer from a 92% reduction in PV, whereas sellers at a higher rating tier only have a 33% decrease in PV. In general, data regulation disproportionately affects those small and new sellers who would benefit more from the adoption of internet commerce. The results are aligned with theoretical predictions on the impact of privacy regulation on market structure (Campbell et al. 2015), but they shed light on a different mechanism; the lack of personal data disables personalized matching and thus, leads to a concentration in product distribution. Small and relatively new merchants in e-commerce are more vulnerable to data regulation and may be discouraged from innovations or even operation. Such inequality created by the data regulation may worth attention of the policy makers.

At the item level, we observe that the decreases in product views and sales are larger for long-tail items as compared with the head items (Table 5). The pattern is consistent with Figure 1; product view is concentrated on a small number of items after the data regulation. Here, head items are defined as the top 1,000 items in the control group, whereas the rest are long-tail items. We find that PV of the head items increases by 448% as compared with the 55% decrease for long-tail items. The sales of long-tail items reduce by 83%, in contrast with the 49% decrease of head items. Interestingly, although the head items gain much more product exposure in the treatment (approximately fivefold), we still see the 49% decrease in the sales on them. Most of these recommendations (PV) are wasted and pushed to customers who are not interested in the products. Without personal data, the product impressions could not be effectively distributed across customers, and both the platform's efforts and customer attention are wasted (Goldfarb 2014).[15]

Table 5. Heterogeneity of the Treatment Effect on Head Items (the Top 1,000 Items) vs. Long Tail

Outcome	(1) PV on Head item	(2) PV on Long-tail item	(3) GMV on Head item	(4) GMV on Long-tail item
No Data	20.40***	−58.42***	−0.0129***	−1.044***
	(0.068)	(0.404)	(0.004)	(0.048)
Constant	7.150	97.15***	0.006	0.568
	(5.280)	(31.38)	(0.314)	(3.728)
% Change	448%	−55%	−49%	−83%
Observations	555,800	555,800	555,800	555,800
R^2	0.143	0.043	0.000	0.001

Notes. GMV indicates the transaction volume in RMB. Head items are the top 1,000 items in the control group; long-tail items are the rest of items.
$^{***}p < 0.01$.

5.4. Heterogeneous Impact Across Customers

On the customer side, we also observe a heterogeneous effect of data regulation. After the personal data are banned, there is a larger decrease for customers who are newer and with less purchase power, female, and from developing regions (Table 6)—users who would benefit more from internet commerce. There is a larger reduction in PV and sales for consumers who registered more recently (positive interaction term *No Data* × *RegisterYear*). Relatedly, customers with less purchase power on the platform significantly reduce their browsing and purchases after the ban. We also see other interesting variations based on customer demographics. When dividing users by gender and city tier, female users and users from low-tier cities are more vulnerable to the ban of personal data in home page recommendations. For instance, female users are likely to browse a much smaller number of products and purchase less when the data are turned off as compared with male users. We also check the correlation between customer characteristics (Table C3 in the online appendix) and run a regression to test all moderators in the same model (rather than testing each moderator in a separate regression as in Table 6). The results (in Table C4 in the online appendix) are robust and qualitatively similar.

We further explore the potential mechanisms underlying the heterogeneous impact across customers. We first examine whether the heterogeneity in the effect across customers can be explained by the differences in the "data volume" accumulated by them. See the detailed analyses and discussions in Online Appendix C. In short, we construct the "data volume" measure using the users' click behaviors in the past 30 days and find the accumulated data volume can explain some heterogeneity of the treatment effect across customers; these users with more data are likely to experience a larger decrease in the recommendation quality as compared with users with less data (Figure F1 and Table F1 in the online appendix) and would also reduce their browsing more (Table C4 in the online appendix). However, even after controlling for heterogeneity caused by data volume, the moderating effects of all customer characteristics still remain significant (Table C4, column (2) in the online appendix). We also examine whether the heterogeneous effect across customers can be explained by the differences in their "preference variety,"

Table 6. Heterogeneity of the Treatment Effect on Different Types of Customers

	(1) *PV*	(2) *PV*	(3) *PV*	(4) *PV*	(5) *Pay_cnt*	(6) *Pay_cnt*	(7) *Pay_cnt*	(8) *Pay_cnt*
No Data	−55.58***	−49.07***	−26.12***	−29.79***	−0.02***	−0.02***	−0.02***	−0.02***
	(0.953)	(0.933)	(0.838)	(1.065)	(0.0007)	(0.0007)	(0.0007)	(0.0008)
No Data × *PurchaseTier*	7.294***				0.0005*			
	(0.369)				−0.0003			
No Data × *RegisterYear*		1.909***				0.0005***		
		(0.155)				−0.0001		
No Data × *Female*			−18.49***				−0.003***	
			(1.004)				(0.0008)	
No Data × *CityTier*				−2.496***				0.00014
				(0.257)				(0.0002)
Constant	91.13	−2,376***	150.4*	167.4*	0.0051	−1.170***	−0.0094	0.0034
	(85.67)	(260.1)	(85.78)	(86.03)	(0.0671)	(0.204)	(0.0671)	(0.0674)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	554,876	555,777	550,753	546,880	554,876	555,777	550,753	546,880
R^2	0.021	0.020	0.021	0.020	0.006	0.006	0.005	0.006

Notes. *Pay_cnt* is the number of purchases. *PurchaseTier* is short for "tier of customer purchase power," which is defined and used by the Alibaba platform based on the historical purchase behaviors of each customer. There are five tiers in total (tiers 1–5). A higher tier indicates more purchase power as inferred from past transactions. *RegisterYear* is the number of years since a customer registered on Alibaba. *CityTier* is the tier of the city that the customer is in according to the Alibaba categorization of all Chinese cities. There are six tiers in total, and smaller cities are assigned a larger number (e.g., Beijing and Shanghai are tier 1 cities in China, whereas small cities and rural area are below tier 3). The Alibaba categorization is in general aligned with the size and population of the city as defined by the National Bureau of Statistics of China. Interpretation of the coefficients of interaction terms (heterogenous impact of data regulation) is as follows: *No Data* × *PurchaseTier* (positive): customers with more purchase power are less affected; *No Data* × *RegisterYear* (positive): customers with more experience in e-commerce are less affected; *No Data* × *Female* (negative): female customers are more affected; and *No Data* × *CityTier* (negative): customers in a smaller city or rural area are more affected.

*$p < 0.1$; ***$p < 0.01$.

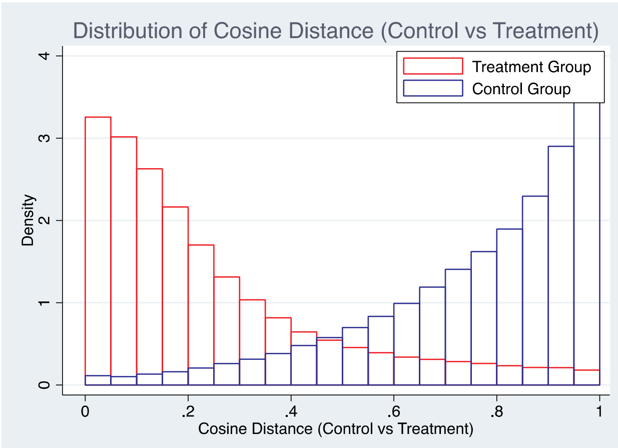
as measured by the number of product categories they have clicked on in the past 30 days. The insights are similar to the case of data volume (Table C4, columns (3) and (4) in the online appendix).

The new analyses allow us to think deeper about the underlying process. We hypothesize that there might be two competing forces underlying the heterogeneous effect across customers: data volume and customer resilience. Each customer is experiencing these two forces at the same time. For instance, customers who are more experienced and in a higher purchase tier usually accumulate more behavior data (e.g., clicks) on the platform; thus, they should be more affected by the data regulation, as a larger volume of data would be removed from the recommendation algorithm for them. On the other hand, they may also be more resilient; thus, even a severe deterioration in the quality of the data-driven recommendation may not affect them too much. These users may be more tolerant to the recommendation, and they may still maintain a high level of interest and keep their engagement with the recommendation on the platform. In contrast, customers who are new and in a lower purchase tier leave less behavior data to the platform, but at the same time, they are also more vulnerable or sensitive to change in the data-driven recommendation. For instance, these customers who are new, less active, and from rural areas are in general not familiar with the digital platform and mobile shopping experience. These users are less resilient; thus, even a slight deterioration in the quality of the recommendation may hurt them. It seems that this second force ("customer resilience or vulnerability to worse recommendation experience") is important given the suggestive evidence from heterogeneity. The competing forces coexist, and the effect of data regulation on a certain customer subgroup may depend on which force is dominating.[16]

5.5. Underlying Mechanisms: Restricting the Use of Personal Data Significantly Worsens Matching Between Product Recommendations and User Preference

Personal data could improve the matching between consumers and recommended products because the platform can infer consumers' preference from previous behaviors and recommend products accordingly. We thus examine the change in recommendation quality at an individual level (rather than at the distribution level as in Section 5.1) and find that (1) use of personal data is of central importance in determining the match between an individual user's preference and the recommended products and that (2) the match could explain a significant portion of the difference in the customers' browsing, clicks, and purchases between the treatment and control groups (PV, CTR, and GMV). Consumers

Figure 3. (Color online) Underlying Mechanisms: Match Between Recommendations and User Preference



Notes. Following the recommender systems literature (Adomavicius and Tuzhilin 2005), we define the "match" using the cosine value between a user's revealed preference and the home page recommendation. Please see the calculation of the "match" score in footnote 11. We find that the match in the treatment group is significantly lower as compared with control group; the distribution is toward zero for the treatment group (without personal data) and toward one for the control group (with personal data). Without personal data, the match quality between the recommendations and user preference becomes significantly worse. Figures D1 and D2 in the online appendix further show the strong correlation between match quality and matching outcomes.

are much more likely to engage with relevant recommendations (more click, purchases, and browsing), which is determined by the availability of personal data.

Specifically, following the recommender systems literature (Adomavicius and Tuzhilin 2005), we define the recommendation "match score" using the cosine value between a user's revealed preference (as measured by the vector of product categories that this user has clicked on before) and the home page recommendations (as measured by a vector of recommended products at the category level).[17] We find that the match in the treatment group is significantly lower as compared with the control group (Figure 3); the distribution is leaning toward zero for the treatment group (without personal data) and toward one for the control group (with personal data). Match score (cosine value) of the control group has a median of 0.81 with a mean of 0.75. In contrast, match score of the treated group has only a median of 0.17 with a mean of 0.25.

Consumers who are exposed to product recommendations with a bad match (as measured by a low cosine value) in general have much less product browsing (PV) and fewer purchases (see the correlation in Figures D1 and D2 in Online Appendix D). Take the control group as an example. When the match is good (defined as a match score of >0.8), customers would on average have 146 product views on the home page and spend 1.55 RMB. However, when the match is less ideal (defined as a match score of <0.2), customers would on average have 24 product views (i.e., scrolling down just six mobile screens) and only spend 0.49 RMB.

To sum up, restricting the use of personal data may significantly worsen matching between product recommendation and user preference, thus reducing the value of e-commerce. With personal data, e-commerce platforms can significantly improve their inference on customers' preference and recommend relevant products accordingly. Such data-driven recommendations can facilitate matching and achieve an effective and even distribution across a large range of merchants and products. In this way, personal data can increase the value of e-commerce by increasing market size and cultivating niche merchants. With personalized distribution, merchants have more incentive to innovate as long-tail products can be exposed.

5.6. Impact of Data Regulation on Customers' Active Search

Consumers may have alternative ways of finding product information, and search is the most prominent way and the main alternative for customers to identify products on the e-commerce platform, especially if they have a specific need in mind. Specifically, in the Alibaba app, customers could type in any words into the keyword bar and perform a subsequent search. When the home page recommendation does not match their interest, customers can perform an active search. We collect all the search activities by subjects in our experiment and examine the impact on their active search.

We find that as consumers in the treatment group receive less relevant recommendations, they search significantly more in the search bar. Specifically, consumers in the treatment perform 7% more search queries and make 7% more browsing (PV) in the searching engine during the experiment period. The increase of product views from the search engine compensates for 22% of the reduction in PV from the home page recommendations. Moreover, on average, consumers also click more products (by 6.3%) and make a larger number of purchases from search (by 7.1%), compensating for part of the loss from the recommendation. Interestingly, the increase in the treatment on search is mostly concentrated on niche keywords.[18] Compared with the keyword queries in the control group, we observe a 7% increase in the volume of niche/long-tail keywords by treated users. Consistently, consumers browse 12% more PVs from niche queries.

To sum up, a portion of customers can adapt and perform an active search after regulation, which may partially compensate for the reduced matching from recommendations (mostly on long-tail demand). However, there is still a net loss in the matching outcomes (both PV and purchases). Another way to interpret this

Table 7. Effect of Turning off Personal Data on Customers' Active Search

Outcome	(1) *PV*	(2) *PV search*	(3) *Click*	(4) *Click search*	(5) *GMV*	(6) *GMV search*
No Data	−39.03***	8.532***	−4.416***	0.310***	−1.106***	0.584*
	(0.462)	(0.793)	(0.019)	(0.0314)	(0.050)	(0.321)
Constant	116.9***	120.1***	5.284***	4.935***	1.363***	9.109***
	(0.325)	(0.558)	(0.0133)	(0.0221)	(0.035)	(0.226)
With control (customer characteristics)	No	No	No	No	No	No
R^2	0.013	0.000	0.090	0.000	0.001	0.000
Observations	555,800	555,800	555,800	555,800	555,800	555,800

Note. *PV* indicates product views from the home page recommendation; *PV search* indicates product views from the search bar.
$^{*}p < 0.1$; $^{***}p < 0.01$.

result is that personal data can potentially enable more relevant recommendations and facilitate better matching between users and products. As a result, it may reduce the necessity for users to actively search for specific items, particularly long-tail products. Personal data play a crucial role in lowering customers' search cost in e-commerce (Goldfarb and Tucker 2019), thus fostering long-tail products and innovations. The results provide policy implications and also shed light on the customer search in e-commerce (Table 7).[19]

6. Discussion and Conclusion

In summary, our experiment suggests that the data regulation would significantly reduce customer engagement and market transaction in internet commerce and affect niche merchants and customers more than others. The data regulation might not only lead to a downsizing but may also bias the development of e-commerce in a certain direction.

The e-commerce platforms are a key part of internet commerce and exist because they can facilitate matching (Bakos 1997, Dinerstein et al. 2018). However, under data regulation, the matching quality would significantly deteriorate; thus, the role and scale of the platform as an intermediary would diminish. The decline of e-commerce platforms will severely limit the scale and scope of the commercial activities on the internet and the accompanied innovation process in the economy.

As discussed in Section 1, personal data shape internet commerce, and the impact of data regulation policy is highly meaningful from an economic perspective when linked to the economy. In 2018, market transactions on the Alibaba platform were 4.8 trillion RMB (about U.S. $768 billion) and accounted for 70% of the market share of e-commerce in China. Personalized matching is accounting for a major share of it. Personal data regulation and the subsequent impact, when scaled up, may lead to a significant loss in GMV and a decline in the digital economy, and they may significantly affect employment and entrepreneurship in internet commerce. Merchants, especially small and niche ones, may have to bear with the loss in revenue and change their operation and innovation strategy.

The experiment findings are likely to have implications for policy makers and e-commerce platforms across the United States, China, and Europe. In Europe, GDPR is gradually being enforced. In the United States, various data regulation acts, like California Consumer Privacy Act, are being proposed and adopted. In China, the "measure" is being finalized and adopted. Although protecting personal data is crucial, our experiment results nevertheless suggest that personal data play a central role in the functioning of internet commerce. Thus, the design of data regulation has to carefully balance the data value and data privacy. The ideal policy would keep the value of personal data while preserving privacy. At an individual level, a customer should be informed of the value of personal data to their shopping experience while also being given the option to monitor and control the collection and use of their personal data (types of data collected and used, purpose of its use on the platform). At a market level, personal data can be preprocessed to maintain privacy while still facilitating the matching between customers and niche products/merchants, therefore reducing market inequality and fostering long-tail innovations and entrepreneurship. Recent technical progress on differential privacy may help achieve a balance (Abowd and Schmutte 2019). In addition, e-commerce platforms also need to prepare for data regulation and should design alternative mechanisms (e.g., navigation tools, search bars, menu systems, voice input) to facilitate the customers' active search of merchants and products and protect the vulnerable merchant and customer groups on the platform.

Our study has several limitations and can be extended in a few ways. First, we focus on the value of personal data in internet commerce by studying their role in facilitating matching between customers and merchants in the marketplace. Personal data may also contribute to the economy in other ways, such as improving the performance of online advertising (Goldfarb and Tucker

2011c, Godinho de Matos and Adjerid 2019), search engines (Yoganarasimhan 2020), fintech and credit borrowing (Chan et al. 2022), and digital media and entertainment platforms (Claussen et al. 2019). In addition, peer-to-peer matching platforms in the service sector (Horton and Tambe 2015, Azevedo and Weyl 2016, Hong and Pavlou 2017, Forman et al. 2018) are also relying on personal data, but various supply-side constraints and geographical variations matter. With the regulation of personal data, all of these systems may also be affected as well. However, the net impact and underlying mechanisms might be different, thus requiring separate research. Second, our experiment simulates the most stringent policy and serves as a benchmark for follow-up evaluation of different aspects of policy (data collection, data retention, and data use). It might be a stronger regulation than we would see in practice depending on how specific data regulation laws would be enforced in different countries and regions. Future research can adopt the field experiment measurement approach and examine the effectiveness of different regulations by testing more policy variants based on the specific practice/law in focus. For instance, researchers can run randomized experiment to simulate a data retention policy with different retention periods or evaluate the effect of a data collection policy when only certain variables could be collected. Third, although the field experiment is highly informative to public policy and firm practice (Harrison and List 2004, Banerjee 2020, Duflo 2020), it is well known that with the field experiment approach, it is hard to address the general equilibrium effect (Duflo et al. 2007). Thus, our field experiment is focused on the short term and the immediate impact of data regulation on one platform. In the long term, platforms may strategically redesign the search interface and reoptimize the matching algorithms under new data regulation regimes. Customers may adapt or find alternative shopping channels. The nature of competition between e-commerce platforms and between online and offline retailers might also change. Observational studies could leverage policy change as an exogenous shock to study such a general equilibrium (Goldfarb and Tucker 2011c). Again, any generalization of our findings to settings with major changes must be made cautiously. Although a major data regulation may generate a large impact in the short run, it may be attenuated in the long run. Fourth, similar to previous empirical studies on recommender systems (e.g., Lee and Hosanagar 2019, Li et al. 2022), we had to commit to a specific collaborative filtering algorithm in our study when varying the use of personal data. We believe the qualitative pattern of our results on the value of personal data might be relevant to a wide range of e-commerce platforms as CF is the standard recommendation algorithm used in the industry. Future research can leverage the field experiment approach and test the value of different types of personal data in other contexts and under alternative algorithms. Finally, we focus on measuring the value of data in this study and did not explicitly solicit the privacy preferences of the customers (Tucker 2014, Acquisti et al. 2016, Godinho de Matos and Adjerid 2019). Future research can combine our measurement of data value as well as the recent studies on customers' privacy choice (Johnson et al. 2020, Lin 2022) to construct a customer's data value and privacy cost at the same time. It may further explore heterogeneity across customers and identify the customer subgroups with differential emphasis on privacy and data value. Such a comprehensive measure across both data value and data privacy can inform customers, policy makers, and platforms and help them make a more informed choice and balance the two considerations.

Acknowledgments

The authors gratefully acknowledge the helpful feedback of several academic and industry colleagues on this work. We also acknowledge Alibaba Group for support in making this research possible. Tianshu Sun wants to acknowledge financial support from CKGSB Research Institute.

Endnotes

[1] See http://www.moj.gov.cn/news/content/2019-05/28/zlk_235861.html (accessed October 21, 2020) Similarly, the California Privacy Act and GDPR also have strict terms on the collection, retention, and use of personal data. See Online Appendix A for more discussions on data policy.

[2] See http://www.miit.gov.cn/n1146285/n1146352/n3054355/n3057709/n3057719/c7574782/content.html (accessed October 21, 2020).

[3] GMV is according to the annual report of the Alibaba Group in May 2018 (https://www.alibabagroup.com/en/ir/presentations/pre180504.pdf (accessed October 21, 2020)). Employment is according to the e-commerce report on China in 2018 from the Ministry of Commerce (http://images.mofcom.gov.cn/dzsws/201905/20190530100539785.pdf) (accessed October 21, 2020) and another report from Renmin University (http://www.sh-zhonghuan.com/static/upload/file/20190408/1554716542420278.pdf) (accessed October 21, 2020).

[4] Our field experiment is focused on the short-term and immediate impacts of data regulation on e-commerce. Any extrapolation of our findings to a different time horizon must be made cautiously as the platforms and customers may strategically adapt in the long run. See the detailed discussion in Section 6.

[5] Recent research also examines specific types or aspects of data regulation policy (Miller and Tucker 2009, Goh et al. 2015, Aziz and Telang 2016, Jin 2018). Adjerid et al. (2016) find that when coupled with *incentives*, privacy regulation with requirements for *patient consent* can positively impact the development of health information exchange. Chiou and Tucker (2017) have studied the impact of *data retention* on search engine performance and find little empirical evidence that reducing the length of storage of past search engine searches affected the accuracy of search. Johnson et al. (2020) finds that GDPR may have another *unintended consequence*; relative concentration of the website vendor market increases by 17%. Johnson et al. (2020) examines the *opt-out policy* and finds that the inability to behaviorally target opt-out users results in a loss of about $8.58 in ad spending per American opt-out consumer. Jia et al. (2018) find a negative effect of GDPR on the *venture capital investment* in new and emerging technology firms.

[6] We provide a detailed discussion on the commonalities and differences between internet commerce and target advertising at the end of Online Appendix B. Specifically, the two differ in customer intent, matching process, search environment, the type of personal data used, and the alignment of objective function with customers.

[7] A separate literature employs firm-level data and finds that data and analytics support decentralized innovations and generate value for firms with process innovation and innovation recombination (Wu et al. 2019, 2020).

[8] See a detailed discussion in Online Appendix B on the differences between internet commerce and target advertising.

[9] Previous literature on recommender systems has studied whether the adoption of recommenders would lead to a change in the consumption behavior at an aggregate level and an individual level (Fleder and Hosanagar 2009, Hosanagar et al. 2014). We complement their work and ask a different question. When the recommender system is already adopted (as this is the case in most e-commerce platforms now), how does data regulation affect consumption behavior at an aggregate level and an individual level? Our study complements and extends their findings (e.g., we show that when data are turned off in the recommender system, consumption diversity will decrease at both levels). Thus, data regulation should also consider its impact on consumption diversity.

[10] According to a report from the Chinese National Bureau of Statistics in February of 2019, e-commerce accounts for 18% of (online and offline) domestic retail sales in the Chinese economy (http://www.stats.gov.cn/tjsj/zxfb/201902/t20190228_1651265.html) (accessed October 21, 2020).

[11] The detailed machinery of the home page recommender systems at Alibaba has been documented in previous research in computer science (graph-embedding CF) (Wang et al. 2018, Lv et al. 2019, Zhao et al. 2019). The objective function of the algorithm is to maximize the matching, regardless of the data input.

[12] Two percent traffic is the minimum bucket size for any recommendation experiment in the Alibaba AB testing infrastructure.

[13] We define CTR as the number of products clicked divided by the number of products viewed. We track the customers' browsing behavior and thus, can measure the number of products viewed in the recommendation. We compare CTR in the control and treatment groups based on Table 3. CTR of the treatment is $(5.3-4.4)/(116.9-39.0)$. CTR of the control is $5.3/116.9$. Thus, the decrease in CTR is $1-[(5.3-4.4)/(116.9-39.0)]/[5.3/116.9]=75.3\%$.

[14] Big sellers and high-tier sellers enjoy a larger number of product views and GMV as compared with small or low-tier sellers. For instance, in our experiment (control group), big sellers on average have 93.6 product views (versus 17.4 for small sellers) and 1.22 RMB in GMV (versus 0.17 RMB for smaller sellers). However, there is a larger number of small sellers on the platform. Thus, we use the relative measure (percentage) to describe changes.

[15] In Online Appendix B, we also examine the relationship between item characteristics (head/long tail) and merchant characteristics (e.g., big versus small seller, high versus low rating). There is some correlation but not very strong; sizable portions of head items are offered by small sellers and low-rating sellers. The heterogeneity results on the merchant convey additional information beyond the heterogeneity results on the item and Figures 1 and 2.

[16] We acknowledge that the analyses of the heterogeneous treatment effect (HTE) using customer characteristics are only suggestive. The reader should be cautious in interpreting them. Just like most heterogeneous effect analysis in field experiment research (Duflo et al. 2007), it is hard to pin down the causal mechanism given that the moderator is an intrinsic characteristic of the customers and can be associated with other characteristics. Thus, we only present these HTE analyses as suggestive evidence for our mechanism discussions and do not claim them as causal.

[17] There are K industries in our database. Let $\boldsymbol{P}_k^{his}=\{p_1^{his},p_2^{his},\ldots,p_K^{his}\}$ represent the click history of a consumer in each industry, where p_k^{his} denotes the fraction of items in industry k the consumer visited within one month from the experiment. Let $\boldsymbol{P}_k^{rec}=\{p_1^{rec},p_2^{rec},\ldots,p_K^{rec}\}$ represent the distribution of industries in the recommendation system for a consumer, where p_k^{rec} denotes the fraction of items in industry k a consumer saw in the experiment. The cosine value between $\boldsymbol{P}^{his}$ and $\boldsymbol{P}^{rec}$ measures the similarity between the set of recommended items and the set of previously clicked items. We define

$$Cos_{his,rec}=\frac{\sum_k p_k^{his}\times p_k^{rec}}{\sqrt{\sum_k (p_k^{his})^2+\sum_k (p_k^{rec})^2}}.$$

[18] Alibaba ranks all query keywords according to the transaction volume of the keyword; niche or long-tail keywords contribute to the bottom one third of the transaction volume, and common keywords contribute to the top one third of the transaction volume.

[19] We have also performed analysis on the heterogeneous treatment effect of data regulation on customers' active search. See Online Appendix G for the results and discussions.

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