Privacy Regulation and Its Unintended Consequence on Consumption Behaviors: Evidence From CCPA

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Completed Research Paper

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Abstract

This study explores the unintended consequences of data protection regulations on consumer behavior. Specifically, we examine the California Consumer Privacy Act, which restricts companies from collecting Californians' personal information. Privacy regulations may limit firms' ability to suggest products aligned with consumers' taste predicted from data, potentially influencing subsequent consumer behavior. These regulations especially pose a challenge to digital platforms, as their success hinges on seamless data flow between firms and consumers. Using a difference-in-differences approach with transaction data, we find that post-CCPA, Californians reduce purchase by 4.1%, increase returns by 2.9%. Moreover, we find that Californians spend more time online and visit more webpages, potentially indicating increased search efforts. Mechanism analysis suggests that firms under CCPA proactively alter their data collection strategy to reduce the liability. These results reveal the complex interplay between privacy regulation and consumer behavior, highlighting the need for a nuanced understanding of the trade-offs between privacy protection and economic outcomes.

Keywords: Privacy Regulation, Consumer Behaviors, Unintended Consequences

Introduction

Personal data of consumers is arguably a crucial asset for businesses in the digital economy. Businesses can use large-scale data analytics to benefit both consumers and themselves, as it can improve consumer satisfaction, personalize recommendations, and enhance marketing campaigns (Johnson et al. 2005; Tambe et al. 2012). However, the vast amounts of personal information also pose a significant risk of data misuse in ways that violate consumers' privacy rights or cause harm the individuals. For instance, companies may leverage personal data to target individuals with unwanted marketing, manipulate their behavior (Fleder and Hosanagar 2009), or use data for reasons that consumers did not consent for (Cimpanu 2018). Additionally, companies may fail to safeguard personal data, leading to data breaches and identity theft. Such incidents have been prevalent in recent years, with notable examples including the Facebook-Cambridge Analytica scandal (Cadwalladr and Graham-Harrison 2018) and data breaches at Yahoo! (McMillan and

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Knutson 2017), Marriott (Perlroth et al. 2018) and Equifax (Lee 2017). Millions of Facebook users' data were harvested without consent and have been shown to be used for political advertising (Cadwalladr and Graham-Harrison 2018). Three billion Yahoo! user accounts, 500 million Marriott guests, and 143 million Equifax users were affected in data breaches. Furthermore, companies may also sell personal data to third parties, which can then exploit them for malicious purposes (Cimpanu 2018).

The heightened risk of companies misusing and mishandling personal data has prompted various governments to intervene and regulate data collection practices. This process has resulted in the implementation of robust privacy regulations, such as the European Union's General Data Protection Regulation (GDPR), California's California Consumer Privacy Act (CCPA), and several country-specific regulations worldwide. These regulations serve to protect individuals' rights to their data privacy and ensure that their personal data is handled responsibly and ethically. For instance, under the CCPA, companies must inform Californian consumers of their rights regarding their personal data and provide them with a simple and accessible means of asserting these rights, which include accessing and obtaining a copy of their data, deleting it, and opting out of its sale.

The governance of data used by firms presents a complex trade-off. On the one hand, privacy regulations can enhance consumer agency by improving transparency and choice over how personal data is leveraged by companies. The credible threat of auditing and enforcement can also nudge firms to prioritize better data practices (Cusumano et al. 2021). Yet, the very prospect of liability can also constrain companies' willingness to learn from the valuable behavioral signals embedded in personal data. The reduced willingness to anticipate consumer needs from data proactively can diminish their capacity to tailor their offerings to evolving consumer preferences and value creation in the digital economy.

Extant literature has recognized this dichotomy by exploring the influence of privacy regulations on firms' strategies and outcomes, including both their advantages and disadvantages (Aridor et al. 2020; Campbell et al. 2015; Goldfarb and Tucker 2011; Janssen et al. 2022; Johnson et al. 2021; Lefrere et al. 2022; Peukert et al. 2022). However, few studies, except for Zhao et al. (2021), have analyzed the impact of privacy regulations by observing consumer behaviors, such as search, purchase, and return.

To address this research gap, we examine how data protection regulations influence consumers' consumption behaviors. We document the unintended consequence of such regulations by leveraging a natural experiment arising from the CCPA, which grants Californians rights over their personal data collected by firms and took effect on January 1, 2020. The CCPA clearly empowers consumers to protect their data, but how it impacts their consumption behaviors remains unclear. The bill's adoption creates a natural experiment that allows us to study the unintended consequence of data protection regulation for Californians, who are protected by the CCPA rules, compared to non-Californians.

We posit that the CCPA affects Californians' purchase and return behaviors through firms' data collection and targeting strategies. Firms may collect less data from Californians and provide less tailored advertising to comply with the regulation and avoid potential liability. Consequently, this reduction affects their precision in recommendations and product-consumer matching, which alters consumers' purchase and return behaviors. Specifically, in this study, we examine the following question empirically: *How do purchase and return behaviors change following the CCPA?*

To answer the question, we leverage a unique dataset from a payment processing gateway that has billions of individual transactions of U.S. consumers. The dataset includes consumer information, such as city-level location, merchant details, credit or debit, etc. We compile a monthly panel to contrast the purchases and returns for Californians with non-Californians in four neighboring states: Arizona, Oregon, Nevada, and Washington. Empirically, we follow the literature on natural experiments (Liu and Lynch 2011; Smith and Todd 2005): we first pre-process the data using propensity score matching (Dehejia and Wahba 2002) and then employ a difference-in-differences (DiD) identification strategy (Meyer 1995).

Our results indicate that Californians decrease their purchases by about $98 per period after the CCPA, a 4.1% drop relative to their matched counterparts in neighboring states. They also increase their returns by $4, a 2.9% increase in return amount relative to non-Californians. Overall, the loss of commerce in California per period is $102. Our results are robust to various alternative model specifications and account for macro changes, such as the pandemic lockdown effect.

The change in the purchase and return patterns may stem from the challenge of finding a suitable product online. We use another proprietary dataset of browsing behaviors to test our hypothesis about the privacy regulation's effect on consumption patterns. We find that Californians increase their time spent browsing for information on the web, with longer sessions and more page visits than residents of the other four states. This implies that Californians may need more time to search for products that match their preferences. This indirectly supports our hypothesis that Californians were less satisfied with firms' recommendations after the privacy regulation.

We delve into the mechanisms by examining how firms adapt to the CCPA and how this affects consumer behavior. We argue that firms' compliance efforts may influence consumers' online activity. For this test, we contrast firms' ad-related web technologies before and after the CCPA. We exploit a natural experiment based on the CCPA's enforcement criteria: only firms with annual revenues above $25 million are subject to the CCPA[1]. We split the firms into two groups according to their revenues and measure their usage of ad technologies. We find firms affected by the CCPA reduce their use of ad technologies, which are often employed for personalized advertising. This suggests that firms limit their targeting practices to comply with the new privacy law.

This study contributes to the extant theory on privacy regulations. We use several proprietary datasets to be among the first to show how data protection laws affect consumer consumption behavior. We also reveal the unintended effects of privacy regulations on consumer surplus. The benefits of data protection regulations are uncertain, but the costs for firms and consumers are clear, as shown by investigations on data protection regulations (Aridor et al. 2020; Janssen et al. 2022; Johnson et al. 2021; Peukert et al. 2022). Our findings also have practical implications for platforms. As regulatory interventions on data collection and processing increase, platforms may benefit from self-regulating and voluntarily limiting data collection by complementors, to avoid the need for public regulations.

Related Literature

Our research bridges two distinct streams of literature: the value of data in the digital economy and the impact of data protection regulations on platforms. To provide context and define our research questions, we first review the literature and identify the research gaps.

Data in Digital Economy

Data has emerged as a critical input in shaping digital societies. Literature has extensively examined the advantages of data collection and analysis across various domains. In the business sector, user-generated content such as online reviews and feedback can help enhance service quality and foster product improvement (Ananthakrishnan et al. 2023; Bertschek and Kesler 2022). Similarly, Niebel et al. (2019) demonstrate a positive relationship between firms' big data analytics usage and product improvement. Transitioning to finance, data sharing can enhance efficiency by increasing lending to safe borrowers and decreasing default rates (Doblas-Madrid and Minetti 2013; Jappelli and Pagano 2002). In fact, there are documented evidence of suppliers trying various tactics to ensure continued data collection (Kummer and Schulte 2019; Mayya and Viswanathan 2023).

Nevertheless, while the corporate strategic harnessing of data offers mutual benefits to not only businesses but also individuals who are the customers of the business, it also presents challenges against consumers, particularly concerning consumer surplus. When firms employ this data to engage in price discrimination to maximize profits, it can potentially erode consumer surplus (Bar-Gill 2021; Bonatti and Cisternas 2020). For instance, personalized pricing based on consumers' web-browsing behaviors can substantially increase profits for companies, but it may also raise concerns about discrimination against specific consumer groups (Shiller 2020). Similarly, product reviews and consumption history can enable dynamic pricing and price discrimination, leading to welfare loss for some consumers (Bonatti and Cisternas 2020; Feng et al. 2019).

[1]Am I Subject to the CCPA? - Higgs Law

Despite an extensive discussion on the pros and cons of data collection, the overall benefit to consumers remains ambiguous (Acquisti et al. 2016). Our study revisits this conundrum, probing whether corporate usage of consumer data indeed brings tangible benefits to the end-users. Specifically, we examine the full arc of the consumers' consumption journey: from the initial search and discovery phase, through the purchasing decision, to the eventual post-purchase satisfaction with the product. More significantly, our study transcends the conventional analysis of the static merits and pitfalls of consumer data utilization, delving into the dynamic antecedents - product searching - and subsequents - product return - of consumer behaviors when exogenous factors limit data collection and trade.

Data Protection Regulations and Platforms

Data protection regulations aim to provide consumers with more control and security over their personal information. Studies indicate benefits from such regulations.Van Ooijen and Vrabec (2019), for instance, assert that the GDPR can enhance individual control over personal information by reducing cognitive processing and decision-making threats. Ke and Sudhir (2022) theoretically establish that privacy regulations can increase consumer surplus in a competitive market. Aridor et al. (2020) present empirical evidence that consumers leveraged the opt-out feature to restrict firms' data collection, leading to fewer browsing cookies following the GDPR's implementation. Goldberg et al. (2022) document that the collective page views declined after the GDPR's introduction. Finally, Lefrere et al. (2022) find that GDPR affected websites to improve their tracking practices, albeit for a short term. Overall, privacy regulations can enable consumers to safeguard their privacy and decrease unauthorized personal data collection.

Data protection regulation can have unintended consequences too, as studies have shown. Early studies found that privacy laws hinder technology diffusion (Miller and Tucker 2009) and reduce online advertising effectiveness (Goldfarb and Tucker 2011). Recent studies have investigated the impact of new privacy regulations, such as the GDPR. For example, Jia et al. (2021) report fewer venture deals in the E.U. than in the U.S. after the GDPR. Bessen et al. (2020) posit that the GDPR imposed new costs upon AI startups, requiring new positions and resource reallocation to address the GDPR concerns. Canayaz et al. (2022) argue that the CCPA hurts firms with voice-AI products, which are heavily reliant on consumer data compared to firms without voice-AI products. Additionally, Johnson et al. (2021), Janssen et al. (2022) and Peukert et al. (2022) demonstrate that the GDPR increased market concentration toward larger players in web technologies or apps, potentially reducing product improvement.

Despite the recognized effects, a gap persists in comprehending the wider ramifications of these regulations, especially their influence on consumer consumption patterns, possibly owing to the scarcity of granular consumer behavior data. While facets such as search behaviors have been addressed (Zhao et al. 2021), the direct impact of data protection regulations on purchase volume, and product returns remains largely untouched.

Gap and Research Questions

Our research seeks to address these gaps. Firstly, we aim to elucidate the influence of privacy regulations on actual purchase behavior. While some studies have shown that privacy regulation can lengthen the process of searching for products and services (Zhao et al. 2021), its impact on purchase quantity remains unanswered. Purchase intention and search efforts may not always reflect actual purchasing behavior, which is crucial for understanding the full effect of privacy regulations on consumer behavior. By studying the actual purchase behavior, we can assess the efficacy of privacy regulations in promoting or discouraging purchases. Therefore, we ask and answer, *do privacy regulations influence the volume of purchases made?*

We also study how privacy regulation affects post-purchase behavior, which have been largely overlooked in extant literature. Firms may need to modify their marketing strategies under new privacy regulations to avoid potential liability, which could affect their ability to offer personalized and effective recommendations to consumers. This could reduce consumer satisfaction with recommendations and may change consumer behavior, such as increasing product search efforts (Zhao et al. 2021) and decreasing ad clicks (Aridor et al. 2020). However, little is known about how privacy regulation influences post-purchase behaviors, such as product returns, which measure purchase satisfaction. Therefore, our study seeks to fill this gap by examining *whether privacy regulations impact the volume of returns made by consumers*. By exploring this aspect, we aim to contribute to understanding the broader implications of privacy regulations on consumer behavior and satisfaction in the context of the digital economy.

Research Context and Data

Background: The California Consumer Privacy Act (CCPA)

The California Consumer Privacy Act of 2018 (CCPA) is a state law intended to provide consumers with the right to protect their personal information gathered by firms. The bill, which took effect on January 1, 2020, grants Californian customers four rights: 1) to know what personal information is collected and how it is used and shared, 2) to delete the data, 3) to opt out of the sale of their personal data, and 4) to not face discrimination for exercising their CCPA rights. The act only covers Californians, but it applies to any firm that does business in California regardless of where they are located. Firms must comply if they have more than $25 million in annual revenue or collect or sell data from over 50,000 Californians, households, or devices, or make more than half of their revenue from selling Californians' data. Firms can face penalties for violating the law. The CCPA covers a wide range of personal data and sales. Personal data includes not only physical identity information but also online activity and profile data. Sales include any communication of personal data to another entity for any benefit[2]. This could expose firms to more liability for handling sensitive data and affect consumer behavior more than expected.

The CCPA offers privacy protections that are comparable to the GDPR, though there are distinctions between them. Both regulations similarly define personal data and grant consumers rights concerning their personal data, such as the right to access and delete it. In addition, they both penalize businesses on violations of the regulation in substacial economic terms with varying scope and amount. One distinction is that the GDPR allows for the restriction of data processing, which the CCPA does not offer, though CCPA assures a right to opt-out of data sales. For a more comprehensive comparison, refer to Jehl, Friel, et al. (2018).

One advantage of using the CCPA as the context for an empirical study is that its localized influence allows for a more controlled analysis. While recent studies about the impact of privacy regulations mostly utilize the GDPR, our study using the CCPA provides a unique perspective. The wide-ranging application of the GDPR across numerous European countries and its spillover effects worldwide create challenges for event studies that aim to identify suitable control groups to examine the regulation's causal impact (Johnson 2022). In contrast, the CCPA is limited to a single state, California, within the United States, ensuring that treatment and control groups are relatively homogeneous, except for the treatment. It enables a more accurate evaluation of the changes before and after the regulation within the same country.

Data

To study the impact of the CCPA on consumption behavior, we construct a proprietary panel dataset using individual-level transaction data obtained from a large financial data provider. The transaction data include an individual customer's daily purchase and return transactions covering credit card and bank account (debit card) transactions.[3] Each observation in the data corresponds to a single card swipe, such as a debit or credit card. In addition to the transaction history, the data provider provides consumer location information for each month, as predicted by their transaction history. It allows us to identify whether a consumer is under the CCPA's effectiveness or not and examine the influence of the privacy regulation on consumer behavior. We focus on consumer transactions that are influenced by firms' targeted promotions by limiting them to 12 focal categories and removing potential business accounts (see appendix).

Each transaction record includes a timestamp of the transaction, dollar amount, name and city-level address of the merchant and description of the transaction. Besides, the panel data also includes each user's monthly location and income classes. The data provider estimates the location and income class based on

[2]It defines sale as "selling, renting, releasing, disclosing, disseminating, making available, transferring, or otherwise communicating orally, in writing, or by electronic or other means, a consumer's personal information by the business to another business or a third party for monetary or other valuable consideration."

[3]The data vendor processes transactions for 3.2% of the U.S. population.

PANEL A: Descriptive Statistics of Consumption Behavior					
	count	mean	s.d.	min.	max.
Purchase	2,730,984	2,842.40	2,188.14	0	102,088
Return	2,730,984	96.10	453.82	0	38,406
IncomeClass	2,730,984	4.70	1.88	1	7
PANEL B: Descriptive Statistics of Browsing Behavior					
	count	mean	s.d.	min.	max.
Duration	20,328	1,709.71	1,711.38	9	10,204
PagesViewed	20,328	1,154.68	1,100.99	10	6,592

Table 1. Descriptive Statistics

the consumer's transaction history. The income class is divided into seven brackets, with the higher income class denoting the higher income level. Based on the transaction data, we calculate the ratio of the number of online purchases to the number of total purchases for each individual every month.

We create a balanced panel data set of 101,389 users from January 2019 to December 2020, 12 months before and after the implementation of the CCPA, by aggregating transaction data at a month-user level. As noted earlier, the panel dataset includes the treated group comprising Californians and the control group of those residing in four neighboring states–Arizona, Oregon, Nevada, and Washington. The treated group has 53,475 Californians, and the control group has 60,316 users from the other four states.

Further, we restrict the treated group to the Californian residents who stay in California for the study duration. It is unclear whether one is under the effect of CCPA or not if we include him who is moving between California and the other states over the study time window. Besides, it may cause bias in the staggered DiD model suggested by Goodman-Bacon (2021), because each individual may have a different treatment time. The DiD estimator employing a two-way fixed effects model estimates a weighted average of various effects, and the weights can be negative if we do not exclude those who move across the treatment and control groups. We believe it is appropriate to exclude those samples, as it is unlikely that an individual would relocate to another state solely for the purpose of avoiding or being affected by the new privacy regulation.

We employ an additional comprehensive dataset on consumers' web browsing history sourced from a large media measurement and analytics company to study changes in browsing behavior following the CCPA implementation. Insights from web browsing patterns alterations shed light on changes in search costs subsequent to the regulation. This dataset represents the browsing history of PCs in California and the other four states for the same study periods, from January 2019 to December 2020. The dataset captures specifics of web browsing sessions, such as the domain of the page, the number of pages viewed during the session, and the duration of each session.

Variable Definitions

Tables 2 provides variable description. In the analysis of consumption behavior, the dependent variables are the individual consumer's monthly expenditure, denoted as $Purchase$, and the monthly refunds, represented by $Return$, both expressed in the dollar amount. For the investigation of web browsing behavior, the dependent variables comprise the quantity of minutes dedicated to web browsing within a month, $Duration$ and the count of pages accessed, $PagesViewed$. To account for potential confounding factors, this study incorporates a consumer's monthly income classification, $IncomeClass$. The details of income class brackets can be found in the appendix.

Empirical Methodology

Difference-in-Differences (DiD) Analysis

The California Consumer Privacy Act of 2018, approved in June 2018, went into effect on January 1, 2020. The bill creates a natural experimental setting that separates the treated group under the bill's effectiveness

PANEL A: Variable Definitions of Consumption Behavior	
Variable	Description
Dependent Variables	
$Purchase_{it}$	Dollar amount that consumer *i* purchased in month *t*
$Return_{it}$	Dollar amount that consumer *i* returned in month *t*
Explanatory/Control Variables	
$Treat_i$	Whether a consumer *i* is a Californian
$Post_t$	Whether a month *t* is post the CCPA
$IncomeClass_{it}$	Predicted income class of consumer *i* in month *t*
PANEL B: Variable Definitions of Browsing Behavior	
Dependent Variables	
$Duration_{jt}$	Number of minutes spent in web browsing for machine *j* in month *t*
$PagesViewed_{jt}$	Number of pages viewed for machine *j* in month *t*
Explanatory Variables	
$Treat_j$	Whether a machine *j* is set in Californian
$Post_t$	Whether a month *t* is post the CCPA

Table 2. Variable Explanation

–Californians–from the control group who are not under its effectiveness–non-Californians, which allows us to evaluate the influence of the CCPA on consumers' purchase and return behaviors. As noted in Data section, we remove consumers who move between California and the states in our analysis to ensure that one's treatment status is clearly defined.

We use a DiD analysis which is commonly used to identify the effect of "treatment" on treated (Meyer 1995) by implementing a two-way fixed effects model to estimate the treatment effect:

$$y_{it} = \beta \times (Treat_i \times Post_t) + X_{it}^{'}\Gamma + \lambda_t + \mu_i + \epsilon_{it}, \tag{1}$$

where, i refers to a consumer, t refers to a month: $t \in T = \{-12, \cdots, 11\}$. Here, $t = 0$ is the month when the CCPA was implemented (January 2020). The dependent variable y_{it} is consumer i's monthly dollar amount of purchases (returns) at month t for the purchase (return) model. $Treat_i = 1$ is the dummy variable indicating the treated group, and $Post_t$ is the dummy indicating post-treatment periods. β is the coefficient of interest to estimate the effect of the privacy regulation on consumers' shopping behaviors in purchase and return. To account for potential time-invariant unobserved heterogeneity among consumers that may affect their consumption patterns, we incorporate individual consumer fixed effects, μ_i, into our model. X_{it} includes dummies of income brackets to control changes in purchases and return due to shift in individual's income. λ_t is year-month fixed effects controlling for common time trends across time; and ϵ_{it} is an error term. The return equation additionally includes the amount of monthly purchases, which can influence the consumer's return amounts and be influenced by the CCPA simultaneously, as a control.

We use a similar model to estimate changes in browsing behavior after the CCPA. The treated group comprises machines located in California, and the control group comprises those in the other four states. The dependent variable y_{jt} is the browsing duration or pages viewed for machine j at month t. The model includes the interaction of $Treat_j$ and $Post_t$; its coefficient, β captures how Californians' web browsing behaviors change after the implementation of the CCPA in contrast to non-Californians. The model, similar to Model 1, includes year-month fixed effects λ_t, machine fixed effect, μ_j, and error term, e_{jt}, but does not include other covariates:

$$y_{jt} = \beta \times (Treat_j \times Post_t) + \lambda_t + \mu_j + \epsilon_{jt}. \tag{2}$$

Matching

Since our setting is quasi-experimental, there is a possibility that the treatment assignment is "nonrandom". To address all concerns related to the quasi-experimental setting, we follow recommendations in the literature. Before conducting the DiD analysis, we perform a Propensity Score Matching (PSM) to account for any potential systematic difference between the treated and control groups for the shopping behavior models (Dehejia and Wahba 2002) (Equation 1). Using PSM in conjunction with DiD for causal analysis is a frequently used and well-established procedure in literature (Liu and Lynch 2011; Mayya et al. 2021; Smith and Todd 2005). We use one-to-one nearest neighbor matching without replacement to match a sample in the treatment group similar to one in the control group. It matches each sample in the treated group with the closest propensity score in the control group within a given caliper. If a sample in the treated group does not have a matched control within the caliper, it is discarded from our data.

We estimate the propensity score with probit regression. The independent variables in the probit model are income class, the fraction of online purchases, and the number of categories returned and purchased before treatment periods. The model also includes pre-treatment dependent variables (purchase amounts and return amounts) and log transformation of them. The matching procedure yields 48,525 samples in the treated group and control group, respectively. Covariate balance between the treated and control groups is evaluated, and Table 3 summarizes the results, indicating a significant reduction in bias following the matching procedure.

	Pre-Matching				Post-Matching			
	Mean(Ctrl)	Mean(Trt)	Difference	t-stats	Mean(Ctrl)	Mean(Trt)	Difference	t-stats
IncomeClass==1	0.060	0.053	0.007	6.19***	0.058	0.057	0.001	0.87
IncomeClass==2	0.154	0.130	0.025	14.15***	0.141	0.141	-0.001	-0.27
IncomeClass==3	0.124	0.105	0.019	13.86***	0.114	0.114	-0.000	-0.10
IncomeClass==4	0.102	0.085	0.018	15.14***	0.091	0.092	-0.001	-0.83
IncomeClass==5	0.181	0.167	0.014	8.49***	0.176	0.178	-0.002	-0.97
IncomeClass==6	0.218	0.225	-0.007	-3.49***	0.228	0.229	-0.001	-0.48
IncomeClass==7	0.159	0.236	-0.076	-36.99***	0.192	0.189	0.003	1.51
Purchase	2790.486	2865.648	-75.161	-7.03***	2840.972	2835.432	5.540	0.48
Return	91.456	92.805	-1.349	-0.60	89.323	87.554	1.768	0.83
OnlinePurchase	0.209	0.219	-0.010	-15.31***	0.215	0.215	-0.000	-0.59
PurchaseCategories	7.519	7.438	0.081	8.79***	7.494	7.492	0.002	0.20
ReturnCategories	0.506	0.552	-0.046	-16.04***	0.535	0.533	0.002	0.64

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3. Covariate Balance Check: Pre-Treatment

Parallel Trend

The DiD analysis relies on the assumption of a parallel trend between the treated and control groups in the absence of treatment to interpret the estimated treatment effect as a causal impact (Autor 2003). In our case, if the CCPA had not been adopted, the purchase and return amounts should have moved in parallel over time between Californians and non-Californians. Although this assumption is not generally testable because of the unobservability of counter-factual of post-treatment outcomes for the treated group, it is widely adopted to evaluate the validity of the parallel trend assumption by examining pre-treatment periods.

Our panels include multiple periods of pre- and post-treatment, enabling us to test the parallel trend during the pre-treatment periods. To assess the validity of this assumption, we replace $Post_t$ with λ_t and β with β_t in Equation 1. We compare the difference in the purchase (return) amounts between the treatment and control groups during all other periods with the difference in $t = -1$. As a baseline, we normalize β_{-1} to zero:

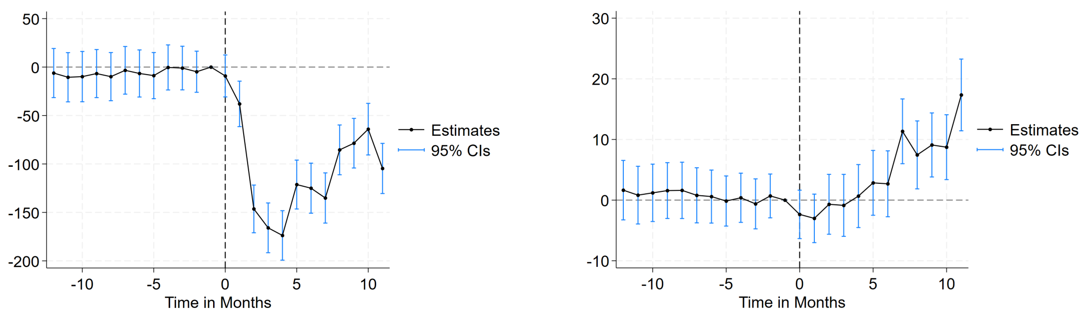
$$y_{it} = \sum_{t \neq -1} \beta_t \times (Treat_i \times \lambda_t) + X_{it}^{'}\Gamma + \lambda_t + \mu_i + \epsilon_{it}. \tag{3}$$

Similarly, we transform the Equation 4 as

$$y_{jt} = \sum_{t \neq -1} \beta_t \times (Treat_j \times \lambda_t) + \lambda_t + \mu_j + \epsilon_{jt}. \tag{4}$$

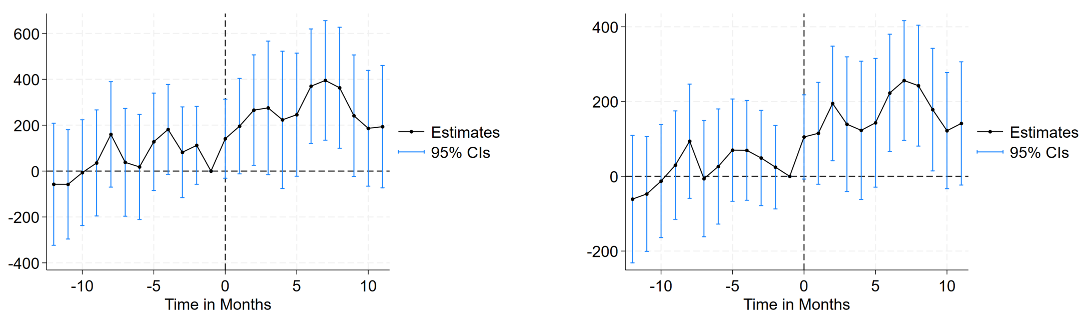
The coefficients before the treatment ($t = -2, \cdots, -12$) should be insignificant in Equation 3 and 4 if our models meet the parallel trend assumption.

Figure 1a and 1b present point estimates and 95% confidence intervals. As shown in the figures, no coefficients before the treatment were significant in each model. It implies that the treated groups would have changed evenly from the control group if they had not received the treatment. Figure 2a and 2b summarize the estimated results of the browsing behavior models, and they show that the dataset also meets the parallel trend assumption. The F-test fails to reject the null hypothesis that the all pre-treatment coefficients are jointly zero for each respective model, thereby reinforcing the validity of the parallel trend assumption.[4]



(a) Purchase **(b) Return**

Figure 1. Parallel Trend: Consumption Behavior



(a) Duration **(b) Pages Viewed**

Figure 2. Parallel Trend: Browsing Behavior

Results and Discussion

Main Results

Table 4 summarizes the effect of the CCPA on consumers' monthly purchase amounts and return amounts. The estimated results column (1) and (2) in Table 4 reveal the consistent negative effect of the privacy regulation on purchase regardless of model specifications. To be specific, the regulation suppresses about $99 per month (column 2); it is about a 4.1% decrease in the monthly spending. The results, presented column (3) and (4) in Table 4, show that the monthly return amounts increase by about $4 per month; it is about a 2.9% increase in the monthly return.

Table 5 shows that post-treatment, Californian residents spend an additional 205 minutes per month and visit 146 more pages compared to the control group.

[4] Purchase: $F(11, 87003) = 0.18, p > F = 0.9984$. Return: $F(11, 87003) = 0.19, p > F = 0.9983$. Duration: $F(11, 846) = 1.24, p > F = 0.2590$. Pages Viewed: $F(11, 846) = 0.82, p > F = 0.6199$

	(1)		(2)		(3)		(4)	
	Purchase		Purchase		Return		Return	
Treat × Post	-98.235***	(6.038)	-98.530***	(5.949)	3.734***	(1.442)	3.696**	(1.441)
Purchase					0.031***	(0.000)	0.031***	(0.000)
IncomeClass=2			107.087***	(6.137)			0.278	(1.685)
IncomeClass=3			177.296***	(8.030)			2.752	(2.108)
IncomeClass=4			227.216***	(9.174)			5.748**	(2.348)
IncomeClass=5			289.813***	(9.794)			5.474**	(2.436)
IncomeClass=6			365.292***	(10.756)			11.152***	(2.599)
IncomeClass=7			478.345***	(12.305)			16.905***	(2.884)
N	2,329,200		2,329,200		2,329,200		2,329,200	
Individual-fixed effects	yes		yes		yes		yes	
Month-fixed effects	yes		yes		yes		yes	
Robust standard errors	yes		yes		yes		yes	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. The Impact on Consumption Behaviors

	(1)		(2)		(3)		(4)	
	Duration		Duration		Pages Viewed		Pages Viewed	
Treat × Post	205.346***	(73.468)	205.346***	(73.508)	145.737***	(46.573)	145.737***	(46.598)
Post	0.577	(59.602)			-73.959*	(38.133)		
N	20,328		20,328		20,328		20,328	
Individual-fixed effects	yes		yes		yes		yes	
Month-fixed effect	yes		yes		yes		yes	
Robust standard errors	yes		yes		yes		yes	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. The Impact on Browsing Behaviors

Discussion

Our findings reveal that privacy regulation 1) curtails consumers' expenditure, 2) augments the volume of returns, and 3) prolong web browsing behaviors. In this section, we elucidate these observations.

To begin, the observed reduction in expenditure could be indicative of diminished consumer surplus. Analyzing through the lens of the demand and supply curve, this reduced expenditure could be attributed to either a shift in the demand curve or the supply curve. Citing Goldfarb and Tucker (2011), privacy regulations reduce the efficacy of advertising, suggesting that the diminished expenditure can be attributed more to a downward shift in demand than a supply shock. In simpler terms, post-regulation advertising may not attract consumers as effective as before, reduce their consumption. Consequently, consumer surplus, which is defined as the area underlying the demand curve and the price of a commodity, diminishes.

It's crucial to emphasize that reduced consumption does not necessarily translate to a decline in consumers' welfare. In essence, reduced consumer surplus is not inherently detrimental to consumers (Orbach 2011). While data-driven personalization can curtail shopping search costs, it also has potential downsides, such as engendering artificial demands that lead to superfluous consumption. If reduced consumption stems from dampened artificial demand, it might actually enhance consumers' well-being.

In the subsequent observation, the amplified volume of returns post-privacy regulation implies reduced post-purchase satisfaction. This surge in returns is not merely a sign of consumer dissatisfaction, especially when considering the hidden costs associated with returns. These include tangible costs like retrieving purchase documentation and repackaging and shipping, intangible costs such as the opportunity cost of time, as well as a potential monetary cost encompassing shipping or restocking charges. In light of these associated costs, the post-regulatory rise in returns accentuates a misalignment between product and consumer expectations post-regulation.

Regarding browsing behaviors, the uptick in both duration and pages per session signifies an elevated consumer search cost. Our results are consistent with the findings of Zhao et al. (2021), wherein post-GDPR, E.U. consumers demonstrated augmented web engagement. In addition, they document that E.U. consumer navigated more pages and allocated more time to find specific products and services until checkout. This translates to enhanced search costs.

In conclusion, our research suggests that privacy regulations might have unintended negative consequences for consumers. The diminished efficacy of advertising leads to a reduction in consumer surplus and increases the search costs associated with identifying products that align with consumer preferences. Despite expending more effort in their search, consumers appear less satisfied with their purchases. Collectively, the elevated search costs, decreased consumer surplus, and reduced post-purchase satisfaction indicate that privacy regulations could be detrimental to overall consumer welfare.

One plausible mechanism underpinning these consumer behavior shifts is firms' recalibrated strategies towards collection, trade and utilization of consumer data. To circumvent potential liabilities and ensure regulatory compliance, firms might be tempering their data-driven activities, resulting in a decrease in the volume of tailored advertisements and their precision. Further dissection of this potential mechanism will be detailed in the Study on Potetntial Mechanism Section, wherein we will probe into company websites.

Robustness Check

Controlling the Impact of the COVID-19 Pandemic

The COVID-19 pandemic has greatly impacted the U.S. economy and society since March 2020, resulting in significant shifts in consumer behavior because of social distancing and lockdown policies. Thus, it is essential to consider its impact when analyzing the effects of privacy regulation on consumer behavior as the pandemic-induced changes in consumption patterns and preferences. For example, consumers may have shifted their purchases online due to stay-at-home orders or concerns about contracting the virus in public spaces. This shift may confound the analysis, if not properly addressed.

We employ two strategies in our analysis to account for these potential confounding effects. First, we include a control variable in Equation 1 that indicates whether each state government implemented a stay-at-home order each month. This variable is set to 1 on and after the month when the state government implemented the order. By controlling for stay-at-home orders, we can isolate the effect of privacy regulation from changes in consumer behavior caused by these orders. Second, we control the COVID-19 cases per state population for each state. By doing so, we can adjust for any differences in consumer behavior across states that could have resulted from variations in the COVID-19 prevalence. For instance, states with higher COVID-19 cases may have experienced more significant changes in consumption patterns than states with lower case numbers. By controlling for the stay-at-home orders or the COVID-19 cases per state population, we can more accurately estimate the effect of privacy regulation on consumer behavior while accounting for potential confounding factors introduced by the pandemic.

Table A1 in the appendix shows that controlling for the effect of the COVID-19 does not significantly alter the significance and magnitude of the effects in the main analysis. In column (1) and (2) Table A1, we can see that the coefficient of the treatment effect remains negative and significant across specifications. The results indicate that privacy regulation has a negative effect on purchases even after controlling for the stay-at-home orders or the COVID-19 cases per state population. Similarly, column (3) and (4) in Table A1 indicate that privacy regulation has a positive effect on returns even after controlling for the COVID effect. Overall, these results suggest that our findings of the impact of the CCPA on consumers' consumption behavior are robust to potential confounding effects introduced by the COVID-19 pandemic.

Addressing Serial Correlation and Estimating Standard Error

To address the potential presence of serial correlation in the dependent variable, we apply a collapsed DiD analysis recommended by Bertrand et al. (2004) to our dataset. Specifically, we collapse our data into pre- and post-treatment periods by calculating the average of the respective variables. For the factor variable, $IncomeClass$, the mode is utilized as a substitute for the average. We also estimate standard errors using bootstrap followed by Austin and Small (2014) and Smith and Todd (2005), who recommend estimating standard errors using bootstrap for the PSM without replacement. The findings from the collapsed analysis and bootstrap standard errors are consistent with the results from the main analysis (Table A2 and A3)

Study on Potential Mechanism

Changes in Advertising Web Technology Usage

We explore the mechanisms behind the shift in consumer behavior following the implementation of the CCPA by examining changes in firms' web advertising technologies used on their websites. As online advertisements are typically personalized to individual consumers, a decrease in advertising web technology may suggest that firms reduce personalized advertising. To explore this issue, we use the threshold requirement of the CCPA, which applies to firms with an annual gross revenue of over $25 million. We distinguish firms subject to the CCPA and those not and exploit a DiD approach to compare changes in the number of advertising web technologies employed by firms on their websites.

We follow several steps to classify firms as subject to the CCPA. We collect the annual gross revenue for 112 companies in 2019 from CompuStat dataset. We then compare the revenues with the transaction amount in our primary dataset to obtain the ratio between revenue and transaction amount. We use this ratio and the transaction data to estimate the revenue for other companies and classify firms with an annual revenue of over $25 million as subject to the CCPA or not. We then match this estimated revenue dataset with the web technology usage panel scraped from firms' websites over time.

The results in Table 6 indicate that firms subject to the CCPA reduce the number of advertising web technologies employed on their websites after the CCPA compared to those not subject to the regulation. This finding suggests that the CCPA may prompt CCPA-affected firms to reduce the use of personalized advertising. Firms may reduce the use of advertising web technologies to comply with the new privacy regulation. Specifically, the analysis reveals that CCPA-affected firms used 1.04 fewer advertising web technologies on their websites post-CCPA enforcement.[5]

	(1)		(2)	
Treat × Post	-1.506***	(0.487)	-1.506***	(0.487)
Post	0.833	(0.454)		
N	157,968		157,968	
Individual-fixed effects	yes		yes	
Month-fixed effect	no		yes	
Robust standard errors	yes		yes	
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.				

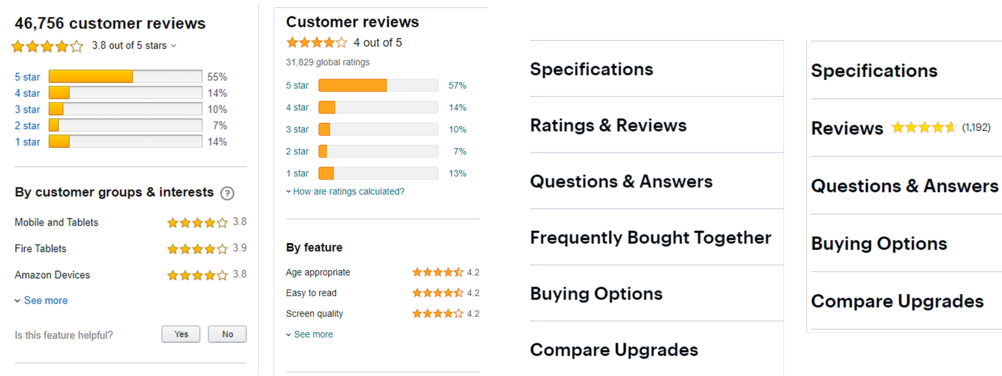
Table 6. Changes in Advertising Web Technology Usage

Anecdotal Evidence: Changes in Product Description

To explore the possible mechanisms, we review product description pages on two prominent e-commerce platforms, BestBuy.com and Amazon.com. Our analysis aims to identify any modifications in web or recommendation technologies employed by these platforms which can influence consumer behavior.

Our examination reveals that companies might have restricted product recommendations and product information derived from users' personal data, potentially contributing to the observed shift in purchasing patterns. A careful analysis indicates that modifications in product pages occurred following the implementation of new privacy regulations. For instance, BestBuy.com eliminated the "Frequently Bought Together" section from its product descriptions, while Amazon.com transitioned from displaying product ratings based on customer groups and interests to ratings centered on product features. Figures 3a and 3b depict product description pages on Amazon.com and BestBuy.com, respectively. The figure on the left represents the year 2019, while the one on the right portrays the year 2020. These adjustments suggest that firms proactively minimize the collection of personal information to avert potential future liabilities.

[5]Firms use an average of 16.1 advertising web technologies on their websites before the treatment.



(a) Product Rating Tab on Amazon.com **(b) Product Description Tab on Bestbuy.com**

Figure 3. Changes in Product Description

Conclusion

In the contemporary data-centric society, personal information is both a treasured resource and a potential privacy risk. While businesses benefit from data insights, there are concerns about consumer welfare impacts, such as price manipulation, artificial demand, and data breaches. This has prompted worldwide data privacy regulations like CCPA and GDPR. It's unarguable that such regulations enhance consumers' data privacy by curtailing unwarranted and unnecessary data collection and emphasizing the onus on firms to safeguard the acquired data. This can substantially reduce risks of data misappropriations such as frequency and severity of data breaches and abuses. Our research reveals these data regulations have unintended effects while they minimize data misuse risks. For instance, Californian consumers showed decreased purchasing behaviors post-CCPA, coupled with increased returns, revealing a decline in purchase satisfaction. This act also leads to lengthier online browsing, hinting at more consumer effort in product searches. We further identify potential mechanisms for these behavioral shifts and substantiate them with evidence.

Our study has several limitations. Firstly, while we have meticulously crafted our methodology for causal inference, it does not offer the level of causal clarity that Randomized Control Trials provide. Secondly, we were unable to evaluate the heterogeneous effects across diverse consumer demographics because of a lack of detailed demographic data. This leaves open an exciting avenue for future research, which could probe deeper into how distinct consumer groups respond to privacy regulations. Thirdly, we did not directly measure post-regulation changes in firms' data utilization patterns to validate our proposed mechanism, though we provide indirect empirical evidence of reduced usage of web advertising technologies. We recognize that while firms decrease their overall use of web technologies, they could intensify their reliance on specific selected ones. Subsequent research endeavors could shine a light on shifts in firms' personalization and advertising approaches to confirm the postulated mechanism. Fourthly, privacy protection goes beyond just safeguarding consumers' economic interests; it's also about preserving individual autonomy against influential entities (Cohen 2017). A series of studies suggest that, while current privacy self-management policies are necessary, they fall short of protecting individuals' autonomy because of the inappropriate assumptions the regulations based on (Kröger et al. 2021; Solove 2012) and new challenges AI may bring (Mühlhoff 2023). Yet, given our study's focus on the economic ramifications of privacy laws and the constraints of data like censorship, we have not ventured into this dimension. Lastly, the emergence of privacy regulations in states such as Colorado, Connecticut, Utah, and Virginia post-2021 points to a ripe opportunity for future research. Assessing the impact of these fresh regulations might yield a richer, more holistic understanding of the data privacy landscape.

Despite the limitation, this study brings significant theoretical contributions. Our research provides multifaceted insights into the dual-edged nature of consumer data. On one hand, consumer data serves as a pivotal driver for advancements in various business arenas such as social media (Bertschek and Kesler 2022), software development (Johnson et al. 2005), health care (Miller and Tucker 2009), finance (Doblas-Madrid and Minetti 2013), among others. Conversely, it can be weaponized to steer economic benefits away from consumers, amplifying corporate profits and potentially leading to discrimination against specific consumer segments (Bar-Gill 2021; Bonatti and Cisternas 2020; Shiller 2020). Our study contributes to this body of literature by demonstrating that consumer data can boost consumer surplus by increasing product satisfaction and reducing search costs through personalized recommendations.

Further, our study enriches the growing body of literature on consequences of privacy regulation. While numerous studies have homed in on the impacts on firms and the broader market, few have directly addressed the tangible effects on consumers. Our investigation fills this gap by dissecting the ramifications of privacy regulations on consumer buying patterns. The findings from our study align with extant literature, indicating that privacy regulation has an adverse impact on the effectiveness of online advertisements in attracting consumers (Aridor et al. 2020; Goldfarb and Tucker 2011) and raises search costs for consumers during shopping (Zhao et al. 2021). Our study adds novel insights to the literature by demonstrating that firms' diminished targeting capabilities lead to an actual reduction in consumption behavior and consumer surplus.

Our research offers valuable insights for businesses and policymakers. For firms, especially those dependent on consumer data for advertising, privacy regulations may lead to reduced sales and revenue. To mitigate this, they may need to enhance and diversify their marketing strategies. The impact could be more pronounced for smaller companies relying on third-party data, given the consumers' right to opt out of data selling under the regulation. For policymakers, our findings emphasize that privacy regulations come with unintended side effects. These include increased operational costs for firms, a decline in their revenue, and augmented search costs for consumers, resulting in lower purchase satisfaction because of the regulatory-induced information gap. Policymakers need to balance these unforeseen challenges against the primary benefits of the regulation, like minimizing the risks of future data breaches and ensuring individuals' autonomy.

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Appendix

List of the 12 Categories

- Automotive/Fuel
- Cable/Satellite/Telecom
- Electronics/General Merchandise
- Entertainment/Recreation
- Gifts
- Groceries
- Home Improvement
- Office Expenses
- Personal/Family
- Pets/Pet Care
- Subscriptions/Renewals
- Travel

Removing Business Accounts

To rule out business accounts that are unimpacted by personalized advertising, we filter out any accounts that have transactions going over $15,000 in a month. Furthermore, accounts that have more than one debit or credit transaction falling between the $5,000 and $15,000 range are removed from the study. After these accounts are taken out of consideration, we proceed to exclude any transactions that exceed $5,000. This is done to prevent the inclusion of large regular transactions, such as rent or income, in our analysis.

Income Class Brackets

(1): $0-25k, (2): $25k-45k, (3): $45k-60k, (4): $60k-75k, (5): $75k-100k, (6): $100k-150k, (7): $150k+

Tables: Robustness Checks

	(1)		(2)		(3)		(4)	
	Purchase		Purchase		Return		Return	
Treat × Post	-96.99***	(6.083)	-98.22***	(5.952)	4.060**	(1.481)	3.736**	(1.442)
Covid19	-10.18	(10.65)	-120.5***	(27.08)	-2.636	(2.332)	-25.20***	(6.660)
Purchase					0.0305***	(0.000456)	0.0305***	(0.000456)
IncomeClass	yes		yes		yes		yes	
N	2,433,336		2,433,336		2,433,336		2,433,336	
Individual-fixed effects	yes		yes		yes		yes	
Month-fixed effects	yes		yes		yes		yes	
Robust standard errors	yes		yes		yes		yes	
Covid19	stay-at-home		cases per population		stay-at-home		cases per population	
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.								

Table A1. The Impact on Consumption Behaviors: Controlling COVID-19

	(1)		(2)	
	Purchase		Return	
Post × Treat	-103.1***	(6.345)	3.836**	(1.442)
Purchase			0.0316***	(0.000758)
Post	7.910	(4.422)	6.778***	(0.976)
Treat	0.436	(9.257)	-1.594	(2.116)
IncomeClass	yes		yes	
N	195,368		195,368	
Individual-fixed effects	yes		yes	
Robust standard errors	yes		yes	
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.				

Table A2. The Impact on Consumption Behaviors: Collapsing Time Windows

	(1)		(2)		(3)		(4)	
	Purchase		Purchase		Return		Return	
Treat × Post	-98.23***	(6.508)	-98.53***	(6.435)	3.734**	(1.272)	3.696**	(1.271)
Purchase					0.0306***	(0.000488)	0.0305***	(0.000488)
IncomeClass	yes		yes		yes		yes	
N	2,433,336		2,433,336		2,433,336		2,433,336	
Individual-fixed effects	yes		yes		yes		yes	
Month-fixed effects	yes		yes		yes		yes	
standard errors	Bootstrap		Bootstrap		Bootstrap		Bootstrap	
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Replication: 200 times.								

Table A3. The Impact on Consumption Behaviors: Bootstrap Standard Errors