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Convenience vs. Confidentiality: Rethinking the Role of Online Purchases at the Era of Rising Privacy Concerns

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Convenience vs. Confidentiality: Rethinking the Role of Online Purchases at the Era of Rising Privacy Concerns*

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Abstract

Consumers leave traces of their shopping behavior both online and offline, which may raise privacy concern. Such concern has become salient in recent years during some high-profile data breaches. This concern is further amplified in health-related contexts because consumers' purchase information could contain sensitive proprietary details. We investigate how consumers' online/offline healthcare-product shopping behaviors are affected by increasing privacy concerns about possible health-information leaks. We leverage the announcement of California Consumer Privacy Act (CCPA), the primary law protecting consumers' data privacy rights, to conduct our analysis. Our data cover a representative panel of California households and their complete online/offline shopping history of multivitamin and health-product purchase. We find that the percentage households' online shopping trips decline sharply after the CCPA announcement, when benchmarked against their offline shopping trips. This effect is more pronounced for health products such as male enhancement products. These findings suggest that consumers are aware of privacy issues and make conscious choices to protect their personal health data. Finally, we find that such a policy-announcement effect diminishes over time.

Keywords— health products, privacy, policy-announcement effect, CCPA

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1 Introduction

Many Americans believe their privacy rights are "seriously threatened" and are concerned about the companies that collect their personal data for business usage (Auxier et al. (2019) and Goswami (2020)). With the spread of news stories such as the Cambridge Analytica Scandal or the 4,395 data breaches that resulted in over 832,000,000 records being exposed from 2017 to 2019 according to Statista, consumers have difficulty dismissing the need to secure their data. In light of this changing trend, the government has begun to step in and regulate data collection. In 2016, the European Parliament and European Council adopted the General Data Protection Regulation (GDPR), which is the most radical privacy and security law in the world. Inspired by GDPR and recognizing the need for privacy protections, the California Consumer Privacy Act (CCPA) was introduced in California on January 3, 2018. It is the first comprehensive piece of legislation in the US that gives people control over the use of their personal data, and it is expected to become the national standard for data protection and handling. With California having the world's fifth-largest economy and being home to giants such as Google and Facebook, the impact of this new act could be even greater than that of GDPR.

Consumers leave traces of their shopping behavior both online and offline, which may raise some privacy concerns. Privacy concerns are more pronounced with respect to health data, which typically contain numerous details about individuals.[1] Therefore, to understand the role privacy concern plays in consumers' online/offline shopping decisions is important. This paper leverages individual-level shopping-behavior data right before and after the introduction of CCPA to shed light on this aspect.

Our study focuses on three questions. First, how does the CCPA announcement affect the composition of customers' online/offline purchasing patterns? Anecdotes and surveys show that consumers value their privacy, but the magnitude of the value is difficult to discern without studying consumers' revealed preferences from data. Second, would consumers' responses vary with the information sensitivity of the products? Given the differentiated nature of the shopping products, one would expect the

[1] "The issue of consumer generated health data is on that is near and dear to my heart," Federal Trade Commission Commissioner Julie Brill told attendees at an event focused on the protection of such health data. "...Big picture, consumer generated health information is proliferating, not just on the web but also through connected devices and the internet of things." As Brill noted, "There is also the now infamous example of companies that are generating their own health data about their customers with respect to their purchases, like Target did with its pregnancy predictor score." https://www.mobihealthnews.com/33393/in-depth-consumer-health-and-data-privacy-issues-beyond-hipaa.

more personal health-related products to be more prone to the announcement than others. Here, we would like to decipher the varying degree of such an impact among commonly consumed basic multivitamin versus health products. Finally, what types of consumers reacted most to CCPA announcement in terms of changes in their shopping patterns? Answers to this question are particularly helpful to policymakers and marketers, who typically need to pin down a "target group" for their work.

To answer these questions, we use proprietary data collected by a leading analytics company. The data cover any online/offline shopping trips that involve multivitamin and health-product purchases by all panelists residing in California from May 1, 2017, to April 30, 2018. The rich purchasing records of multivitamin and health products embedded in these data allow us to investigate how consumers' health-product shopping habits are affected by concerns that their health information may be at risk, cautioned by the CCPA announcement on January 3, 2018.

Our empirical design exploits the fact that people have different degrees of privacy concerns when purchasing different categories of goods. For example, when purchasing daily vitamins, people generally do not mind letting others know they purchased the product. However, when purchasing more private products, such as sexual performance enhancement and weight-loss products, they are more concerned about privacy issues, such as the embarrassment of letting others know they purchased the product, feeling shamed when interacting with medical professionals to receive the drugs and concerns that their personal information will be compromised. Therefore, we utilize a difference-in-differences (DID) design to study different reactions of people to different products before and after CCPA was formally introduced.

Theoretically, predicting consumers' responses ex ante to the announcement of the policy is hard. On the one hand, CCPA provides consumers with a near-term commitment of online privacy protection. Anticipating the new legislation would be enacted soon, consumers may feel more comfortable trying to engage in more online activities, such as shopping for their health products. On the other hand, the CCPA announcement could spark more privacy concerns about online shopping, leading to fewer online purchases. Such concern will arise when consumers were previously not fully aware of the amount of their personal data collected by companies. Our results reveal the introduction of CCPA resulted in a reduction of approximately 8.63% of the total share of online purchases, demonstrating that consumers are more concerned about the privacy protections involved in their online purchases following the release of CCPA. In addition, we find that such policy effect fades over time, which could be due to a gradual but consistent memory decay among many consumers. An alternative explanation for the observed diminishing pattern is that, consumers who switched from shopping online to offline found it to be so cumbersome that the additional cost incurred from shopping offline outweighed the elevated privacy concerns of shopping online. Consequently, a good amount of households switched back to the online shopping mode.

Furthermore, we discover people make 11.4% fewer online purchases for health products with specific purposes, such as male sexual enhancement pills and improving weight control, than that for regular daily vitamins. Unsurprisingly, people's degree of privacy concerns depend on the product. For example, people do not usually conceal the fact that they purchase daily vitamins. They are, however, concerned about others discovering they use male enhancement products. Under the influence of the same bill, people will take shopping of health products that are more privacy related more seriously.

Finally, looking at the heterogeneous effects among different demographic groups, results reveal the portion of the California population that reacts the most to privacy factors is the one that is younger and has higher income and a higher level of education (consumers with a college or post-graduate degree). This finding is important to understand the heterogeneous effect of the same regulation, which has important implications for policymakers and retailers to enhance privacy while serving consumers better.

We explore the mechanisms behind the reduction in online shopping. One plausible explanation is that introduction of CCPA has stirred consumer concerns about personal privacy breaches in an environment where data breaches are prevalent, so consumers choose to make more offline purchases, a traditionally more secure and private shopping route, in place of online shopping.[2]

Studying such an announcement effect is essential but not trivial because such discussion could help consumers better prepare for implementation of the policy and thus provide policymakers better understanding the implementation effect before its implementation. However, such analysis has not received the attention it should. Our setting is ideal for studying the announcement effect. The announcement of CCPA differs from actual implementation because it has little effect on the actual shopping safety environment yet. Specifically, the suppliers do not need to respond

[2] We look at the total number of online/offline trips. We discover an increase in total offline trips while total online trips decreases, indicating a substitution from online to offline trips.

to it in terms of modify the online shopping webpages, readjusting the prices or varieties of products carried on the online and offline modes. Therefore, studying the announcement effect gives a clear understanding of how consumers feel about privacy concerns when online shopping, unlike the implementation effect, which combines responses from both consumers and sellers and hard to disentangle between them.

First, our study is related to the growing literature on consumer privacy and the impact of privacy regulations (Goldfarb and Tucker (2011), Goldfarb and Tucker (2012), Tucker (2014), Bleier et al. (2020), Lin (2022), and Acquisti et al. (2015)). Previous research has looked into how concerned consumers are about the privacy of their data (Hoofnagle et al. (2010) and Jai et al. (2013)). The majority of earlier research, on the other hand, used questionnaires to ask consumers about their attitudes, and a gap exists in the analysis of privacy regulations in relation to consumers' real shopping behavior. As a result, our study contributes to the existing literature by investigating how CCPA privacy regulations affect consumers' attitudes toward data privacy by analyzing online/offline shopping history of California customers purchasing multivitamin and health-product.

Second, this paper adds to the growing body of empirical research on the effect of privacy regulations on health products and services (Miller and Tucker (2018), McGraw and Mandl (2021), and Kwon and Johnson (2013)). Much of the existing research on CCPA is concerned with its breadth in terms of eligibility criteria, exemptions, and penalties for non-compliant healthcare organizations. Several papers have also looked at how it affects advertising technology (Maalouf and Rozen (2020)) and e-commerce businesses (Brazhnik (2013)). Nowadays, companies that operate mobile apps, search engines, social media platforms, and health-related websites have more information about their users' health than hospitals do about the majority of their patients. However, this information is not covered by Health Insurance Portability and Accountability Act (HIPAA), a federal law that protects the privacy and security of certain health information, but rather by CCPA (Harris (2020)). Our study provides a unique angle in understanding whether and to what extent consumers value privacy when purchasing health products, as opposed to other general merchandise.

Lastly, our paper contributes to a growing but small literature studying the "policy-announcement effect". The last decade has seen a growing recognition of the value of publicity in raising product awareness and demand (Ching et al. (2016)). Publicity, typically in the form of news conveyed to potential customers, has the potential to reach a wide range of consumers. Despite the growing interest in publicity, policy research has rarely examined the impact of publicity on people's awareness and behavior. Typically, researchers investigate policy-implementation effects by comparing outcomes before and after the policy is implemented, ignoring the fact that a lot of publicity and media exposure occurs prior to policy implementation. People may have reacted to the policy when they first heard about it, but the effect will be mitigated at the time of policy implementation as they become more familiar with the issue, and they may even have no reaction because they have grown accustomed to it. This paper attempts to improve this deficiency by providing empirical evidence for the presence of the announcement effect. Our paper thus supplements the literature studying the implementation effect. Existing studies show consumers respond positively to privacy policies set by firms (Tsai et al. (2011)) and dislike sellers that use their personal information to target them in their ads. This paper expands this literature by showing how the anticipation effect generated by the announcement of a policy aimed at increasing online activity actually had the opposite effect. We call this response the "wake-up" effect of policy, which points out potential issues in previous literature that uses the actual implementation date as a cutoff. The true reaction has likely already occurred and will not be captured when the policy is implemented.

The rest of the paper is structured as follows. Section 2 describes the data and the institutional background. Section 3 elaborates on the empirical strategy and the main findings. Section 4 includes several robustness tests to back up the findings in Section 3. Section 5 discusses a possible mechanism for the decrease in the percentage of household online trips. Finally, section 6 concludes.

2 Data and Institutional Background

2.1 Data Privacy Legislative Development

As web and mobile applications continue to access and exploit online personal information to further pursue their corporate goals, digital privacy has become increasingly critical. Unlike the European Union, which has developed the now well-known General Data Protection Framework (GDPR), the US lacks a comprehensive framework that regulates data collection and usage, to protect consumers. A number of federal and state restrictions apply to various sectors and types of personal information. For example, HIPPA was issued to oversee the collection and usage of individuals' health information, which can suffer detrimental damages in the event of a data breach.

HIPAA requires entities that collect and store health information to have the required processes and technical controls in place to protect that information. It also gives victims legal recourse in the event of a breach.

Nonetheless, HIPPA is still fairly limited in scope, and more importantly, the definition of "health data" is far more broad than what can be regulated by this law. When HIPAA was passed, most health data were held by traditional healthcare providers or health plans. Nowadays, other organizations on the web hold far more health data than the information held by traditional health organizations. Today, companies operating mobile applications, search engines, social media platforms, and health-oriented websites have more information about the health of many users than hospitals have about most patients. However, these technology companies are often not subject to any health privacy laws.[3] The amount and importance of health information held by these companies are growing by the day.

In light of this trend, the new privacy law, CCPA, was proposed in January 2018 and was signed into law in June 2018.[4] This landmark rule affects California's 40 million residents and 500,000 firms, including 10% of Fortune 1000 companies, which are among the most profitable and cutting-edge technological companies in the world. Although the rule is intended to assist consumers and industries such as ad tech, retail, and e-commerce, looking at its impact on the health-products industry is not just interesting but also important, for the reasons discussed above. This article examines the influence of CCPA on various healthcare items.

California residents now have more control over their personal information online according to CCPA, which provides them with the ability to decide how corporations use it. The Act specifies particular limitations and exclusions for specific types of data. Consumers can now request that a business delete any personal information, and opt out of third-party transfers of information. In principle, CCPA offers California customers more control over their personal data by granting them data-subject rights.

[3]Belfort, R., Dworkowitz, A., Bernstein, William S., Pawlak, B. and Yi, P. A Shared Responsibility: Protecting Health Data Privacy in an Increasingly Connected World, June 2020, available at http://www.manatt.com/Manatt/media/Media/PDF/White%20Papers/Healthcare-Whitepaper-RWJFProtecting-Consumer-Health-Data-Privacy-in-an-Increasingly-Connected-World_e.pdf (Manatt White Paper).

[4]Source from Wikipedia: https://en.wikipedia.org/wiki/California_Consumer_Privacy_Act. It can also be found though the timeline of CCPA: https://fpf.org/blog/california-privacy-legislation-a-timeline-of-key-events/.

2.2 Data

We use proprietary data collected by a leading analytics company. The data cover all online/offline shopping trips that involve multivitamin and health-product purchases by all panelists tracked by the company residing in California from May 1, 2017, to April 30, 2018.

This dataset is uniquely suited to the research questions of this paper in several ways. First, the legislation was introduced on January 3, 2018, in the California legislature led by Representative Ed Chau during the time period covered by our data. Second, the dataset covers consumers' actual purchases of multivitamin and health-product, which enables us to analyze consumers' real-life behaviors and complements the existing literature. Third, multivitamins and health products are an excellent starting point for investigating people's degrees of privacy concerns. People have different degrees of privacy concerns for various products. In a health-related context, privacy concerns are amplified because the specific products purchased may reveal personally sensitive and proprietary health conditions. As a result, studying consumers' purchases of a diverse range of multivitamins and health-products, can help us better understand this critical issue. Fourth, the rich variety of vitamins and health products provides us with the possibility of further research: analyzing the different effects of CCPA on multivitamin and health-product. Finally, consumer-level data provide us with rich research space, enabling us to evaluate the impact of CCPA on different consumer demographic groups, which provides a direction for subsequent policy development and marketing strategies for businesses.

2.2.1 Descriptive Statistics

Our data record detailed shopping information including the number of shopping trips in our data period, total dollars spent on a trip (the total basket size, not simply dollars spent on multivitamin and health-product), Item units (the number of multivitamin and health product items purchased in a single transaction), Cost per unit (the average unit price of multivitamins and health goods), and Item dollars (the total spending on the multivitamins and health products). We present information for these variable in Table 1 by shopping mode (Panel A: Shop Offline and Panel B: Shop Online), and the difference between the online and offline groups (Panel C).

Two features are worth noticing from Table 1. First, the number of units for each trip is slightly higher for offline purchases. The difference between the two groups is statistically significant, as shown in Panel C. Second, although offline shopping constitutes most of the volume, the vitamin supplement cost per unit is significantly higher when consumers buy it online. ($21.48 online vs. $11.87 offline).

Table 1. Descriptive Statistics of purchase patterns

Panel A: Offline Trips

	N	Mean	St. Dev.	Min[5]	Max
TripDollars Avg Trip	35,696	114.13	116.43	0.27	2641.24
ItemDollars Avg Trip	35,696	14.61	28.02	0	1955.97
ItemUnits Avg trip	35,696	1.20	1.44	1	103
CostperUnit	35,696	11.99	9.07	0	987.48

Panel B: Online Trips

	N	Mean	St. Dev.	Min[5]	Max
TripDollars Avg Trip	6,203	43.41	42.57	0	503.64
ItemDollars Avg Trip	6,203	22.56	20.52	0	298
ItemUnits Avg trip	6,203	1.13	0.53	1	10
CostperUnit	6,203	19.98	14.32	0	269.4

Panel C: T-Test: diff ==0

	Mean (Offline)	Mean (Online)	diff	St_Err	t_value	p_value
TripDollars Avg Trip	114.13	43.41	70.73	1.50	47.30	0.00
ItemDollars Avg Trip	14.61	22.56	-7.95	0.37	-21.38	0.00
ItemUnits Avg trip	1.20	1.13	0.07	0.02	3.65	0.00
CostperUnit	11.99	19.98	-7.99	0.14	-57.98	0.00

Our data provide rich demographics including gender, age, education, income group, and ethnicity. For each characteristic, we provide the proportion of the choice of shopping modes separately for online and offline in Table 2. We can see that consumers that shop online are younger, more educated, have higher incomes, and have a smaller household. First, as people get older, their proclivity to be online unsurprisingly decreases. In contrast, young people use new technologies to aid in the consumption process, such as identifying needs, searching for information, and purchasing products and services. Because of the internet's accessibility and mastery of technological skills, they account for a sizable proportion of online consumers. Second, in comparison to having a college degree, not having graduated from college

Table 2. Descriptive statistics: Demographics

Demographics		Offline Trips	Online Trips
Age	Seniors [<1945]	646(93.08%)	48(6.92%)
	Boomers [1945-1964]	8,256(87.55%)	1,174(12.45%)
	Gen X [1965-1981]	16,343(84.99%)	2,886(15.01%)
	Millennials [1982-2004]	10,187(83.10%)	2,071(16.90%)
Education	No College Degree	19,373(87.38%)	2,799(12.62%)
	College Degree or Higher	16,059(82.61%)	3,380(17.39%)
Income	Low [<40K$]	10,581(88.03%)	1,439(11.97%)
	Middle [40K$-80K$]	10,480(85.59%)	1,764(14.41%)
	High [>80K$]	14,242(82.83%)	2,953(17.17%)
Gender	Female	28,978(85.29%)	4,999(14.71%)
	Male	6,839(84.44%)	1,177(15.56%)
Ethnicity	Asian	10,188(87.52%)	1,453(12.48%)
	African American	1,367(83.51%)	270(16.49%)
	Hispanic/Latino	6,755(87.57%)	959(12.43%)
	White	15,295(82.53%)	3,238(17.47%)
	Other	1,827(87.58%)	259(12.42%)
Household Size	Household size <= 3	20,537(83.50%)	4,059(16.50%)
	Household size > 3	14,895(87.54%)	2,120(12.46%)

lowers the likelihood of online shopping. Thirdly, online consumers have a higher income and a smaller household. Fourth, white consumers have a higher percentage of online shopping. Finally, there is not obvious different choice of shopping modes for males and females.

2.3 Classification of multivitamin and health-product

This paper examines how the announcement of CCPA has affected consumers' online/offline multivitamin and health-product shopping behavior. We hypothesize that people have different degrees of privacy concerns when purchasing different categories of goods. For example, consumers might be more conscious of their privacy when purchasing specific health products that contain their health information. Therefore, to explore the different announcement effects of CCPA on different products, we need to classify health products. Breaches of privacy and confidentiality not only may affect a person's dignity, but also can cause financial lost. When personally identifiable

[5] We examined the data and found that 0.5% of multivitamins and health products had a unit price of 0. We confirmed with the data provider that these products were given away as freebies or redeemed with coupons.

health information is disclosed to a potential employer, insurer, or family member, it can lead to stigma, embarrassment, and discrimination. Moreover, control of when the information is shared or breached is minimal.

According to the National Institutes of Health (NIH),[6] we categorize multivitamin and health-product into two groups and present some samples in Table 10 in the appendix.[7]

- (Non-specialized) Multivitamins:
  1. Basic: daily multivitamins that contain all or most vitamins and minerals.
  2. High-Potency: multivitamins that contain amounts of some vitamins and minerals that are substantially higher than the daily values.
- (Specialized) Health Products: health products for special purposes such as those for Male Sexual Enhancement.

Table 3 provides the summary statistics of multivitamin and health-product separately and their differences. Specifically, trips involving health products occur more frequently, a higher number of units (1.21), and a higher cost per unit ($17.24) than trips involving multivitamins purchases.

2.4 Data Pattern

Figure 1 graphs the evolution of the percentage of household online shopping trips over time, with the vertical line on January 3, 2018, indicating the introduction of CCPA. This graph shows the online shopping fraction decreases slightly from the start onwards, then jumps substantially after the announcement of CCPA. The average online fraction is 15.57%, with an estimated gap around the cutoff of 8.63% using linear fitting, accounting for nearly half of the online fraction level prior to announcement of CCPA. Additionally, note this gap closes quickly after the introduction, indicating this effect is only temporary. Such a finding is consistent with our intuition. Note that because the event we study here is an announcement, or information release, we see, as expected, a short-term impact. Specifically, people may gradually forget about the announcement, resulting in the diminishing trend of the impact.

[6] NIH website: https://ods.od.nih.gov/factsheets/MVMS-HealthProfessional/.

[7] The detailed definition of each group can be found in the appendix.

Table 3. Descriptive statistics of purchase patterns

Panel A: Health Products					
	N	Mean	St. Dev.	Min	Max
Number of trips	1,192	6.33	6.26	1	59
ItemDollars Avg Trip	6,581	21.06	19.98	0	489.86
ItemUnits Avg trip	6,581	1.21	0.78	1	15
CostperUnit	6,581	17.24	10.47	0	105.95

Panel B: Multivitamins					
	N	Mean	St. Dev.	Min	Max
Number of trips	6,705	5.12	5.77	1	83
ItemDollars Avg Trip	35,318	14.80	28.22	0	1955.97
ItemUnits Avg trip	35,318	1.18	1.42	1	103
CostperUnit	35,318	12.42	10.23	0	987.48

Panel C: T-Test: diff(Health Products - Multivitamins) ==0						
	Mean (HealthP)	Mean (Multivitamins)	diff	St_Err	t_value	p_value
Number of trips	6.33	5.12	1.20	0.18	6.53	0.0000
ItemDollars Avg Trip	21.06	14.80	6.25	0.36	17.19	0.0000
ItemUnits Avg trip	1.21	1.18	0.03	0.02	1.72	0.0859
CostperUnit	17.24	12.42	4.83	0.14	35.03	0.0000

We also provide the percentage of household online shopping trips over time for multivitamin and health-product in the top and bottom panel of Figure 2, respectively. A few interesting comparisons between the two categories are worth noting. First, households prefer online shopping for health products to online shopping for multivitamins in general: 25.54% versus 12.80% on average. Second, the distribution of health-product purchases is more dispersed. The standard deviation (SD) for health products is 0.44, which is higher than the SD for multivitamins, which is 0.33. Finally, the percentage of online trips drops immediately after CCPA announcement for both multivitamin and health-product. Overall, both outcomes follow similar trends across the entire sample. More importantly, we see a clear jump around the introduction of CCPA, motivating us to investigate the effect of CCPA announcement further in our empirical strategy below.[8]

[8] Note that we focus on changes in responding to the announcement of CCPA. That means, in principle one does not expect the supply side to have enough incentive and time to take measures to react to this announcement. However, firms might still respond in anticipation of the consumers' responses. We cannot fully rule out such possibility since our data only record the households' shopping history. However, we do find that the distributions of the variety of brands carried and the price are similar before and after the CCPA announcement (Figure 5 in the appendix). Such results help mitigate the concern of change from the supply side.

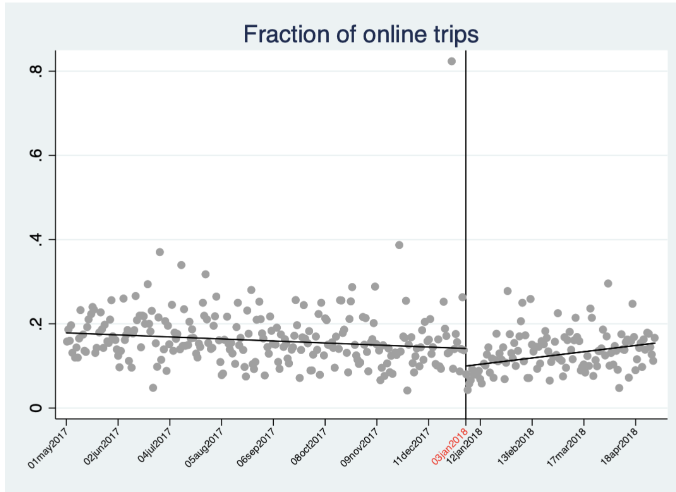

Figure 1. Fraction of online trips over time

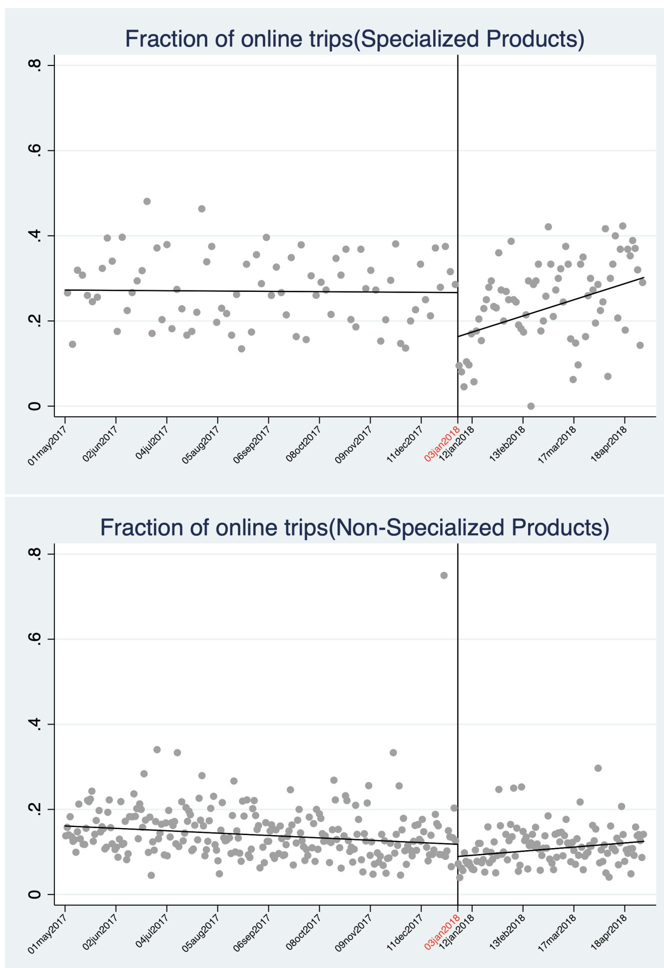

Figure 2. Fraction of online trips over time (subsample)

3 Empirical Strategy and Results

The previous section provides some preliminary evidences that consumers' online relative to offline shopping activity decreased immediately after the announcement of CCPA. In this section, we answer the three questions raised in the introduction. First, we study the CCPA announcement for the general tradeoff between online versus offline decision. Second, we examine whether such an announcement effect could be amplified by the more private health-related product by comparing the shopping mode decisions between basic multivitamin with specialized health products. Third, we investigate what types of consumers reacted most strongly to the CCPA announcement. Moreover, we quantify the value of the privacy concern using the cost of commute and commute time as a proxy.

3.1 Privacy Concerns in General

To begin, we study consumers' response to the announcement of CCPA when deciding on their shopping modes. Here, the privacy concern might be about the leaking of credit card information or personal addresses when shopping online. The announcement of CCPA might have provoked consumers to rethink the potential risk of shopping online and thus respond to the announcement of the policy, even though the implementation date of the policy is uncertain. We consider the following regression model:

$$Online_{it} = \beta_0 + \beta_1 \text{CCPA}_t + \beta_2 X_{it} + \epsilon_{it}, \tag{1}$$

where $Online_{it}$ is a dummy variable that equals 1 if this purchase is done online by household i on date t, and 0 otherwise; $CCPA_t$ is 1 if the purchase date is on or after the announcement of CCPA, January 3, 2018, and 0 otherwise; and the trip characteristics X_{it} include log(trip dollars), item units, and log(cost per unit).[9] We log-transform the trip dollars and costs per unit to account for any skewness in the distributions. The demographics include gender, whether the consumer has children, education, income, age, marital status, and ethnicity.

We estimate Model (1) via logit regression and present the estimation results in Table 4. We can see the announcement effect is significantly negative and robust

[9]Note that the "trip dollars" refers to overall dollars spent on a trip, i.e., the basket size, which is different from the total dollars spent on multivitamins and health products.

across all three specifications, indicating the announcement of CCPA provokes consumers' privacy concerns and thus reduces online shopping.

Table 4. General announcement effect

Dep Var: Online	(1) Baseline	(2) Add Covariates 1	(3) Add Covariates 2
CCPA	-0.282***	-0.208***	-0.213***
	(0.0301)	(0.0355)	(0.0367)
log_TripDollars		-1.622***	-1.653***
		(0.0229)	(0.0235)
ItemUnits		0.0651***	0.0720***
		(0.00760)	(0.00837)
log_CostperUnit		2.544***	2.575***
		(0.0389)	(0.0400)
Demographics	N	N	Y
Observations	41,899	41,682	41,097

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

3.2 Privacy Concerns Regarding Health-Related Products

The previous section suggests consumers responded to the CCPA announcement by reducing online shopping. In this section, we take a closer look at how consumers' online activity changed for more-privacy-sensitive products, namely, health products, relative to the less-privacy-sensitive products, namely, basic multivitamins. For this purpose, we consider the following regression model:

$$Online_{it} = \alpha_0 + \alpha_1 \mathrm{CCPA}_t + \alpha_2 \mathrm{HealthP}_i + \alpha_3 CCPA_t \times \mathrm{HealthP}_i + \alpha_4 X_{it} + \epsilon_{it}, \quad (2)$$

where $\mathrm{HealthP}_i$ is a dummy variable indicating this product is a health product or daily multivitamin.

In our model, α_1 captures the announcement effect of CCPA on multivitamins when consumers choose to shop online versus offline, which reflects the general concerns about online shopping, including credit card and address information. Note this effect might also include some macro environmental changes over time that influence consumers' shopping-mode decisions. Given that our sample only includes shopping trip data for California residents, all shopping is affected or treated by the introduction of CCPA. We have no control group, so we cannot fully attribute the change in the shopping patterns regarding basic multivitamins to the introduction of CCPA. However, we can locally identify such an impact by narrowing down the data window around the introduction of CCPA.

α_2 captures the gap between the more privacy-sensitive products and the less privacy-sensitive products on purchasing patterns. According to the graphs in section 2.4, consumers have a greater preference for shopping for more sensitive products online than they do for shopping for basic products online. α_2 captures this aggregate tendency before the announcement of CCPA.

α_3 captures an additional effect in the outcome variable for health products to multivitamins after the introduction of CCPA, which is additional concerns about the security of health information in addition to general concerns about online shopping, including the leaking of credit card and address information. We can identify this component of interest if, in the absence of CCPA, both multivitamin and health-product had similar online/offline patterns, or if the parallel-trends assumption held. We verify this assumption in the following section.

Such an identification strategy ultimately estimates the difference in the impact of CCPA on health products and multivitamins. Note the multivitamins serve as the control group in this specification. However, this "control group" is not the same as the control groups we see in standard DID analysis. In our context, shopping for multivitamins was also affected by the CCPA announcement. We predict that shopping for basic multivitamins will be less affected by the announcement of CCPA, because, in general, information about the purchase of generic vitamins does not expose consumers to physical health judgments. However, given that some consumers may still be concerned about privacy even when purchasing everyday goods, this coefficient should be interpreted as a differential impact of the CCPA announcement on the more sensitive products.

Besides the policy changes in California in our sample period, other macro environmental changes could have affected consumers' shopping behaviors. To better control for other macro changes, we gradually narrow down the time window around the policy change to examine the policy effect. We reasonably believe a narrower time window contains fewer other macro changes so we can better quantify the impact of the introduction of CCPA. We provide the estimation results for Model (2) with columns (1) - (3) in Table 5 for the full sample, one month, and ten days, respectively.

Table 5. Announcement effect for health-related products (DID)

	(1)			(2)			(3)		
		Full Year			One Month			Ten Days	
Dep Var: Online	Baseline	Add Cov 1	Add Cov 2	Baseline	Add Cov 1	Add Cov 2	Baseline	Add Cov 1	Add Cov 2
CCPA × HeathP	-0.00565	-0.00324	-0.00372	-0.0685**	-0.0570**	-0.0536**	-0.139***	-0.114***	-0.109***
	(0.0117)	(0.00990)	(0.00975)	(0.0268)	(0.0231)	(0.0230)	(0.0414)	(0.0362)	(0.0364)
CCPA	-0.0335***	-0.0223***	-0.0216***	-0.0355***	-0.0334***	-0.0328***	-0.0523***	-0.0411***	-0.0403***
	(0.00360)	(0.00328)	(0.00328)	(0.00799)	(0.00730)	(0.00733)	(0.0121)	(0.0111)	(0.0112)
HeathP	0.129***	0.0704***	0.0716***	0.154***	0.0929***	0.0941***	0.167***	0.105***	0.106***
	(0.00712)	(0.00603)	(0.00595)	(0.0221)	(0.0189)	(0.0188)	(0.0374)	(0.0328)	(0.0328)
log_TripDollars		-0.142***	-0.144***		-0.120***	-0.123***		-0.109***	-0.112***
		(0.00173)	(0.00175)		(0.00409)	(0.00417)		(0.00636)	(0.00653)
ItemUnits		0.00396***	0.00568***		0.00341	0.00700**		-0.00114	0.00133
		(0.000753)	(0.00108)		(0.00258)	(0.00292)		(0.00560)	(0.00560)
log_CostperUnit		0.204***	0.207***		0.174***	0.178***		0.163***	0.164***
		(0.00275)	(0.00278)		(0.00657)	(0.00670)		(0.0104)	(0.0105)
Constant	0.140***	0.246***	0.231***	0.123***	0.220***	-0.0341	0.118***	0.197***	-0.0801
	(0.00228)	(0.00752)	(0.0213)	(0.00655)	(0.0176)	(0.0540)	(0.0104)	(0.0267)	(0.0621)
Demographics	N	N	Y	N	N	Y	N	N	Y
Observations	41,899	41,682	41,139	7,488	7,450	7,360	3,077	3,060	3,017
R-squared	0.019	0.236	0.260	0.022	0.202	0.226	0.028	0.198	0.222

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Estimation results show the introduction of CCPA reduces online relative to offline shopping. Such a pattern is robust and statistically significant across different samples, suggesting that the announcement of CCPAs make consumers aware of privacy concern and reduce their online shopping.

More importantly, consumers responded with a larger decrease in online shopping for health products than for multivitamins, suggesting consumers are more concerned about online privacy issues when purchasing items containing more personal information. Also note that as we narrow the time span, the effect becomes more pronounced, from -0.0372 in probability in the full year sample to -0.0536 within one month, and then to -0.109 within ten days. That means, if we focus on the results of the specification with the one-month window, the impact of the announcement of CCPA translates to a statistically significant reduction of 5.36 percent in the fraction of households' online trips to purchase health products, as opposed to the fraction of online trips to purchase multivitamins. Thus, when consumers choose online over offline shopping, they are 5.36% less likely to buy male enhancement products online than they are to buy vitamin C. Furthermore, this difference is statistically significant at the 1% level using a ten-day window and at the 5% level using a one-month window, even though it is insignificant in column (1) for the full sample, which could be because the policy has a short-term effect on the dependent variable, and when we look at the full year, the short-term effect is averaged out and becomes moderate at the aggregate level.

3.3 Heterogeneous Effects

We next study whether the estimated announcement effect of CCPA on the mode of shopping is heterogeneous across consumers. Specifically, we examine social-group-specific CCPA announcement effects by estimating Model (2) separately for subsamples defined by gender, education, age, and income.[10] The estimation results presented in Tables 12 - 18 in the Appendix indicate that male, more educated, younger, and richer individuals are more concerned about the privacy issue.

These findings are novel given that little is known about the heterogeneity of the "wake-up" effect. We contend that the disparity between groups can be attributed to the following factors. First, high-income/more educated people rely more on the online channel. In fact, because low-income communities are disproportionately plagued by real-life physical safety threats, they are unsurprisingly far less concerned about virtual privacy threats. Therefore, low-income users' disproportionate reliance on the mobile internet makes them partially influenced by internet concerns. Second, low-income/less educated people may not fully understand the implications the privacy law can have on their lives. Third, lower-income communities rarely have access to the same level of technology that higher-income groups do in their access to education, opportunity, and quality.

In addition to education and income, we discovered that there is significant difference between male and female in responding to CCPA announcement. Intuitively, women might be more sensitive to privacy issues than men. However, our findings show that after the introduction of CCPA, men respond more strongly than women do in terms of switching from online to offline shopping, indicating that men are more concerned about privacy security than women. One possible rational is that men prefer shopping online over in person because it saves them time. Therefore, men are more concerned about potential risks and react more strongly to the introduction of CCPA. Moreover, according to Forbes, men (66%) were slightly more likely than women (61%) to report having experienced security issues such as having an account compromised or hacked, or accidentally installing spyware, malware, or a virus.[11] This supports the finding that men are more concerned about online privacy than women.

[10]In addition to using sub-sample regressions, we run a regression with all demographics fixed effect at once. The outcomes are comparable to sub-sample outcomes. The results can be obtained upon request.

[11]Source from Forbes: https://www.forbes.com/sites/kevinmurnane/2016/04/11/how-men-and-women-differ-in-their-approach-to-online-privacy-and-security/?sh=179503987d88

Furthermore, larger families are more concerned about privacy issues, which might be due to the fact that when families are larger, the medical needs of the entire family are more diverse, requiring more privacy. Furthermore, large families are more likely to have children, and parents may be more concerned about their children's privacy. Finally, we discovered that Asians are more concerned with privacy products. Because Asian cultures are more traditional and conservative, Asians might be more sensitive when it comes to purchasing more private products, such as male enhancement products, and are more cautious when purchasing products that involve their health status.

3.4 Quantify the value of privacy concerns

We proceed to quantify the value of privacy. According to the findings above, a portion of consumers switch from online to offline purchases due to privacy concerns. We know that online purchases are more convenient than offline purchases, allowing people to save commute time as well as the time and effort required to select products. Due to their privacy concern, some consumers are willing to take the additional costs incurred by offline shopping to avoid the risk of data breaches. Therefore, we can use this additional time cost to roughly approximate the value of privacy.[12]

We quantify the value of privacy concerns as follows. First, we calculate the additional cost of offline relative to online shopping using the time of travel and the minimum hourly wage. Specifically,

$$AdditionalCost = CommuteTime \times HourlyWage = \frac{41}{60} \times 15 = 10.25, \tag{3}$$

because the average shopping trip takes 41 minutes[13] and the minimum hourly wage in California is 15 \$.[14] Next, we know after the announcement of CCPA, people are 21.3% less likely to shop online using the estimates of column (3) in Table 4. Only those people are willing to incur the additional cost to because they were concerned that online shopping would reveal more information about themselves, such as credit card and home address information. Therefore, the approximate value of privacy

[12]An alternative approach to quantify the value of privacy concern is to model consumers' indirect utility of shopping online and offline explicitly and estimate a random coefficient demand model by allowing the policy to alter the consumer's utility toward online shopping. We leave this structural approach for future research.

[13]The Time Use Institute: https://www.creditdonkey.com/grocery-shopping-statistics.html.

[14]https://minimumwage.com/state/california/.

concern can be calculated as

$$Value = AdditionalCost \times PercentageSwitching = 10.25 \times 21.3\% = \$2.18, \quad (4)$$

indicating that on average consumers are willing to pay $2.18 per trip to protect their privacy rights, which amounts to about 15% of consumers' online health product spending per trip ($14.15 in Table 1). This relative percentage emphasizes the importance of consumer privacy protection and demonstrates that it is a critical factor when it comes to modes of shopping decisions.

Furthermore, we discovered that people are 10.9% more likely to buy health products online than they are to buy basic multivitamins using estimates of column (3) in Table 5. Using similar calculations, we quantify the additional value of privacy concerns, that is, consumers are willing to pay an extra $1.12 to protect their privacy rights when purchasing male enhancement products as opposed to vitamin C.

Lastly, we quantify heterogeneous privacy values among different people.[15] When purchasing more sensitive products, males are willing to pay an extra $1.63 more than females. Using the same logic, we find that people who are more educated are willing to pay an extra $0.11 than those who are less educated, that Millennials are willing to pay an extra $1.03 more than people in the boomer generation, and that higher-income people are willing to pay an extra $0.31 more than middle-income people and $1.29 more than low-income people.

4 Robustness Checks

To validate our findings in the previous section, we conduct several robustness checks. First, we study the parallel trends before and after the announcement of CCPA to validate the DID approach. Second, we use the number of online/offline trips as an alternative measure of the shopping patterns and examine how such a measure responds to the CCPA announcement. Lastly, we test for the structural break in our data period.

[15] Using 10-day window estimates, we quantify the heterogeneous effect of privacy values. We are specifically using the estimates of column (3) from Tables 12 - 18.

4.1 Validating the DID Model: Parallel Trends

The validity of the DID approach in Model 2 relies on the parallel-trends assumption that the fraction of online purchases had parallel demand trends for health products and basic multivitamins prior to the announcement. A leads-lags relative time model is a standard method for assessing the parallel-trends assumption. Following the existing literature (Agrawal and Goldfarb (2008)), we add a series of period dummy variables to the model to decompose the pre-treatment periods. Specifically, we consider the following the relative-time model:

$$\begin{aligned} Online_{it} &= \alpha_0 + \sum_j \lambda_j \left(Pre_{it}(j) \times HealthP_i\right) + \sum_k \gamma_k \left(Post_{it}(k) \times HealthP_i\right) \\ &+ \sum_j \beta_j Pre_{it}(j) + \sum_k \eta_k Post_{it}(k) + \alpha_1 HealthP_i + \alpha_2 X_{it} + \varepsilon_{it}, \end{aligned} \tag{5}$$

where $Pre_{it}(j)$ is an indicator function that equals 1 if period t is j days prior to treatment, and $Post_{it}(k)$ is an indicator function that equals 1 if the period t is k months after the announcement of CCPA. The added period-specific interaction term, $\sum_j \lambda_j \left(Pre_{it}(j) \times HealthP_i\right)$, allows us to examine the possibility of falsely-significant treatment effects prior to the treatment. The coefficient λ_j captures the pre-treatment trend in the impact of CCPA introduction on the percentage of households' online shopping trips. Similarly, γ_k enables us to examine dynamics in the treatment effect. Validation of the DID model relies on λ_j, which indicates whether the estimated treatment effect began prior to the introduction of CCPA.

Our negative findings via DID are valid only if λ_j is not significantly from 0. Following prior work (Agrawal and Goldfarb (2008)), we set the announcement date as the reference period (i.e., we normalize the coefficient of January 3, 2018, to 0) and consider the preceding five-period interval for better interpretability. That is, we consider $j = -15, -12, \ldots, -3$, and $k = 0, 3, \ldots, 12, 15$ and beyond.[16]

Furthermore, we investigate the parallel trend over a one-month window. We use a shorter time frame because, in the longer time span, many other factors may occur that could interfere with the treatment's effectiveness. Seasonality, for example, plays a role when people try to decide which types of supplements to buy. In addition, other legislative updates occurred around the same time window, although they are less relevant to consumers' health-product purchases. As a result, the parallel-trends

[16] In addition to using 3 days as an interval, we also try 4 days and 5 days as robustness checks. The results are comparable to those obtained after 3 days. The results can be obtained upon request.

assumption for DID is more likely to hold over a shorter time period, enabling us to obtain a clean estimate of the announcement effect.

We estimate Model 5 using a linear probability model and present the estimates in Table 19. In addition, we illustrate the estimates using results in column (3) for multivitamin and health-product in the top and bottom panel of Figure 3, respectively. These estimates confirm the validity of the DID analysis. Specifically, the coefficients of the pretreatment indicators are not statistically significant for both categories, suggesting (1) the percentage for the treated group was not declining relative to the percentage for the control group prior to the CCPA announcement, and (2) the DID estimation of the impact of CCPA introduction will not be falsely inflated by trends that began before treatment.

Moreover, a few interesting patterns arise regarding the duration of the announcement effect. First, we can see that the negative response to online shopping was significant for both multivitamin and health-product immediately after the introduction of the CCPA. However, this effect decreased gradually. Moreover, such a negative additional impact for the more sensitive health products became statistically insignificant after 2 periods, suggesting a differential impact of the same announcement on those sensitive health products than the other products.

4.2 Alternative Measurement of Shopping Patterns

In section 3, we find individual consumers reduced their online shopping for both more-privacy-sensitive and less-privacy-sensitive products. We want to test if our findings hold up for different measures. To do so, we model the number of household trips per week, using a Poisson regression. That is,

$$\log\left(E(\lambda_{it}|CCPA_t, HealthP_i)\right) = \beta_0 + \beta_1 CCPA_t + \beta_2 HealthP_{it} + \beta_3 CCPA_t \times HealthP_{it}, \quad (6)$$

where λ_{it} is the number of online(offline) trips household i makes in week t, which is assumed to follow a Poisson distribution whose mean depends on whether CCPA has been introduced and the categories of the product. Here, we are interested in the sign of β_3, which is the change in the outcome variable for health products after CCPA relative to basic items.

Table 6 displays the Poisson regression results.The full-year panel in column (1) shows the CCPA announcement effect for online shopping is negative, whereas it is positive for offline shopping, indicating a decrease in trips via the online mode but an

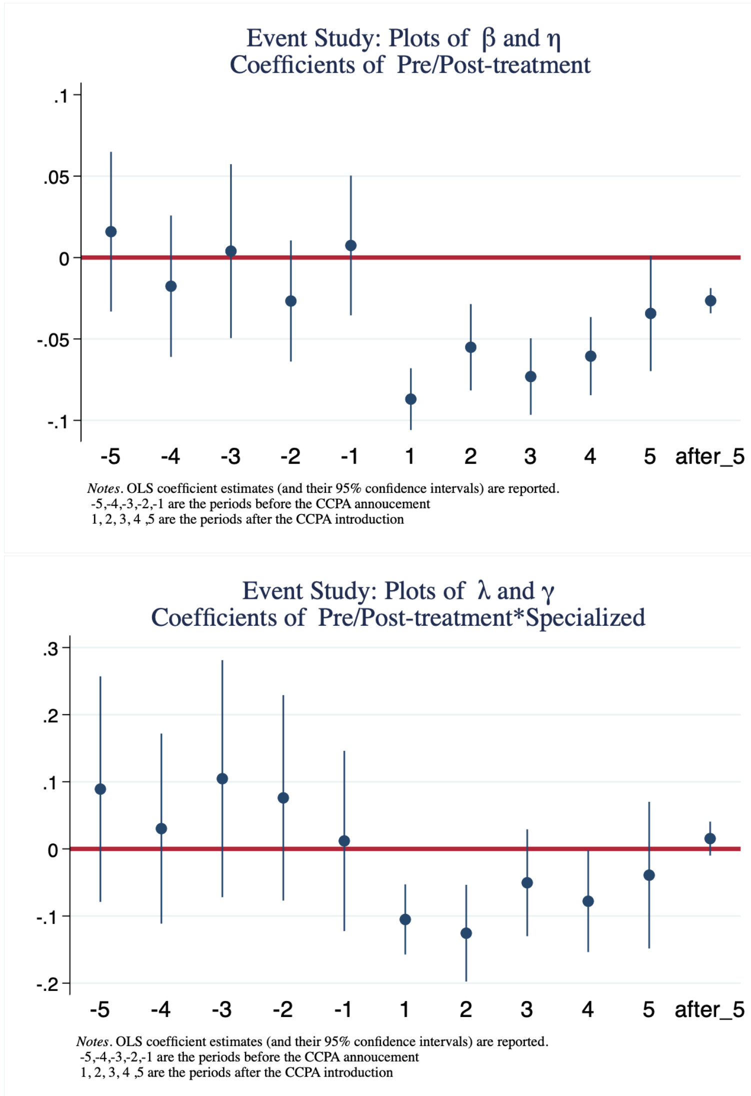

Figure 3. Plot of estimated coefficients in the pre-/post-treatment periods

increase via the offline mode. The log difference in the expected number of trips before CCPA is projected to reduce by 0.268 unit relative to the number of trips after CCPA, while the log difference in the expected number of trips for offline trips is predicted to increase by 0.0434 unit. Furthermore, these patterns are robust across a wide range of time windows. The additional effect of CCPA on health products becomes more pronounced as the time window is narrowed, which is consistent with our findings in section 3. One rational for this phenomenon is that the CCPA's announcement was a brief shock that consumers quickly forgot about.

Table 6. Announcement effect using household-weekly trip count

	(1)		(2)		(3)	
	Full Year		One month		Ten Days	
Dep Var: Trip count	Online	Offline	Online	Offline	Online	Offline
CCPA	-0.268***	0.0434***	-0.290***	0.0876***	-0.489***	0.102***
	(0.0398)	(0.00974)	(0.0939)	(0.0220)	(0.162)	(0.0362)
HealthP	-1.022***	-1.841***	-0.897***	-1.897***	-0.874***	-1.964***
	(0.0392)	(0.0189)	(0.143)	(0.0582)	(0.218)	(0.0993)
CCPA × HealthP	0.111	0.00781	-0.160	0.0696	-0.578*	0.238**
	(0.0705)	(0.0317)	(0.186)	(0.0738)	(0.316)	(0.119)
Constant	-1.834***	-0.0143**	-1.968***	-0.00267	-1.987***	0.0443
	(0.0210)	(0.00587)	(0.0676)	(0.0168)	(0.106)	(0.0285)
Observations	61,548	61,548	10,878	10,878	4,320	4,320

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.3 Structural Break Test

In this section, we perform a structural break test[17] to check whether the coefficients vary over the periods defined by an unknown break date. By combining the test statistics computed for each possible break date in the sample, it constructs a test statistic for a structural break without imposing a known break date. Any identified break in the data can in turn be used as a test of plausible causality, because a break occurring at a date far from policy implementation suggests some other factor is causing the change. This exercise serves as an alternative method to validate consumers' change in shopping modes following the CCPA announcement.

We present the estimation result in Table 7. The overall estimated break date is December 26, 2017, which is very close to the actual announcement date of CCPA. Although the estimated date is a few days earlier than the official date, the difference is reasonable, because some media exposure always occur before the government officially announces a law or regulation, and we would expect to see impacts prior to the CCPA announcement date. Therefore, this result validates our DID estimation and supports our findings.

[17]We apply a Stata function, "estat sbsingle" (https://www.stata.com/manuals/tsestatsbsingle.pdf)."estat sbsingle" uses the maximum, an average, or the exponential of the average of the tests computed at each possible break date. The test at each possible break date can be either a Wald or an LR test.

Table 7. Structural break estimates

Dep Var: fraction_online_trips	(1) Full_sample	(2) HealthP	(3) Multivitamin
Avg_trip_dollor	-0.00169***	-0.00110***	-0.00150***
	(0.0001)	(0.0002)	(0.0001)
_cons	0.327***	0.379***	0.285***
	(0.0154)	(0.0192)	(0.0149)
N	365	365	365
sbsingle_p	0.000126	0.00281	0.00000627
sbsingle_breakdate	12/26/2017	12/20/2017	12/26/2017

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5 Exploring the Mechanism: Privacy Concerns Revealed by Google Trends

Our main finding in section 3 is that people reduced their online shopping immediately after the introduction of CCPA. To investigate the mechanism behind this change, we look at how people's privacy concerns are linked to their actual shopping behavior. We believe the announcement of CCPA raised concerns about online purchases. That is, consumers may be unaware of the amount of personal information that businesses have collected in the past. However, they are becoming more aware of how firms use their data, due to the CCPA announcement.

In the absence of readily available surveillance data on the impact of CCPA announcements on privacy issues and people's perceptions of privacy, we use Google Trends data as a potential alternative measure. Google Trends is a Google website that analyzes the popularity of top Google Search queries across various regions and languages. The website uses graphs to compare the search volume of various queries over time. For over a decade, scholars have been using Google Trends, a publicly available source of near-real-time internet search data (Nuti et al. (2014), Schaub et al. (2020), Sinyor et al. (2020)). For example, Knipe et al. (2020) investigated the evolving pattern of public concern (indexed by internet searches) related to sentinel dates in international and selected countries during the first weeks of the COVID-19 pandemic to March 30, 2020, when approximately 200,000 people had died worldwide.

Note the absolute magnitude of the Google Trends search index does not have economic meaning. The reason is that Google Trends employs a sampling method that creates a representative dataset of all Google searches each time the data are taken; thus, the results may alter each time a query is done on Google Trends. Google does not provide the total number of searches. Instead, it shows search activity for a certain term or topic at a specific time and location using a normalized value. The total number of searches for a certain region during the provided time period is split by each data point. The resulting value, called the Relative Search Volume(RSV), is then indexed from 0 to 100, with 100 signifying the highest level of interest in that topic/term at that time and location. RSVs show how popular an issue is in a specific location during a specific period. As a result, we just consider the sign of the coefficients in this case and ignore their magnitude.

For this paper, we looked at the search index from Google Trends in California from May 1, 2017, to May 1, 2018. Figure 4 shows the search index for the keywords "California Consumer Privacy Act" and "Ed Chau."[18] Ed Chau, who introduced and passed the landmark privacy law in 2018, served as the Chairman of the Assembly Committee on Privacy and Consumer Protection from 2016 to 2021. The red vertical line denotes the date on which CCPA was officially announced. Figure 4 shows a spike right after the introduction of CCPA, indicating an increased interest in CCPA immediately after its introduction that gradually faded after a short period.

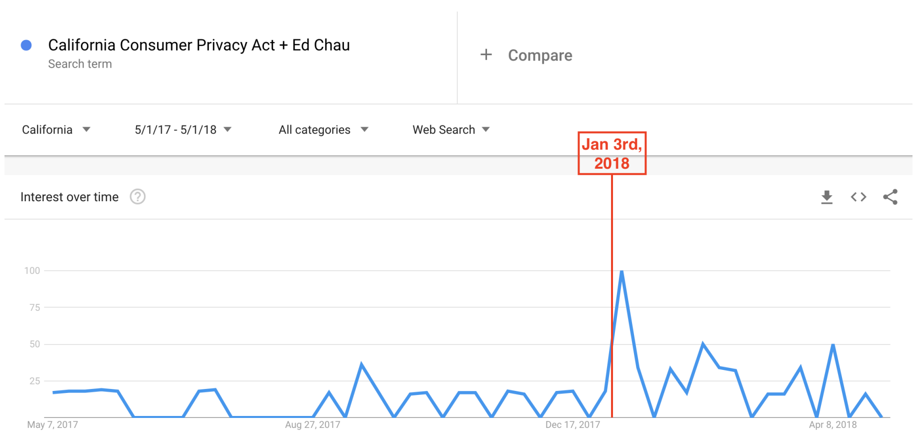

Figure 4. Google Trends for CCPA

Motivated by the graph, we regress the Google Trend index on a dummy variable that indicates whether the date is before or after the CCPA's announcement and present the regression results in Table 8. The positive coefficient of the CCPA announcement indicates people searched for CCPA-related topics more frequently after

[18]One possible concern is that the GDPR may contribute to increased consumer privacy concerns. We examined the Google Trends for search term "GDPR" and discovered that it is fairly flat around January 2018.

the CCPA announcement, which is not surprising given that a policy receives more attention after its official disclosure. The magnitude of the coefficient decreases with the time window of the announcement, again supporting the intuition that people gradually forgot about or got used to the announcement.

Table 8. CCPA searches responding to CCPA announcement

	(1)	(2)	(3)
Dep Var: Google_Trend_CCPA	Full Sample	One Month	Ten Days
CCPA	11.37***	22.30**	54.06**
	(3.989)	(10.75)	(25.64)
Constant	6.222***	5.613	-0.000
	(1.380)	(3.913)	(0.000)
Observations	365	61	21
R-squared	0.032	0.069	0.205

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

To further connect consumers' search with their shopping behaviors, we run a logit regression using the fraction of online shopping as the dependent variable and include the search volume of CCPA-related topics as one independent variable, together with other covariates. To avoid the problem of adverse causality, we use the lagged Google Trends search index as the independent variable. We present the estimation results in Table 9, where the fraction of online shopping is negatively correlated with search intensity. In other words, the more people search, the less they shop online.

Table 9. The prediction power of Google Trends on people's online shopping behavior

	(1)	(2)	(3)	(4)
Dep Var: Online	Baseline	Add Trip Covariates	Add Consumer Covariates	Add FE
Lag1_Google_Trend_CCPA	-0.000839*	-0.000948*	-0.000958*	-0.00118**
	(0.000457)	(0.000534)	(0.000536)	(0.000551)
log_TripDollars		-1.624***	-1.629***	-1.655***
		(0.0228)	(0.0229)	(0.0235)
ItemUnits		0.0658***	0.0657***	0.0728***
		(0.00754)	(0.00768)	(0.00831)
log_CostperUnit		2.549***	2.558***	2.580***
		(0.0390)	(0.0392)	(0.0400)
Constant	-1.742***	-2.199***	-2.191***	-4.440***
	(0.0144)	(0.0829)	(0.0856)	(0.233)
Demographics	N	N	N	Y
Observations	41,898	41,681	41,327	41,096

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In addition, to support the hypothesis that the CCPA announcement raised privacy concerns, we performed some robustness checks. Because the search volume for the specific policy is quite low, we constructed a "Consumer Privacy Awareness Index" to better understand consumers' reactions to the law's announcement. Other popular search terms for privacy concerns, in addition to the preceding two, are included in this index: "Consumer Privacy," "Consumer Privacy Law," and "Data Concern." This enriched data index allows us to investigate trends in how people search for CCPA-related topics and provides a clear picture of how people's attention shifts over time. We then repeated the regression analysis using the new "Consumer Privacy Awareness Index."

Table 20 shows the search volume of the "Consumer Privacy Awareness Index" increases following the CCPA announcement. Further, as we narrow the time window, we find the effects become stronger, with the effects being concentrated primarily in the first two weeks of the policy's implementation. This finding is direct evidence that the CCPA raised people's privacy concerns. Likewise, the results in Table 21 support the argument that the search volume of "Consumer Privacy Awareness Index" has a negative relationship with online shopping fractions, in the same direction as we see in Table 8 when the keywords include only "CCPA" and "Ed Chau."

Together, the findings show CCPA raises people's privacy concerns. Although we cannot directly measure the concern, this result suggests people who conduct more searches are more concerned about the topics they are researching, which may be driving fewer online trips.

6 Conclusions

CCPA is considered a landmark legislation concerning data privacy in the digital era for US consumers. Our paper focuses on two effects of its introduction on consumers' purchase patterns of multivitamin and health-product: it extends the privacy protections offered to California residents and helps them feel safer while browsing online content, and it raises privacy concerns about online shopping, leading to fewer online purchases. Ex ante, the net result of these two opposing effects is unclear. We use a panel of consumer purchasing records in California to document evidence of the combined effect and investigate changes in consumers' online/offline shopping behavior for healthcare products.

Our findings highlight that California consumers' engagement in online shopping decreased after the CCPA announcement relative to before the policy announcement. Further research revealed consumers react differently to privacy and non-privacy products. Since the enactment of CCPA, California consumers became more cautious when shopping online for more privacy-related drugs, preferring to shop offline instead.

These findings are insightful for managers and policymakers. When designing policies concerning data privacy, policymakers should consider the accessibility of fundamental data privacy rights for the general public. Due to the heterogeneous response, policymakers should also pay special attention to different subpopulations. First, policymakers should make every effort to educate the elderly, the poor, and the uneducated. Second, policymakers should make particular attempts to detect data breaches involving health products by taking into account consumers' desire to protect their health information related to those specialized products. Finally, the lack of a long-lasting effect on consumer behavior calls for periodical efforts by policymakers to remind consumers of the potential risks of health-information breaches. In addition, our findings suggest marketing managers, particularly those of e-commerce platforms, should be better prepared in terms of their marketing efforts when CCPA is actual implemented.

We conclude by emphasizing the negative unintended consequences of a policy announcement. However, our study does not assess CCPA's actual effectiveness. The privacy act went into effect at the start of 2020. The actual interaction between this policy and the effect of COVID-19 on online shopping deserves future analysis.

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References

Acquisti, A., Brandimarte, L., and Loewenstein, G. (2015). Privacy and human behavior in the age of information. *Science*, 347(6221):509–514.

Agrawal, A. and Goldfarb, A. (2008). Restructuring research: Communication costs and the democratization of university innovation. *American Economic Review*, 98(4):1578–90.

Auxier, B., Rainie, L., Anderson, M., Perrin, A., Kumar, M., and Turner, E. (2019). Americans and privacy: Concerned, confused and feeling lack of control over their personal information. *Pew Research Center*.

Bleier, A., Goldfarb, A., and Tucker, C. (2020). Consumer privacy and the future of data-based innovation and marketing. *International Journal of Research in Marketing*, 37(3):466–480.

Brazhnik, T. (2013). Cookies in e-commerce: Balancing privacy and business. *Available at SSRN 2366262*.

Ching, A. T., Clark, R., Horstmann, I., and Lim, H. (2016). The effects of publicity on demand: The case of anti-cholesterol drugs. *Marketing Science*, 35(1):158–181.

Goldfarb, A. and Tucker, C. (2011). Online display advertising: Targeting and obtrusiveness. *Marketing Science*, 30(3):389–404.

Goldfarb, A. and Tucker, C. (2012). Shifts in privacy concerns. *American Economic Review*, 102(3):349–53.

Goswami, S. (2020). The rising concern around consumer data and privacy. *Forbes, https://www.forbes.com/sites/servicenow/2022/04/29/the-cybersecurity-risk-no-one-talks-about-until-its-too-late/?sh=60a5a4d970d9.*

Harris, R. (2020). Forging a path towards meaningful digital privacy: Data monetization and the ccpa. *Loy. LAL Rev.*, 54:197.

Hoofnagle, C. J., King, J., Li, S., and Turow, J. (2010). How different are young adults from older adults when it comes to information privacy attitudes and policies? *Available at SSRN 1589864*.

Jai, T.-M. C., Burns, L. D., and King, N. J. (2013). The effect of behavioral tracking practices on consumers' shopping evaluations and repurchase intention toward trusted online retailers. *Computers in Human Behavior*, 29(3):901–909.

Knipe, D., Evans, H., Marchant, A., Gunnell, D., and John, A. (2020). Mapping population mental health concerns related to covid-19 and the consequences of physical distancing: a google trends analysis. *Wellcome open research*, 5.

Kwon, J. and Johnson, M. E. (2013). Health-care security strategies for data protection and regulatory compliance. *Journal of Management Information Systems*, 30(2):41–66.

Lin, T. (2022). Valuing intrinsic and instrumental preferences for privacy. *Marketing Science*.

Maalouf, M. and Rozen, M. (2020). Ccpa reflections on the eve of enforcement and in the midst of a global pandemic. *Computer Law Review International*, 21(3):65–69.

McGraw, D. and Mandl, K. D. (2021). Privacy protections to encourage use of health-relevant digital data in a learning health system. *NPJ digital medicine*, 4(1):1–11.

Miller, A. R. and Tucker, C. (2018). Privacy protection, personalized medicine, and genetic testing. *Management Science*, 64(10):4648–4668.

Nuti, S. V., Wayda, B., Ranasinghe, I., Wang, S., Dreyer, R. P., Chen, S. I., and Murugiah, K. (2014). The use of google trends in health care research: a systematic review. *PloS one*, 9(10):e109583.

Schaub, S., Huber, R., and Finger, R. (2020). Tracking societal concerns on pesticides–a google trends analysis. *Environmental Research Letters*, 15(8):084049.

Sinyor, M., Spittal, M. J., and Niederkrotenthaler, T. (2020). Changes in suicide and resilience-related google searches during the early stages of the covid-19 pandemic. *The Canadian Journal of Psychiatry*, 65(10):741–743.

Tsai, J. Y., Egelman, S., Cranor, L., and Acquisti, A. (2011). The effect of online privacy information on purchasing behavior: An experimental study. *Information systems research*, 22(2):254–268.

Tucker, C. E. (2014). Social networks, personalized advertising, and privacy controls. *Journal of marketing research*, 51(5):546–562.

A Appendix

The Appendix includes the detailed classification of the two categories by NIH, the DID regression for subpopulation according to demographics, supplement results for the parallel trend, and the robustness check for the CCPA searches.

Table 10. Examples of different categories of multivitamin and health products

Multivitamins	Health Products
Kirkland Signature Vitamin E 400 IU, 500 Softgels	Alphaman Xl Male Sexual Enhancement Pills 2+ Inches In 60 Days - Enlargement Booster Increases Energy Mood & Stamina Best Performance Supplement For Men - 1 Month Supply
Vitafusion Women's Daily Multivitamin, Gummy	Lipozene Mega Bottle Fat Burner & Appetite Suppressant Weight Loss Pills, Capsules, 120 Ct
Spring Valley Vitamin E Supplement, 400IU, 500 Softgel Capsules	Best Kidney Cleanse (Vegetarian) Supports Bladder Control & Urinary Tract - Powerful VitaCran Cranberry Extract - Natural Herbs Supplement - Kidney Health, Flush & Detox - 60 Capsules (No Pills)

Table 11. Classification of multivitamin and health-product

Category		Definition
Multivitamins	Basic	Multivitamins taken once a day that contain all or most vitamins and minerals, most in amounts that do not exceed the Daily Values (DVs), Recommended Dietary Allowances (RDAs), or Adequate Intakes (AIs) for these nutrients.* This fact sheet focuses primarily on these basic, broad-spectrum multivitamin and health-product. Formulations for children, adult men and women, pregnant people, and seniors typically provide different amounts of the same vitamins and minerals to meet the needs of these populations.
	High potency	Some multivitamins contain amounts of some vitamins and minerals that are substantially higher than the DV, RDA, AI, or even, in some cases, the established Tolerable Upper Intake Level (UL).These multivitamin and health-product might also include other nutrients and botanical ingredients. Manufacturers sometimes offer these multivitamin and health-product in packs of two or more pills for users to take daily.
Health Products	Condition specific	Products for energy, enhanced athletic performance, weight control, improved immune function, or eye health often combine several vitamins and minerals with botanical and specialty ingredients, such as coenzyme Q10, probiotics, or glucosamine. Some of these products might contain amounts of nutrients that are substantially above the DV, RDA, AI, or even UL.

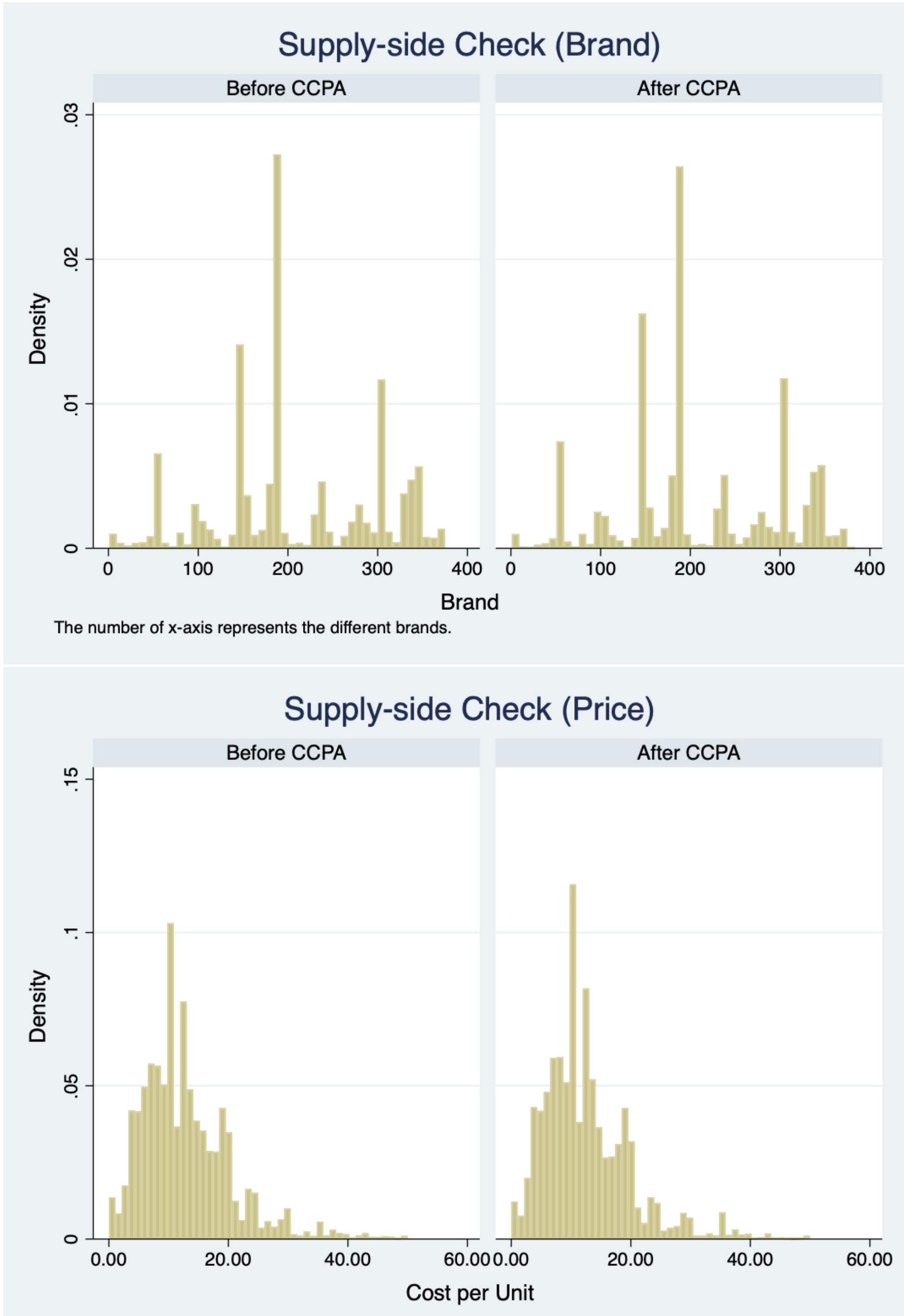

Figure 5. Supply-side Check

Table 12. Announcement effect (Gender)

	(1)		(2)		(3)	
	Full Year		One month		Ten Days	
Dep Var: Online	Female	Male	Female	Male	Female	Male
CCPA × HealthP	-0.00462	-0.00115	-0.0354	-0.145***	-0.0760*	-0.235***
	(0.0110)	(0.0230)	(0.0255)	(0.0535)	(0.0393)	(0.0821)
CCPA	-0.0193***	-0.0362***	-0.0316***	-0.0440**	-0.0366***	-0.0609**
	(0.00366)	(0.00755)	(0.00810)	(0.0171)	(0.0122)	(0.0279)
HealthP	0.0611***	0.113***	0.0646***	0.208***	0.0601*	0.258***
	(0.00670)	(0.0141)	(0.0207)	(0.0445)	(0.0356)	(0.0726)
log_TripDollars	-0.143***	-0.144***	-0.119***	-0.133***	-0.106***	-0.128***
	(0.00194)	(0.00406)	(0.00456)	(0.00956)	(0.00710)	(0.0150)
ItemUnits	0.00322***	0.0132***	0.000436	0.0174**	-0.00400	0.00235
	(0.000628)	(0.00330)	(0.00292)	(0.00817)	(0.00616)	(0.0116)
log_CostperUnit	0.200***	0.227***	0.171***	0.195***	0.149***	0.217***
	(0.00304)	(0.00669)	(0.00730)	(0.0157)	(0.0114)	(0.0246)
Constant	0.265***	0.165***	0.232***	0.185***	0.217***	0.150**
	(0.00840)	(0.0172)	(0.0198)	(0.0408)	(0.0299)	(0.0595)
Observations	33,793	7,535	6,100	1,293	2,516	519
R-squared	0.234	0.258	0.191	0.276	0.174	0.320

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 13. Announcement effect (Education)

	(1) Full Year		(2) One month		(3) Ten Days	
Dep Var: Online	No College	College	No College	College	No College	College
CCPA × HealthP	-0.00474	-0.00204	-0.0258	-0.0982***	-0.118**	-0.128**
	(0.0135)	(0.0147)	(0.0305)	(0.0349)	(0.0464)	(0.0567)
CCPA	-0.0133***	-0.0314***	-0.0199**	-0.0476***	-0.0125	-0.0686***
	(0.00429)	(0.00506)	(0.00945)	(0.0113)	(0.0140)	(0.0171)
HealthP	0.0794***	0.0619***	0.0757***	0.119***	0.109***	0.119**
	(0.00819)	(0.00890)	(0.0241)	(0.0293)	(0.0415)	(0.0520)
log_TripDollars	-0.123***	-0.163***	-0.106***	-0.137***	-0.0870***	-0.132***
	(0.00238)	(0.00253)	(0.00573)	(0.00590)	(0.00873)	(0.00933)
ItemUnits	0.00195***	0.0164***	-0.000797	0.0114*	-0.0180**	0.00903
	(0.000419)	(0.00359)	(0.00335)	(0.00621)	(0.00882)	(0.00698)
log_CostperUnit	0.175***	0.232***	0.144***	0.204***	0.128***	0.188***
	(0.00360)	(0.00431)	(0.00867)	(0.00991)	(0.0136)	(0.0154)
Constant	0.216***	0.274***	0.212***	0.233***	0.173***	0.260***
	(0.00936)	(0.0130)	(0.0222)	(0.0293)	(0.0353)	(0.0434)
Observations	22,070	19,325	3,929	3,473	1,603	1,438
R-squared	0.200	0.274	0.162	0.248	0.138	0.264

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 14. Announcement effect (Age)

		(1) Full Year			(2) One month			(3) Ten Days	
Dep Var: Online	Boomers	Gen X	Millennials	Boomers	Gen X	Millennials	Boomers	Gen X	Millennials
CCPA × HealthP	-0.00361	-0.0132	0.00460	-0.0275	-0.0717**	-0.0665	-0.0344	-0.143**	-0.135**
	(0.0189)	(0.0148)	(0.0189)	(0.0419)	(0.0356)	(0.0432)	(0.0630)	(0.0563)	(0.0673)
CCPA	0.00527	-0.0299***	-0.0317***	0.000352	-0.0522***	-0.0360**	-0.0195	-0.0284*	-0.0849***
	(0.00692)	(0.00467)	(0.00647)	(0.0155)	(0.0103)	(0.0148)	(0.0251)	(0.0154)	(0.0214)
HealthP	0.0275**	0.103***	0.0610***	0.0194	0.142***	0.0809**	-6.39e-05	0.146***	0.119*
	(0.0112)	(0.00901)	(0.0118)	(0.0326)	(0.0289)	(0.0364)	(0.0557)	(0.0505)	(0.0621)
log_TripDollars	-0.136***	-0.145***	-0.145***	-0.124***	-0.127***	-0.110***	-0.136***	-0.108***	-0.0995***
	(0.00382)	(0.00249)	(0.00329)	(0.00966)	(0.00589)	(0.00736)	(0.0162)	(0.00903)	(0.0110)
ItemUnits	0.0121**	0.00339***	0.00311	-0.000565	0.00600**	-0.00423	0.0356*	0.00490	-0.0176**
	(0.00520)	(0.000612)	(0.00402)	(0.00744)	(0.00295)	(0.00953)	(0.0201)	(0.00908)	(0.00840)
log_CostperUnit	0.176***	0.214***	0.216***	0.155***	0.184***	0.182***	0.159***	0.163***	0.176***
	(0.00550)	(0.00399)	(0.00544)	(0.0131)	(0.00971)	(0.0125)	(0.0224)	(0.0153)	(0.0185)
Constant	0.255***	0.240***	0.242***	0.274***	0.234***	0.176***	0.272***	0.176***	0.178***
	(0.0166)	(0.0111)	(0.0149)	(0.0377)	(0.0274)	(0.0312)	(0.0617)	(0.0403)	(0.0457)
Observations	9,381	19,133	12,190	1,655	3,447	2,195	623	1,450	921
R-squared	0.208	0.273	0.215	0.176	0.254	0.172	0.202	0.204	0.221

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 15. Announcement effect (Income)

	(1)			(2)			(3)		
		Full Sample			One Month			Ten Days	
Dep Var: Online	Low	Medium	High	Low	Medium	High	Low	Medium	High
CCPA × HealthP	-0.0131	-0.00978	0.0114	0.0376	-0.104**	-0.0755**	-0.0350	-0.131*	-0.161***
	(0.0180)	(0.0182)	(0.0155)	(0.0389)	(0.0412)	(0.0371)	(0.0574)	(0.0705)	(0.0582)
CCPA	-0.00774	-0.0207***	-0.0325***	-0.0394***	-0.0155	-0.0444***	-0.0530***	-0.0372	-0.0307*
	(0.00588)	(0.00605)	(0.00524)	(0.0136)	(0.0133)	(0.0115)	(0.0192)	(0.0227)	(0.0172)
HealthP	0.0661***	0.0664***	0.0712***	-0.00527	0.0978***	0.145***	0.0226	0.101	0.171***
	(0.0110)	(0.0112)	(0.00934)	(0.0299)	(0.0355)	(0.0298)	(0.0515)	(0.0665)	(0.0509)
log_TripDollars	-0.115***	-0.138***	-0.166***	-0.0967***	-0.117***	-0.140***	-0.0847***	-0.125***	-0.122***
	(0.00320)	(0.00328)	(0.00269)	(0.00735)	(0.00798)	(0.00638)	(0.0105)	(0.0134)	(0.0102)
ItemUnits	0.00215***	0.0125***	0.0102***	-0.000382	0.00586	0.0101	-0.0202***	0.00280	0.0124
	(0.000314)	(0.00423)	(0.00325)	(0.00333)	(0.00598)	(0.00840)	(0.00699)	(0.00854)	(0.0119)
log_CostperUnit	0.163***	0.196***	0.229***	0.143***	0.169***	0.195***	0.128***	0.163***	0.183***
	(0.00497)	(0.00497)	(0.00441)	(0.0116)	(0.0121)	(0.0105)	(0.0176)	(0.0195)	(0.0169)
Constant	0.198***	0.236***	0.306***	0.192***	0.204***	0.268***	0.186***	0.266***	0.193***
	(0.0126)	(0.0142)	(0.0137)	(0.0314)	(0.0301)	(0.0316)	(0.0411)	(0.0531)	(0.0464)
Observations	11,965	12,180	17,099	2,158	2,179	3,038	898	869	1,260
R-squared	0.169	0.218	0.297	0.136	0.182	0.272	0.152	0.184	0.252

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 16. Announcement effect (Household Size)

	(1)		(2)		(3)	
	Full Year		One month		Ten Days	
Dep Var: Online	$hhsize \leq 3$	$hhsize > 3$	$hhsize \leq 3$	$hhsize > 3$	$hhsize \leq 3$	$hhsize > 3$
CCPA × HealthP	-0.0138	0.0118	-0.0318	-0.104***	-0.105**	-0.133**
	(0.0130)	(0.0154)	(0.0286)	(0.0386)	(0.0457)	(0.0578)
CCPA	-0.0279***	-0.0138***	-0.0333***	-0.0348***	-0.0382**	-0.0482***
	(0.00452)	(0.00474)	(0.00988)	(0.0109)	(0.0154)	(0.0159)
HealthP	0.0700***	0.0724***	0.0503**	0.166***	0.0782*	0.144***
	(0.00793)	(0.00932)	(0.0229)	(0.0323)	(0.0410)	(0.0528)
log_TripDollars	-0.150***	-0.131***	-0.123***	-0.118***	-0.119***	-0.0975***
	(0.00234)	(0.00262)	(0.00561)	(0.00608)	(0.00880)	(0.00937)
ItemUnits	0.0104***	0.00296***	-0.00256	0.00554**	-0.0134*	0.0128
	(0.00367)	(0.000470)	(0.00796)	(0.00255)	(0.00698)	(0.00954)
log_CostperUnit	0.215***	0.186***	0.180***	0.168***	0.186***	0.131***
	(0.00356)	(0.00436)	(0.00863)	(0.0101)	(0.0145)	(0.0140)
Constant	0.255***	0.229***	0.224***	0.224***	0.200***	0.208***
	(0.0108)	(0.0113)	(0.0244)	(0.0268)	(0.0355)	(0.0403)
Observations	24,458	16,937	4,361	3,041	1,744	1,297
R-squared	0.235	0.235	0.191	0.227	0.210	0.189

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 17. Announcement effect (Ethnicity)

	(1) Full Sample				(2) One Month			
Dep Var: Online	Asian	African American	Hispanic	White	Asian	African American	Hispanic	White
CCPA × HealthP	-0.0227	0.0256	0.00121	0.00651	-0.163***	0.0374	-0.0579	0.00341
	(0.0168)	(0.0530)	(0.0235)	(0.0154)	(0.0438)	(0.124)	(0.0587)	(0.0340)
CCPA	-0.0212***	-0.0103	-0.0244***	-0.0193***	-0.0411***	0.0499	-0.0223	-0.0394***
	(0.00577)	(0.0180)	(0.00706)	(0.00524)	(0.0129)	(0.0372)	(0.0164)	(0.0116)
HealthP	0.0549***	0.0909***	0.0710***	0.0783***	0.189***	0.126	0.100**	0.0371
	(0.0109)	(0.0310)	(0.0143)	(0.00913)	(0.0396)	(0.0965)	(0.0460)	(0.0261)
log_TripDollars	-0.136***	-0.0987***	-0.119***	-0.162***	-0.118***	-0.0555**	-0.0950***	-0.138***
	(0.00327)	(0.00903)	(0.00390)	(0.00264)	(0.00750)	(0.0222)	(0.00907)	(0.00635)
ItemUnits	0.00923***	0.0533***	0.0377***	0.0131***	0.00747	0.0819	0.0302**	-0.00375
	(0.00212)	(0.0197)	(0.00812)	(0.00423)	(0.00517)	(0.0726)	(0.0130)	(0.0134)
log_CostperUnit	0.202***	0.219***	0.193***	0.223***	0.148***	0.220***	0.181***	0.194***
	(0.00606)	(0.0129)	(0.00650)	(0.00398)	(0.0133)	(0.0298)	(0.0168)	(0.00966)
Constant	0.179***	0.000981	0.120***	0.306***	0.236***	-0.239*	0.0519	0.294***
	(0.0150)	(0.0458)	(0.0188)	(0.0133)	(0.0334)	(0.142)	(0.0425)	(0.0334)
Observations	11,588	1,628	7,665	18,436	2,176	349	1,310	3,217
R-squared	0.218	0.201	0.206	0.278	0.220	0.201	0.173	0.235

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 18. Announcement effect (Ethnicity)–Continued

	(3) Ten Days			
Dep Var: Online	Asian	African American	Hispanic	White
CCPA × HealthP	-0.148**	-0.165	-0.0203	-0.119**
	(0.0661)	(0.199)	(0.100)	(0.0532)
CCPA	-0.0423**	0.0122	-0.0288	-0.0491***
	(0.0191)	(0.0631)	(0.0243)	(0.0180)
HealthP	0.156**	0.0243	0.0565	0.0968**
	(0.0624)	(0.151)	(0.0848)	(0.0476)
log_TripDollars	-0.112***	-0.122***	-0.0850***	-0.117***
	(0.0116)	(0.0398)	(0.0141)	(0.0102)
ItemUnits	-0.000106	0.144*	0.0379	-0.00706
	(0.00541)	(0.0848)	(0.0247)	(0.0200)
log_CostperUnit	0.152***	0.208***	0.174***	0.169***
	(0.0197)	(0.0570)	(0.0280)	(0.0151)
Constant	0.212***	0.0190	0.00929	0.250***
	(0.0478)	(0.215)	(0.0781)	(0.0479)
Observations	950	131	529	1,287
R-squared	0.235	0.177	0.159	0.208

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 19. Pre-trend test of DID

Dep Var: Online	(1) 3-Periods	(2) 4-Periods	(3) 5-Periods
HealthP	0.0869***	0.0845***	0.0780***
	(0.0213)	(0.0228)	(0.0237)
pre_treatment(-1)	0.0284	0.0278	0.0310
	(0.0212)	(0.0214)	(0.0215)
pre_treatment(-2)	-0.00284	-0.00345	-0.000193
	(0.0181)	(0.0183)	(0.0185)
pre_treatment(-3)	-0.0124	-0.0129	-0.00954
	(0.0246)	(0.0247)	(0.0249)
pre_treatment(-4)		-0.00510	-0.00182
		(0.0209)	(0.0210)
pre_treatment(-5)			0.0243
			(0.0240)
pre_treatment(-1)_HealthP	-0.0305	-0.0280	-0.0215
	(0.0650)	(0.0655)	(0.0659)
pre_treatment(-2)_HealthP	0.0584	0.0608	0.0673
	(0.0714)	(0.0719)	(0.0723)
pre_treatment(-3)_HealthP	0.0611	0.0635	0.0700
	(0.0818)	(0.0822)	(0.0825)
pre_treatment(-4)_HealthP		0.0190	0.0255
		(0.0641)	(0.0645)
pre_treatment(-5)_HealthP			0.0565
			(0.0783)
post_treatment_1	-0.0541***	-0.0548***	-0.0516***
	(0.0115)	(0.0118)	(0.0120)
post_treatment_2	-0.0287**	-0.0294**	-0.0261*
	(0.0142)	(0.0144)	(0.0146)
post_treatment_3	-0.0507***	-0.0513***	-0.0480***
	(0.0128)	(0.0131)	(0.0133)
post_treatment_4		-0.0348**	-0.0316**
		(0.0137)	(0.0139)
post_treatment_5			-0.0172
			(0.0185)
after_3_3days	-0.0233***		
	(0.00903)		
after_4_3days		-0.0209**	
		(0.00999)	
after_5_3days			-0.0177*
			(0.0107)
post_treatment_1_HealthP	-0.114***	-0.112***	-0.106***
	(0.0315)	(0.0326)	(0.0333)
post_treatment_2_HealthP	-0.102***	-0.0996**	-0.0931**
	(0.0383)	(0.0392)	(0.0397)
post_treatment_3_HealthP	-0.0643	-0.0619	-0.0554
	(0.0407)	(0.0415)	(0.0420)
post_treatment_4_HealthP		-0.0544	-0.0480
		(0.0414)	(0.0419)
post_treatment_5_HealthP			-0.0571
			(0.0541)
after_3_HealthP	-0.0198		
	(0.0285)		
after_4_HealthP		-0.00763	
		(0.0317)	
after_5_HealthP			0.0108
			(0.0342)
log_TripDollars	-0.119***	-0.119***	-0.119***
	(0.00410)	(0.00411)	(0.00411)
ItemUnits	0.00384	0.00398	0.00394
	(0.00260)	(0.00259)	(0.00260)
log_CostperUnit	0.174***	0.174***	0.174***
	(0.00657)	(0.00657)	(0.00658)
Constant	0.213***	0.212***	0.209***
	(0.0185)	(0.0189)	(0.0190)
Observations	7,450	7,450	7,450
R-squared	0.206	0.206	0.207

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 20. CCPA searches responding to its introduction (Robustness check)

Dep Var: Google_Trend_Awareness_Index	(1) Three Weeks	(2) Two Weeks	(3) One Week
after_ccpa_anouncement	8.966*	14.15**	15.88*
	(5.280)	(6.288)	(8.654)
Constant	6.767**	2.693	5.386
	(3.135)	(2.697)	(5.421)
Observations	41	27	13
R-squared	0.070	0.175	0.238

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 21. The prediction power of Google Trends on people's online shopping behavior (Robustness check)

Dep Var: Online	(1) One month	(2) Three Weeks	(3) Two Weeks	(4) One Week
Lag1_Google_Trend_Awareness_Index	-0.00397*	-0.00366	-0.00903**	-0.0122**
	(0.00231)	(0.00288)	(0.00366)	(0.00565)
log_TripDollars	-1.651***	-1.659***	-1.751***	-1.717***
	(0.0624)	(0.0756)	(0.0899)	(0.126)
ItemUnits	0.149***	0.147***	0.132***	0.0778
	(0.0392)	(0.0355)	(0.0313)	(0.200)
log_CostperUnit	2.509***	2.441***	2.498***	2.570***
	(0.104)	(0.126)	(0.156)	(0.221)
Constant	-5.219***	-5.206***	-5.050***	-5.145***
	(0.695)	(0.873)	(1.158)	(1.367)
Demographics	N	N	N	Y
Observations	7,353	5,298	3,775	1,993

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1