Risk Perception of COVID-19 and Consumption Changes in California *

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Abstract

This paper studies the causal relationship between the risk perception of COVID-19 and consumption expenditure changes in the U.S. at the early stages of the pandemic. Although providing empirical evidence of the causal relationship between risk perception and spending is challenging due to possible endogeneity problems, I address this problem using a two-stage instrumental variable (IV) approach. Specifically, I use the weekly growth rate of COVID-19 cases in New York as a source of exogenous variation in consumer risk perception of COVID-19 in California. Two datasets are used for this purpose: (i) The University of Southern California (USC) Center for Economic and Social Research's Understanding Coronavirus in America Survey and (ii) The Opportunity Insights Economic Tracker. I focus on the period from April 1, 2020 to January 2, 2021, before the COVID-19 vaccine was publicly available in California. The results show that the growth rate of confirmed cases in New York is a strong instrument that has a positive and statistically significant effect on California residents' risk perception of death, infection, money loss, and job loss due to COVID-19. Moreover, I find a statistically significant causal relationship between risk perception and consumption expenditures. This effect is negative for major consumption categories, such as accommodation and food services, health care and social assistance, and sporting goods and hobbies. On the other hand, the effect is positive for grocery and food stores and arts, entertainment, and recreation.

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1 Introduction

The World Health Organization declared the rapid spread of COVID-19 a global public health emergency in March 2020. According to International Monetary Fund (IMF), coronavirus infection has not only become a public health crisis but has also caused the worst recession globally since the Great Depression. According to the Bureau of Economic Analysis (2020), GDP decreased by $2 trillion, at an annual rate of 31.4 percent, from the first quarter of 2020 to the second quarter of 2020. The primary reason for the GDP drop was a reduction in personal consumption expenditures, which decreased by $1.45 trillion. On the other hand, the personal saving rate rocketed to 33.8 percent in April 2020, more than doubling its 2019 value.

The literature suggests four possible channels to explain why households increased savings and reduced consumption expenditures during the COVID-19 crisis. First, increased uncertainty about future income and employment prospects reduced consumption incentives and generated so-called precautionary saving (Lelan, 1968; Kimball, 1990), as was also the case during the Great Recession (Mody, 2012). Second, legal shut-down orders gave rise to the practice of forced savings (Dossche et al., 2020). Third, spending decreased due to loss of income. Finally, households reduced their consumption expenditures due to the risk perception of COVID-19, i.e., individuals' subjective assessment of risks, such as infection or death, associated with the coronavirus. People's risk perception affects how they evaluate external threats, make decisions, and act. When individuals perceive an external threat, they take various actions, including conservative ones, to deal with risk and uncertainty. Therefore, risk perception and risk-related behaviors may amplify the economic impact of disasters far beyond their direct consequences (Burns and Slovic, 2012). This paper examines how individuals change expenditures in response to risks and uncertainties caused by the COVID-19 crisis.

Studies concerning the third channel, the income component of the COVID-19 crisis, argue that households who lost their jobs during the pandemic, mostly lower-income individuals, were more than compensated by the Coronavirus Aid, Relief, and Economic Security (CARES)

Act[1] payments (Chetty et al., 2020; Farrell et al., 2020). They also argue that the spending of these households increased after receiving these supplemental payments (Baker et al., 2020; Farrell et al., 2020). In addition, Baker et al. (2020) show that the propensity to consume was significantly lower among individuals expecting a job loss than those who considered losing a job unlikely, consistent with the precautionary saving channel.

The subjective expected utility (SEU) model of Savage (1951) is one of the most widely used economic models for representing preferences under uncertainty. Savage assumes that choices arise from maximizing an expected utility calculated by an individual's perceived or subjective assessments of risk. As in the subjective expected utility model of Savage, this paper studies agents' subjective beliefs about the states of the world and their updated beliefs when new information arrives. According to Savage, deviations from the subjective expected utility (SEU) framework indicate irrationality. Nevertheless, his theory is based on ideal economic assumptions. For example, it breaks when there is a new event that individuals do not have enough information about, such as a new virus where data and technology are scarce. However, the process of choice is a complex and multidetermined phenomenon in reality because individuals are confronted with a diverse array of information. People change their beliefs in the face of new information, and these changes in beliefs result in alterations in their choices, such as consumption and saving. Therefore, more empirical analyses of how individuals make choices when faced with new threats are needed to improve public policies.

This paper shows how the risk perception of COVID-19 changed consumption expenditures in California from April 1, 2020 to January 2, 2021, the period before the vaccine was publicly available. By merging two datasets: (i) The University of Southern California (USC) Center for Economic and Social Research's Understanding Coronavirus in America Survey and (ii) The Opportunity Insights (O.I.) Economic Tracker, I obtain information on California residents' subjective assessment of the level of risk associated with COVID-19 and changes in personal consumption expenditures in California. I analyze the relationship by using an

[1] Coronavirus Aid, Relief, and Economic Security (CARES) Act was a $2 trillion emergency assistance package approved in 2020 in response to COVID-19. The package also included expanded unemployment insurance (UI) benefits, such as the Pandemic Unemployment Assistance (PUA) and the Pandemic Emergency Unemployment Compensation (PEUC).

instrumental variable (IV) approach. Specifically, I use the weekly growth rate of COVID-19 cases in New York as a source of exogenous variation in consumer risk perception in California.

In the analysis, I first investigate the effect of the weekly growth rate of COVID-19 cases in New York on the perceived risk of COVID-19 in California. I use four measures for risk perception: death, infection, money loss, and job loss. The results show a significant positive relationship between the growth rate of COVID-19 cases in New York and California residents' risk perception for all four measures before the COVID-19 vaccine was publicly available in California. In particular, the F-statistics associated with the instrument, the weekly growth rate of COVID-19 cases in New York, are well above conventional thresholds. These results give me confidence that I have a strong instrument in the first stage that will help me to identify the causal effect of risk perception on consumption expenditure changes. Accordingly, in the second stage, I use the predicted values of risk perception measures from the first stage to estimate their impact on spending changes in California. I use two-stage least squares (2SLS) estimation and robust standard errors. The results show that California residents' perceived risk of death, infection, running out of money, and job loss due to COVID-19 increases when the weekly rate of confirmed cases increases in New York. The results also show a significant negative effect of risk perception on consumers' spending on major consumption categories such as accommodation and food services, health care and social assistance, and sporting goods and hobbies. On the other hand, the effect is positive for two categories of consumption: grocery and food stores and arts, entertainment, and recreation. The results show that individuals substitute spending for necessities and entertainment goods during the COVID-19 pandemic.

The literature on risk perception of a health threat comes from studies of previous pandemics such as the SARS epidemic (de Zwart et al., 2009), the H1N1 influenza pandemic (Rudisill, 2013; Poletti et al., 2011), and the Ebola outbreak (Yang and Chu, 2018; Prati and Pietrantoni, 2016). Recently, studies have applied theories of risk perception to the COVID-19 epidemic (Dryhurst et al., 2020; Savadori and Lauriola, 2021). Studies analyzing the relationship between the risk perception of COVID-19 and consumption provide consistent evidence that consumers' saving and spending decisions are affected by their assessment of the likelihood of infection (Chetty et al., 2020; Guglielminetti et al., 2021; Jin et al., 2021). For instance, Goolsbee and Syverson (2021), using cellular phone records of consumer visits to various businesses, show that legal shut-down orders accounted for only seven percent of the massive decline in consumer visits in the United States during the pandemic. Most of this decline in consumer visits was associated with the reported number of COVID-19 deaths, consistent with hypotheses that fear of infection was the main driver of consumption changes. Immordino et al. (2022), using a survey of Italian households, find that fear of the virus and income uncertainty reduced the probabilities of consumption and increased saving during the pandemic. Finally, Jin et al. (2021) find that the severity of the pandemic increased the risk perception of individuals and hence their saving (vs. spending) willingness.

Given that there is convincing evidence that risk perception has altered the spending behavior of consumers during the COVID-19 crisis, it is possible that the impact of government policies implemented at the macroeconomic level to stimulate consumption during the pandemic was much smaller than anticipated. Therefore, it is important to provide a further and more comprehensive analysis of the behavioral component of spending changes during the pandemic.

This study has several contributions to the existing literature. First, to the best of my knowledge, this paper is the first that analyzes the causal relationship between risk perception of the coronavirus and spending changes by using an instrumental variable (IV) approach. Identifying this relationship is challenging due to possible endogeneity problems. For example, a standard ordinary least squares (OLS) regression of consumption expenditures on risk perception might ignore confounding variables in the error term, which may be simultaneously correlated with consumer risk perception and spending. For instance, having a family history of common disorders such as heart and kidney diseases may simultaneously affect one's perception of the coronavirus and his consumption expenditures. This paper is the first to address this problem by using the weekly growth rate of COVID-19 cases in different geographical locations as an instrument.

The second contribution of this paper to the existing literature is to provide quantitative evidence of *how much* risk perception affected consumption expenditure changes during the pandemic. Previous studies have only observed whether risk perception changed an individual's spending behavior. This paper, however, demonstrates how much of the change in spending is attributable to risk perception. Thirdly, while the literature mainly focuses on two subjective measures of risk associated with the coronavirus-fear of contagion and fear of job loss-I have two additional measures of risk perception driven by COVID-19; perceived risk of death and running out of money due to COVID-19. The results show that the risk perception of death has the largest impact on consumption expenditure changes compared to the risks of infection, money loss, and job loss. This finding adds to the previous studies that examined the infection and income risks to explain changes in consumption behavior, often finding a bigger impact from the latter.

The last contribution of this paper to the existing literature is to provide a clearer picture of the role of risk perception on spending changes by looking at its effect on different consumption categories. In particular, this paper presents evidence that consumers' perceived risk of COVID-19 caused them to substitute spending for groceries and online entertainment products and services during the COVID-19 crisis.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 details the sample, methodology, and descriptive statistics. Section 4 describes the empirical strategy. Section 5 reports the main results of consumption changes. Finally, Section 6 concludes the paper and provides policy implications.

2 Data

This study merges two datasets: (i) The University of Southern California (USC) Center for Economic and Social Research's Understanding Coronavirus in America Survey and (ii) The Opportunity Insights (O.I.) Economic Tracker. USC's Understanding Coronavirus in America Survey is a probability-based online panel data started in March 2020 that includes US residents aged eighteen and older.[2] Most of the panel repeats on a fourteen-day cycle. Respondents are randomly assigned to fourteen survey invitation days to randomize the responses over the survey period. Each respondent has two weeks to complete the paper-based survey

[2]Respondents are randomly drawn from the universe of US Postal addresses and are provided with a tablet and broadband internet if needed.

questionnaire after the invitation date.[3] Surveys include core questions related to COVID-19, such as personal experiences with the coronavirus, subjective COVID-19 risk perceptions, coping behaviors, etc.

The O.I. Economic Tracker provides seasonally-adjusted high frequency and granular-level data on credit and debit card spending, employment, and several other outcomes. The data come from leading private companies, credit card processors to payroll firms, such as Affinity Solutions, Womply, and Burning Glass Technologies. The O.I. team makes the data publicly available by making several modifications to protect the confidentiality of the provider companies and their clients. For instance, the team reports the data values as percentages, where each value represents the change of the mean values in the first four weeks of January 2020 (Chetty et al., 2020). Also, the team provides all data values as 7-day moving averages to smooth out spikes and account for weekly patterns.

To analyze the effect of the pandemic on consumers, I gathered the daily total number of COVID-19 cases from the Centers for Disease Control and Prevention (CDC). CDC provides daily total cases for each state in the U.S. This paper uses the weekly growth rate of total COVID-19 cases in New York from April 1, 2020 to January 2, 2021.[4]

2.1 Consumption expenditures

The O.I. Economic Tracker collects consumption expenditures from Affinity Solutions Inc. through credit and debit card spending. Affinity Solutions captures approximately 10 percent of total credit and debit card spending in the U.S. (Chetty et al., 2020).

One of the potential concerns with card-based measures of spending is that they might be biased by substitution for cash purchases. To assess the importance of such substitution, the O.I. team examined cash purchases by obtaining cash receipts from CoinOut. This com-

[3] The first survey wave was in the field from March 10, 2020 to March 31, where all respondents received the survey on the same day, March 10, 2020. Starting after April 1, 2020, each survey period is administered bi-weekly and respondents are randomly assigned over fourteen survey invitation days.

[4] I use the daily values to construct a daily series of the weekly growth rate of the COVID-19 cases. Specifically, I take the average of the current day and the previous six days of COVID-19 cases to smooth any spikes that may arise due to the daily reporting of COVID-19 cases.

pany provides a mobile app where individuals receive rewards by uploading photos of their receipts. The findings show that aggregate fluctuations in card spending and cash spending have similar time trends. In other words, changes in card spending do not appear to be offset by opposite-signed changes in cash spending (Cetty et al., 2020). Therefore, O.I. Economic Tracker provides only card spending data due to larger sample sizes and greater granularity (daily) of such spending.

The data are available for all states and the District of Columbia (D.C.). My sample consists of households residing in California. Therefore, this paper obtains daily estimates of spending changes in California for five different consumption categories: spending on accommodation and food services, spending on arts, entertainment, and recreation, spending on grocery and food stores, spending on health care and social assistance, and spending on sporting goods and hobbies. Figure 1 shows the time trend for each category over the sample period, April 1, 2020 to January 2, 2021.

2.2 GPS measures

The O.I. Economic Tracker obtains GPS mobility records from Google COVID-19 Community Mobility Reports. Google provides mobility estimates for each state based on data from individuals who enable the Location History setting. The GPS measures indicate percentage changes in hours spent at different places for each day compared to a baseline value for that day of the week. The baseline is the median value for the corresponding day of the week over the period January 3 to February 6, 2020.

This paper uses daily estimates of GPS mobility changes in California for seven different categories of location: time spent outside of residential locations,[5] at retail and recreation locations, grocery and pharmacy locations, parks, workplaces, residential locations, and inside

[5]The difference between an estimate of time spent inside residential locations for each date and waking hours in the day provides an estimate for hours spent outside of residential locations. The O.I. team calculates the estimate of time spent inside the residential locations in two steps. First, the mean values of hours spent inside a home (excluding time asleep) in January 2018 are obtained from the American Time Use Survey. Second, the mean values are multiplied by Google's percent change in hours spent at residential locations for each date.

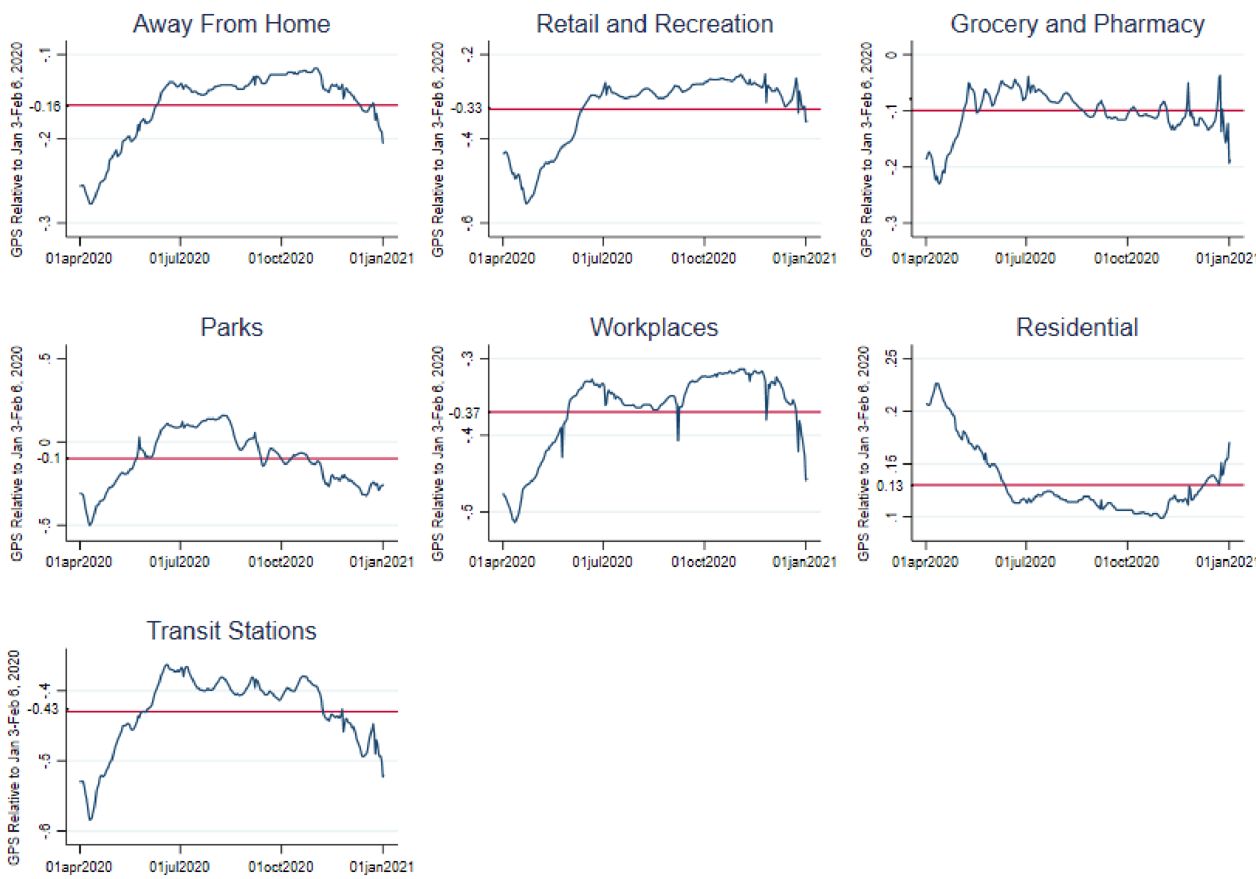
Figure 1: Changes in Credit and Debit Card Spending, CA

Note: Average values are marked for each spending category.

transit stations.[6] All data values are reported as 7-day moving averages. Figure 2 shows the time trend for each category over the sample period, April 1, 2020 to January 2, 2021.

[6]Retail and recreation includes places such as restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters. Grocery and pharmacy includes grocery markets, food warehouses, farmer's markets, specialty food shops, drug stores, and pharmacies. Parks includes local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens. Lastly, transit stations includes public transport hubs such as subway, bus, and train stations.

Figure 2: Changes in GPS mobility, CA

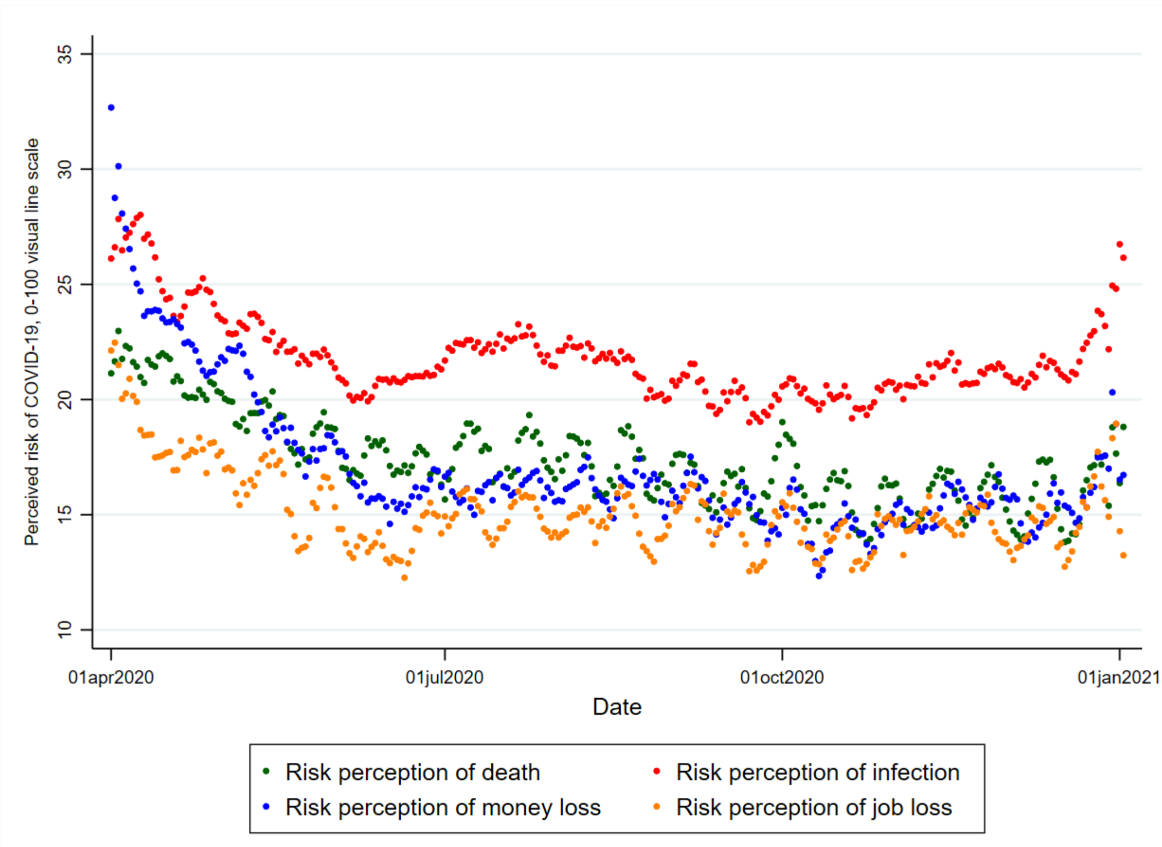


Note: Average values are marked for each GPS mobility category.

2.3 *Consumer risk perception of COVID-19*

To quantify individuals' perceived risk of COVID-19 in California, this paper uses four questions from the USC's Understanding Coronavirus in America Survey: "what is the chance that you will get the coronavirus in the next three months?" "if you do get the coronavirus, what is the percentage chance you will die from it?" "what is the percentage chance that you will lose your job because of the coronavirus within the next three months?" and "what is the percentage chance you will run out of money because of the coronavirus in the next three months?" All the questions use a 0 to 100 visual linear scale. Also, the questions align with measurements used in the literature to assess risk perception during the COVID-19 pandemic. Furthermore, since the O.I. Economic Tracker provides consumption expenditures and several other control variables on a daily basis, the USC's Understanding Coronavirus in America Survey is aggregated at a daily level based on the time respondents completed each survey.[7] Lastly, this paper uses 7-day moving averages of the risk perception measures in the analyses to maintain the integrity between the two datasets. Figure 3 shows how risk perception of death, infection, money loss, and job loss are distributed over time.

Figure 3: Risk Perception of COVID-19



2.4 Control Variables

I use a wide range of demographic characteristics and some indicator variables from USC's Understanding Coronavirus in America Survey as control variables. Since the survey data are aggregated among respondents at a daily level, the demographic and indicator variables

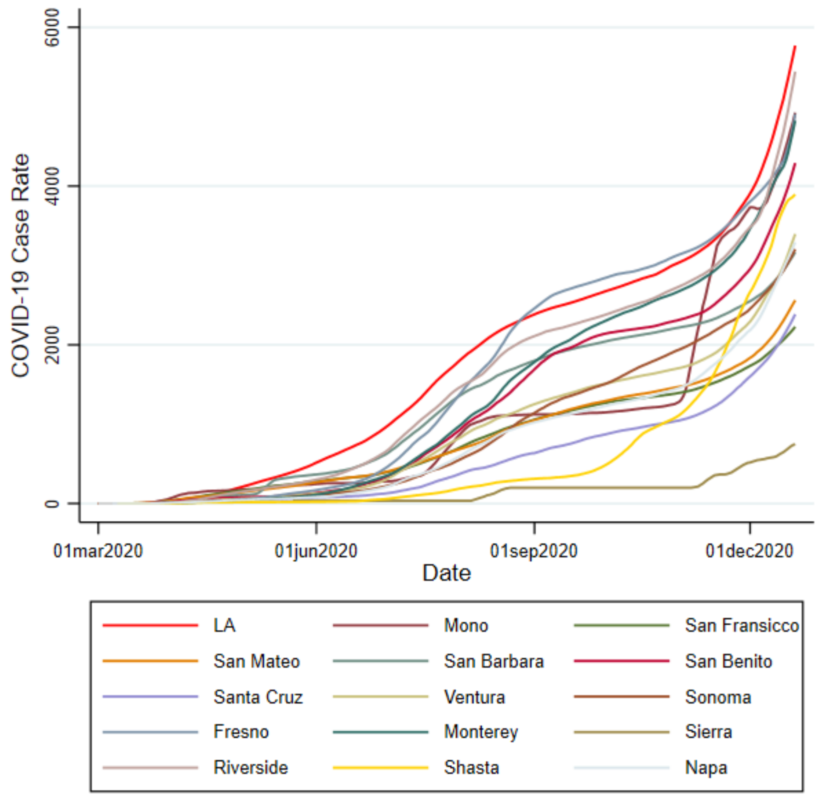
[7]Since responses are randomized over the survey period with different survey invitation days, I have a data point for each day from April 1, 2020 to January 2, 2021.

are included as shares of the sample. The demographic characteristics include age, gender, marital status, citizenship status, immigrant status, and income. Specifically, share variables represent the ratio of respondents with the above characteristics on the relevant survey day to the total number of respondents on the same day. As these variables may affect individuals' risk perceptions and willingness to spend, they are used as control variables. For example, using a survey of over 1,500 Americans, Bordala et al. (2020) document a striking finding that perceived health risks associated with COVID-19, such as contracting the virus, being hospitalized, and dying, decline with age. According to the authors, COVID-19 was a "disease and death" shock for young people, which was unexpected and salient. Therefore, this shock inflated COVID-19 and other non-COVID-19-related health risks among youth.

On the other hand, the indicator variables include if an individual has insurance, if the individual is disabled, if the individual is diagnosed with coronavirus, if the individual works or studies from home, if the individual has been placed in isolation or quarantine in the past seven days, and if the individual has sought care from a hospital or a health care facility in the past seven days. Again, the ratio of respondents who have the above characteristics on the relevant survey day to the total number of respondents on the same day is included as a control. Controlling these characteristics is important because they may alter individuals' risk perceptions. For instance, direct experience with the virus may change individuals' risk perception (Savadori and Lauriola, 2021). Similarly, the perceived risk of COVID-19 may be lower for people who work from home because they are less likely to go out to meet other people. If the number of respondents who work from home is high on the relevant survey day, they may alter the results. In addition to the above variables, the share of Los Angeles (LA) County residents in the sample is added as a control variable for two main reasons. First, the coronavirus case rates in Los Angeles may differ from other California counties. Figure 4 shows daily COVID-19 case rates for fifteen counties in California with the highest case rates during the pandemic. The graph shows that rates are much higher in Los Angeles than in the other counties, presumably due to demographic differences in this location. Figure 5 maps the geographic location of California counties.

Second, Los Angeles followed different local policy strategies to prevent the spread of the virus. For instance, LA mayor Eric Garcetti enacted a non-essential business closure order

Figure 4: Confirmed COVID-19 Cases Per 100,000 by California County



Note: The COVID-19 case rates are presented as a 7-day moving average.

earlier than statewide stay-at-home orders.[8] Therefore, controlling for the share of LA residents in the sample is essential to eliminate any variations in individuals' risk perceptions and spending behaviors that may arise from the above differences in Los Angeles.

This paper focuses on how changes in consumer spending respond to individuals' subjective judgments of COVID-19, such as their perceptions of contracting the virus, dying, running out of money, and losing their jobs due to the virus. However, other factors also affected consumer spending during the pandemic. The revenues and employment of small businesses, such as food and accommodation services, changed remarkably. Studies show that the economic impact of the pandemic on entrepreneurship and small businesses was harsh, with many busi-

[8]On March 16, 2020, Los Angeles implemented a non-essential business closure order, whereas California's statewide stay-at-home order began on March 19, 2020.

Figure 5: California County Map

ness closures. Therefore, changes in net revenues for small businesses and the number of business closures are obtained from the O.I. Economic Tracker and added as controls.[9] Lack of purchasing power due to unemployment is another reason, but this is thought to be offset by government policies such as unemployment benefits. As the COVID-19 pandemic brought the U.S. economy to a sudden decline in March 2020, the government enacted the Coronavirus Aid, Relief, and Economic Security (CARES) Act program on March 27, 2020 to help workers impacted by the pandemic. The program included a $2 trillion coronavirus emergency stimulus package as well as expanded unemployment insurance (UI) benefits, such as

[9]The O.I. Economic Tracker measures small business revenues from Womply through records from credit card transactions for small businesses.

the Pandemic Unemployment Assistance (PUA) and the Pandemic Emergency Unemployment Compensation (PEUC). Studies show that CARES Act has played a crucial role in mitigating spending reductions in several industries, including health care (Chetty et al., 2020; Evangelist et al., 2022). Therefore, California's state-level unemployment insurance claims rates[10], the pandemic unemployment assistance (PUA), and the pandemic emergency unemployment compensation (PEUC) claims rates are included as controls along with the consumer price index to observe the actual impact of risk perception on spending changes.[11]

3 Sample, methodology, and descriptive statistics

The sample contains California state residents from April 1, 2020 to January 2, 2021. The sample period consists primarily of 2020 as COVID-19 vaccines became publicly available in California after January 2021. According to San Francisco Chronicle (2020), health care workers in California received their first coronavirus vaccinations on December 14, 2020. The vaccine became available to everyone aged 65 and over after January 13, 2021. And finally, it became available to all adults starting on April 15, 2021. Since this paper uses many questions related to subjective COVID-19 risk perceptions in the analyses, the sample period is limited to 2020 to avoid a potential impact of the vaccines on individuals' risk perception.

There are 36,348 households representing adult residents in California in the survey dataset. The USC's Understanding Coronavirus in America survey randomizes responses over the survey period by assigning individuals a different survey invitation day where they have 14-days to complete the survey. In other words, the data gives a set of randomized responses each day from April 1, 2020 to January 2, 2021. On the other hand, O.I. Economic Tracker provides data at a daily level. Thus, I aggregated the Understanding Coronavirus in America survey at a daily level, based on the time respondents completed each survey, to merge these values with the consumption changes from O.I. Economic Tracker. In addition, I included all

[10]The O.I. Economic Tracker calculates unemployment insurance (UI) claims rates by dividing unemployment claims counts by the Bureau of Labor Statistics labor force estimates from 2019.

[11]PUA and PEUC are funded by the federal government but adopted and administered by the states. See the Appendix C for the details of California's unemployment compensation program administered by the Employment Development Department (EDD).

responses from the survey data when aggregating the sample at a daily level.[12] As a result, merging two datasets gave me the final sample with a total of 277 observations, i.e., 277 days representing the relation between consumption changes and risk perception. This final sample is used in all the regression analyses in this paper.

Table 1 provides descriptive statistics of the outcome variables, risk perception categories, and control variables. The share variables are included in the regressions on each survey day, representing the percent of respondents with specific characteristics. For example, the mean value of the *share of females* indicates that the average ratio of women to men per 277 days (April 1, 2020-Jan 2, 2021) is 60%. The aim of adding the share variables is to control for any differences in responses that may arise from differences in individuals' characteristics.

Risk perception of infection has the highest sample mean among other risk perception categories. The average risk perception of infection per 277 days is 21.81 out of 100-scale. Similarly, the average risk perception of death, job loss, and money loss due to COVID-19 per 277 days are 17.35, 15.15, and 17, respectively. In other words, people's perceived probability of contracting the virus is higher than the probability of death, running out of money, and losing their jobs due to COVID-19 during the sample period. When we look at the spending categories, people, on average, decrease their spending for all the consumption categories except grocery and food stores and arts, entertainment, and recreation. Also, notice that spending on grocery and food stores never goes below 0 during the whole sample period. On the other hand, the GPS mobility categories show that people decrease the amount of time (hours) spent outside of residential locations. Changes in time spent at parks has the highest volatility, presumably due to changing stay-at-home orders during the sample period.

Table 1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Outcome Variables					
Spending on grocery and food stores	277	0.14	0.04	0.03	0.31
Spending on arts, entertainment, recreation	277	-0.64	0.06	-0.80	-0.50
Spending on sporting goods and hobby	277	0.34	0.21	-0.24	0.65

[12]Missing observations because the survey was not fully completed, or the respondent did not know the answer or refused to answer the question were excluded.

Table 1 continued

Variable	Obs	Mean	Std. Dev.	Min	Max
Spending on accommodation and food services	277	-0.45	0.13	-0.71	-0.29
Spending on health care and social assistance	277	-0.15	0.20	-0.59	0.23
Time spent away from home	277	-0.16	0.04	-0.28	-0.12
Time spent at grocery and pharmacy	277	-0.10	0.04	-0.23	-0.04
Time spent at retail and recreation	277	-0.33	0.08	-0.55	-0.25
Time spent at parks	277	-0.10	0.16	-0.50	0.16
Time spent at inside transit stations	277	-0.43	0.05	-0.58	-0.36
Time spent at workplaces	277	-0.37	0.05	-0.51	-0.31
Time spent at residential locations	277	0.13	0.03	0.10	0.23
Risk Perceptions					
Risk perception of infection	277	21.81	1.79	19.01	28.02
Risk perception of death	277	17.35	1.94	13.81	22.97
Risk perception of job loss	277	15.15	1.73	12.27	22.47
Risk perception of losing money	277	17.00	3.12	12.34	32.68
Other Controls					
Employment level for all workers	277	-0.15	0.04	-0.25	-0.13
Percent change in net revenue for small businesses	277	-0.31	0.08	-0.55	-0.19
Percent change in small businesses open	277	-0.32	0.04	-0.44	-0.23
Continued claims rate, regular UI	277	11.72	4.40	2.06	24.80
Continued claims rate, PUA	277	11.27	7.73	0.00	36.00
Continued claims rate, PEUC	277	2.89	2.54	0.00	7.12
Consumer price index	277	0.97	0.40	0.24	1.40
Share of females	277	0.60	0.06	0.00	1.00
Share of US citizens	277	0.93	0.04	0.50	1.00
Share of married people	277	0.47	0.07	0.00	1.00
Share of white people	277	0.68	0.08	0.00	0.88
Share of Asian people	277	0.13	0.06	0.00	1.00
Share of LA county residents	277	0.57	0.09	0.00	0.67
Share of disabled people	277	0.05	0.02	0.00	0.13
Medicaid people share	277	0.08	0.07	0.00	1.00
Medicare people share	277	0.23	0.08	0.00	1.00
Share of people who have health insurance	277	0.89	0.05	0.50	1.00
Age (mean)	277	47.47	1.94	36.00	52.50

Table 1 continued

Variable	Obs	Mean	Std. Dev.	Min	Max
Age squared (mean)	277	2523.91	195.52	1296.00	3006.76
Share of first-generation immigrants	277	0.23	0.08	0.00	1.00
Share of people diagnosed with COVID-19	277	0.01	0.03	0.00	0.50
Share of people seeking care from a health facility	277	0.07	0.07	0.00	1.00
Share of people who works/studies from home	277	0.56	0.08	0.00	1.00
Share of people placed in isolation/quarantine	277	0.05	0.04	0.00	0.50
Share of income less than $5,000	277	0.05	0.02	0.00	0.18
Share of income $5,000 - $7,499	277	0.02	0.01	0.00	0.11
Share of income $7,500 - $9,999	277	0.02	0.01	0.00	0.10
Share of income $10,000 - $12,499	277	0.03	0.01	0.00	0.11
Share of income $12,500 - $14,999	277	0.02	0.02	0.00	0.15
Share of income $15,000 - $19,999	277	0.03	0.03	0.00	0.50
Share of income $20,000 - $24,999	277	0.04	0.03	0.00	0.50
Share of income $25,000 - $29,999	277	0.04	0.02	0.00	0.12
Share of income $30,000 - $34,999	277	0.05	0.06	0.00	1.00
Share of income $35,000 - $39,999	277	0.05	0.02	0.00	0.18
Share of income $40,000 - $49,999	277	0.07	0.04	0.00	0.50
Share of income $50,000 - $59,999	277	0.07	0.03	0.00	0.33
Share of income $60,000 - $74,999	277	0.09	0.03	0.00	0.31
Share of income $75,000 - $99,999	277	0.12	0.04	0.00	0.22
Share of income $100,000 - $149,99	277	0.14	0.04	0.00	0.25
Growth rate of COVID-19 cases, NY	277	0.08	0.17	0.01	1.29

Note: Risk perception values are based on responses using a 0 to 100 visual linear scale. Mobility measures show the changes in hours spent compared to the base period (Jan 3-Feb 6). The share control variables do not represent the whole population. They are added in the regressions for each survey day to represent the portion of respondents with the above characteristics. They aim to control for any deviation in individuals' risk perception that may arise from the differences in their characteristics. For example, the mean value of *share of females* indicates that the average ratio of women to men per sample day (277 in total) is 60%.

4 Empirical strategy and results

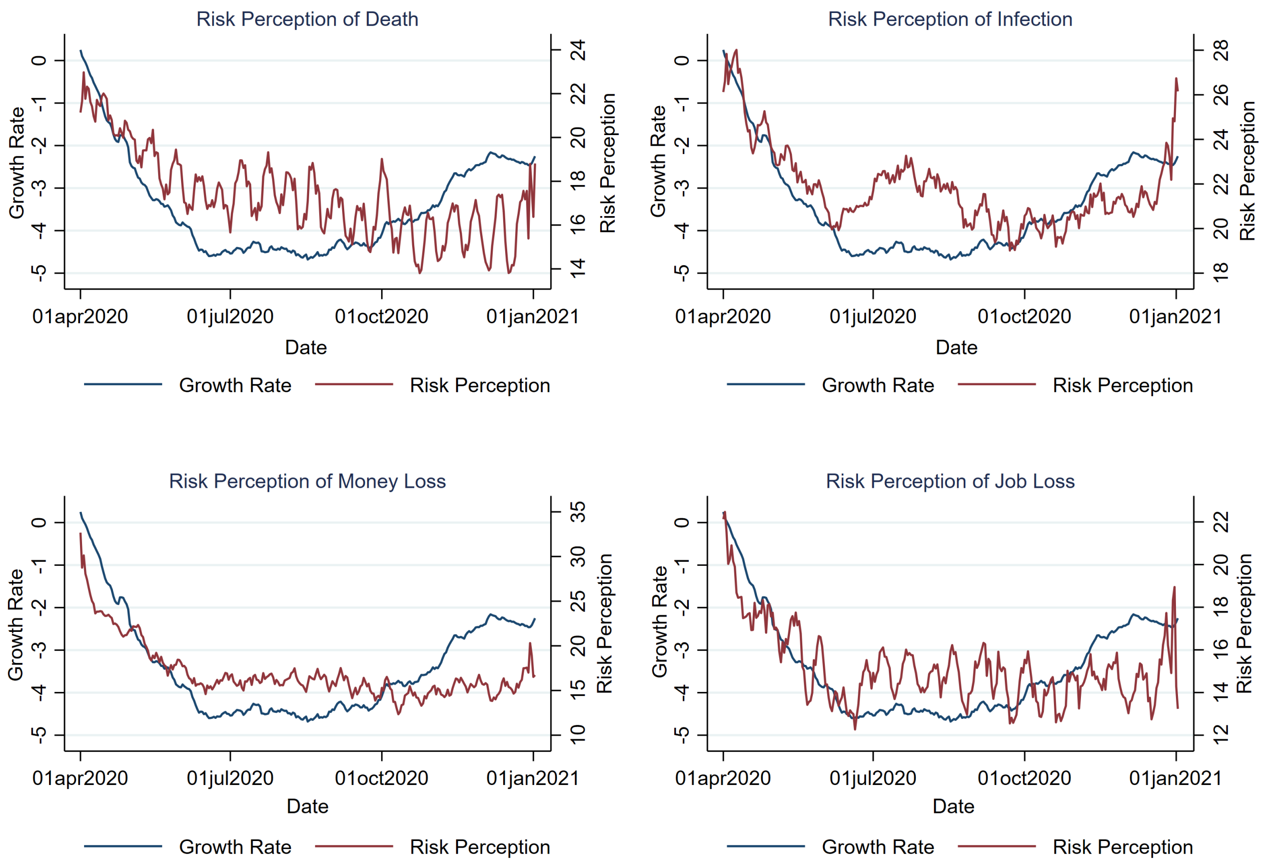
To analyze the effect of the perceived risk of COVID-19 on consumption expenditures, I use a two-stage instrumental variable regression (2SLS-IV) framework to control for potential endogeneity issues. Standard ordinary least squares (OLS) regressions yield biased estimates if unobserved factors in the error term correlate with risk perception and consumption expenditures. For example, if a person knows that he has a genetically weak immune system, this might influence his perception of death or infection and consumption. The same reason might also affect one's perceived risk of job loss by making him feel insecure because of the fear that his boss might find out about the situation. Another example that might cause a potential bias is one's personality. For instance, introverts might feel less likely to contract the virus than outgoing people who have potentially different preferences over different consumption categories.

This paper overcomes the potential endogeneity problem by using an instrumental variable approach to identify the causal impact of risk perception on spending. The severity of the pandemic in the State of New York (NY), as captured in the weekly growth rate of COVID-19 cases (ΔCC_t^{NY}), is used as an instrument for the risk perception of COVID-19 in California (RP_t) in the first stage along with other control variables (X_t). Monthly time-fixed effects (α_t) are included in all regressions to control for time-variant shocks that may be related to changes in consumption expenditures (ΔC_t).

Figure 6 provides a graphical overview of the relationship between the growth rate of COVID-19 cases in New York and California residents' perceived risk of COVID-19 for each of the four risk perception measures: death, infection, money loss, and job loss. The figures show graphically that the growth rate of COVID-19 cases in New York and the risk perception of COVID-19 move in the same direction.

To obtain unbiased estimates of the causal impact of risk perception on consumption expenditure changes in California, the instrument must meet two conditions. First, the estimated covariance between the instrument and risk perception must be non-zero (relevance). In other words, the weekly growth rate of COVID-19 cases in New York must cause variation in California residents' risk perception in the first stage. Second, the instrument must affect consumption expenditures only through the variation it creates in risk perception (exclusion restriction). The first condition is based on Kasperson et al.'s (1988) social amplification of risk framework (SARF) suggests that social media often plays a crucial role in influencing how the risks associated with particular hazards and events are perceived and responded to

Figure 6: Risk Perception in CA and Growth Rate of COVID-19 Cases in NY



Note: The figure plots the relationship between the growth rate of COVID-19 cases in New York and the perceived risk of COVID-19 for each of the four risk perception measures: death, infection, money loss, and job loss. The sample covers the period from April 1, 2020 to January 2, 2021.

by the public. In particular, the means of social media might function as a "social amplification station" in shaping the social experience of a hazard and social perception of risk through either the amplification (Ali et al., 2019; Tsoy et al., 2021) or reduction of the public risk perception (Kasperson et al., 1988). This paper focuses on the first (risk amplification) stage and assumes that media outlets increase perceptions of risk, risk-related behaviors, and consequences of the risk (Kasperson et al., 2022; Kasperson et al., 1988). Various national media outlets and social media platforms had daily reports and updates on the number of COVID-19 cases in New York during the sample period because the coronavirus outbreak started very early and ravaged New York very quickly. For example, according to NBC News, the reported caseload in New York was more than in any country observed by April 10, 2020 (Millman, 2020). Based on the above literature on the role of media in shaping risk perception, I assume that the increased exposure to news on the growth rate of COVID-19 cases in New York causes variation in California residents' consumption expenditure changes through media channels. Second, the instrument is assumed to satisfy the exclusion restriction. One of the potential violations of the exclusion restriction is the possibility that COVID-19 cases in New York directly affected consumption in California by disrupting freight flows from New York to California. However, there is no compelling evidence that goods transported from New York to California were interrupted during the pandemic. According to the INRIX report (2020), analyzing long-haul freight movements during the pandemic, changes in freight movements across the country reflect imbalances in demand due to stay-at-home orders. The American Transportation Research Institute (2020) also supports the argument that legal shut-down orders were responsible for changing truck activities during the pandemic.

There is also the possibility that COVID-19 cases in New York influenced stay-at-home regulations in California, which, in turn, affected consumption in California. California was the first state to issue a stay-at-home order on March 19, 2020. [13] On the other hand, New York was one of the earliest states to experience high surges in COVID-19 cases. Figure 9 in the Appendix D shows the daily trends in the number of COVID-19 cases in California and New York. Due to the rapid increase in COVID-19 cases in California from February 2 to March 19 (675 in total), the state issued a stay-at-home order to curb the coronavirus. However, COVID-19 cases only started to accelerate in New York *after* the stay-at-home order in California. On this basis, it seems unlikely that the growth rate of COVID-19 cases in New York affects California's legal restrictions. Based on the lack of evidence for disruption in freight flows from New York to California and the point that regulations in California were not influenced by COVID-19 cases in New York, the instrument seemingly satisfies the exclusion restriction.

[13] Transportation providers are exempt from state-issued stay-at-home orders as transportation qualifies as an essential business.

Then, the first stage analysis is based on the following econometric specification:

$$RP_t = \alpha_t + \beta_t \Delta CC_t^{NY} + \gamma_t X_t + u_t \tag{1}$$

where the variable ΔCC_t^{NY} is the instrument that denotes the weekly growth rate of COVID-19 cases in New York. The variable RP_t corresponds to one of four risk perception questions (death, infection, money loss, and job loss) for California residents. X_t is a vector of control variables. The variables α_t and u_t denote monthly time-fixed effects and a disturbance term, respectively. First stage results with alternative controls are shown in Table 2 for each of the four risk perception categories.

Table 2: First Stage Regressions

Growth rate of COVID-19 Cases and Risk Perceptions

	(1)	(2)	(3)	(4)	(5)
			Risk perception of death		
Growth rate of cases	1.930**	1.895**	1.850**	2.817**	2.961**
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Observations	277	277	277	277	277
F-stat.	11.08	9.64	9.54	10.58	11.22
R-squared	0.850	0.851	0.853	0.876	0.877
Adjusted R-squared	0.826	0.826	0.828	0.851	0.851
			Risk perception of infection		
Growth rate of cases	3.738***	3.711***	3.687***	4.589***	4.565***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	277	277	277	277	277
F-stat.	36.01	34.54	34.18	43.32	41.33
R-squared	0.894	0.895	0.895	0.922	0.922
Adjusted R-squared	0.877	0.877	0.877	0.906	0.906
			Risk perception of money loss		
Growth rate of cases	8.452***	8.450***	8.445***	12.640***	12.663***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	277	277	277	277	277
F-stat.	176.12	173.19	174.23	193.36	215.13
R-squared	0.926	0.926	0.926	0.954	0.957
Adjusted R-squared	0.914	0.914	0.914	0.944	0.947
			Risk perception of job loss		
Growth rate of cases	4.593***	4.542 ***	4.514***	5.792***	5.918***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 2 continued

	(1)	(2)	(3)	(4)	(5)
Observations	277	277	277	277	277
F-stat.	177.64	152.89	157.94	46.52	49.16
R-squared	0.801	0.804	0.805	0.825	0.826
Adjusted R-squared	0.769	0.772	0.772	0.790	0.789

Note: Column (1) uses only demographics as control variables. Column (2) is the same as column (1) but adds diagnosed share as a control. Column (3) is the same as column (2) but adds clinic share as a control. Column (4) is the same as column (3) but adds local economy controls and the consumer price index. Column (5) is the same as column (4) but adds work home and isolated share as controls. All estimations control for monthly fixed effects. The F-statistic tests whether the coefficient on the growth rate of cases is equal to zero. P-values are in parentheses, * p<0.05, ** p<0.01, *** p<0.001.

The first stage relationship between the growth rate of COVID-19 cases and the perceived risk of COVID-19 is strongly positive for each risk perception category. Also, the relationship is robust to the inclusion of several different controls, including local economy measures and isolated share. The COVID-19 cases in New York are correlated with an individual's perceived risk of the pandemic in California. The observed positive relationship is not surprising due to the significant role of mass media in shaping individuals' risk perception. The Sanderson-Windmeijer (SW) first stage F-statistics for weak identification is used to test if the endogenous regressors are weakly identified. The F-statistics tests whether the coefficient on the growth rate of cases is equal to zero. The magnitude of the statistics documents the strength of the instrument. As shown in Table 2, the estimated SW F-statistics for the risk perception of death, infection, money loss, and job loss are far beyond the critical values.[14] The reported F-statistics indicates that the growth rate of COVID-19 cases is a strong instrument for risk perception. Note that the instrument is weaker for the risk perception of death, suggesting that the instrumental variable estimates for this regressor may be somewhat biased. The estimated first stage F-statistics also provides statistical evidence that the instrument satisfies the relevance condition.

The second stage equation estimates the impact of risk perception on the changes in con-

[14]Stock and Yogo (2005) weak ID F-test critical values for a single endogenous regressor: 10% maximal IV size is 16.38. 15% maximal IV size is 8.96. 20% maximal IV size is 6.66. 25% maximal IV size is 5.53.

sumption expenditures in California:

$$\Delta C_t = \sigma_t + \delta_t \widehat{RP_t} + \theta_t X_t + \zeta_t \tag{2}$$

where δ_t is the parameter of interest, which captures the causal effect of the risk perception of COVID-19 on consumption expenditure changes. The variable $\widehat{RP_t}$ corresponds to the predicted values of one of the risk perception measures (death, infection, money loss, and job loss) from the estimation of Eq. (1). X_t is a vector of control variables. The variables σ_t and ζ_t denote monthly time-fixed effects and a disturbance term, respectively.

Before giving the estimation results from Eq. (2), which shows the relationship between spending changes and risk perception of COVID-19 in California, I start by showing reduced-form evidence of the relationship between spending changes in California and the growth rate of COVID-19 cases in New York. Figure 7 provides some graphical evidence that California residents' consumption expenditure changes and the growth rate of COVID-19 cases in New York move together, although not perfectly. Also, Table 15 in the Appendix A reports the reduced-form estimates.

Also, this paper finds a high correlation between all four risk perception variables (death, infection, money loss, and job loss) with each other. Table 3 shows that the risk perception measures have a positive relationship with each other.

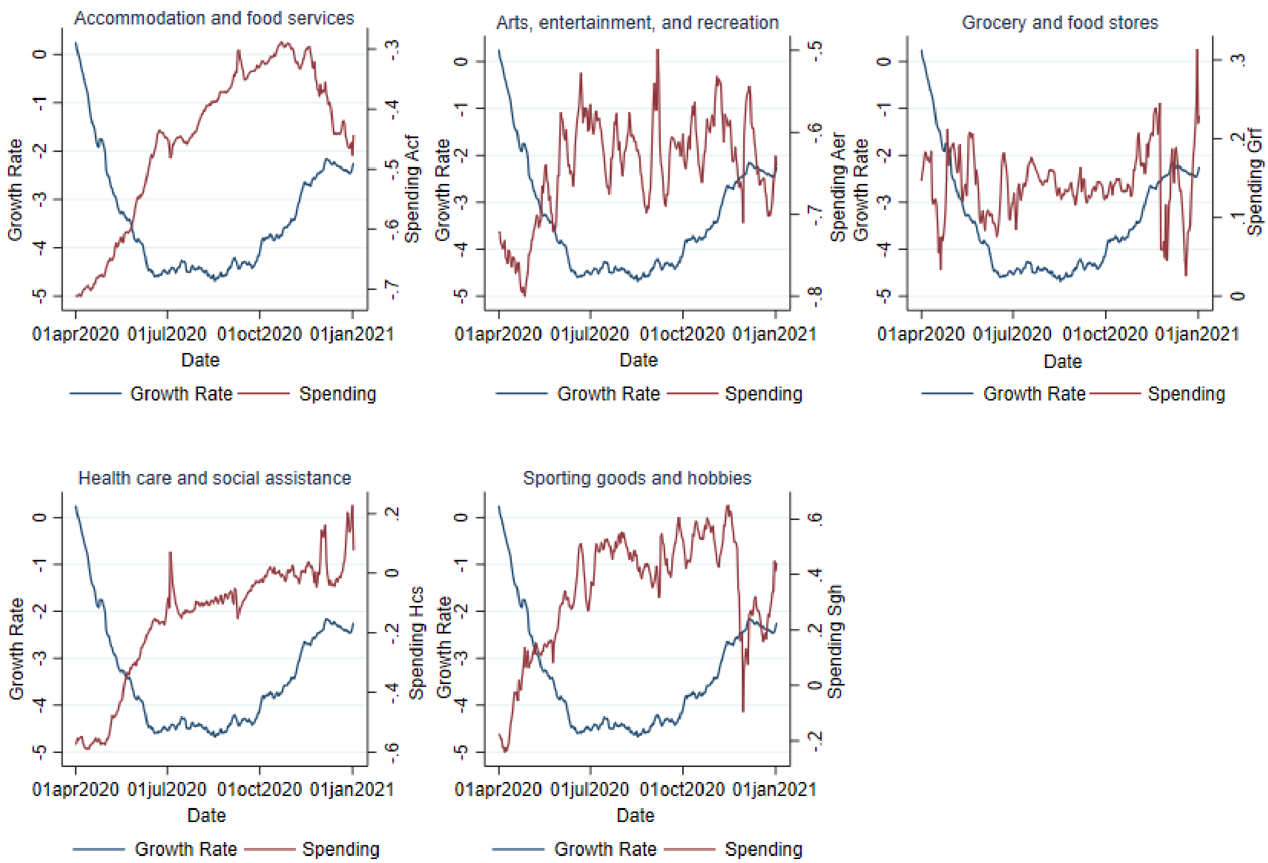
Table 3: Correlation Table

	Death	Infection	Money loss	Job loss
Death	1.0000			
Infection	0.7900	1.0000		
Money loss	0.8243	0.8423	1.0000	
Job loss	0.8004	0.8217	0.8377	1.0000

Note: This table shows the correlation among risk perception of death, infection, money loss, and job loss due to COVID-19.

The following tables report the estimation of Eq. (2) for five major consumption categories: (i) Accommodation and food services, (ii) Arts, entertainment, and recreation, (iii) Grocery and food store, (iv) Health care and social assistance, and (v) Sporting goods and hobbies. The tables and their interpretation are addressed below.

Figure 7: Consumption Expenditure Changes in CA and Growth Rate of COVID-19 Cases in NY



Note: The figure plots the relationship between the growth rate of COVID-19 cases in New York and consumption expenditure changes in California for each of the five consumption categories: accommodation and food services, arts, entertainment, and recreation, grocery and food stores, health care and social assistance, and sporting goods and hobbies. The sample covers the period from April 1, 2020 to January 2, 2021.

4.1 Accommodation and food services

Table 4 reports the estimation results for accommodation and food services considering various control variables. The results indicate that all risk perception measures decrease accommodation and food services spending. Considering that food and accommodation services require high levels of physical interaction, the negative results of spending changes are reasonable. Individuals reduced their consumption expenditures on restaurants, bars, coffee shops, and hotels as their perceived probability of contracting the virus, dying, running out of money, and losing their jobs due to COVID-19 increases.

Table 4: Second Stage Regressions

Risk Perceptions and Spending on Accommodation and Food Services

	(1)	(2)	(3)	(4)	(5)
	Accommodation and food services				
Risk perception of death	-0.021***	-0.023***	-0.023***	-0.032**	-0.029**
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Risk perception of infection	-0.011***	-0.012***	-0.012***	-0.020***	-0.019***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Risk perception of money loss	-0.005***	-0.005***	-0.005***	-0.007***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Risk perception of job loss	-0.009***	-0.009***	-0.010***	-0.016***	-0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	277	277	277	277	277
R-squared	0.971	0.971	0.971	0.986	0.987
Adjusted R-squared	0.966	0.967	0.967	0.984	0.984
Monthly fixed effects	Y	Y	Y	Y	Y
Demographic controls	Y	Y	Y	Y	Y
Diagnosed share		Y	Y	Y	Y
Clinic share			Y	Y	Y
Local economy controls and CPI				Y	Y
Work home and isolated share					Y

Note: The columns show percentage changes in the relevant consumption categories. Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

The coefficient estimates are all highly significant and negative for all the risk perception measures. They also generally increase in magnitude as we control for more local economy measures. My main specification, the last column, shows that an individual's perception of death risk has the largest impact on spending drop in this consumption category, followed by the infection risk. Table 4 demonstrates that an individual's perception of death risk is responsible for 2.9% of the change in expenditure reductions in accommodation and food services. The effect is 1.9% for the perception of infection risk, 0.7% for running out of money risk, and 1.4% for the job loss risk.

4.2 Arts, entertainment, and recreation

Table 5 shows the estimation results for arts, entertainment, and recreation. The coefficient estimates are significant and positive for all the risk perception measures. Also, the coefficient estimates again generally increase as we add more control variables.

Table 5 demonstrates that an individual's perception of death risk has the largest impact on spending increase in this consumption category, followed by the infection risk. From the last column of Table 5, it can be seen that an individual's perception of death risk is responsible for 2.2% of the increase in expenditures on accommodation and food services. The effect is 1.4% for the perception of infection risk, 0.5% for running out of money risk, and 1.1% for the job loss risk.

The positive impact of the perceived risk of the pandemic on this consumption category is presumably because of the growing digital entertainment industry during the pandemic. According to the Motion Picture Association (MPA) THEME Report (2020), digital streaming subscriptions, for instance, Netflix, Amazon Prime, Hulu, HBO, Twitch, and Disney+, increased significantly during the pandemic with the growing number of stay-at-home viewers. Figure 10 in the Appendix D shows that digital revenue in the U.S. increased 33% over the year 2020 ($26.5 billion) compared to 2019 values. Furthermore, Figure 11 in the Appendix D shows that online video subscriptions increased by 32% in 2020 as more addictive and habit-forming games were introduced. Revenue from online video subscriptions in the U.S. grew by 35% in 2020, totaling $24.7 billion (MPA Theme report, 2020).

Table 5: Second Stage Regressions

Risk Perceptions and Spending on Arts, Entertainment, and Recreation

	(1)	(2)	(3)	(4)	(5)
	Arts, entertainment, and recreation				
Risk perception of death	0.021**	0.020**	0.020**	0.021*	0.022*
	(0.003)	(0.004)	(0.005)	(0.039)	(0.034)
Risk perception of infection	0.011***	0.010***	0.010***	0.013*	0.014*
	(0.000)	(0.000)	(0.000)	(0.019)	(0.016)
Risk perception of money loss	0.005***	0.005***	0.004***	0.005*	0.005*
	(0.000)	(0.000)	(0.000)	(0.022)	(0.017)
Risk perception of job loss	0.009***	0.009***	0.008***	0.010*	0.011*
	(0.000)	(0.000)	(0.000)	(0.017)	(0.014)
Observations	277	277	277	277	277
R-squared	0.707	0.708	0.708	0.762	0.764
Adjusted R-squared	0.660	0.659	0.659	0.714	0.714
Monthly fixed effects	Y	Y	Y	Y	Y
Demographic controls	Y	Y	Y	Y	Y
Diagnosed share		Y	Y	Y	Y
Clinic share			Y	Y	Y
Local economy controls and CPI				Y	Y
Work home and isolated share					Y

Note: The columns show percentage changes in the relevant consumption categories. Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

4.3 *Grocery and food stores*

Table 6 shows that spending on grocery and food stores increases with all the risk perception categories. As before, the coefficient estimates are robust to the inclusion of several different control variables and tend to increase in size as more controls are introduced. The positive effect of risk perception measures on grocery and food stores is consistent with the psychological studies showing that panic buying is one of the most typical behavior responses to the pandemic (Arafat et al., 2020). Individuals cope with the stress and fear of COVID-19 by increasing their purchases of certain products, such as necessities (Jin et al., 2020).

The positive relationship between the perceived risk of the pandemic and spending on grocery and food stores is also consistent with growing online grocery and food delivery services such as Walmart, Whole Foods, DoorDash, and UberEats. In other words, there is a shift from eating at restaurants or cafeterias to picking up groceries curbside or getting them delivered to homes.

Table 6: Second Stage Regressions

Risk Perceptions and Spending on Grocery and Food Stores

	(1)	(2)	(3)	(4)	(5)
	Grocery and food stores				
Risk perception of death	0.035**	0.035**	0.034**	0.055**	0.052**
	(0.006)	(0.005)	(0.008)	(0.002)	(0.001)
Risk perception of infection	0.018***	0.018***	0.017***	0.034***	0.034***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Risk perception of money loss	0.008**	0.008**	0.007**	0.012***	0.012***
	(0.003)	(0.004)	(0.005)	(0.000)	(0.000)
Risk perception of job loss	0.015**	0.014**	0.014**	0.027***	0.026***
	(0.002)	(0.002)	(0.003)	(0.000)	(0.000)
Observations	277	277	277	277	277
R-squared	0.365	0.385	0.399	0.457	0.457
Adjusted R-squared	0.263	0.284	0.298	0.348	0.342
Monthly fixed effects	Y	Y	Y	Y	Y
Demographic controls	Y	Y	Y	Y	Y
Diagnosed share		Y	Y	Y	Y
Clinic share			Y	Y	Y
Local economy controls and CPI				Y	Y
Work home and isolated share					Y

Note: The columns show percentage changes in the relevant consumption categories. Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

As before, an individual's perception of death risk has the largest impact on spending increase in this consumption category, followed by the infection risk. The last column of Table 6 demonstrates that an individual's perception of death risk is responsible for 5.2% of the increase in expenditures on grocery and food stores. The effect is 3.4% for the perception of infection risk, 1.2% for running out of money risk, and 2.6% for the job loss risk.

4.4 Health care and social assistance

Table 7 shows that spending on health care and social assistance[15] decreases with all the risk perception measures. Notice that the coefficient estimates increase in magnitude and become statistically significant after controlling for the local economy measures and the consumer price index. Columns 4 and 5 show that individuals reduce their health care spending relative to pre-pandemic levels as the risk perception of the pandemic increases. The results confirm that controlling for the local economy measures and the consumer price index is vital to obtain the pure effect of the risk perception of COVID-19 on health services spending.

Once again, Table 7 shows that an individual's perception of death risk has the largest impact on spending drop in this consumption category, followed by the infection risk. From the last column of Table 7, we see that an individual's perception of death risk is responsible for 6.8% of the decrease in expenditures on health care and social assistance. The effect is 4.4% for the perception of infection risk, 1.6% for running out of money risk, and 3.4% for the job loss risk.

The negative effect of the risk perception of COVID-19 and expenditures on health services is because an individual's perception of a hospital turned into danger and fear instead of safe and shelter in the early stages of the pandemic. Hartnett et al. (2020) find that the number of people seeking emergency medical care for reasons other than COVID-19 in the early stages of the pandemic dropped significantly as the number of COVID-19 cases and deaths increased. Similarly, a study from a community hospital in California, Adventist Health Lodi Memorial (LMH), finds that the number of patients presenting to the LMH emergency department dropped significantly after the California shelter-in-place order. Studies also show that the decline in patient visits continued for months after shelter-in-place orders due to fears of contracting the virus (Wong et al., 2020).

[15] This category includes several non-essential health care services such as cosmetic dentistry, optical goods, and eyeglasses. It also excludes payments covering health insurance premiums and prescription drugs purchased through retail pharmacies.

Table 7: Second Stage Regressions

Risk Perceptions and Spending on Health care and Social Assist.

	(1)	(2)	(3)	(4)	(5)
	Health care and social assistance				
Risk perception of death	-0.006	-0.006	-0.008	-0.071**	-0.068**
	(0.370)	(0.366)	(0.265)	(0.002)	(0.002)
Risk perception of infection	-0.003	-0.003	-0.004	-0.043***	-0.044***
	(0.327)	(0.312)	(0.203)	(0.000)	(0.000)
Risk perception of money loss	-0.001	-0.001	-0.002	-0.016***	-0.016***
	(0.314)	(0.296)	(0.184)	(0.000)	(0.000)
Risk perception of job loss	-0.002	-0.003	-0.003	-0.034***	-0.034***
	(0.318)	(0.303)	(0.190)	(0.000)	(0.000)
Observations	277	277	277	277	277
R-squared	0.953	0.954	0.954	0.984	0.984
Adjusted R-squared	0.946	0.946	0.946	0.980	0.980
Monthly fixed effects	Y	Y	Y	Y	Y
Demographic controls	Y	Y	Y	Y	Y
Diagnosed share		Y	Y	Y	Y
Clinic share			Y	Y	Y
Local economy controls and CPI				Y	Y
Work home and isolated share					Y

Note: The columns show percentage changes in the relevant consumption categories. Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

4.5 *Sporting goods and hobbies*

Table 8 shows that spending on sporting goods and hobbies decreases with all the risk perception measures. All the coefficient estimates are significant and negative. As usual, they increase in magnitude and statistical significance as more controls are included.

As before, Table 8 shows that an individual's perception of death risk has the largest impact on spending drop in this consumption category, followed by the infection risk. The last column of Table 8 demonstrates that an individual's perception of death risk is responsible for 9.5% of the decrease in expenditures on sporting goods and hobbies. The effect is 6.2% for the perception of infection risk, 2.2% for running out of money risk, and 4.8% for the job loss risk.

Table 8: Second Stage Regressions

Risk Perceptions and Spending on Sporting Goods and Hobbies

	(1)	(2)	(3)	(4)	(5)
	Sporting goods and hobbies				
Risk perception of death	-0.154***	-0.159***	-0.168***	-0.104**	-0.095**
	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)
Risk perception of infection	-0.080***	-0.081***	-0.084***	-0.064***	-0.062***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Risk perception of money loss	-0.035***	-0.036***	-0.037***	-0.023***	-0.022***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Risk perception of job loss	-0.065***	-0.067***	-0.069***	-0.050***	-0.048***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	277	277	277	277	277
R-squared	0.860	0.862	0.867	0.882	0.882
Adjusted R-squared	0.838	0.839	0.844	0.858	0.857
Monthly fixed effects	Y	Y	Y	Y	Y
Demographic controls	Y	Y	Y	Y	Y
Diagnosed share		Y	Y	Y	Y
Clinic share			Y	Y	Y
Local economy controls and CPI				Y	Y
Work home and isolated share					Y

Note: The columns show percentage changes in the relevant consumption categories. Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

There are two possible explanations for the negative relationship between the risk perception of the pandemic and spending on sporting goods and hobbies. First, people avoided crowded places such as gyms, pools, and baseball/softball fields, to limit contact with other individuals. Therefore, personal expenditures in this category declined compared to their pre-pandemic levels. Second, people cut back on unessential expenses as individuals' perceived probability of contracting the coronavirus, dying, running out of money, and losing their jobs due to COVID-19 increases. In addition, the results are also consistent with the growing literature on individuals' changing physical activity behavior and habits during the COVID-19 pandemic.

Table 16 in the Appendix B reports coefficients from ordinary least squares (OLS) regressions of the effect of all four risk perception measures on spending changes. To compare the main specification results, the last column in the IV-2SLS regression tables, with the OLS coefficients, I include all the control variables in the OLS regressions: demographics, diagnosed share, clinic share, local economy, the consumer price index, work home, isolated share, and monthly fixed effects. The OLS coefficients are either statistically insignificant or significant but always biased downward relative to the estimates using instrumental variables. These results support our concerns that OLS regressions result in unreliable coefficient estimates. Thus, they do not represent the true relationship between the perceived risk of COVID-19 and spending changes.

5 The effect of risk perception on GPS mobility records

I follow the same instrumental variable (IV) method to estimate the causal effect of risk perception on changes in hours spent at places such as retail and recreation, grocery and pharmacy, parks, workplaces, residential, and transit stations. The same first stage equation, Eq. (2), is estimated with the same control variables for that purpose. Again, the first stage results show that the weekly growth rate of COVID-19 cases in New York has a positive and statistically significant effect on California residents' perceived risk of COVID-19.

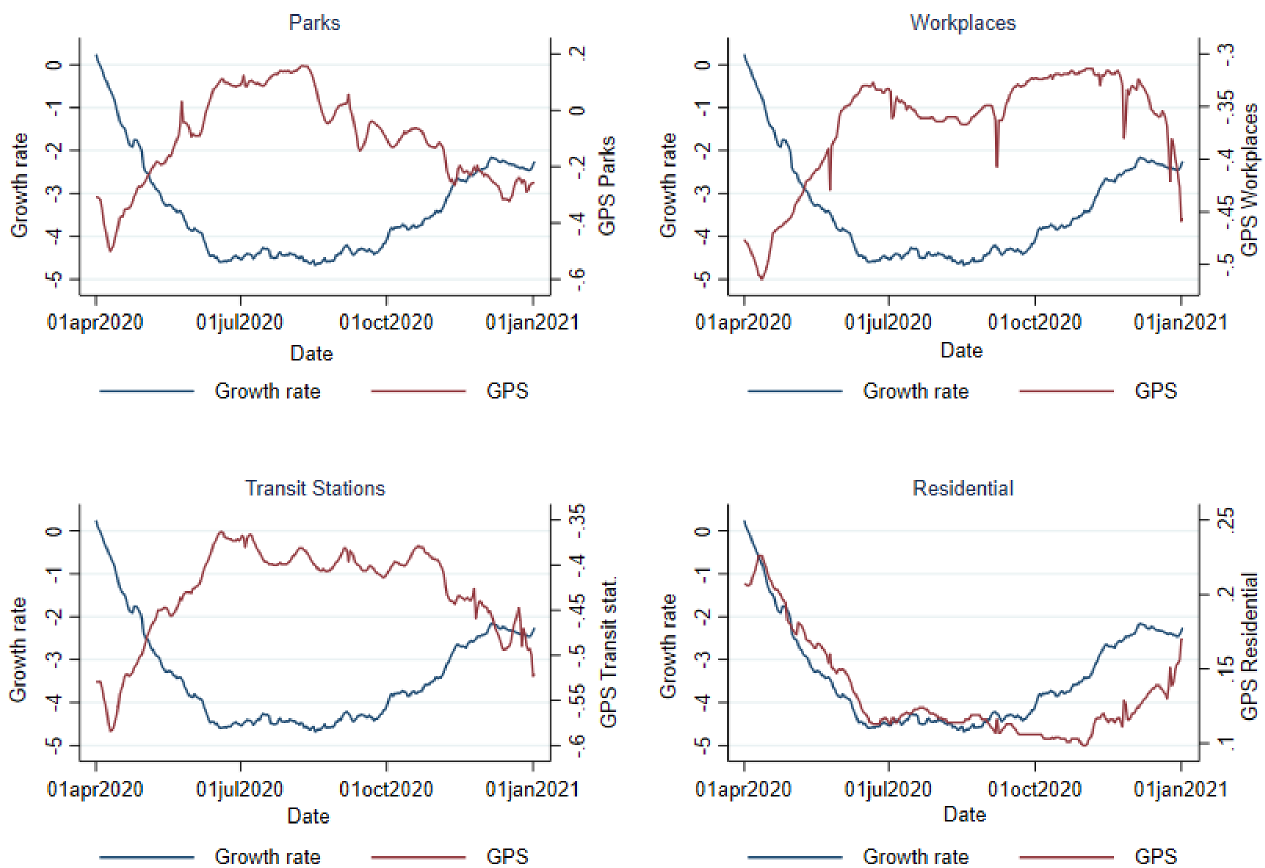
The second stage regression is as follows,

$$\Delta GPS_t = \gamma_t + \phi_t \widehat{RP_t} + \rho_t X_t + \eta_t \tag{3}$$

where η_t is a disturbance term. I use the predicted values of risk perception, $\widehat{RP}$, from the estimation of Eq. (1) to fit the above second stage equation. The variable ΔGPS corresponds to the main measure of mobility changes through the sample period.

Figure 8 plots the weekly growth rate of COVID-19 cases in New York and changes in mobility records in California. The figure provides some evidence that the growth rate of COVID-19 cases in New York tracks changes in hours spent at parks, workplaces, transit stations, and residential places in California, although not perfectly.

Figure 8: GPS Mobility changes in CA by Growth Rate of COVID-19 Cases in NY



Note: The figure plots the relationship between the growth rate of COVID-19 cases in New York and the GPS mobility changes in California for each of the four place categories that I found a significant effect of the growth rate of COVID-19 cases in New York on GPS mobility records. These place categories are parks, workplaces, transit stations, and residential locations. The sample covers the period from April 1, 2020 to January 2, 2021.

The tables below report the estimation of Eq. (3) for six place categories: (i) Retail and recreation, (ii) Grocery and Pharmacy, (iii) Parks, (iv) Workplaces, (v) Residential, and (vi) Transit stations. Overall, the perceived risk of COVID-19 has a statistically significant and negative impact on hours spent at parks, workplaces, and transit stations. In contrast, the effect is statistically significant and positive for residential places.

The last columns of the below tables, my main specification, indicates that the perceived risk of COVID-19 increases time spent at residential places by 0.7 percentage points, on average. Conversely, the average negative impact of risk perception on time spent at parks, workplaces, and transit stations is 3, 1.1, and 0.8 percentage points, respectively. On the other hand, the results show a statistically insignificant effect–after controlling for the local economy measures–of the risk perception of COVID-19 on time spent at retail and recreation places and grocery and pharmacy locations. These results imply that individuals reduced their time outside of residential locations and started spending more hours inside homes, excluding time asleep, as the perceived risk of COVID-19 increases. This result confirms Goolsbee and Syverson' (2021) broader finding in this setting: fear of the virus is an overriding determinant of consumers' decisions about where to visit.

Also, similar to the results obtained in the analysis of consumption expenditure changes, the risk perception of death has the largest impact on the GPS mobility changes compared to the other risk perception measures. This finding adds to previous studies examining the changes in consumer mobility records to avoid contracting the coronavirus.

Overall, the changes in hours spent by California residents at certain places during the early stages of the pandemic seem to be consistent with the changes in their consumption expenditures. For example, as the perceived risk of the COVID-19 pandemic increased, individuals spent more hours at home, leading to higher spending on home entertainment products and services such as online TV and video subscriptions. This finding is also consistent with the increased consumer spending on online grocery and food delivery services. The broader conclusion from the findings in this section is that increased risk perception of COVID-19 turned individuals' perception of places outside of residential locations into danger.

Table 9: Second Stage Regressions

Risk Perceptions and GPS Retail and Recreation Locations

	(1)	(2)	(3)	(4)	(5)
	GPS retail and recreation locations				
Risk perception of death	0.056***	0.057***	0.058***	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.908)	(0.910)
Risk perception of infection	0.029***	0.029***	0.029***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.908)	(0.910)
Risk perception of money loss	0.013***	0.013***	0.013***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.909)	(0.911)
Risk perception of job loss	0.023***	0.024***	0.024***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.909)	(0.911)
Observations	277	277	277	277	277
R-squared	0.950	0.950	0.950	0.977	0.977
Adjusted R-squared	0.942	0.942	0.942	0.972	0.972
Monthly fixed effects	Y	Y	Y	Y	Y
Demographic controls	Y	Y	Y	Y	Y
Diagnosed share		Y	Y	Y	Y
Clinic share			Y	Y	Y
Local economy controls and CPI				Y	Y
Work home and isolated share					Y

Note: The columns show percentage changes (relative to Jan 3-Feb 6, 2020 baseline values) in hours spent in retail and recreation places such as restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters. Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 10: Second Stage Regressions

Risk Perceptions and GPS Grocery and Pharmacy Locations

	(1)	(2)	(3)	(4)	(5)
	GPS grocery and pharmacy locations				
Risk perception of death	-0.006	-0.006	-0.005	-0.008	-0.007
	(0.288)	(0.310)	(0.369)	(0.205)	(0.282)
Risk perception of infection	-0.003	-0.003	-0.003	-0.005	-0.004
	(0.292)	(0.313)	(0.373)	(0.200)	(0.282)
Risk perception of money loss	-0.001	-0.001	-0.001	-0.002	-0.002
	(0.310)	(0.331)	(0.388)	(0.176)	(0.263)
Risk perception of job loss	-0.002	-0.002	-0.002	-0.004	-0.003
	(0.315)	(0.337)	(0.394)	(0.185)	(0.271)
Observations	277	277	277	277	277
R-squared	0.827	0.828	0.830	0.873	0.874
Adjusted R-squared	0.800	0.800	0.801	0.847	0.847
Monthly fixed effects	Y	Y	Y	Y	Y
Demographic controls	Y	Y	Y	Y	Y
Diagnosed share		Y	Y	Y	Y
Clinic share			Y	Y	Y
Local economy controls and CPI				Y	Y
Work home and isolated share					Y

Note: The columns show percentage changes (relative to Jan 3-Feb 6, 2020 baseline values) hours spent in grocery and pharmacy places such as grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies. Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 11: Second Stage Regressions

Risk Perceptions and GPS Parks

	(1)	(2)	(3)	(4)	(5)
	GPS parks				
Risk perception of death	-0.025	-0.026	-0.027	-0.056**	-0.051**
	(0.161)	(0.172)	(0.156)	(0.003)	(0.003)
Risk perception of infection	-0.013	-0.013	-0.013	-0.035***	-0.033***
	(0.158)	(0.164)	(0.153)	(0.000)	(0.000)
Risk perception of money loss	-0.006	-0.006	-0.006	-0.013***	-0.012***
	(0.230)	(0.235)	(0.226)	(0.000)	(0.000)
Risk perception of job loss	-0.011	-0.011	-0.011	-0.027***	-0.026***
	(0.223)	(0.229)	(0.220)	(0.000)	(0.000)
Observations	277	277	277	277	277
R-squared	0.887	0.887	0.887	0.939	0.939
Adjusted R-squared	0.869	0.868	0.868	0.927	0.927
Monthly fixed effects	Y	Y	Y	Y	Y
Demographic controls	Y	Y	Y	Y	Y
Diagnosed share		Y	Y	Y	Y
Clinic share			Y	Y	Y
Local economy controls and CPI				Y	Y
Work home and isolated share					Y

Note: The columns show percentage changes (relative to Jan 3-Feb 6, 2020 baseline values) in hours spent at park places such as local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens. Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 12: Second Stage Regressions

Risk Perceptions and GPS Workplaces

	(1)	(2)	(3)	(4)	(5)
			GPS workplaces		
Risk perception of death	-0.016***	-0.017***	-0.017***	-0.021**	-0.019***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Risk perception of infection	-0.008***	-0.009***	-0.009***	-0.013***	-0.013***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Risk perception of money loss	-0.004***	-0.004***	-0.004***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Risk perception of job loss	-0.007**	-0.007**	-0.007**	-0.010***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Observations	277	277	277	277	277
R-squared	0.932	0.932	0.932	0.973	0.973
Adjusted R-squared	0.921	0.921	0.921	0.968	0.967
Monthly fixed effects	Y	Y	Y	Y	Y
Demographic controls	Y	Y	Y	Y	Y
Diagnosed share		Y	Y	Y	Y
Clinic share			Y	Y	Y
Local economy controls and CPI				Y	Y
Work home and isolated share					Y

Note: The columns show percentage changes (relative to Jan 3-Feb 6, 2020 baseline values) in hours spent at places of work. Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 13: Second Stage Regressions

Risk Perceptions and GPS Residential Locations

	(1)	(2)	(3)	(4)	(5)
	GPS residential locations				
Risk perception of death	0.009***	0.010**	0.010**	0.013***	0.012***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Risk perception of infection	0.005***	0.005***	0.005***	0.008***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Risk perception of money loss	0.002**	0.002**	0.002**	0.003***	0.003***
	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)
Risk perception of job loss	0.004**	0.004**	0.004**	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)
Observations	277	277	277	277	277
R-squared	0.951	0.951	0.951	0.984	0.985
Adjusted R-squared	0.943	0.943	0.943	0.981	0.981
Monthly fixed effects	Y	Y	Y	Y	Y
Demographic controls	Y	Y	Y	Y	Y
Diagnosed share		Y	Y	Y	Y
Clinic share			Y	Y	Y
Local economy controls and CPI				Y	Y
Work home and isolated share					Y

Note: The columns show percentage changes (relative to Jan 3-Feb 6, 2020 baseline values) in hours spent at places of residence. Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Table 14: Second Stage Regressions

Risk Perceptions and GPS Inside Transit Stations

	(1)	(2)	(3)	(4)	(5)
	GPS inside transit stations				
Risk perception of death	-0.017**	-0.017**	-0.017**	-0.015**	-0.013**
	(0.004)	(0.007)	(0.006)	(0.003)	(0.003)
Risk perception of infection	-0.009***	-0.009**	-0.009**	-0.009***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Risk perception of money loss	-0.004*	-0.004*	-0.004*	-0.003***	-0.003***
	(0.014)	(0.015)	(0.015)	(0.000)	(0.000)
Risk perception of job loss	-0.007*	-0.007*	-0.007*	-0.007***	-0.007***
	(0.012)	(0.014)	(0.014)	(0.000)	(0.001)
Observations	277	277	277	277	277
R-squared	0.912	0.912	0.912	0.965	0.965
Adjusted R-squared	0.898	0.897	0.897	0.958	0.958
Monthly fixed effects	Y	Y	Y	Y	Y
Demographic controls	Y	Y	Y	Y	Y
Diagnosed share		Y	Y	Y	Y
Clinic share			Y	Y	Y
Local economy controls and CPI				Y	Y
Work home and isolated share					Y

Note: The columns show percentage changes (relative to Jan 3-Feb 6, 2020 baseline values) in hours spent at transit stations such as public transport hubs such as subway, bus, and train stations. Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

6 Conclusion and policy implications

This paper uses two datasets from two different data sources. The first data source is the University of Southern California (USC) Center for Economic and Social Research's Understanding Coronavirus in America Survey. This data source is a state-representative survey of California adults that quantifies individuals' perceived risk of COVID-19 by focusing on four risk perception categories; death, infection, money loss, and job loss. The aim is to analyze the causal effect of the risk perception of COVID-19 on changes in California residents' consumption expenditures during the early stages of the pandemic. To this end, the second data source is obtained from the Opportunity Insights Economic Tracker, which provides different categories of spending changes in California. Finally, I merge the two datasets to analyze the relationship between the risk perception of COVID-19 and consumption expenditure changes using an instrumental variable (IV) approach. The analysis covers the period between April 1, 2020 to January 2, 2021, before the COVID-19 vaccine was publicly available in California.

Also, I use the same data sources and follow the same instrumental variable (IV) method to estimate the causal effect of the risk perception of COVID-19 on changes in hours spent by California residents at places such as retail and recreation, grocery and pharmacy, parks, workplaces, residential, and transit stations. Again, the analysis covers April 1, 2020 to January 2, 2021, before the COVID-19 vaccine was publicly available in California.

The analyses generate four primary conclusions. First, the weekly growth rate of COVID-19 cases in New York has a positive and statistically significant effect on all four risk perception measures. Moreover, the results indicate that the weekly growth rate of COVID-19 cases is a strong instrument, with F-statistics beyond conventional thresholds. However, the instrument is weaker for the risk perception of death, suggesting that the instrumental variable estimates for this regressor may be somewhat biased. Overall, the weekly growth rate of COVID-19 cases in New York affects California residents' subjective assessment of risks associated with COVID-19.

Second, the results show that individuals' perceived risk of COVID-19 has a statistically significant causal impact on their consumption expenditure changes at the early stages of the pandemic. The impact is negative for three consumption categories: accommodation and food services, health care and social assistance, and sporting goods and hobbies. On average, the risk perception of COVID-19 reduces spending changes in accommodation and food services by 1.7 percentage points. The average reduction is 4 percentage points for health care and social assistance and 5.7 percentage points for sporting goods and hobbies. In contrast, the perceived risk of COVID-19 has a statistically significant and positive impact on spending changes in grocery and food stores and arts, entertainment, and recreation. On average, risk perception increases spending changes by 3.1 and 1.3 percentage points for grocery and food stores and arts, entertainment, and recreation, respectively.

Third, the results show that individuals' perceived risk of dying from the coronavirus has the largest impact on all the categories of expenditure changes compared to the risk perception of infection, money loss, and job loss due to COVID-19. This finding is interesting and adds to the previous studies that examined the infection and income risks to explain changes in consumer behavior during the COVID-19 pandemic, often finding a bigger impact from the latter.

Lastly, the results show that the risk perception of COVID-19 has a statistically significant causal impact on changes in the hours spent at places such as parks, workplaces, transit stations, and residential locations during the early stages of the pandemic. The effect is positive for residential places whereas negative for parks, workplaces, and transit stations. On average, the risk perception of COVID-19 increases time spent at residential places by 0.7 percentage points. In contrast, the risk perception of COVID-19 decreases time spent at parks, workplaces, and transit stations by 3, 1.1, and 0.8 percentage points, respectively. On the other hand, the results show a statistically insignificant effect–after controlling for the local economy measures–of the risk perception of COVID-19 on time spent at retail and recreation places and grocery and pharmacy locations.

The analysis in this paper is relevant since the government's policy responses to public health emergencies such as COVID-19 are based on traditional macroeconomic tools aimed at stimulating consumption by providing liquidity to consumers and businesses. However, spending patterns during the COVID-19 recession differ sharply from those observed in previous recessions. For example, during the Great Recession, almost all the reduction in consumption expenditures arose from a reduction in spending on goods, whereas spending on services was almost unchanged (Chetty et al., 2020). However, spending reductions during the COVID-19 pandemic were primarily due to reductions in services that require face-to-face interaction (Alexander and Karger, 2020; Chetty et al.; 2020, Cox et al., 2020). Correspondingly, this paper, analyzing different consumption categories, shows that expenditures on health care, sporting goods and hobbies, and accommodation and food services, which mostly require in-person services, decreased during the pandemic. In addition to these differences in spending patterns, the findings seem to support the hypothesis that the government's supplemental payments compensated the households who lost their jobs during the pandemic. A reduction in wealth or income would lower expenditures on all goods as predicted by their Engel curves. However, since the results show that spending changes differ by consumption categories, the government's policy responses aimed at stimulating the economy by increasing consumers' purchasing power seem inadequate in reinvigorating the economy during the COVID-19 crisis.

This paper shows that individuals' perceived probability of contracting the coronavirus, dying, running out of money, and losing their jobs due to COVID-19 also affects consumption expenditures through consumer psychology and behavior channels. Therefore, government policies during public health emergencies should penetrate consumer psychology to be sufficient. In other words, future policies should better analyze consumers' psychology during health emergencies. For instance, the government can disseminate scientific knowledge of the virus through various media channels to reduce residents' subjective evaluation of external risks.

Appendices

A Reduced-form regressions

Table 15: Reduced-Form Regressions

Growth rate of COVID-19 Cases and Consumption Expend.

	(1)	(2)	(3)	(4)	(5)
			Accommodation and food services		
Growth rate of cases	-0.041***	-0.043***	-0.043***	-0.090***	-0.085***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	277	277	277	277	277
R-squared	0.971	0.971	0.971	0.986	0.987
Adjusted R-squared	0.966	0.967	0.967	0.984	0.984
			Arts, entertainment, and recreation		
Growth rate of cases	0.040***	0.039***	0.038***	0.060*	0.065*
	(0.000)	(0.000)	(0.000)	(0.033)	(0.027)
Observations	277	277	277	277	277
R-squared	0.707	0.708	0.708	0.762	0.764
Adjusted R-squared	0.660	0.659	0.659	0.714	0.714
			Grocery and food stores		
Growth rate of cases	0.068**	0.065**	0.063**	0.154***	0.155***
	(0.002)	(0.004)	(0.005)	(0.000)	(0.000)
Observations	277	277	277	277	277
R-squared	0.365	0.385	0.399	0.457	0.457
Adjusted R-squared	0.263	0.284	0.298	0.348	0.342
			Health care and social assistance		
Growth rate of cases	-0.011	-0.012	-0.015	-0.199***	-0.202***
	(0.348)	(0.329)	(0.217)	(0.000)	(0.000)
Observations	277	277	277	277	277
R-squared	0.953	0.954	0.954	0.984	0.984
Adjusted R-squared	0.946	0.946	0.946	0.980	0.980
			Sporting goods and hobbies		
Growth rate of cases	-0.297***	-0.302***	-0.311***	-0.292***	-0.282***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	277	277	277	277	277
R-squared	0.860	0.862	0.867	0.882	0.882
Adjusted R-squared	0.838	0.839	0.844	0.858	0.857

Note: Column (1) uses only demographics as control variables. Column (2) is the same as column (1) but adds diagnosed share as a control. Column (3) is the same as column (2) but adds clinic share as a control. Column (4) is the same as column (3) but adds local economy controls and the consumer price index. Column (5) is the same as column (4) but adds work home and isolated share as controls. All estimations control for monthly fixed effects. The columns show percentage changes in the relevant consumption categories. P-values are in parentheses,* p<0.05, ** p<0.01, *** p<0.001.

Higher levels of weekly growth rates of COVID-19 cases in New York are associated with significantly less spending in California for three consumption categories in the reduced-form regressions; accommodation and food services, health care and social assistance, and sporting goods and hobbies. Table 15 shows that coefficient estimates are statistically significant, and the changes in reduction get higher in almost all three consumption categories as we add more control variables (regressions from columns 1 to 5). In the case of health care and social assistance, coefficient estimates become statistically significant after controlling for the local economy measures and the consumer price index (column 4). On the other hand, the coefficient estimates for arts, entertainment and recreation, and grocery and food stores are statistically significant and positive. The results indicate that higher levels of the weekly growth rate of COVID-19 cases in New York are associated with significantly more spending in California for these two consumption categories. Also, spending changes increase as we add more control variables. That is the first indication that the growth rate of COVID-19 cases in New York impacts spending behaviors in California for various consumption categories.

B OLS regression tables

The below table shows the OLS regressions between risk perception and spending changes.

Table 16: OLS Regressions

Risk Perceptions and Spending Changes

Accommodation and food services				
Risk perception of death	-0.005***			
	(0.000)			
Risk perception of infection		-0.003		
		(0.192)		
Risk perception of money loss			-0.004***	
			(0.000)	
Risk perception of job loss				-0.003*
				(0.023)
Observations	277	277	277	277
R-squared	0.986	0.985	0.986	0.985
Adjusted R-squared	0.983	0.982	0.983	0.982
Arts, entertainment, and recreation				
Risk perception of death	0.001			
	(0.605)			
Risk perception of infection		0.009**		
		(0.004)		
Risk perception of money			0.000	
			(0.853)	
Risk perception of job loss				0.006*
				(0.012)
Observations	277	277	277	277
R-squared	0.760	0.768	0.760	0.766
Adjusted R-squared	0.710	0.719	0.709	0.716
Grocery and food stores				
Risk perception of death	0.002			
	(0.567)			
Risk perception of infection		0.016***		
		(0.000)		
Risk perception of money loss			0.005*	
			(0.021)	
Risk perception of job loss				0.003
				(0.189)
Observations	277	277	277	277
R-squared	0.406	0.453	0.420	0.409
Adjusted R-squared	0.281	0.338	0.298	0.285

Table 16 continued

Health care and social assistance				
Risk perception of death	0.002			
	(0.465)			
Risk perception of infection		-0.003		
		(0.285)		
Risk perception of money			-0.008***	
			(0.000)	
Risk perception of job loss				-0.008**
				(0.001)
Observations	277	277	277	277
R-squared	0.980	0.980	0.982	0.981
Adjusted R-squared	0.976	0.976	0.978	0.977
Sporting goods and hobbies				
Risk perception of death	-0.008			
	(0.198)			
Risk perception of infection		-0.023**		
		(0.002)		
Risk perception of money loss			-0.017**	
			(0.002)	
Risk perception of job loss				-0.012*
				(0.049)
Observations	277	277	277	277
R-squared	0.877	0.880	0.882	0.878
Adjusted R-squared	0.851	0.855	0.857	0.852

Note: The above regressions include demographics, diagnosed share, clinic share, local economy, the consumer price index, work home, and isolated share as controls. All estimations control for monthly fixed effects. The columns show percentage changes in the relevant consumption categories. P-values are in parentheses,* p<0.05, ** p<0.01, *** p<0.001.

C Unemployment programs in California under the CARES Act

C.1 Pandemic Unemployment Assistance (PUA)

Pandemic Unemployment Assistance (PUA) benefits is one of the federal assistance programs designed to provide compensation to unemployed California residents who were not usually eligible for regular unemployment insurance benefits and were out of business or had significantly reduced their services as a direct result of the COVID-19 pandemic. Pandemic unemployment assistance included up to 86 weeks of benefits between February 2, 2020 and September 4, 2021. Individuals who are eligible for PUA benefits include self-employed workers, business owners, independent contractors, individuals with limited work history, individuals who had used all their regular unemployment insurance (UI) benefits and any extended benefits, and lastly, individuals who were serving false statement penalty weeks on their regular UI claim.

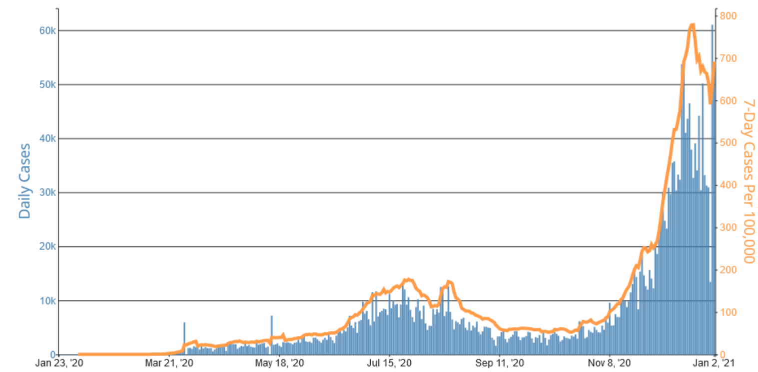
C.2 Pandemic Emergency Unemployment Compensation (PEUC)

Pandemic Emergency Unemployment Compensation (PEUC) is a federal assistance program that provides an extended benefit period to Californians who have used all their unemployment benefits. PEUC provides eligible individuals up to 13 weeks of federally funded unemployment compensation between March 29, 2020 and September 4, 2021. California extended this period after September 4, 2021, providing up to 53 additional weeks of compensation payments.

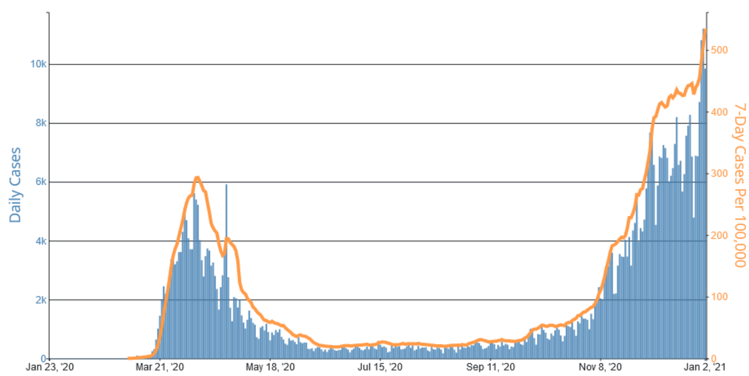
D Additional figures

Figure 9: Daily Trends in the Number of COVID-19 Cases Reported to CDC

(a) California



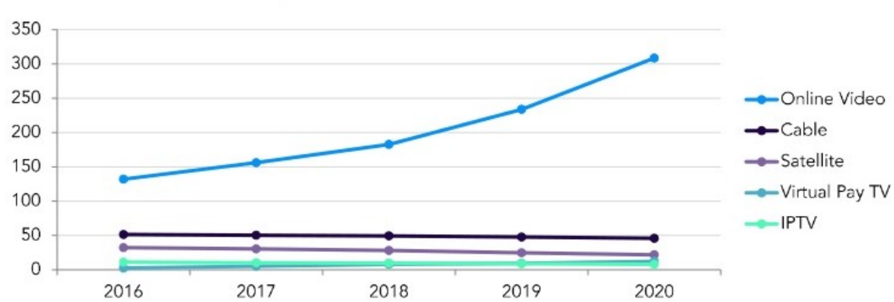
(b) New York



Note: The blue bars show daily COVID-19 cases. The orange line represents cases in the last 7 days per 100,000 population, allowing for comparisons between areas with different population sizes.

Figure 10: U.S. Home and Mobile Entertainment Market (US$ Billions)

Figure 11: U.S. Pay T.V. and Online Video Subscription (Millions)



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