Risk Perception of COVID-19 and Consumption Changes in California

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Abstract

This paper studies the role of risk perception in explaining consumption expenditure changes during the COVID-19 pandemic and the mechanism behind such a relationship. Under the framework of the two-stage instrumental variable (IV) analysis, I identify a causal relationship between consumer risk perception and spending by focusing on the period between April 1, 2020 to January 2, 2021, before the vaccine was publicly available. 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. 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. Under this empirical framework, I find that California residents' risk perception of death, infection, money, and job loss due to COVID-19 increases with an increase in the growth rate of confirmed cases in New York. Furthermore, the results show a negative and significant effect of risk perception on consumers' spending on major consumption categories, whereas the effect is positive for others. Specifically, this paper finds that individuals substitute spending on some categories of consumption for necessities and entertainment goods during the COVID-19 crisis.

1 Introduction

The World Health Organization declared the rapid spread of COVID-19 a global public health emergency in March 2020. The 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 of the GDP drop was a reduction in personal consumption expenditures, which decreased by $1.45 trillion. On the other hand, personal saving rate rocketed to 33.8 percent in April 2020, more than doubling its 2019 value.

There are 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 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 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).

Studies concerning 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 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.

Decision-making under uncertainty is broadly studied in economics. One of the most relevant ones is the subjective expected utility (SEU) model of Savage (1951). Savage's model assumes that choices arise from the maximization of an expected utility calculated by an individual's perceived or subjective assessments of risk. Deviations from the subjective expected utility (SEU) framework indicate irrationality. However, Savage's 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. The process of choice is a complex and multidetermined phenomenon in reality because individuals are confronted with a diverse array of information. Therefore, a better analysis of how individuals make their choices in the face of emerging health threats is needed to improve public policies.

In this paper, I show how the perceived risk of COVID-19 changed consumption expenditures in the U.S. during the period before the vaccine was 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 instrumental variable approach. Specifically, I use the weekly growth rate of COVID-19 cases in New York state as a source of exogenous variation in consumer risk perception in California. I show that California residents' perceived risk of death, infection, running out of money, and job loss due to COVID-19 increases when the growth rate of confirmed cases goes up in New York. The results 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 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 the saving and spending decisions of consumers 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. It is therefore important to provide 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 provides quantitative evidence of the impact of risk perception on consumption 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. Second, it provides 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 the perceived risk of the virus caused individuals to substitute spending on several consumption categories, including health care, for groceries and entertainment goods during the COVID-19 crisis.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 details sample selection, 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.[1] 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 survey after the invitation date.[2] Surveys include a core of 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 total number of COVID-

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

[2]The first survey wave is fielded on March 10, 2020, where all respondents receive the survey on the same date. And the first survey was in the field until March 31, 2020. Each survey period is administered on a bi-weekly basis starting after April 1, 2020, where randomization to fourteen survey invitation days start.

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.[3]

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 company 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.

[3] I construct daily values of the COVID-19 growth rate series by taking the average of the current day and the previous six days of COVID-19 cases.

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

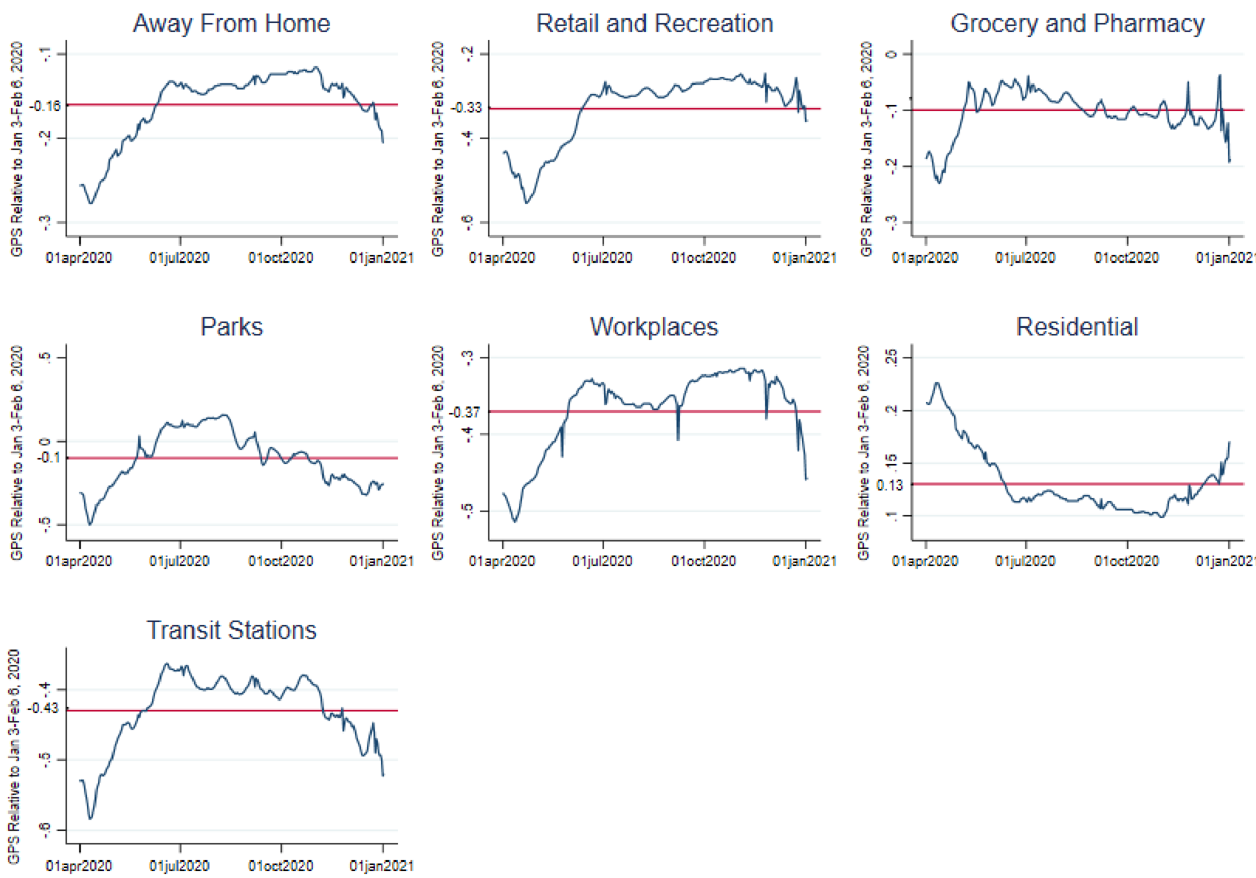
Note: Average values are marked for each spending category.

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 visits and length of stay 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,[4] at retail and recreation locations, grocery and pharmacy locations, parks, workplaces, residential locations, and inside transit stations. 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.

Figure 2: Changes in GPS mobility, CA



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

[4] The difference between an estimate of time spent inside residential locations for each date and waking hours in the day provides an estimate for time spent outside of residential locations. The O.I. team calculates the estimate of time spent inside the residential locations in two steps. First, mean values of time 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 time spent at residential locations for each date.

2.3 *Consumer risk perception of COVID-19*

To quantify the COVID-19 risk perception 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.[5] Lastly, this paper uses 7-day moving averages of the risk perception measures in the analyses to maintain the integrity between the two datasets.

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 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 who have 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

[5] Since the 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.

"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.

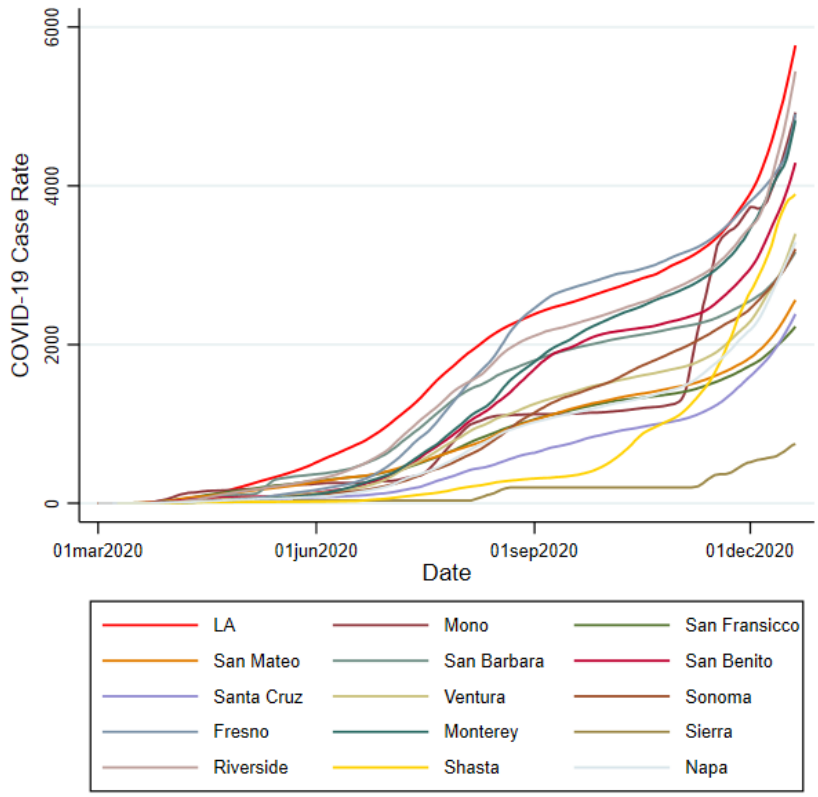
On the other hand, the indicator variables include if an individual has insurance, if the individual is disabled, if the individual is diagnosed with coronavirus, if the individual works or studies from home, if the individual has been placed in isolation or quarantine in the past seven days, and if 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 for 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 3 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 4 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 earlier than statewide stay-at-home orders.[6] 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 the pandemic and their concerns regarding the future. However, other factors also affected consumer spending during the pandemic. The revenues and employment of small

[6] 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 3: Confirmed COVID-19 Cases Per 100,000 by California County



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

businesses changed remarkably. Studies show that the economic impact of the pandemic on entrepreneurship and small businesses was harsh, with many business 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.[7] 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 ex-

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

Figure 4: California County Map

panded unemployment insurance (UI) benefits, i.e. 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, these variables are included as controls along with the Consumer Price Index to observe the actual impact of risk perception on health services spending.

3 Sample selection, 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 responses from the survey data when aggregating the sample at a daily level.[8] 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 *share of females* means that the average ratio of women to men per sample day (277 in total) is 60%. The aim of adding the share variables is to control for any differences in

[8]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.

responses that may arise from differences in individuals' characteristics.

Risk perception of infection has the highest sample mean among other risk perception categories. In other words, people are more concerned about contracting COVID-19 than dying, running out of money, and experiencing a job loss due to the virus. 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 spent outside of residential locations. 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
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

Table 1 continued

Variable	Obs	Mean	Std. Dev.	Min	Max
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
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

Table 1 continued

Variable	Obs	Mean	Std. Dev.	Min	Max
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: The share variables do not represent the whole population. They are added to the regressions on each survey day to represent the percent of respondents with the above characteristics. The aim is to control for any deviation in individuals' responses that may arise from the differences in their characteristics. For example, the mean value of *share of females* in the above table 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, this paper uses a two-stage instrumental variable regression framework to control for potential endogeneity issues. 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 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).

To obtain unbiased estimates of the causal impact of risk perception on the consumption expenditure changes in California, the instrument must meet three main conditions First, it must cause variation in risk perception (relevance) in the first stage. Second, the instrument must not share unmeasured common causes with the expenditure changes (independence). In other words, the instrument must be randomly assigned to units. Lastly, the instrument must affect expenditures only through the variation it creates in risk perception (exclusion restriction).

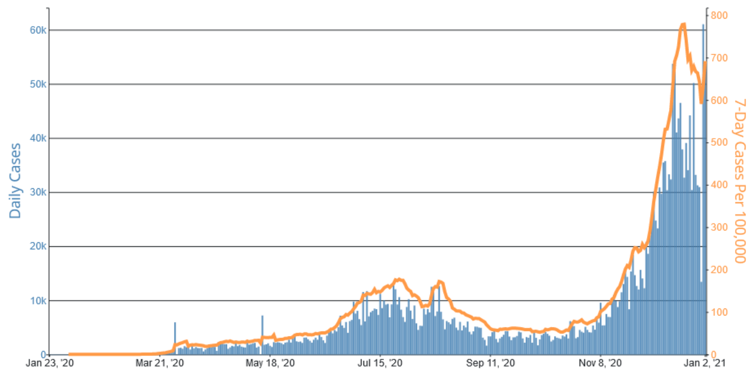
First of all, it is intuitively plausible to assume that the growth rate of COVID-19 cases in New York is exogenous and does not share any common characteristics with consumption changes in California. Secondly, it is assumed that mass media plays an important role in shaping individuals' risk perception (Snyder and Rouse, 1995; Bomlitz and Brezis, 2008). 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. According to NBC News, the reported caseload in the state of New York was more than in any country observed by April 10, 2020 (Millman, 2020). Based on this assumption, the instrument satisfies the relevance condition. Finally, it is assumed that the instrument satisfies the exclusion restriction. The only potential violation 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.[9] On the other hand, New York was one of the earliest states to experience high surges in COVID-19 cases. Figure 5 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, Figure 5 shows that 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 did not affect 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.

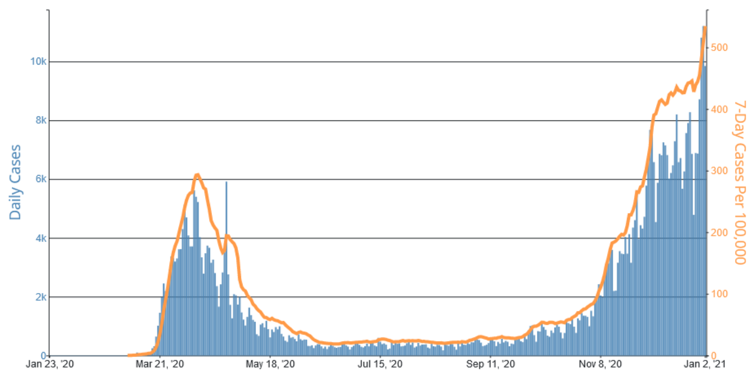
[9]Transportation providers are exempt from state-issued stay-at-home orders as transportation qualifies as an essential business.

Figure 5: Daily Trends in 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.

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 u_t is a disturbance term. 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, weak id	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, weak id	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			
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, weak id	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)
Observations	277	277	277	277	277
F-stat, weak id	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. 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. As shown in Table 2, the estimated SW F-statistics for the risk perception of death, infection, money, and job loss exceed the critical values.[10] Thus, the null hypothesis of weak identification can be rejected at the conventional level of significance. These estimated first stage F-statistics provides supporting evidence that the instrument satisfies the relevance condition. Also, 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 second stage equation estimates the impact of risk perception on the changes in consumption expenditures in California:

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

where ζ_t is a disturbance term.

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.

4.1 Accommodation and food services

Table 3 reports the estimation results for accommodation and food services considering various control variables. The results indicate that all the risk perception measures decreases

[10] Stock and Yogo (2005) weak ID F-test critical values for 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.

spending on accommodation and food services. 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 they became more concerned about the coronavirus.

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, 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 money risk, and 1.4% for job loss risk.

4.2 Arts, entertainment, and recreation

Table 4 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.

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, Disney+, increased significantly during the pandemic with the growing number of stay-at-home viewers. Figure 6 shows that digital revenue in the U.S. increased 33% over the year 2020 ($26.5 billion) compared to 2019 values. Furthermore, Figure 7 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).

4.3 Grocery and food stores

Table 5 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

Table 3: 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	-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

control variables and tend to increase in size as more controls are introduced. The perceived risk of death has noticeably bigger impact on grocery and food stores spending than the other risk perception categories. However, it is hard to make a conclusion because the effect of risk perception measures might be related to each other.

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 response 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).

Table 4: Second Stage Regressions

Risk Perceptions and Spending on Arts, Entertainment, and Recreation

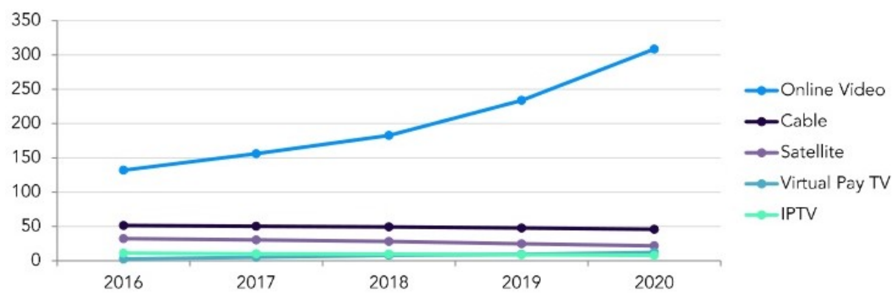
	(1)	(2)	(3)	(4)	(5)
	Arts, entertainment, and recreation				
Risk perception of death	0.021**	0.020**	0.020**	0.021*	0.022*
	(0.003)	(0.004)	(0.005)	(0.039)	(0.034)
Risk perception of infection	0.011***	0.010***	0.010***	0.013*	0.014*
	(0.000)	(0.000)	(0.000)	(0.019)	(0.016)
Risk perception of money	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

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.

Figure 6: U.S. Home and Mobile Entertainment Market (US$ Billions)

Figure 7: U.S. Pay T.V. and Online Video Subscription (Millions)



4.4 *Health care and social assistance*

Table 6 shows that spending on health care and social assistance[11] decreases with all the risk perception measures. Notice that the coefficient estimates increase in magnitude and become statistically significant after controlling for 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 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.

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

[11]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 5: 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	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

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).

Table 6: 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	-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 7 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.

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 the uncertainty of the pandemic rises and concerns about the pandemic increase. 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 7: 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	-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

5 Conclusion and policy implications

This paper uses data from USC Center for Economic and Social Research's Understanding Coronavirus in America Survey to quantify the perceived risk of COVID-19 by focusing on four risk perception categories; death, infection, money, and job loss. The aim is to analyze the impact of risk perception on changes in California residents' consumption expenditures during the early stages of the pandemic. To this end, data on different categories of spending changes are obtained from Opportunity Insights Economic Tracker. Merging two datasets and using the weekly growth rate of COVID-19 cases in New York as a source of exogenous variation in consumer risk perception in California, I show that individuals' perceived risk of the coronavirus has a significant causal impact on the expenditure changes in California during 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, risk perception 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 significant 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.

The analysis in this paper is relevant since the government's policy responses to public health emergencies are based on 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 mostly 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, accommodation, and food services, which mostly require in-person services, decrease during the pandemic. Moreover, 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 spending changes differ by consumption categories, the government's policy responses aimed at stimulating economy by increasing consumers' purchasing power seem inadequate in reinvigorating the economy during the COVID-19 crisis. This paper shows that uncertain conditions and fear of infection during the COVID-19 crisis also affect consumption expenditures through consumer psychology and behavior channels. Therefore, the 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. In addition, the government should emphasize that the effect of the pandemic is short-term to comfort the residents and promote economic stability.

Appendices

A Reduced-form regressions

Table 8: Reduced-Form Regressions

Growth rate of COVID-19 Cases and Consumption Expenditures

	(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 8 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 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.

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