BEHAVIORAL RESPONSES TO THE COVID-19 PANDEMIC:

THREE ESSAYS ON MENTAL HEALTH AND FINANCIAL DECISION MAKING

by

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(Under the Direction of Patryk Babiarz)

ABSTRACT

This dissertation consists of three essays that focus on consumer behavioral responses to the COVID-19 pandemic. Each essay describes a separate empirical study conducted to examine: (1) how the pandemic affected Internet search for mental health-related keywords, (2) how the pandemic-induced financial adversities affected the variation in mental health symptomatology of older Americans, and (3) how COVID-19-related income shocks affected financial decision-making of older Americans regarding spending and saving of the government stimulus transfers.

In Essay 1, I compare the intensity of Google.com queries for keywords related to mental health in the United States before and during the pandemic. Assuming the volume of online searches proxied for the psychological condition of the society, I explore the roles of COVID-19-related deaths and the performance of the U.S. economy (as measured by the unemployment rate and the housing price index) as distinct potential contributors to changes in online search behavior. I find that a significant amount of variation in the Internet search intensity of mental health keywords during the pandemic can be explained by both COVID-19-related deaths and the unemployment rate.

In Essay 2, I utilize microdata from the Health and Retirement Study and narrow the focus of my study to the vulnerable population segment, older adults. I examine the effect of financial adversities experienced during the COVID-19 pandemic on changes in the mental health of older adults as measured by the Center for Epidemiological Studies Depression scale, an instrument developed to measure depressive symptoms. I demonstrate that financial adversities experienced during the pandemic contributed to the deterioration of the mental health of older adults. The estimated effects are heterogeneous among the groups of respondents defined by retirement status and history of psychiatric problems.

In Essay 3, I investigate how older adults responded to the pandemic-induced income shocks regarding their overall spending and spending out of 2020 Coronavirus Aid, Relief, and Economic Security Act stimulus payments. I establish that the negative income shocks experienced during the COVID-19 pandemic put downward pressure on household spending. The estimation results also reveal that, relative to those who did not experience an income shock, stimulus recipients who experienced income losses were more likely to use the stimulus transfer to increase spending, pay off debt, or for other purposes rather than to save.

INDEX WORDS: COVID-19 pandemic, Mental health, Financial adversities, Spending, Stimulus spending

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DEDICATION

I dedicate this dissertation work to my dear husband who has been a constant source of support and encouragement during the ups and downs of graduate school. I also dedicate this work to my parents who always inspired me to work hard for the things that I aspire to achieve. A special feeling of gratitude to my parents-in-law who have persuaded me in all ways to complete the journey which I have started.

I dedicate this work and give special thanks to my wonderful daughter, Khusi, for her unconditional love and support. Khusi's question, "Mom, are you done with your study/dissertation?" was a great push for me to complete the work.

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CHAPTER 1

INTRODUCTION

This dissertation comprises three essays on behavioral responses to the COVID-19 pandemic, with a specific focus on the internet search for mental health-related keywords, mental health symptomatology, and financial decision-making. The COVID-19 pandemic created both health and economic crises, disrupting nearly every aspect of people’s lives in the United States and around the globe. Nevertheless, not all people were equally affected by the pandemic, and older adults almost certainly faced much greater health risks, economic challenges, and disruptions in their lives. The unprecedented psychological and financial burdens created by the outbreak of coronavirus disease necessitate investigations aimed at a better understanding of the extent of the impacts experienced by different groups of individuals, designing effective targeted interventions, and protecting the at-risk populations.

In the first essay, I test empirically the difference in frequencies of online search for mental health-related keywords in the United States before and during the pandemic. I assume that the underlying variation in onsets of mental health problems in the general population can be gauged by the volume of internet searches for information. Furthermore, I examine the distinct roles of COVID-19-related deaths and indicators of the state of the economy as potential mechanisms of the change in online search behavior. Toward this purpose, I use weekly Google Trends data on the intensity of the search for mental health-related keywords measured at the state level and regress it on the number of COVID-19-related deaths, monthly unemployment rate, and values of the quarterly house price index. My estimations control for the state fixed effect regressions which allows me to eliminate the state-level heterogeneity in search behavior.

In the second essay, I narrow the focus of my study to the vulnerable population segment, older adults. The threat of job loss, income loss, and financial hardship during the COVID-19 pandemic makes older adults vulnerable to anxiety and depression. I utilize micro data from the Health and Retirement Study and examine the role of financial adversities, as measured by experiences of income shocks and financial hardship, on the mental health of older adults. I also explore the heterogeneity in these relationships by retirement status and history of psychiatric problems. Mental health outcomes in my study are measured with the scale developed by the Center for Epidemiological Studies Depression.

In the third essay, I examine the spending behavior of older adults. To mitigate the economic impact of COVID-19, the federal government implemented the 2020 CARES Act, the largest economic stimulus package in U.S. history. Using data from the 2020 Health and Retirement Study COVID-19 project and restricting the sample to older adults, I examine household responses to the pandemic-induced income shocks regarding their overall spending and spending out of 2020 CARES stimulus payments.

CHAPTER 2

ESSAY I: INTERNET SEARCH QUERIES FOR MENTAL HEALTH KEYWORDS DURING THE COVID-19 PANDEMIC: LONGITUDINAL ANALYSIS OF THE U.S. GOOGLE TRENDS DATA

2.1 INTRODUCTION

The COVID-19 pandemic has caused health and economic crises in the United States and across the world. Apart from its effect on physical health, the coronavirus outbreak is widely suspected to have inflicted severe damage on the population's mental health. Concerns about the psychological burden of the pandemic in the general population have grown steadily since early 2020. A policy brief issued by the United Nations (2020) underscores the urgency to include in national COVID-19 responses both short- and long-term interventions aiming to address mental health challenges faced by the citizens. A fast-growing volume of research demonstrates an increased level of anxiety and depression among the general population in the U.S. during the pandemic (Donnelly & Farina, 2021; Ettman et al., 2020; Fitzpatrick et al., 2020; Hertz-Palmor et al., 2021; Twegne & Joiner, 2020; Wilson et al., 2020).

Most of the studies on mental health during the COVID-19 outbreak have adopted cross-sectional designs with measurements that reveal only a one-time snapshot of the situation during the pandemic, making it difficult to track the changes in the population's mental health over time. In addition, studies on mental health have generally relied on traditional questionnaire-based data collection instruments. Such survey-based data have several drawbacks. For instance, subjective reports of emotions could be prone to bias from misreporting or misunderstanding (Kassas et al., 2022; Meier, 2013). In addition, surveys use limited-size samples due to a lack of voluntary participation, which might introduce small-sample bias in the responses (Wang et al., 2020; Brodeur et al., 2021).

Considering the limitations of traditional approaches exemplified by previous studies, I use a novel data set, Google Trends (GT), to examine the pandemic-induced variation in information search about mental health issues in the U.S. population. GT data provide the aggregate measure of search activity (as opposed to self-reported measures) for a particular period and geographic location. Hence, it is less prone to small-sample and self-reporting biases (Baker & Fradkin, 2017; Brodeur et al., 2021). Several studies have used GT data to predict real-world phenomena such as disease outbreaks, unemployment, or personal finance decisions (Askitas & Zimmerman, 2009; Carneiro & Mylonakis, 2009; Preis et al., 2013; Siliverstovs & Wochner, 2018). Most of these studies find a significant association between internet search behavior and subsequent real-world developments, implying that search volumes effectively predict many events. Following previous studies, I assume that Google queries related to mental health proxy for the real-world mental health condition of society. In other words, the higher the volume of online searches, the higher the rates of mental health problems experienced in the population.

Using GT data, I first compare the volumes of mental health-related searches before and during the pandemic. Furthermore, focusing on two potential pathways through which the pandemic could affect mental health: the number of COVID-19-related deaths and the condition of the national economy, I examine changes in mental health information search behavior brought about by each of these two distinct contextual mechanisms. Previous studies have indicated that the state of the national economy inflicts consequences on the psychological condition of the society (Di Tella et al., 2001; Ruhm, 2000, 2003). Nevertheless, the economic turmoil caused by the COVID-19 pandemic is different from previous recessions. Unlike most previous economic downturns, the pandemic is believed to be both a health and an economic crisis as the COVID-19 era economic disruptions are direct reactions to policy measures introduced to protect public health. This aspect of the economic slowdown in early 2020 followed by first-rapid and then-steady expansion in the second part of 2020 and 2021 provide a unique background to study the associations between economic climate and population mental health. The novel contribution of this research comes from the parallel use of the state-level GT data along with macroeconomic indicators data in order to better understand the determinants of collective behavioral responses to the health crisis and economic downturn that occurred during the pandemic.

This study utilizes the weekly number of COVID-19-caused deaths as a proxy for the severity of the health crisis. The number of COVID-19 deaths reflects the intensity of the pandemic, which I hypothesize translates into fear and mental distress. I expect that this increase in mental stress would subsequently increase online searches for information on mental health. Furthermore, the rapidly deteriorating economic conditions, especially during the first phase of the pandemic, are also considered to be among the important determinants of mental health problems. An increase in the local unemployment rate proxies for job losses and could gauge an independent mechanism of how the change in material living conditions leads to the worsening mental health of the society. During the pandemic, the unemployment rate hit a record high of 14.7% in April 2020 (Bureau of Labor Statistics, 2020). Given the pro-cyclical nature of mental health with the unemployment rate (Tefft, 2011), I hypothesize that the unemployment rate is a significant contributor to change in mental health information search behavior. Moreover, housing costs have dramatically increased during the pandemic. House prices play a vital role in driving the U.S. business cycle (Leamer, 2015). Given that housing constitutes a significant proportion of wealth for most Americans, and changes in local house prices might influence households' psychological state (Joshi, 2016), I also consider the house price index as a potential contributor to changes in mental health information search behaviors.

This research makes several contributions to the literature. To the best of my knowledge, this is the first study to simultaneously examine two distinct pathways of the COVID-19 pandemic's effect on mental health information search: the virus-caused deaths and the economic turmoil. Google search index constitutes an aggregated measure of online information search behavior for the entire population. This feature of my measures circumvents the issues of self-reporting bias and small sample bias. Finally, this study adds to the growing body of literature documenting the impacts of the ongoing COVID-19 outbreak on mental health (Donnelly & Farina, 2021; Ettman et al., 2020; Fitzpatrick et al., 2020; Hertz-Palmor et al., 2021; Twegne & Joiner, 2020; Wilson et al., 2020).

2.2 LITERATURE REVIEW

Several studies have been conducted recently to examine the effect of COVID-19 on mental health. A systematic review of such publications revealed a pattern of relatively high rates of anxiety, depression, post-traumatic stress disorder, and psychological distress, reported during the COVID-19 pandemic across different countries, including the U.S. (Xiong et al., 2020). For instance, Twenge and Joiner (2020) utilized the nationally representative data from a survey administered by the U.S. Census Bureau and compared the prevalence rates of anxiety and depressive disorder before and during the pandemic. They found that U.S. adults in mid-2020 were three times more likely to experience depressive and anxiety disorders than in 2019.

Similarly, Ettman et al. (2020) estimated the prevalence of depression and associated risk factors among U.S. adults before and during the COVID-19 pandemic. They employed survey data from the COVID-19 and Life Stressors Impact on Mental Health and Well-being study (conducted from March 31, 2020, to April 13, 2020) to derive the COVID-19-period estimates and the National Health and Nutrition Examination Survey (conducted from 2017 to 2018) to derive pre-COVID-19-period estimates. Results indicated that the prevalence of depression symptoms was 3-fold higher during the COVID-19 outbreak compared to estimates obtained with pre-pandemic data.

Fitzpatrick and colleagues (2020) examined the association between individual stressors and depressive symptoms among U.S. adults. They found elevated depressive symptoms among socially vulnerable groups (such as women, Hispanics, unmarried, and not working) and persons with moderate-to-high levels of food insecurity. In addition, they also observed a significant relationship between COVID-19-related fear and mental health conditions such as depression, and anxiety. Killgore et al. (2020) administered the UCLA Loneliness Scale-3 and Public Health Questionnaire to U.S. adults and assessed the impact of social isolation on mental health. They observed a significant association of loneliness with increased depression and suicidal ideation. Sloan et al. (2021) conducted a national-level survey through Amazon's Mechanical Turk platform in March 2020 to assess the extent of fear about the virus and its impact on the mental health of the American population. They noted both increased fear and psychological distress among study participants.

While much attention has been placed on the fear associated with contracting the coronavirus disease and death (Fitzpatrick et al., 2020; Sloan et al., 2021), prolonged social distancing and social isolation (Kampfen et al., 2020; Killgore et al., 2020; Smith et al., 2020), or bereavement (Grace, 2021) as the causes for adverse mental health, psychological challenges may also arise from the economic downturn that ensued from public policies designed to protect public health during the pandemic. Hertz-Palmor et al. (2021) investigated the associations between pandemic-related income loss and financial strain on adults' depressive symptoms in U.S. and Israel and observed that income loss and financial stress were the important risk factors associated with onsets of depressive symptoms.

Donnelly and Farina (2021) used the U.S. Census Bureau's Household Pulse Survey data to study the differences in the effect of income shock on mental health between states characterized by varying generosity of social policies. They found that living in a state with more supportive social policies such as Medicaid or unemployment insurance during the pandemic weakened the association between household income shocks and mental health. Their findings signal that, in addition to the direct negative psychological effect of the coronavirus, mental distress could be caused by the declining performance of the national economy. The COVID-19 response regulations consisted of forced quarantines, non-essential business closures, stay-at-home orders, and other restrictive measures aimed to reduce community transmission of the virus (Czeisler et al., 2021). Wilson et al. (2020) collected data from U.S. residents through Qualtrics during the period of the highest unemployment rate, from April 6-12, 2020, and demonstrated that the greater job insecurity due to the COVID-19 pandemic was related to greater depressive symptoms. Using mediation analysis, the authors also showed that greater job insecurity was indirectly related to greater anxiety symptoms due to financial concerns. Similarly, Kampfen et al. (2020) analyzed survey data from Understanding America Study conducted in March 2020 and found a strong association between worsening mental health and concerns about the economic consequences of the pandemic.

Evidence of the psychological impacts of worsening macroeconomic trends dates to previous recessions. Ruhm (2000) investigated the relationship between economic conditions and health by utilizing 1987-1995 Behavioral Risk Factor Surveillance System microdata and found total mortality to exhibit a pro-cyclical fluctuation with the performance of the economy. Still, the mortality from suicides was positively associated with the state unemployment rates. Using U.S. General Social Survey from 1972 to 1994, Di Tella et al. (2001) confirmed that lower unemployment levels were associated with higher reported happiness. Consistent with the previous study, Ruhm (2003), observed a positive relationship between unemployment and self-reported prevalence of non-psychotic mental illness in the National Health Interview Survey (NHIS) data from 1972-1981. Finally, Wang and Smith (2022) found a significant positive correlation between county-level unemployment rates and mental health distress.

Unlike the unemployment rate, findings on the relationship between the house price index and mental health remain mixed. For example, Lin et al. (2013) examined the impact of the housing crisis on the demand for mental health therapy by employing nationwide county-level prescription drug claims data from 2004 to 2009. They observed a negative relationship between the house price index and antidepressant use among the near-elderly (55-65 years old). Joshi (2016) utilized the Behavioral Risk Factor Surveillance System data for the years 2005-2011 and investigated the impact of county-level house prices on self-reported mental health. The results showed that individuals were likely to report worse mental health when local house prices declined, and the association was the most pronounced among homeowners. Contrarily, utilizing a dataset of 32 Chinese cities from 2013 to 2017, Wei et al. (2021) found that a short-term increase in house prices increased the number of people consulting with doctors about their mental disorders.

Several studies have successfully utilized Google Trends data to predict a wide range of real-world events. For instance, Carneiro and Mylonakis (2009) applied such data to predict regional outbreaks of influenza. Siliverstovs and Wochner (2018) demonstrated that Google Trends search data accurately predicted tourist flows in Switzerland. By analyzing changes in Google query volumes for search terms related to finance, Preis et al. (2013) found patterns that were indicative of early warning signs of changes in trade day closing values Dow Jones Industrial Average. Finally, Askitas and Zimmerman (2009) used internet search data from Germany to successfully forecast changes in unemployment rates.

Only a small number of studies have utilized GT data to study mental health. Tefft (2011) explored if the number of unemployment insurance claims and unemployment rates predict Google search volumes for depression and anxiety in the U.S. between 2004 and 2009. He found a positive correlation between unemployment rates and the depression search index and a negative relationship between initial unemployment insurance claims and the depression and anxiety search indexes while controlling for unemployment rates. Jacobson et al. (2020) used Google search queries from March 2020 to examine the change in mental health symptoms caused by stay-at-home orders in the U.S. They observed a significant drop in searches for suicidal ideation, anxiety, negative thoughts, and sleep disturbances with the implementation of stay-at-home orders, with the most prominent decrease in suicidal ideation and anxiety. Recently, Brodeur et al. (2021) used GT data to investigate the effect of lockdowns in Europe and the U.S. on changes in well-being as measured by search frequencies for several wellness-related keywords or phrases. The results were quite ambiguous as they found that lockdowns increased the frequency of searches for keywords such as boredom, loneliness, worry, or sadness, but decreased the prevalence of searches for keywords such as stress, suicide, and divorce.

2.3 METHOD

2.3.1 DATA

2.3.1.1 GOOGLE TRENDS (GT)

GT is the public database that provides summary data on the popularity of queries entered into the Google.com search engine. Instead of the total number of searches, GT provides relative search volume (RSV) data for specific search keywords and general query topics. To account for the geographic differences in search volume, GT normalizes the actual search numbers to the time and location of a query. Each data point is divided by the total searches for the specified geographical area and time range. The resulting number is an index between 0 and 100, where the value of 100 represents the highest search popularity for a term during a specified time in a defined geographical location; the value of 0 means the periods with the lowest search activity in the specified area. For a keyword search, GT provides unfiltered results for searches that include the keyword. For example, if we search for the word banana, we get results like "banana" and "banana sandwich." However, GT does not filter for any keyword variants, misspellings, or synonyms.

I obtained data on search queries from GT for the time ranging from the pre-pandemic period and the period when more than 60% of the U.S. population became fully vaccinated against coronavirus disease (2018/01/01 – 2021/12/31). Weekly RSVs for seven mental health terms: "sad", "depression", "empty", "guilty", "suicide", "fatigue", and "insomnia" were downloaded at the state level, representing the public interest in mental health for each state in the U.S. While selecting the mental health-related keywords, I chose words representing the symptoms and terms listed by the American Psychiatric Association as indicative of major depressive disorder (Torres, 2020). To account for random variance in the search keywords due to internet traffic, I also downloaded GT data on popular internet search terms: "Google", "Youtube", "Facebook", "sports", and "news" across similar periods (Azzam et al., 2021; Wang et al., 2022). Some of the states did not have enough search data to be recorded in GT over the specified period for some of the keywords; hence, it was impossible to get the complete data using individual keywords. Thus, I divided search terms into three groups because GT only allows for the direct comparison of five keywords at the same time. Group 1 included the search terms "sad", "depression", "empty", "guilty", and "suicide". Group 2 included the search terms "fatigue" and "insomnia". Group 3 included the internet search terms "Google", "Youtube", "Facebook", "sports", and "news". The data for each group were extracted using the unofficial Google Trends API, Pytrends in Python.

2.3.1.2 COVID-19 DEATHS

First, I obtained data on daily COVID-19 deaths for all 50 states in the U.S. from the Centers for Disease Control and Prevention website. I then aggregated the daily data into weekly data and merged it with the GT data by week and state. I coded the value of the COVID-19 deaths variable in the period before the pandemic as 0.

2.3.1.3 MACROECONOMIC DATA

To operationalize the economic conditions variables, I recorded state-level monthly unemployment rates published by the U.S. Bureau of Labor Statistics and merged them with the GT data by month, year, and state. Then, I obtained the values of the House Price Index based on all quarterly transactions published by the U.S. Federal Housing Finance Agency (FAFH) for each state and merged them with the GT data by quarter, year, and state. Both macroeconomic series were obtained from the Federal Reserve Economic Data internet portal.

2.3.2 ANALYTICAL STRATEGY

I estimated the following model specifications:

$$y_{i,w} = \alpha_0 + \alpha_1 COVID_w + \alpha_2 X_{\mathrm{i,w}} + \lambda_i + \varepsilon_{i,w} \quad (2.1)$$

$$y_{i,w} = \beta_0 + \beta_1 ln(COVID\_deaths_{iw}) + \beta_2 unemp_{iw} + \beta_3 \ ln(HPI_{iw}) + \beta_4 X_{\mathrm{iw}} + \pi_i + \upsilon_{i,w} \quad (2.2)$$

where i indexes the state and w represent the week; Y is the RSVs of mental health keywords (either sad, depression, empty, guilty, suicide, fatigue, or insomnia); $COVID$ is the binary indicator for the COVID-19 period (any time after 1/21/2020); $COVID\_deaths$ is the number of COVID-related deaths; $unemp$ is the unemployment rate; HPI is the FHFA House Price Index; X is the covariate matrix; λ and π represent unobserved state-level heterogeneity differenced out via the fixed-effect estimation method; and ε and υ are stochastic error terms. To account for the seasonal variation in search volumes, X in model (2.1) included season dummies and RSVs for the popular internet terms (Google, YouTube, Facebook, sports, and news). X in model (2.2) included dummies representing the year-quarter combination, and RSVs for the popular internet search terms (Google, YouTube, Facebook, sports, and news). To capture the variation in covid deaths in different quarters, I used the year and quarter dummies in the model (2.2). The models were estimated using the Ordinary Least Squares regression of $y_{i,w} - \overline{y_i}$ on time demeaned regressors (i.e., the so-called within estimator). The parameters of interest are $\alpha_1 , \beta_1 , \beta_2 , and\ \beta_3$, where α_1 compares the RSVs of keywords before and during COVID-19 pandemic, and $\beta_1 , \beta_2 , and\ \beta_3$ show the relationship between RSVs and covid-related deaths, the unemployment rate, and the average house prices, respectively.

2.4 RESULTS

2.4.1 DESCRIPTIVE STATISTICS

Table 2.1 presents the summary statistics of three key predictors. For the COVID-19 period considered in my sample, the average weekly covid deaths were 150.35 with a standard deviation of 278.46. The minimum number of weekly deaths was 0, and the maximum of 3,797. The average monthly unemployment rate prior to the pandemic was 3.63 and increased to 6.16 during the COVID-19 period. The value of the FHFA House Price Index increased from 418.14 prior to the COVID-19 period to 481.36 during the outbreak.

2.4.2 CHANGE IN RSVs OF MENTAL HEALTH KEYWORDS DURING THE PANDEMIC

The estimation results of equation (2.1) are presented in Table 2.2. Panels A and B report the estimates for the search keywords in groups 1 and 2, respectively. The coefficient on the COVID variable was statistically significantly associated with the search popularity of all keywords. While the search intensity for sad, empty, guilty, fatigue, and insomnia increased during the COVID-19 period, the search intensity for depression and suicide decreased during the pandemic compared to the pre-COVID period. My result regarding the search intensity of suicide is broadly consistent with Brodeur et al. (2021) who also found a significant drop in search intensity for this keyword during lockdowns. The Centers for Disease Control and Prevention reported a 3% reduction in the number of suicides in 2020 compared to 2019 in the Vital Statistics Surveillance Report (Curtin et al., 2021). Thus, the search intensity for this term in my study correctly reflects the actual reduction in suicides during 2020 in the U.S.

Comparing the estimates of the COVID variable in panel A, the pandemic period increase in search popularity for guilty was the largest, followed by empty and sad. On the other hand, the reduction in search popularity for depression was more pronounced in magnitude than the reduction in search popularity for suicide. Moreover, results in panel B reveal that the increase in search popularity for insomnia was greater than the increase in search popularity for fatigue.

I also find a significant seasonality effect in the search intensity for mental health-related keywords. The search intensity of sad, depression, and guilty was significantly higher during the fall, winter, and spring than in summer. Contrarily, the search intensity for suicide was lower during the fall, winter, and spring than in summer. Compared to the summer, the word, empty also was used less often during winter. There was also a statistically significant drop in search intensity for fatigue during fall, winter, and spring compared to the summer. Similarly, the search intensity of insomnia significantly reduced during the spring compared to the summer.

2.4.3 COVID-19 INTENSITY, MACROECONOMY, AND RSVs OF MENTAL HEALTH KEYWORDS

To better understand the mechanism of change in search intensity for mental health-related keywords, I considered the measures of COVID-19 intensity and macroeconomic indicators as simultaneous determinants of online search behavior. COVID-19 intensity was measured as the number of coronavirus-related deaths. The unemployment rate and the FHFA House Price Index were the two measures of macroeconomic indicators. Table 2.3 present the results from the estimation of equation (2.2). As before, the results in panels A and B represent parameter estimates of equation (2.2) for the search keywords in groups 1 and 2, respectively. The search intensity for keywords empty, fatigue, and insomnia was a positive function of the number of COVID-19-related deaths. Consistently with previous results, the search intensity for suicide significantly decreased with the rise in COVID-19-related deaths. As mentioned earlier, this observation matches the reduction in the official count of suicides in 2020 when COVID-19-related deaths were increasing.

Among the two macroeconomic indicators, only the unemployment rate was associated with the change in search intensity of mental health-related keywords. The positive relationship between unemployment and the depression search index in the U.S. has also been shown in the literature (Tefft, 2011). In addition, a study conducted in Europe showed the unemployment rate as a powerful indicator of hospital admission rates due to mental illness among individuals under 65 years (Kammerling & O'Connor, 1993). Results suggest that the search intensity for sad, depression, empty, suicide, and insomnia significantly increased with the increase in the unemployment rate. However, the search intensity for guilty and fatigue did not have a significant association with the unemployment rate. Comparing the magnitudes of estimated parameters in panel A, the relationship between search intensity and the unemployment rate was the highest for depression, followed by suicide, sad and empty. In panel B, the coefficient on unemployment rate was significant only for insomnia but not for fatigue.

2.5 SUMMARY AND CONCLUSION

The COVID-19 pandemic has profound consequences on mental health. Along with the fear of the disease itself, the economic downturn resulting from public health policies may have caused stress and worries among the general population, influencing their mental health. As the COVID-19 infections continue to wear on around the world, the concerns that many people continue to experience mental health impacts necessitate nuanced investigations into the mechanism of such effects. This study compares mental health-related online information searches before and during the pandemic by utilizing Google Trends data. More importantly, this study explores the two potential pathways, COVID-19-related deaths, and economic climate, as the contributors to the change in mental health-related searches.

Results indicate that the pandemic had a significant influence on people's mental health. Americans have increased the frequency with which they searched for keywords such as sad, empty, guilty, fatigue, and insomnia during the COVID-19 pandemic. Moreover, the search intensity for keywords such as empty, fatigue, and insomnia increased with the increase in the number of deaths caused by COVID-19. However, the search intensity for suicide went down with the rise in COVID-19-related deaths. It is possible that, by implementing restrictions that forced people to spend more time with their families, public health authorities achieved a positive side-effect of reducing the number of suicide rates.

Results also provide strong evidence for the effect of the unemployment rate on mental health search intensity. The search intensity for keywords such as sad, depression, empty, suicide, and insomnia significantly increased with the increase in the unemployment rate. Meanwhile, I find no evidence for the variation in FHFA House Price Index determined any meaningful change in the search for mental health-related keywords.

My study, as well as the broader body of research in this area, provides evidence and justification to incorporate public health measures protective of mental health as part of the national COVID-19 response. The increasing search intensity for mental health keywords, especially during the pandemic, signifies the increasing need for monitoring and treating patients with mental health problems. Healthcare professionals and policymakers should be mindful of the ongoing increase in mental health symptomatology and be prepared to provide services to meet the increasing demand for mental health services. Moreover, results also imply that policymakers should consider the health of the labor sector as one of the key initiatives to promote mental health.

While this study adds to the literature about the mental health consequences of the pandemic, it comes with some limitations. First, younger individuals are relatively more likely to use Google for online information search. According to the survey conducted by Pew Research Center in 2021, while 99% of young adults from 18-29 years reported using the internet, only 75% of adults over 65 years reported themselves as internet users (Johnson, 2022). The results in this study could not be fully representative of older individuals. Second, patients with severe mental health problems may not be able to make a Google search because of their hospitalization. This could lead to the inadvertent exclusion of certain populations. Next, Google Trends data cannot capture the demographic profiles of google users; hence, I could not explore the heterogeneity in searches for mental health information during the pandemic by demographics. For instance, older adults are among the vulnerable population segments, and they could respond differently to the pandemic than younger individuals. Furthermore, my study models mental health keyword searches for the U.S. only. The increase in search intensity of mental health keywords is indicative of an increase in help-seeking behavior. Future studies should gain more insight by considering the mental health service-seeking behavior in a particular geographical area. Overall, the insights gained from the GT data can be very useful in monitoring mental health problems, making it possible for prompt preventive and remedial actions.

Table 2.1: Summary Statistics

	Pre-COVID				During COVID			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Covid deaths	0.00	0.00	0.00	0.00	150.35	278.46	0.00	3797
Monthly unemployment rate	3.63	0.89	1.30	7.10	6.16	3.22	1.50	27.50
Quarterly House Price Index	418.14	122.40	224.98	832.34	481.36	148.68	238.18	1010.42
Observations	5,350				5,040			

Table 2.2: Effect of COVID-19 on RSVs of Mental Health Keywords

	Panel A				
	Sad	Depression	Empty	Guilty	Suicide
COVID	0.478***	-1.565***	0.999***	1.181***	-1.243***
	(0.095)	(0.157)	(0.089)	(0.079)	(0.156)
Season					
Fall	0.306**	1.894***	-0.046	1.463***	-5.187***
	(0.148)	(0.164)	(0.087)	(0.081)	(0.211)
Winter	0.699***	2.932***	-0.319***	0.620***	-5.354***
	(0.154)	(0.214)	(0.075)	(0.069)	(0.143)
Spring	0.395***	3.284***	0.114	0.450***	-5.506***
	(0.108)	(0.167)	(0.060)	(0.064)	(0.145)
Internet search traffics	Yes	Yes	Yes	Yes	Yes
Within R^2	14.20	39.59	7.29	12.78	6.06

	Panel B	
	Fatigue	Insomnia
COVID	5.651***	7.294***
	(0.517)	(0.827)
Season		
Fall	-4.107***	-0.894
	(0.510)	(0.586)
Winter	-4.004***	-0.750
	(0.563)	(0.530)
Spring	-1.020**	-2.865***
	(0.502)	(0.528)
Internet search traffics	Yes	Yes
Within R^2	3.79	11.69

Notes: N=10,400. All estimations control for internet search traffic (RSVs for Google, YouTube, Facebook, sports, and news). Robust standard errors are in parentheses. Standard errors are clustered at the state level. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 2.3: Effect of COVID-19 Deaths, Unemployment, and Housing Price Index on RSVs of Mental Health Keywords

	Panel A				
	Sad	Depression	Empty	Guilty	Suicide
ln (COVID deaths)	0.042	0.045	0.044*	0.003	-0.179**
	(0.036)	(0.046)	(0.023)	(0.020)	(0.061)
Unemployment rate	0.110***	0.218***	0.040*	-0.040	0.137*
	(0.039)	(0.065)	(0.023)	(0.024)	(0.075)
ln (House Price Index)	1.122	1.866	-2.552	0.201	-2.748
	(3.225)	(2.885)	(1.937)	(1.418)	(3.771)
Year quarter dummies	Yes	Yes	Yes	Yes	Yes
Internet search traffics	Yes	Yes	Yes	Yes	Yes
Within R^2	21.41	44.56	7.95	29.81	24.24
	Panel B				
	Fatigue	Insomnia			
ln (COVID deaths)	0.236**	0.492***			
	(0.094)	(0.127)			
Unemployment rate	0.032	0.465***			
	(0.184)	(0.165)			
ln (House Price Index)	-7.527	-8.975			
	(7.627)	(15.827)			
Year quarter dummies	Yes	Yes			
Internet search traffics	Yes	Yes			
Within R^2	6.67	16.05			

Notes: N=10,390. All estimations control for year quarter dummies and internet search traffics (RSVs for Google, YouTube, Facebook, sports, and news). Robust standard errors are in parentheses. Standard errors are clustered at the state level. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

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CHAPTER 3

ESSAY II: THE EFFECT OF FINANCIAL ADVERSITIES EXPERIENCED DURING THE COVID-19 PANDEMIC ON MENTAL HEALTH OF OLDER AMERICANS

3.1 INTRODUCTION

The economic downturn during the COVID-19 pandemic posed enormous challenges for retired Americans and those nearing retirement (Abrams et al., 2021). Apart from the physical health risk, older adults are vulnerable to pandemic-induced anxiety and depression due to the threat of job loss, income loss, or financial hardship. Unlike prior recessions when older Americans experienced lower unemployment relative to mid-career counterparts, the COVID-19 recession flipped the age pattern of unemployment (Davis et al., 2020). Older adults faced high unemployment (Bui et al., 2020; Davis et al., 2020), high furloughs (Kobayashi et al., 2021), and forced or early retirement (Coibion et al., 2020). A national longitudinal cohort study conducted from April to May 2020 revealed that nearly one in five workers aged 55-64 years and one in three workers aged ≥ 75 years were placed on a leave of absence or furloughed since the beginning of the pandemic (Kobayashi et al., 2021).

Prior research on the health impacts of recessions among older workers found unemployment and its associated financial strain detrimental to mental health (Pruchno et al., 2017; Wilkinson et al., 2016). Job loss and income insecurity could trigger a series of additional adversities such as economic distress, lower self-esteem, social withdrawal, family life disruptions, anxiety, depression, and the overall decline in physical and psychological well-being

(Brand, 2015; Donnelly & Farina, 2021). The polls conducted by the Kaiser Family Foundation and the Pew Research Center in March 2020 revealed that most Americans who lost their jobs or experienced a pay cut reported a negative impact on their mental health, and the impact was higher among low-income respondents (Keeter, 2020; Purtle, 2020). Evidence from empirical literature generally supports the notion that an unexpected job loss and a sizeable loss of income or financial hardship are among the critical risk factors for developing depression (Mandal et al., 2011; Prause et al., 2009). Furthermore, with over 14% prevalence among adults aged 50 and older, mental health problems are already common among U.S. adults (NIMH, 2019). Considering these stylized facts and prior academic literature, I expect that income shocks and financial hardship experienced during the COVID-19 pandemic have sparked new mental health problems or exacerbated the existing ones among older Americans.

Understanding the mental health burden of COVID-19 has become a public health priority and attracted a significant amount of attention from researchers, practitioners, and policymakers. Designing targeted interventions to alleviate the adverse psychological impacts of the current and future outbreaks requires a better understanding of associated risk factors and the extent of mental health issues experienced by individuals, particularly the members of at-risk populations. Given the unique challenges to both physical and mental health, older adults constitute a sizable and thus particularly important at-risk population. Despite the compelling need for a better understanding of how COVID-19-induced economic difficulties affect the mental health of older adults, only a few studies attempted to address this topic. For example, Kobayashi et al. (2021) examined the effects of pandemic-associated stressors on the mental health and well-being of adults aged 55 and older and found that nearly one in three individuals screened positive for depression, anxiety, and loneliness. Abrams et al. (2021) examined the relationship between various job disruptions and life satisfaction, loneliness, as well as depressive and anxiety symptoms. The authors reported a significant association between COVID-19-related job transitions, such as losing a job, getting furloughed, reduced hours or income, and mental health outcomes.

This study aims to examine the effect of financial adversities (income shock and financial hardship) experienced during the COVID-19 pandemic on changes in mental health of older adults. Additionally, I explore the potential heterogeneity of this relationship by retirement status and history of psychiatric problems. These tests help to better identify the vulnerable populations which, in turn, could aid financial and mental health practitioners and policymakers make evidence-based decisions. The contribution of this study to the extant literature comes from the simultaneous consideration of two critical periods: pre-pandemic and pandemic, and two important life domains: financial and psychological. Unlike past papers that mostly relied on cross-sectional comparisons, this analysis utilizes longitudinal data that allows me to model within-individual variation in mental health.

3.2 LITERATURE REVIEW

The COVID-19 pandemic created unprecedented disruptions to daily lives across the globe. The negative psychological impacts of changes in daily life routines were likely exacerbated by feelings of uncertainty and fears of the global economic recession. Many public health actions intended to curb the spread of the virus led to household economic strain. Research on mental health consequences of the COVID-19 pandemic is expanding rapidly, with numerous studies across the globe procuring evidence that the pandemic led to onsets and increased severity of anxiety, depression, and psychological distress (e.g., Bareket-Bojmel et al., 2021; Das et al., 2022; Ettman et al., 2020; Fitzpatrick et al., 2020; Li et al., 2020; Reger et al., 2020; Twenge & Joiner, 2020).

Bareket-Bojmel et al. (2021) reported that the economic anxiety experienced by survey respondents in the U.S., U.K., and Israel at the peak of the COVID-19 outbreak was at a similar level to the health-related anxiety and concluded that economic anxiety should receive increased policy makers' attention. Das et al. (2022) found that the timing of state-level lockdown orders in the U.S. coincided with significantly increased mental health symptoms. Similarly, Ettman et al. (2020) estimated that the prevalence of depressive symptoms among U.S. adults increased more than 3-fold during the COVID-19 pandemic compared to previous years. Fitzpatrick and colleagues (2020) examined the relationships between individual stressors and depressive symptomatology among U.S. adults during the pandemic. Their findings suggest that depressive symptomatology was elevated among socially vulnerable groups (women, Hispanic, unmarried, not working) and persons expressing moderate to a high level of food insecurity. Li et al. (2020) observed that the prevalence of anxiety and depression in the Chinese adult population during the peak of COVID-19 increased compared to a year before and that the high levels of mental distress were associated with specific worries about income, job, study, or inability to pay loans. Twenge and Joiner (2020) used data from the U.S. Census Bureau survey to compare the prevalence rates of anxiety and depressive disorders before and during the pandemic. They observed that U.S. adults in mid-2020 were three times more likely to screen positive for depressive and anxiety disorders than in 2019.

The studies mentioned above indicate that, although the crisis originated in a physical health context, individuals experienced economic stress and anxiety, which could further lead to more severe mental health consequences. However, all these studies focused on the general adult population, whereas older adults likely were particularly at risk of experiencing mental health adversities during the COVID-19 pandemic. Furthermore, these studies did not attempt to attribute the changes in mental health outcomes specifically to income shocks experienced during the pandemic.

Only a few studies looked into the relationship between pandemic-related income loss and mental health outcomes. Hertz-Palmor et al. (2021) investigated the relationships between income loss, financial strain, and depressive symptoms with two separate samples of adult respondents recruited in the U.S. and Israel. They observed that income losses and financial strain were associated with greater depressive symptoms in both countries. Donnelly and Farina (2021) used the Census Bureau's Household Pulse Survey data to document that the onsets of depression and anxiety were more frequent and severe among adults who experienced income shocks, especially if they lived in states with less generous social policies. Huato and Chavez (2021) also found that the probability of reporting various symptoms of anxiety and depression among adult Americans was the function of pandemic-related employment income loss. Although all these studies modeled the mental health consequences of income loss, the surveys used in these studies did not focus on adults around the retirement age, who were especially vulnerable to the effects of the recent economic downturn associated with coronavirus disease.

Abrams et al. (2021) studied the disturbances to working life and mental health among Americans aged at least 55 during the early months of the pandemic. The authors utilized data from the University of Michigan’s nationwide COVID-19 Coping Study to investigate the association between job transitions and mental health outcomes. Their findings indicate that workers who experienced job losses had the lowest life satisfaction, the highest loneliness, and depressive symptoms, followed by workers who experienced furloughed or reduced work hours/income. Some evidence of the pandemic's psychological health impacts on older adults emerged from studies conducted in Europe. Mendez-Lopez et al. (2022) assessed changes in mental health in the population aged 50 years and older in 26 European countries at the peak of the European outbreak of COVID-19. They found that, depending on the country, between 16% and 55% of study participants reported worsening mental health since the beginning of the pandemic, with various socioeconomic factors (e.g., gender, job loss, financial hardship), the stringency of physical distancing measures, and the generosity of social protection policies playing important roles on the change in mental health. In another European study of older adults, Pacccagnella and Pongiglione (2022) aimed to determine how depressive symptoms changed during the pandemic's first wave and identify risk factors related to the reports of depression. The authors observed that gender and pre-existing mental or physical health disorders were among the critical determinants of worsening mental health. They also found that job loss was an important factor in mental health decline for men, but not for women.

This study is similar to the papers mentioned above in the sense that my target population also comprises older adults, albeit those residing in the U.S. However, I examine the effects of different potential economic risk factors for mental health deterioration, such as the types of income shock (i.e., loss of earnings, business income, retirement income) and financial hardship experienced during the pandemic. To the best of my knowledge, none of the extant studies examined the heterogeneity in the mental health effects procured by different types of income shocks. Moreover, unlike the one-time snapshot of mental health portrayed in most extant papers, I focus on health deterioration over time. I consider longitudinal data which allows me to consider the difference in mental health for the same individuals between two time periods: before and during the pandemic. Such an approach offers the advantage of controlling for the confounding influence of unobserved or unmeasured time-invariant individual heterogeneity that might bias the estimates of the pandemic effects in studies based solely on cross-sectional comparisons.

3.3 METHOD

3.3.1 DATA

The data was drawn from the 2018 and 2020 waves of the Health and Retirement Study (HRS), a nationally representative longitudinal survey of Americans above 50 years of age and their spouses. The data for the 2020 wave was collected from March through May 2021. The HRS provides detailed information on older adults' socioeconomic characteristics, demographics, health, income, and assets. The sample was limited to individuals who responded to the 2020 COVID-19 module because the variables of interest were coded based on answers to questions that appeared in this sub-survey. I dropped respondents younger than 51 as they did not constitute the age-eligible core HRS sample. I further excluded observations with missing values on variables used in the analysis. Consequently, the baseline sample comprised 8,019 respondents.

3.3.2 MEASURES

Before the execution of the HRS COVID-19 questionnaire, respondents were primed with the following statement: "*Next, we have some questions about the coronavirus pandemic, also known as COVID-19.*" This conditioning allows me to assume that the subsequent questions about economic status reflect the exogenous impacts of the pandemic. I used three different measures of financial adversities experienced during the pandemic: i) income shock, ii) income shock type, and iii) financial hardship.

3.3.2.1 FINANCIAL ADVERSITIES

Income Shock

The HRS COVID-19 module includes a question, "*Since the start of the coronavirus pandemic, has your income gone up or down or stayed about the same because of the pandemic?*" with response options: "*income went up*", "*income went down*", "*about the same*". The income shock variable was constructed as the binary indicator equal to one if the respondents' income went down and zero otherwise.

Income Shock Type

To explore how the type of income shock translates into worsening mental health, I used the response to the next question that inquired about the type of income change of respondents who acknowledged a change in their income. The response options to this follow-up question were: "*earnings from work*", "*income from retirement plan or other assets*", "*income from business*", and "*other*". Combining responses to these two questions, I constructed a set of mutually exclusive indicator variables to signify: (1) increased or unchanged income, (2) decrease in earnings, (3) decrease in retirement/assets income, (4) decrease in business income, and (5) decrease in income from other sources.

Financial Hardship

Survey respondents were asked if they missed any regular payments on rent or mortgage, credit cards or other debt, utilities or insurance, medical bills, and other payments because of the pandemic. Following Liu et al. (2021), I constructed a composite index financial hardship variable by summing affirmative responses to these five questions on missed financial obligations.

3.3.2.2 MENTAL HEALTH

The Center for Epidemiological Studies Depression scale (CES-D) is a self-report instrument developed to measure depressive symptoms. Two versions of the CES-D scale, one based on the 8-item, and one based on the 20-item questionnaire are utilized widely in social science research to measure depressive symptomatology (Luo et al., 2020; Xiang & An, 2015). While some studies rely solely on the total CES-D score as the measure of overall mental health, others use a specific cut-off score as a marker for being at risk for clinical depression (Swallen et al., 2005; Xiang & An, 2015). Relying on the total CES-D score makes it difficult to extrapolate findings to the populations of clinically depressed individuals. Thus, I employed both the continuous CES-D score and the binary indicator of being at risk for clinical depression.

CES-D Score

Depression symptoms in HRS data were assessed using the 8-item CES-D instrument, a scale with good validity properties that is frequently utilized in clinical studies of older adults (Turvey et al., 1999; Xiang and An, 2015). The 8-item CES-D scale consists of six negative and two positive binary indicators of mental health status. The negative indicators measure whether the respondent experienced the following sentiments "*much of the time*" in the past week: "*depression*", "*everything is an effort*", "*sleep is restless*", "*felt alone*", "*felt sad*", and "*could not get going*". The positive indicators measure whether the respondent "*felt happy*" and "*enjoyed life*" much of the time in the past week. The total CES-D score is the sum of binary indicators of six negative feelings and the absence of two positive feelings. The score ranges from 0 to 8, with a higher score corresponding to worse mental health.

Depression

The cut-off score of 3 on the 8-item CES-D scale has a sensitivity of 71% and a specificity of 79% in predicting major depressive episodes (Turvey et al., 1999). Following Xiang and An (2015), I first classified respondents as having clinically relevant depressive symptoms if they scored three or higher on the CES-D scale. I constructed a binary indicator variable to identify the respondents who did not have clinically relevant depressive symptoms in 2018 but reported such symptoms in 2020.

3.3.3 ANALYTICAL STRATEGY

I began the empirical analysis by testing the increase in CES-D score of individuals who experienced income shocks during the pandemic in 2020 compared to their pre-pandemic score using a one-tailed paired t-test. Correspondingly, I also conducted one-tailed two-sample tests of proportions of individuals considered at risk of depression pre-pandemic vs. during the pandemic among individuals who experienced income shocks. To further shed light on the effect of financial adversities on change in mental health, I estimated variants of the following regression specification using the ordinary least squares:

$$Y_{i,t} - Y_{i,t-2} = \beta_0 + \beta_1 * A_{it} + \beta_2' X_{it} + \beta_3' Z_{it-2} + \varepsilon_{i,t}, \qquad (3.1)$$

where *i* indexes the respondent, *t* and *t-2* stand for the years 2020 and 2018, respectively; Y is the CESD score; A is a measure of financial adversity (income shock, indicators for different types of income shock, or the financial hardship score); *X* represents demographic control variables (age, gender, race, ethnicity, marital status, educational attainment, number of resident children); Z represents other control variables (self-reported health, whether the respondent was working for pay, logged household income, and hyperbolic sine transformed wealth) included to account for potential confounders of the investigated relationships. I also controlled for the survey month fixed effects to account for the difference in the timing of mental health deterioration during the pandemic. Given that the first-difference mental health outcomes were regressed against income shock and financial hardship, they effectively represented respondent-level fixed-effect models that controlled for unobserved individual heterogeneity. In other words, the first differencing swept out correlation from the omitted unobserved time-invariant characteristics, such as preferences or health endowments, that could otherwise confound the identification of effects of interest. To examine if the experiences of income shocks affect mental health independently of the effect of financial hardship, I also estimated the effect of income shock and income shock types with added control variable $Finhrdshp$.

Next, I conducted analogous logistic regression analyses with the second dependent variable, i.e., depression, measured as a binary indicator for the onset of clinically relevant depressive symptoms between 2018 and 2020. Furthermore, I tested the heterogeneity of the relationship between financial adversities and mental health by estimating Equation (3.1) separately for retired and non-retired adults, as well as for adults who were and those who were not pre-diagnosed with psychiatric problems before the pandemic.

3.4 RESULTS

3.4.1 DESCRIPTIVE STATISTICS

Table 3.1 displays the descriptive statistics. Slightly more than 18% of households experienced an income shock during the pandemic. Among the respondents who reported a decline in their income, about 13.38% reported that their earnings from work went down, 1.17% reported income from a retirement plan or other assets went down, 1.64% reported business income went down, and 2.01% reported a decrease in income from other sources. The average financial hardship score was 0.41, with the index value roughly 3 times higher among the respondents who experienced an income shock relative to those who did not.

The descriptive statistics also reveal the magnitude of mental health deterioration experienced by older adults during the pandemic. The average CES-D score increased from 1.48 in 2018 to 1.56 in 2020. Similarly, a higher proportion of individuals met the threshold for clinically relevant depression symptomatology in 2020 (23%) compared to 2018 (21%). Over 12% of the respondents who experienced an income shock became at risk for clinical depression in 2020, compared to less than 10% of those whose income did not decrease. Expectedly, the average CES-D score increased between 2018 and 2020 by a wider margin among households who experienced income shock relative to households whose income did not decline. Likewise, respondents in households who experienced income shocks were more likely to report clinically relevant symptoms that classified them as being at risk for depression.

Information on demographic, health, and various socioeconomic variables are also available in Table 3.1. More than half of my sample comprises individuals 65 years old or older, 60% were females, 64% were Whites, 52% were married, and 31% had a high school diploma or GED. Before the pandemic, nearly 73% of the respondents reported good, very good, or excellent health, and 44% worked for pay. Regarding economic resources before the pandemic, the median household income and wealth were $45,304, and $137,000, respectively.

3.4.2 PRELIMINARY RESULTS

The results of the paired t-test presented in Table 3.2 indicate a significant increase in the CES-D score of individuals who experienced income shock during the pandemic, t (1471) = 3.433, p = .0003. An increase in the CES-D score corresponds to mental health deterioration because the higher the CES-D score, the worse is the mental health. However, the effect size (d = 0.09) is small[1].

The results of the two-sample z-test in Table 3.3 indicate that among respondents who experienced household income shock, there was a significant increase in the proportion of individuals who met the threshold of clinically relevant depression symptoms in 2020 as compared to 2018, z (1472) = 2.583, p = .0005, suggesting the mental health deterioration during the pandemic.

3.4.3 EFFECT OF FINANCIAL ADVERSITIES ON MENTAL HEALTH

Coefficient estimates from OLS regressions are reported in Table 3.4. Results reveal that, relative to those households who did not experience income shocks, adults who experienced an income shock reported a 0.173 (p < .01) point increase in their CES-D score. Among different types of income shock, only the effect of income shock from retirement assets was sizable enough to reach statistical significance. On average, adults who experienced a decline in income from retirement/assets reported a 0.795 (p < .001) point increase in their CES-D score relative to adults whose households did not experience an income shock. Estimates in column 3 indicate that a unit increase in financial hardship score increased the CES-D score by 0.088 (p < .01) points. When I re-estimated the models with simultaneous controls for income shocks and financial hardship (columns 4 and 5), I observed that all coefficients of interest preserved their statistical significance and the effect magnitudes remained similar. This suggests that the effects of income shock and financial hardship on mental health operate independently from each other rather than one effect proxying the other.

[1] In behavioral studies, which are conducted outside of the lab, uncontrollable noises might make the signal difficult to detect, producing a small effect size (Cohen, 1988).

Odds ratios from logistic regressions reported in Table 3.5 reveal a similar story for depression. Estimates in column 1 show that adults residing in households that experienced income shocks during the pandemic had 33% ($p < .01$) greater odds of becoming at risk of clinical depression compared to adults who did not experience a household income shock. Estimates in column 2 indicate that, compared to the same reference group, adults whose income from retirement/assets went down had 141% ($p < .001$) greater odds of experiencing the onset of severe depression. The odd ratio for financial hardship in column 3 suggests that a unit increase in financial hardship score increased the odds of having the onset of clinical depression by 19% ($p < .001$). Notably, in estimations that simultaneously controlled for overall income shocks and financial hardship, the effect of financial hardship remained statistically significant, and the effect of income shock lost its significance (column 4). Thus, the effect of the decline in overall income on the onset of depression seems to be significant only if it leads to financial hardship. However, the decline in retirement/assets income remained a significant contributor to depression onset. Altogether, echoing the results from the previous recessions (Wilkinson, 2016), my results suggest that experiencing financial adversities during the pandemic contributed to the deterioration of mental health of older adults.

3.4.4 HETEROGENEITY ANALYSES

Experiences of financial adversity could have different effects on working vs. retired adults. I estimated variants of Equation (3.1) separately for the sub-samples of retired and non-retired adults. Panels A and B in Table 3.6 present results for change in CES-D score and depression, respectively. While retirement/assets income shock was the significant contributor to change in CES-D score among retired individuals, the variation in mental health symptomatology among non-retired individuals was determined primarily by the experience of earnings shock. Retired individuals whose retirement/assets income decreased during the pandemic saw a 0.828 ($p < 0.001$) point increase in CES-D score compared to retired adults whose income remained the same or went up. An experience of financial hardship was another statistically significant factor contributing to retired adults' mental health deterioration. A point increase in the financial hardship score increased the CES-D score by 0.121 ($p < 0.05$) points. Non-retired individuals whose earnings decreased during the pandemic saw a 0.159 ($p < 0.05$) point increase in CES-D score compared to non-retired adults whose income remained the same or went up. Although the sign of the estimated coefficient was as expected, the association of financial hardship with the change in CES-D score was not significant for non-retired adults.

Income shock type and financial hardship were also significant predictors of being at risk for clinical depression for both retired and non-retired adults. Being behind in one more financial obligation increased the odds of having the onset of clinical depression during the pandemic in both retired and non-retired adults by 25% and 16%, respectively. Compared to their counterparts whose income remained the same or went up, a decrease in retirement/assets income (117% greater odds, $p < 0.05$) and earning income (41% greater odds, $p < 0.05$) during the pandemic increased the odds of onset of clinical depression among retired and non-retired individuals, respectively.

Experiencing financial adversity could spark mental health problems or exacerbate preexisting mental health problems. I examined whether or not the effect of financial adversity on mental health differed by having pre-diagnosed psychiatric problems. Panels A and B in Table 3.7 show results of estimations for the change in CES-D score and depression, respectively, separately for sub-samples of adults who were/were not diagnosed with psychiatric problems before 2020.

Income shock and financial hardship were found to be significant risk factors affecting the mental health of adults who did not have pre-diagnosed psychiatric problems. Adults in this group who experienced a drop in retirement/assets income saw a 0.813 ($p < 0.001$) point increase in the CES-D score compared to adults whose income remained the same or went up. In addition, the unit increase in financial hardship score increased the CES-D score by 0.097 ($p < 0.01$) points. I observed a similar pattern with depression. Among respondents who did not have pre-diagnosed psychiatric problems, individuals who experienced a drop in retirement/assets income had 165% ($p < 0.001$) greater odds of having the onset of clinical depression during the pandemic. Also, a unit increase in financial hardship score increased the odds of having the onset of clinical depression by 25% ($p < 0.001$).

3.5 SUMMARY AND CONCLUSION

The COVID-19 pandemic caused health and economic crises across the world. Coping with a loss of income or financial hardship constitute distressing experiences that could lead to the deterioration of mental health. Using the 2018 and 2020 waves of the Health and Retirement Study, this research examined the effect of financial adversities experienced during the pandemic on the mental health of older adults, with a specific focus on income shocks and financial hardship.

Results revealed that, relative to individuals whose income remained the same or went up, individuals who experienced pandemic-related income shocks, particularly those whose income from retirement/assets went down, reported more symptoms of deteriorating mental health and were more likely to become at risk of depression in 2020. Results also pointed to an unambiguous effect of financial hardship measured as financial arrears. Experiences of such economic hardship had a positive association with the change in the number of reported depressive symptoms and significantly increased the risk of the onset of depression. Overall, results support the hypothesis that financial adversities experienced during the pandemic led to the deterioration of mental health of older adults.

Furthermore, I tested the heterogeneity in the effect of financial adversities on mental health among retired and non-retired adults. I found significant variation in the number of mental health symptoms and the onset of clinical depression in response to experiences of financial hardship or shocks to income from retirement or other assets among retired individuals. For non-retired individuals, the unexpected drop in earnings was the primary significant determinant of mental health symptoms and depression. Non-retired respondents also responded to the experience of financial hardship by reporting depressive symptomatology in the range indicative of clinical depression. Moreover, the magnitude of the effect of financial adversities was more pronounced among retired individuals than among non-retired individuals, which could be related to the fact that fewer retired individuals had labor earnings, and it was likely more difficult for them to re-enter the labor market.

Considering the status of preexisting psychiatric problems, results were indicative of the increase in the CES-D score and the onset of clinically relevant depression during the pandemic among adults with no pre-diagnosed psychiatric problems. I did not observe evidence for the exacerbation of preexisting mental health problems. The difference in the effect of financial adversities on mental health by preexisting psychiatric diagnosis might imply that adults with pre-diagnosed problems had already reported elevated symptoms on the CES-D scale in 2018.

This study has several implications for personal finance professionals, mental health counselors, and policymakers. It reveals that the retirement/asset income shocks might be more important determinants of mental health among older adults than income from labor. In light of growing concerns about retirement income adequacy, the findings suggest that the ability to manage an investment portfolio in working life is not only crucial for later life economic security but also can be beneficial for the mental health of older adults. To work in the best interest of clients and provide suitable recommendations, financial planners and mental health counselors need to be cognizant of this relationship. Financial therapy is a relatively new practice that integrates both the financial and psychological aspects of counseling and addresses the needs of clients facing economic strain (Ross et al., 2021). Nevertheless, financial advisors should take into consideration future uncertainties while helping clients to formulate retirement saving goals in the early life stage and advising appropriate portfolio withdrawal rates to help them maintain sustainable retirement income in later life. For example, financial practitioners could consider Solution Focused Financial Therapy, a goal-focused therapy for financial stress relief (Archuleta et al., 2020). Furthermore, financial educators and counselors can coach working adults to improve their financial management skills and help them understand the negative consequences of inadequate retirement income on their mental health.

Some limitations of this study should be acknowledged. First, I was able to identify only the sources of income shocks, and individuals who experienced income losses of varying magnitude were not distinguished from each other. Those with larger income loss might be more mentally stressed than those who experienced smaller income loss. Second, I examined the short-term effect of income shock on mental health. It is conceivable that the effects of the pandemic on mental health will persist over the long term and could be evident in later waves of HRS. Future studies examining the long-term effect of income shock on health are encouraged. Additionally, the small sample size for some subgroups renders it difficult to test possible mechanisms of the relationship. For instance, the sources of retirement income and other assets could moderate the relationship between income shock and mental health. Lim and Lee (2021) found significant variation in subjective financial wellbeing and the retirement income source. Upon data availability, delving further into the underlying mechanism of the relationship between income shock and mental health is an avenue for future research.

Table 3.1: Descriptive Statistics

	Overall (N = 8,019)	Income Shock (N=1,472)	No Income Shock (N=6,547)
	Mean/Percent	Mean/Percent	Mean/Percent
Income shock (Yes = 1)	18.36		
Income shock type			
Income same/up (Ref. category)	81.80		
Work earnings down	13.38		
Retirement plan/assets income down	1.17		
Business income down	1.64		
Other income down	2.01		
Financial Hardship	0.41	0.94	0.29
CES-D score (2018)	1.48	1.57	1.46
CES-D score (2020)	1.56	1.75	1.52
Depression (2018) (Yes = 1)	21.31	22.15	21.12
Depression (2020) (Yes = 1)	23.12	26.22	22.42
Depression (2018 = 0 and 2020 = 1)	10.31	12.36	9.85
Age			
51-64 yrs. (Ref. category)	44.34	64.88	39.73
65-74 yrs.	29.04	24.80	30.00
≥ 75yrs.	26.61	10.33	30.27
Gender (Female = 1)	60.46	57.27	61.17
Race			
White/Caucasian (Ref. category)	64.25	56.79	65.92
Black/African American	23.73	24.05	23.66
Other	12.02	19.16	10.42
Ethnicity (Hispanic = 1)	17.31	28.33	14.83
Marital Status			
Married (Ref. category)	52.43	54.01	52.07
Divorced/Separated	21.07	25.20	20.15
Widowed	17.86	11.75	19.23
Never Married	8.64	9.04	8.55
Educational attainment			
Less than high school (Ref. category)	14.54	15.29	14.37
High school graduate/GED	30.78	26.36	31.77
Some college	28.43	31.45	27.75
College and above	26.25	26.90	26.10
Self-reported health (2018)			
Excellent (Ref. category)	7.64	8.08	7.55
Very good	30.52	27.92	31.10
Good	34.41	33.97	34.50
Fair	21.84	25.27	21.06
Poor	5.60	4.76	5.79
Pre-existing psychiatric problems (Yes = 1)	21.14	19.23	21.57
Working for pay (2018) (Yes = 1)	43.68	69.57	37.86
Non-retired (2018) (Yes = 1)	40.85	66.50	34.99
Number of resident children (2020)	0.41	0.58	0.37
HH Income (2018) (median in thousands)	45.30	51.00	44.34
HH Wealth (2018) (median in thousands)	137	105	146

Table 3.2: Paired Sample T-Test of CES-D Score among Individuals Experiencing Income Shock

	Mean	Mean Difference	Std. Error Difference	Std. Dev Difference	t	df	Pr (T > t)
				1.997	3.4	14	
CES-D score in 2020	1.751	0.179	0.052		33	71	.0003
CES-D score in 2018	1.572						

Table 3.3: Two Sample Z-Test of Proportions of Depression among Individuals Experiencing Income Shock

	Mean	Mean Difference	Std. Error Difference	z	Pr (Z > z)
Depressed in 2020	0.262	0.041	0.016	2.583	.0005
Depressed in 2018	0.221				

Table 3.4: OLS Estimates of Change in CES-D Score

	Dependent Variable: Change in CES-D Score				
	(1)	(2)	(3)	(4)	(5)
Income shock (Yes = 1)	0.173**			0.131*	
	(0.059)			(0.061)	
Income shock type					
Earnings		0.098			0.054
		(0.066)			(0.067)
Retirement/assets		0.795***			0.758***
		(0.208)			(0.208)
Business		-0.081			-0.125
		(0.170)			(0.171)
Other		0.359			0.319
		(0.195)			(0.194)
Financial hardship			0.088**	0.073*	0.074*
			(0.031)	(0.032)	(0.032)
Age					
65-74 yrs.	0.096	0.094	0.101	0.105*	0.104
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)
≥ 75yrs.	0.119	0.117	0.125	0.133*	0.131*
	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)
Gender (Female = 1)	0.024	0.024	0.020	0.022	0.022
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
Race					
Black/African American	-0.065	-0.062	-0.082	-0.079	-0.077
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)
Other	0.014	0.016	0.011	0.009	0.012
	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)
Ethnicity (Hispanic = 1)	-0.027	-0.028	-0.020	-0.031	-0.031
	(0.068)	(0.069)	(0.068)	(0.069)	(0.069)
Marital Status					
Divorced/Separated	-0.003	-0.007	-0.010	-0.010	-0.016
	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)
Widowed	0.106	0.103	0.104	0.103	0.100
	(0.066)	(0.065)	(0.066)	(0.066)	(0.065)
Never Married	-0.018	-0.017	-0.028	-0.025	-0.024
	(0.083)	(0.083)	(0.083)	(0.083)	(0.083)
Educational attainment					
High school graduate/GED	-0.237**	-0.233**	-0.240	-0.240**	-0.236**
	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)
Some college	-0.272***	-0.266***	-0.270	-0.274***	-0.268***
	(0.076)	(0.075)	(0.075)	(0.076)	(0.075)
College and above	-0.222**	-0.220**	-0.218	-0.222**	-0.219
	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)

Self-reported health					
Very good	-0.010	-0.008	-0.008	-0.007	-0.005
	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
Good	-0.027	-0.026	-0.030	-0.030	-0.029
	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)
Fair	-0.176*	-0.176*	-0.185	-0.188*	-0.188*
	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)
Poor	-0.514***	-0.515***	-0.537***	-0.535***	-0.536***
	(0.134)	(0.134)	(0.134)	(0.134)	(0.134)
Working for pay (Yes = 1)	-0.059	-0.031	-0.031	-0.052	-0.024
	(0.052)	(0.052)	(0.051)	(0.052)	(0.052)
Number of resident children	-0.019	-0.013	-0.021	-0.023	-0.017
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Log (HH income)	0.013	0.012	0.014	0.014	0.013
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
HIS (HH wealth)	0.003	0.003	0.005	0.005	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
R^2	0.012	0.014	0.012	0.013	0.015
Observations	8,019	8,009	8,019	8,019	8,009

Notes: Heteroskedastic robust standard errors in parentheses. All regressions control for survey month fixed effects. Household income is log-transformed, and household wealth is hyperbolic inverse sine transformed. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Table 3.5: Odds Ratios from Logistic Regressions of Depression

	Dependent Variable: Depression				
	(1)	(2)	(3)	(4)	(5)
Income shock (Yes = 1)	1.333**			1.208	
	(0.128)			(0.123)	
Income shock type					
Earnings		1.210			1.092
		(0.137)			(0.130)
Retirement/assets		2.410**			2.219**
		(0.614)			(0.572)
Business		1.102			0.994
		(0.322)			(0.300)
Other		1.428			1.311
		(0.314)			(0.289)
Financial hardship			1.187***	1.162***	1.164***
			(0.046)	(0.047)	(0.047)
Age					
65-74 yrs.	1.094	1.088	1.115	1.124	1.118
	(0.104)	(0.104)	(0.107)	(0.108)	(0.107)
≥ 75yrs.	0.993	0.984	1.021	1.034	1.026
	(0.115)	(0.114)	(0.119)	(0.121)	(0.120)
Gender (Female = 1)	1.266**	1.264**	1.262**	1.266**	1.264**
	(0.104)	(0.104)	(0.104)	(0.104)	(0.104)
Race					
Black/African American	0.819*	0.825	0.788*	0.792*	0.797*
	(0.081)	(0.081)	(0.078)	(0.078)	(0.079)
Other	1.042	1.038	1.034	1.032	1.029
	(0.128)	(0.128)	(0.127)	(0.126)	(0.126)
Ethnicity (Hispanic = 1)	1.063	1.076	1.074	1.056	1.067
	(0.125)	(0.126)	(0.124)	(0.123)	(0.125)
Marital Status					
Divorced/Separated	1.148	1.137	1.126	1.128	1.116
	(0.119)	(0.118)	(0.118)	(0.118)	(0.117)
Widowed	1.422**	1.418**	1.410**	1.410**	1.405**
	(0.154)	(0.153)	(0.152)	(0.152)	(0.152)
Never Married	1.378*	1.371*	1.349*	1.357*	1.349*
	(0.191)	(0.190)	(0.188)	(0.189)	(0.188)
Educational attainment					
High school graduate/GED	0.720**	0.727**	0.713**	0.713**	0.720**
	(0.084)	(0.085)	(0.083)	(0.083)	(0.084)
Some college	0.804	0.814	0.803	0.798	0.808
	(0.096)	(0.098)	(0.096)	(0.096)	(0.097)
College and above	0.859	0.866	0.860	0.856	0.863
	(0.112)	(0.113)	(0.112)	(0.111)	(0.112)

Self-reported health					
Very good	1.113	1.118	1.119	1.121	1.127
	(0.201)	(0.202)	(0.201)	(0.202)	(0.203)
Good	1.671**	1.676**	1.661**	1.662**	1.666**
	(0.292)	(0.293)	(0.289)	(0.290)	(0.291)
Fair	2.134***	2.146***	2.080***	2.077***	2.088***
	(0.389)	(0.391)	(0.379)	(0.379)	(0.381)
Poor	1.694*	1.717*	1.609*	1.621*	1.642*
	(0.385)	(0.390)	(0.367)	(0.370)	(0.375)
Working for pay (Yes = 1)	0.847	0.875	0.893	0.864	0.892
	(0.077)	(0.080)	(0.080)	(0.079)	(0.081)
Number of resident children	0.980	0.990	0.973	0.970	0.981
	(0.054)	(0.054)	(0.053)	(0.053)	(0.054)
Log (HH income)	1.015	1.013	1.016	1.017	1.015
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
HIS (HH wealth)	0.995	0.995	0.999	0.998	0.998
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Pseudo R^2	0.028	0.029	0.029	0.030	0.031
Observations	8,019	8,009	8,019	8,019	8,009

Notes: Heteroskedastic robust standard errors in parentheses. Each regression model controls for survey month fixed effects. Household income is log-transformed, and household wealth is hyperbolic inverse sine transformed.
$*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 3.6: Effect of Financial Adversities on CES-D Score and Depression by Retirement Status

	Panel A. Dependent Variable: Change in CESD Score			
	Retired		Non-retired	
	(1)	(2)	(3)	(4)
Income shock type				
Earnings	-0.093		0.159*	
	(0.109)		(0.080)	
Retirement/assets	0.828***		0.379	
	(0.228)		(0.515)	
Business	0.053		-0.153	
	(0.270)		(0.218)	
Other	0.325		0.435	
	(0.232)		(0.363)	
Financial hardship		0.121*		0.069
		(0.051)		(0.039)
R^2	0.020	0.018	0.016	0.015
Observations	4,584	4,588	3,162	3,168
	Panel B. Dependent Variable: Depression			
	Retired		Non-retired	
	(1)	(2)	(3)	(4)
Income shock type				
Earnings	0.758		1.409*	
	(0.180)		(0.192)	
Retirement/assets	2.165*		2.420	
	(0.659)		(1.392)	
Business	1.736		0.894	
	(0.746)		(0.358)	
Other	1.279		1.776	
	(0.372)		(0.642)	
Financial hardship		1.247***		1.159**
		(0.070)		(0.063)
Pseudo R^2	0.036	0.037	0.031	0.030
Observations	4,584	4,588	3, 162	3, 168

Notes: Coefficient estimates from OLS presented in panel A. Odds ratio from logistic regression presented in panel B. Heteroskedastic robust standard errors in parentheses. All regressions control demographic covariates, health status, socioeconomic conditions, and survey month fixed effects. *p < 0.05, **p < 0.01, ***p < 0.001.

Table 3.7: Effect of Financial Adversities on CES-D Score and Depression by Psychiatric Problems

	Panel A. Dependent Variable: Change in CESD Score			
	Pre-diagnosed		Not Pre-diagnosed	
	(1)	(2)	(3)	(4)
Income shock type				
Earnings	0.185		0.077	
	(0.198)		(0.067)	
Retirement/assets	0.715		0.813***	
	(0.470)		(0.228)	
Business	0.425		-0.164	
	(0.387)		(0.188)	
Other	0.329		0.360	
	(0.371)		(0.230)	
Financial hardship		0.076		0.097**
		(0.065)		(0.035)
R^2	0.023	0.021	0.014	0.012
Observations	1,691	1,694	6,312	6,319
	Panel B. Dependent Variable: Depression			
	Pre-diagnosed		Not Pre-diagnosed	
	(1)	(2)	(3)	(4)
Income shock type				
Earnings	1.087		1.219	
	(0.263)		(0.158)	
Retirement/assets	1.978		2.653**	
	(0.965)		(0.782)	
Business	1.154		1.095	
	(0.704)		(0.364)	
Other	1.227		1.478	
	(0.531)		(0.383)	
Financial hardship		1.048		1.252***
		(0.079)		(0.056)
Pseudo R^2	0.021	0.019	0.042	0.044
Observations	1,691	1,694	6,312	6,319

Notes: Coefficient estimates from OLS presented in panel A. Odds ratio from logistic regression presented in panel B. Heteroskedastic robust standard errors in parentheses. All regressions control demographic covariates, health status, socioeconomic conditions, and survey month fixed effects. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

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CHAPTER 4

ESSAY III: SPENDING BEHAVIOR AND STIMULUS TRANSFER USE IN RESPONSE TO INCOME SHOCKS AMONG OLDER AMERICANS: EVIDENCE FROM THE COVID-19 PANDEMIC

4.1 INTRODUCTION

The COVID-19 pandemic caused substantial ramifications to the economic status of American families. The pandemic resulted in a collapse of industries and a slowdown of economic activities, creating record job losses and widespread wage cuts (Donnelly & Farina, 2021). In April 2020, the unemployment rate in the U.S. hit a record high of 14.7% (Bureau of Labor Statistics, 2020). Additionally, many individuals experienced income loss through a reduction in work hours (Brenan, 2020; Collins et al., 2021). To mitigate the economic impact of COVID-19, the federal government implemented the 2020 CARES Act, the largest economic stimulus package in U.S. history, amounting to approximately 10% of GDP. Starting in April 2020, many Americans received stimulus checks and enhanced unemployment benefits. The objective of this study is to examine the behavioral responses (consumption/saving) to the exogenous income shock caused by the COVID-19 pandemic and shed some light on the relationship between the experience of income shock and the use of government stimulus money.

Research on consumer spending in the U.S. during the coronavirus crisis is mounting (Asebedo et al., 2020; Baker et al., 2020; Cox et al., 2020; Chetty et al., 2020). For example, Chetty et al. (2020) constructed a dataset from several private companies that included daily statistics on consumer spending, business revenues, and employment rates. The data showed a sharp reduction in spending, especially in areas with high rates of COVID-19 and in sectors that required in-person interactions. Additionally, the statistics demonstrated that stimulus checks increased spending among low-income households. Similar aggregate results were reported by Cox et al. (2020), who used commercial banks' data. Asebedo et al. (2020) utilized data collected via Amazon's MTurk platform to examine how individuals allocated their CARES stimulus payments into broad categories such as needs, wants, or financial transactions, as well as narrowly defined sub-categories such as housing, food, transportation, clothing, hobby, etc.

While the previous studies reached a consensus that the COVID-19 pandemic negatively affected overall consumer spending, studies examining consumption responses specifically to pandemic-related income shocks are scant. I address this gap and test how households respond to pandemic-induced income shocks in terms of their overall spending, as well as spending out of government stimulus. Unlike previous studies that used business and/or aggregated data, I use microdata compiled from a consumer survey – the COVID-19 module of the Health and Retirement Study. As far as I know, this is the first study to provide insights into the effect of income shocks on choices regarding the spending of the 2020 CARES stimulus payments.

4.2 CONCEPTUAL FRAMEWORK

The life cycle and permanent income hypotheses posit that consumption is proportional to permanent income. Put simply, consumers adjust their consumption in response to the change in transitory income only to the degree to which the change in transitory income affects the permanent income. This implies limited heterogeneity in the marginal propensity to consume (MPC). However, the literature suggests that many factors contribute towards heterogeneity in MPC. For instance, the borrowing constraints and precautionary saving motives complicate the predictions of consumption/saving decisions. Moreover, Caroll et al. (2017) identify household resources as an important source of MPC heterogeneity. Likewise, Christelis et al. (2019) characterized the distribution of MPC in response to unexpected transitory income change using the survey of the Dutch population. They detected asymmetries between MPC in response to positive and negative income shocks, with MPC response to a negative shock being larger than to a positive shock.

An unambiguous prediction of consumption/saving response to the income shock would require me to adopt an explicit assumption on whether consumers interpret pandemic-induced variations in income as transitory or permanent. In light of past studies, I expect that individuals who experience negative income shocks would be more likely to reduce their spending compared to individuals who do not experience income shocks. Meanwhile, how the income shock affects the choice of spending the stimulus money remains an empirical question, which this study attempts to answer.

4.3 LITERATURE REVIEW

The major challenge encountered in estimating consumption responses to unanticipated income shocks is to isolate the exogenous shocks to income. The empirical literature has traditionally considered three approaches to address this difficulty in modeling the consumption responses to the unanticipated income change. The first method identifies policy interventions that generate an income change and evaluates consumption responses to such changes in a quasi-natural experimental setting (Aaronson et al., 2012; Johnson et al., 2006; Parker et al., 2013). For example, Johnson et al. (2006) estimated the causal effect of income tax rebates on household consumption by comparing the expenditures of households who received rebates at different times. Aaronson et al. (2012) used a similar approach to assess the spending and debt responses to minimum wage hikes. Parker et al. (2013) measured the household spending responses to economic stimulus payments by exploiting the random variation in the timing of transfer receipt.

The second approach relies on the statistical decomposition of the income process into permanent and transitory movements and bivariate distribution of income and consumption (Blundell et al., 2008). The third approach focuses on survey-based responses to intended or hypothetical changes in income (Bracha & Cooper, 2013; Jappeli & Pistaferri, 2014). Bracha and Cooper (2013) used the data from the 2013 survey conducted by the Federal Reserve Bank of Boston and found asymmetric spending responses to payroll tax hikes and tax refunds. In 2014, Jappelli and Pistaferri utilized the 2010 Italian Survey of Household Income and Wealth and observed substantial heterogeneity in consumption responses to the unexpected transitory income change. This study relates to these earlier contributions by sharing an emphasis on the spending responses to the income change. The novelty of my study comes from the fact that this study relies on the survey responses from the 2020 HRS COVID-19 Module and focuses on the self-reported income shock (of either sign) experienced by households during the pandemic.

At the time when I wrote this dissertation, several studies have been conducted to assess consumer spending during the pandemic (Baker et al., 2020; Coibion et al., 2020; Cox et al., 2020; Chetty et al., 2020). For example, Baker et al. (2020) analyzed the heterogeneity in households' spending responses by income levels, income declines, liquidity, and economic expectations using high-frequency data from the financial technology industry. The authors found that households increased their spending as a consequence of receiving stimulus payments and the responses were stronger among households with lower income, large income declines, and lower levels of liquidity. Using large-scale surveys on U.S. households, Coibon et al. (2020) found a large decline in consumer spending with the COVID-19 lockdown. Cox et al. (2020)

utilized household-level bank data on U.S. consumers and showed that individuals across the entire income distribution cut spending at the start of the pandemic.

While all the mentioned studies focus on spending responses, none of them examined the joint dynamics of income change and spending responses. To address this literature gap, I study the dynamics of income shock and spending responses by utilizing microdata compiled from a consumer survey – the COVID-19 module of the Health and Retirement Study. My study is similar to Hanspal et al. (2020). They modeled the expected change in spending as a function of pandemic-induced income loss and found that households exposed to larger income losses were more likely to decrease their total expenditures. Despite the significant difference between the two studies, my findings are consistent with Hanspal et al. (2020). However, my study is different in that I employ different data, measures, and estimation techniques. Moreover, I focus on the retirement and near-retirement population. Finally, my study complements Hanspal et al. (2020) by investigating the differential spending responses to 2020 CARES stimulus payments.

4.4 METHOD

4.4.1 DATA

I utilized data from the 2020 Health and Retirement Study (HRS) COVID-19 project (Early Version 1.0), conducted by the Institute for Social Research at the University of Michigan. The COVID-19 module was administered to the random subsample of 50% of households interviewed as part of the regular 2020 HRS. The sample was further split into two subsamples. This study used information from the first random subsample of 3,266 respondents (interviews started in June 2020), accounting for approximately 25% of the original HRS sample. All interviews were conducted via telephone due to restrictions on social contact. The HRS is a nationally representative dataset of Americans aged 51 and older but includes information on spouses of core respondents even if the spouse is younger than 51. Since individuals younger than 51 do not constitute the age-eligible core of the HRS sample, I excluded 54 such respondents from the analysis. I further excluded respondents with missing values on variables used in the analysis. The final sample included 2,958 respondents.

4.4.2 MEASURES

Before being asked the HRS COVID-19 module questions, respondents were primed with the following statement: "*Next, we have some questions about the coronavirus pandemic, also known as COVID-19.*" This conditioning allows me to assume that the subsequent questions about economic status reflect the exogenous impacts of the pandemic.

4.4.2.1 INCOME SHOCK

The measurement of income shock is based on the question: "*Since the start of the coronavirus pandemic, has your income gone up or down or stayed about the same because of the pandemic?*", with response options: "*went up*", "*went down*", "*about the same*". I constructed the binary indicator variables signifying each of these answers.

4.4.2.2 SPENDING

The HRS asked the question "*Has your household spending gone up or down or stayed about the same?*" with response options: "*went up*", "*went down*", and "*about the same*". I constructed the categorical variable "Spending" with values signifying each of these responses.

4.4.2.3 STIMULUS USE

The stimulus spending decision was measured using two questions. The first one inquired whether the respondent or spouse/partner received the government payment. Response options were: "*yes, both received*", "*yes, but only one received*", and "*no*". The second question measured the use of the payment, with response options: "*increase spending*", "*increase saving*", "*pay off* *debt*", "*give to charity*", "*give to family or friends*", "*other purpose*". Combining these two items, I constructed the categorical variable "Stimulus Use" coded into mutually exclusive groups: "*increase spending*" if the respondent or both respondent and spouse received the stimulus payment and it primarily led to increased spending, "*increase saving*" if the respondent or both spouses received the payment and it led to increased saving, "*payoff debt*" if the respondent or both received the payment and it led to paying off debt, and "*other*" if the payment was given to charity, family, friends or used for other purposes.

4.4.3 ANALYTICAL STRATEGY

To examine household spending decisions in response to the income shock, I first estimated the multinomial logistic regression for the Spending variable. Then, focusing on respondents who received the government stimulus, I examined the stimulus spending decisions by estimating another multinomial logistic regression for the Stimulus Use variable. The estimations controlled for sociodemographic covariates, including gender (1= female), age groups (51-64 years (reference), 65-74 years, 75 years and older), marital status (married (reference), divorced/separated, widowed, never married), race (White/Caucasian (reference), Black/African American, "other" races), ethnicity (non-Hispanic (reference), Hispanic), educational attainment (less than high school (reference), high school graduate/GED, some college, college and above), self-reported health (excellent (reference), very good, good, fair and poor), number of resident children, whether respondents were working for pay prior to the pandemic (1 = yes), log of household income prior to the pandemic. To capture the availability of resources, households were divided into five quintiles based on the net value of total wealth (excluding secondary residence) prior to the pandemic and controlled for those quintiles. Models also controlled for survey month fixed effects to account for the difference in timing of income shock during the pandemic.

4.5 RESULTS

4.5.1 DESCRIPTIVE STATISTICS

Weighted descriptive statistics based on the sample of 2,875 respondents are presented in Table 4.1. In terms of spending behavior, 16% of respondents reported increased spending, 28% reported reduced spending, and 56% reported stable spending. Out of a sub-sample of 1,765 respondents who received the stimulus, 40% used the payment to pay off debt, 32% reported saving, 16% reported spending, and the remaining 12% reported giving money to charity, friends, family, or using the money for other purposes. About 16% of respondents experienced a decline in their income due to the pandemic. Some people also reported an increase in their income (4%). The percentages of respondents in age groups 51-64, 65-74, and 75+ were 53%, 34%, and 22%, respectively. Around 80% of respondents were white, and about 11% were Black. Moreover, 10% reported Hispanic ethnicity. In terms of marital status, 59% of the sampled individuals were married. Only 31% of the respondents had completed college, and about 72% reported being in good, very good, or excellent health. About 45% of the respondents were working for pay during the pre-pandemic period. The pre-pandemic median income and net wealth among the respondents amounted to $58, 000, and $225,000, respectively.

4.5.2 EFFECT OF INCOME SHOCK ON SPENDING

The relative risk ratios from multinomial logistic regression of spending on income shock are presented in Table 4.2. Results indicate that the pandemic-induced negative income shock reduced spending. Compared to individuals whose income did not change, individuals who experienced income losses during the pandemic were more likely to reduce their household spending rather than keep spending stable (*Relative Risk Ratio* = 2.596; $p < 0.001$). However, individuals whose income increased did not differ in terms of their spending behavior from those whose income remained constant.

There are several possible explanations for the difference in spending responses to positive vs. negative income shocks. Income shock expectation plays a vital role in consumption decisions (Bracha & Cooper, 2013). Differences in spending responses might be attributed to the difference in expectations regarding income shock. For instance, consumers who experienced negative income shock might have expected the shock as permanent and responded by reducing spending. In contrast, the consumers who experienced positive income shock might have anticipated the shock to be temporary and did not change their spending. Financial constraints might also contribute toward the heterogeneous spending responses to income shocks (Bracha & Cooper, 2013; Kaplan & Violante, 2014). It is possible that households reduce spending to make up for income loss even in the face of negative income shock that is expected to be temporary due to borrowing constraints, illiquid assets, and dissaving. Next, it may also be the case that households burdened with large amounts of debt could have reacted to the positive change in income by repaying their debt rather than increasing their spending.

4.5.3 EFFECT OF INCOME SHOCK ON STIMULUS USE

Focusing on the primary use of stimulus payment, results presented in Table 4.3 indicate that, relative to recipients whose income remained the same, individuals who experienced an income loss were more likely to spend rather than save the transfer money (*Relative Risk Ratio* = 2.119; $p < 0.01$). Relative to recipients whose income remained the same, individuals who experienced an income loss were also more likely to allocate the transfer money to repay debt rather than increase savings (*Relative Risk Ratio* = 2.296; $p < 0.001$). Finally, compared to recipients whose income remained the same, those who experienced an income loss were more likely to designate the transfer to charity, friends, family, or use it for other purposes rather than increase savings (*Relative Risk Ratio* = 2.629; $p < 0.001$).

4.6 SUMMARY AND CONCLUSION

Results revealed differences in consumption expenditures and saving responses to the pandemic-induced income shocks among older adults. Households that experienced negative income shocks were more likely to reduce their spending compared to households whose income remained unchanged. However, no change in expenditures was noted among those whose income increased. The observed spending cuts signal that households might have perceived the pandemic-induced income shocks to have a significant effect on their permanent (i.e., lifetime average) income. Moreover, results revealed that stimulus transfer recipients who experienced negative income shocks were more likely to use the stimulus benefit to increase spending, pay off debt, or for other purposes, rather than to save. Hence, stimulus checks played an important role in buffering the negative income shock experienced by older adults and smoothing consumption during the pandemic. Altogether, results provide some evidence that at least two of the CARES Act statutory objectives, increasing consumer spending through direct cash payments and providing an extended safety net to Americans were achieved. A more nuanced policy evaluation of the consequences of CARES Economic Impact Payments should be undertaken in the future as more data on the affected consumers’ behavior becomes available. Future research could examine the intensive margin of income shocks and spending/saving responses as the data did not include such measurements. Subsequent research could also examine the expenditure and saving behavior of individuals younger than 51 as they were not included in this analysis.

Table 4.1: Descriptive Statistics

Variables	Percent	Mean/Median
Spending		
Increased spending	16.35	
Reduced spending	27.59	
Stable spending	56.06	
Stimulus use		
Increase spending	16.26	
Increase saving	32.31	
Payoff debt	39.90	
Other purpose	11.53	
Income shock		
Income went down	16.35	
Income went up	4.47	
Income same	79.18	
Age		
51-64 years	43.01	
65-74 years	34.19	
75 years and above	22.80	
Gender (Female=1)	52.86	
Race		
White/Caucasian	79.78	
Black/African American	10.84	
Other	9.38	
Ethnicity (Hispanic = 1)	10.00	
Marital status		
Married	58.95	
Divorced/Separated	18.79	
Widowed	14.85	
Never married	7.41	
Educational attainment		
Less than high school	10.58	
High school graduate/GED	30.31	
Some college	28.04	
College and above	31.08	
Self-reported health		
Excellent	8.26	
Very good	33.27	
Good	33.78	
Fair	18.88	
Poor	5.81	
Working for pay (Yes = 1)	44.98	
Number of resident children		0.35/0
Income (in thousands)		107.47/58
Wealth (in thousands)		758.00/225

Notes: N = 2,875. The HRS survey weights were applied.

Table 4.2: Relative Risk Ratios from Multinomial Logistic Regression of Spending

Variables	Reduced Spending	Increased Spending
Income shock (Ref: About the same)		
Income went down	2.596***	1.335
Income went up	0.943	1.263
Age (Ref: 51-64 years)		
65-74 years	0.676**	0.873
75 years and above	0.407***	0.819
Gender (Female = 1)	1.290	1.350**
Race (Ref: White/Caucasian)		
Black/African American	0.588***	1.518**
Other	0.759	0.892
Ethnicity (Hispanic = 1)	0.471***	1.536**
Marital status (Ref: Married)		
Divorced/Separated	0.989	1.114
Widowed	0.847	0.988
Never married	0.872	0.910
Educational attainment (Ref: Less than high school)		
High school graduate/GED	1.527	1.063
Some college	2.056**	1.116
College and above	3.491***	1.171
Self-reported health (Ref: Excellent)		
Very good	1.377	1.342
Good	1.200	1.687*
Fair	0.965	2.019**
Poor	0.550	2.028*
Working for pay (Yes = 1)	1.167	0.770*
Number of resident children	0.897	1.125
Income (log)	1.025	1.030
Wealth quintiles (Ref: First quintile)		
Second	1.368	1.079
Third	1.620**	0.949
Fourth	1.690**	0.956
Fifth	2.067***	0.621*

Notes: N = 2,958. The regression also controlled for survey month dummies.
Reference Outcome: “Stable Spending”. Significance levels: *** $p < 0.001$. ** $p < 0.01$. *$p < 0.05$.

Table 4.3: Relative Risk Ratios from Multinomial Regression of Stimulus Use

Variables	Increase Spending	Payoff Debt	Other Purpose
Income shock (Ref: About the same)			
Income went down	2.119**	2.296***	2.629***
Income went up	1.201	0.660	0.261
Age (Ref: 51-64 years)			
65-74 years	1.201	0.873	0.950
75 years and above	0.850	0.645*	1.086
Gender (Female = 1)	0.848	1.270	1.023
Race (Ref: White/Caucasian)			
Black/African American	0.803	1.562**	0.607
Other	0.926	1.146	0.797
Ethnicity (Hispanic = 1)	1.600	2.195***	1.546
Marital status (Ref: Married)			
Divorced/Separated	1.166	0.924	1.091
Widowed	1.149	1.019	1.523
Never married	1.522	0.919	1.098
Educational attainment (Ref: Less than high school)			
High school graduate/GED	1.149	0.648*	0.600
Some college	1.211	0.843	0.833
College and above	1.125	0.648	0.781
Self-reported health (Ref: Excellent)			
Very good	0.889	1.319	0.458*
Good	0.794	1.770*	0.612
Fair	0.746	1.623	0.489*
Poor	0.813	2.210*	0.777
Work for pay (Yes = 1)	0.701	1.114	0.780
Number of resident children	1.240	1.265	1.040
Income (log)	1.016	1.030	1.019
Wealth quintiles (Ref: First quintile)			
Second	0.621	0.773	0.762
Third	0.610	0.514**	0.746
Fourth	0.560*	0.318***	0.610
Fifth	0.623	0.238***	0.785

Notes: N = 1,803. The regression also controlled for survey month dummies.
Reference Outcome: "Increase Saving". Significance levels: *** p < 0.001. ** p < 0.01. *p < 0.05.

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CHAPTER 5

CONCLUSIONS

The outbreak of the COVID-19 pandemic has resulted in both health and financial crises. The economic downturn caused by the pandemic poses severe economic challenges to individuals, which in turn, inflicts serious damage to their mental health. Furthermore, the pandemic induced people to change their spending behavior, i.e., spending less and saving more, which could have obstructed economic recovery. To mitigate the economic impact of COVID-19, the U.S. federal government executed the economic stimulus package under the CARES Act. How people used the stimulus amount is a question of significant concern. Did the stimulus help smooth out the consumption? Understanding the psychological burden and financial behavior during the pandemic has been of great interest to policymakers. The dissertation presented here is an attempt to investigate the impact of the COVID-19 pandemic on both the general population and one of its most vulnerable segments, i.e., older adults in the United States.

My results indicate that COVID-19-related deaths and the state-level unemployment rate both explained a significant amount of variation in the internet search intensity for mental health keywords during the pandemic. However, I find no evidence for the role of the FHFA House Price Index. The explanation for this could be that the increase in house prices led to the improved mental health of homeowners and this effect offset the corresponding decline in the psychological well-being of renters who faced increasing housing-related expenditures. My results also suggest that the financial adversities experienced by older adults during the pandemic contributed to the deterioration of their mental health. The estimated effects are heterogeneous among the groups of respondents defined by retirement status and history of psychiatric problems.

Finally, my results also indicate that older adults reduced household spending as a response to the negative income shocks experienced during the pandemic. Regarding the use of stimulus transfers, the results reveal that, relative to those who did not experience an income shock, stimulus recipients who experienced income losses were more likely to use the stimulus transfer to increase spending, pay off debt, or for other purposes rather than to save.

The key insights gained from my research are that the statistics on the internet search for mental health information could be a very useful tool for policymakers and public health officials in monitoring mental health problems, making it possible to implement prompt preventive and remedial actions. Furthermore, my results provide data-driven evidence that at least two of the CARES Act statutory objectives, increasing consumer spending through direct cash payments and providing an extended safety net to Americans, were achieved. In addition, financial planners, and mental health counselors, by understanding the relationship between financial adversities and mental health, could make suitable recommendations to their older clients.