Does a Pandemic Affect Household Portfolio Choices? Evidence from the 2009 H1N1 Pandemic*

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September 7, 2023

Abstract

This paper examines the short- and long-term effect of the 2009 H1N1 pandemic on household portfolio choices using the Panel Study of Income Dynamics. Using the cross-state variations in the H1N1 death rate during the pandemic, the difference-in-differences estimates suggest that the H1N1 pandemic does not affect stock market participation but reduces the share of liquid assets invested in risky assets (the conditional risky share). A 1 percent increase in the H1N1 death rate reduces the conditional risky share by 0.27 percent. The event study further shows that the impact of H1N1 has a two-year lag and remains persistent eight years after the pandemic. The decomposition analysis suggests that the decline in risky share associated with the pandemic is mainly due to households' rebalancing decisions rather than their realized asset returns. Furthermore, the effect of H1N1 on risky share is more substantial for households whose household heads are females, singles, have larger income fluctuation, do not work in a government job, and are not represented by a union. The findings suggest that the portfolio choices for households with larger income risks are more sensitive to the pandemic shock.

Keywords: Pandemic, Portfolio Choice, Heterogeneity
JEL Classification: D10, G50, I10

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1 Introduction

Over the last century, viruses have taken more lives than all armed conflicts (Adda, 2016). For instance, the 1918 Spanish flu, the most severe influenza pandemic in recent history, resulted in about 50 million deaths (Taubenberger and Morens, 2006). The 2019 COVID-19 outbreak, as of May 2023, has infected 760 million people and caused over 6.9 million deaths.[1] Given its uncontrollable emergence, unpredictable consequences, and uncertain duration, such public health crisis exposes people to increased risks and thus elicits behavior responses in different aspects (Rasul, 2020). Previous research has established that influenza pandemics can change health behaviors (Lau et al., 2005; Agüero and Beleche, 2017), alter household consumption (Baker et al., 2020; Chetty et al., 2020) and savings (Hurwitz et al., 2021), affect time allocation decisions (Restrepo and Zeballos, 2020), and shape household expectations (Hanspal et al., 2021). Still, we know little about how a pandemic affects households' risk preferences and portfolio choices. As such, this study focuses on the impact of the 2009 H1N1 pandemic on US household portfolio choices.

The H1N1 pandemic was detected first in the US in April 2009, which was caused by a novel human-to-human transmissible A (H1N1) virus. Following the epidemiological literature, we alternatively refer to the 2009 H1N1 influenza virus as "(H1N1)pdm09 virus" or "novel H1N1 virus" throughout this paper.[2] The H1N1 pandemic was the first influenza pandemic in 40 years[3], infecting 11 to 21 percent of the world population at the time (Kelly et al., 2011). In particular, the US had the world's largest number of infections and deaths during the pandemic (43.3–89.3 million infections and 8,868–18,306 deaths, see Section 2.1). Although WHO declared an end to the pandemic on August 11, 2010, the (H1N1)pmd09 virus continues to circulate as a regular seasonal flu virus and affects human life.

As the H1N1 pandemic was arguably unexpected, it can be used as a natural experiment to analyze whether and how households adjust their portfolio choices in response to a pandemic. Several possible channels can be explored in this regard. First, the pandemic may increase the household's background risk, which is referred to as the exogenous risks that are not under the agent's control (Eeckhoudt et al., 1996). Specifically, the background risks

[1]See statistics on the World Health Organization website, `https://covid19.who.int/` (accessed May 13, 2023). Pandemics can also incur severe economic costs at the macro level: the annual global cost of moderately severe to severe pandemics accounts for 0.7% of global income. See the World Report in 2017, https://www.worldbank.org (accessed May 13, 2023).

[2]This new virus was initially referred to as "swine flu" because its gene components were analogous to viruses that were known to infect pigs. However, this virus cannot circulate by eating pork products.

[3]Before the 2009 H1N1 pandemic, the most recent pandemic occurred in 1968, caused by the H3N2 virus.

driven by the pandemic can affect household finance through multiple aspects. For instance, Almond and Mazumder (2005) show that a pandemic can have a persistent effect on health, and an increase in health risk can affect stock holdings (Fan and Zhao, 2009). Similarly, a pandemic can affect labor market outcomes, such as employment, occupational choice, and earnings (Albanesi and Kim, 2021; Larrimore et al., 2022), which will also change portfolio choices (Guiso et al., 1996; Heaton and Lucas, 2000). Second, a pandemic can lead to a temporary or permanent change in risk preference and, therefore, investment in risky assets. Following the literature, we study both the extensive margin (i.e., whether to participate in the stock market or not) and the intensive margin (i.e., the share of the risky asset, conditional on the stock market participation) (Fagereng et al., 2017).

Our analysis mainly uses data from three sources. First, to measure the intensity of the H1N1 pandemic, we manually collect state-level H1N1 deaths during the pandemic (i.e., April 2009–August 2010) on an online forum *FluTracker* and calculate the death rate of each state, which is defined as the number of laboratory-confirmed deaths per 100,000 people. We also gather laboratory-confirmed case counts at the Health and Human Services (HHS) region level from the Centers for Disease Control and Prevention (CDC) website as a robustness check.[4] Second, we pool data from nine waves of the Panel Study of Income Dynamics (PSID) (2001–2017, in odd-numbered years) to obtain a comprehensive data set on wealth, investments, and demographics at the household level. The longitudinal nature of the data set allows us to separate the household fixed effects and identify the effects of covariates on the portfolio choices. We construct two measures for portfolio choices, stock market participation (an indicator variable of whether owning any risky assets) and risky share (share of risky assets among liquid assets conditional on positive risky asset holdings). Third, we collect state-by-year macroeconomic indicators and medical resources from various sources.

The major challenge for identifying the causal impact of the H1N1 pandemic on household portfolio choices is that the source of variations in H1N1 intensity is cross-sectional. Even if a negative correlation exists between H1N1 intensity and stock holdings, households in higher H1N1 intensity states may intrinsically hold less risky assets. We use a difference-in-differences identification strategy to overcome this problem by exploiting the state-level differences in the H1N1 intensity and the differences between the pre- and post-pandemic period *within households*. The panel data allows us to control for time-invariant household

[4] Due to data limitations, we can only obtain case numbers at the HHS level because the CDC did not disclose state-level data. See the description of the H1N1 data in Section 2.2.1.

characteristics and analyze the dynamic effects of the pandemic. In our main specification, we also include a large set of time-varying household- and state-level controls that may be correlated with the outcome variables and the measure of H1N1 intensity.

Our empirical analysis clearly shows that the exposure to the 2009 pandemic affects the intensive margin (risky share) but not the extensive margin of stock holdings (stock market participation). The effect on the intensive margin emerges after the pandemic. In particular, in 2009, when the crisis emerged, the risky share did not change. In contrast, from the second to the eighth year after the pandemic, a 1 percent increase in the 2009 H1N1 death rate led to a decline in the risky share by 0.27 percent. We address the potential confounding effect of the 2007–2008 financial crisis by adding interactions between year dummies and cross-state variations in economic indicators during the financial crisis (i.e., GDP per capita, unemployment rate, and housing price). Our results are also robust to different criteria of sample selections and alternative measures of the H1N1 intensity. In addition, we test the effect of exposure to seasonal influenza on risky shares as a placebo test. Unlike the seasonal flu, which is regular, anticipated, and under control, the novel H1N1 virus had never been detected before and could invalidate existing vaccines. Hence, we conjecture that households will only respond to an unexpected and more dangerous influenza virus but not the seasonal flu, and the data confirm our speculation.

To inspect how the impact changes over time, we estimate the year-specific effects of exposure to the H1N1 pandemic in an event study framework by taking advantage of the multi-waves of the PSID data set we use. The changes in the risky share are small and statistically insignificant before 2007, which supports the parallel trends assumption. The difference is also little in 2009, thus suggesting that investment decisions have some lagged effects. In 2011 and onward, the coefficient estimates for the risky share started becoming statistically different from zero. They stabilized at about -0.24 by 2017 (the end of the sample period), thus implying that the impact of the H1N1 pandemic is long-lasting.

Understanding structural changes in household portfolio choices can provide insight into households' evolving risk preferences and investment strategies. The decline in the risky share with the H1N1 death rate can result from a reduction in the number of risky assets, an increase in liquid assets, or a combination of both. Our findings reveal that a 1% rise in the H1N1 mortality rate leads to a roughly 40-dollar decrease in the net investment in stocks at the household level. However, no significant change in the amount of liquid assets is observed. Therefore, the decrease in the intensive margin of stock holdings in response to the H1N1 pandemic is mainly driven by the net sales of risky assets rather than the change in liquid assets.

However, households may exhibit inertia in rebalancing their portfolios, as noted by Brunnermeier and Nagel (2008) and many other studies. Furthermore, measurement errors may occur in the net amount put in risky assets. To address these issues, we follow Calvet et al. (2009) and decompose the risky share into passive changes resulting solely from realized asset returns and active changes that stem from households' rebalancing decisions. Our analysis shows that the passive change remains unaffected by H1N1 intensity, while the active change falls by around 0.07 percentage points in response to a 1% increase in the H1N1 death rate. Therefore, households exposed to the pandemic appear to be actively reducing risky assets and shifting their assets from risky investments to safer, risk-free assets.

We also find rich heterogeneity in the effect of the H1N1 pandemic on risky shares. The pandemic impact is more substantial for households whose heads are females or single than those whose heads are males or married. The effect is also stronger for households whose heads earn more unstable income, do not have a government job, or are not represented by a union. These results suggest that households with more volatile incomes are more likely to be influenced by the pandemic.

Moreover, we examine the life-cycle effect of the pandemic. The exposure effect of the pandemic on the share of risky assets displays a hump shape over the life cycle. Specifically, the effect (in magnitude) of the H1N1 pandemic is largest for households whose heads are aged 20–29. The effect decreases at age 20–59 and slightly increases at age 60–69. Considering that risk aversion decreases with age (e.g., Schooley and Worden, 1996) and people who approach retirement tend to rebalance their portfolio composition away from stocks (Fagereng et al., 2017), our findings suggest that the pandemic has larger effects on more risk-averse individuals.

In addition to focusing on the exposure impact of the H1N1 pandemic on liquid assets, we also investigate its potential effect on illiquid assets. We show that a 1 percent increase in the H1N1 death rate reduces the probability of being an incorporated business owner by 0.028 percent significantly. We also observe an increase in the probability of owning an unincorporated business by 0.021 percent associated with a 1 percent increase in the H1N1 intensity, despite this coefficient being statistically insignificant. However, little evidence indicates that the probability of owning a house or car will change with the H1N1 intensity.

Finally, we conduct an investigation to shed light on why the H1N1 pandemic affects risky assets. We examine a range of factors related to health, demographics, and labor market outcomes, such as self-reported health status, marital status, number of children, income, and employment status. While these characteristics may be affected by the pandemic and could result in background risks that lead to changes in stock holdings, our findings reveal that the pandemic does not contribute to these potential factors. This rules out the health, demographics, and labor market assumptions. We also find that family wealth remains unaffected by H1N1 intensity and does not influence the proportion of risky shares.

This study contributes to the literature that examines the socioeconomic consequences of pandemics. Despite a growing body of literature on pandemics, the effect of exposure to a pandemic on household portfolio choice has been insufficiently explored.[5] To complement the works on the ongoing COVID-19 pandemic, the current study investigates the effect of the 2009 H1N1 pandemic on portfolio choices. Using panel data from 2001 to 2017, we can analyze the contemporaneous and *long-term* effects of the H1N1 pandemic on stock holdings' extensive and intensive margins. In addition, we use the difference-in-differences framework to control for time-invariant unobserved characteristics at the household level, which provides more rigorous causal evidence of the pandemic impact.

Our study also adds to the literature on the determinants of household portfolio choices. A broad list of factors that determine household asset choices includes housing (Cocco, 2005; Chetty et al., 2017), income risk (Angerer and Lam, 2009; Betermier et al., 2012), physical health (Fan and Zhao, 2009), mental health (Bogan and Fertig, 2013), financial literacy (Li et al., 2020), cognitive ability (Christelis et al., 2010), and social interaction (Hong et al., 2004; Liang and Guo, 2015). We contribute to this literature by shedding light on the role of pandemics in household asset allocations. We provide one of the first pieces of evidence that exposure to a pandemic can affect the intensive margin but not the extensive margin of stock holdings, which deepens our understanding of how portfolio choices can be affected by a public health crisis.

[5] To the best of our knowledge, there are three extant studies related to this topic (Yue et al., 2020; Coibion et al., 2020; Agarwal et al., 2020), all of which examine the impact of the COVID-19 pandemic on the intensive margin of assets holding using a survey conducted within a few months. Yue et al. (2020), and Coibion et al. (2020) show that COVID-19 exposure reduces household investments. By contrast, Agarwal et al. (2020) find that more confirmed COVID-19 cases in a city result in more upward and downward adjustments of risky assets.

This paper is organized as follows. Section 2 introduces the background of the 2009 H1N1 pandemic and describes the data we use. Then, Section 3 discusses our difference-in-differences empirical strategy. Section 4 reports findings on how exposure to the H1N1 pandemic affects household stock holdings. Afterward, Section 5 focuses on the heterogeneous effect of the pandemic on the risky share. Section 6 examines the exposure effect of the pandemic on illiquid assets. Next, Section 7 provides a discussion on the possible explanation of why the H1N1 pandemic affects household portfolio choices. The last section provides the conclusion of the study.

2 Background and Data

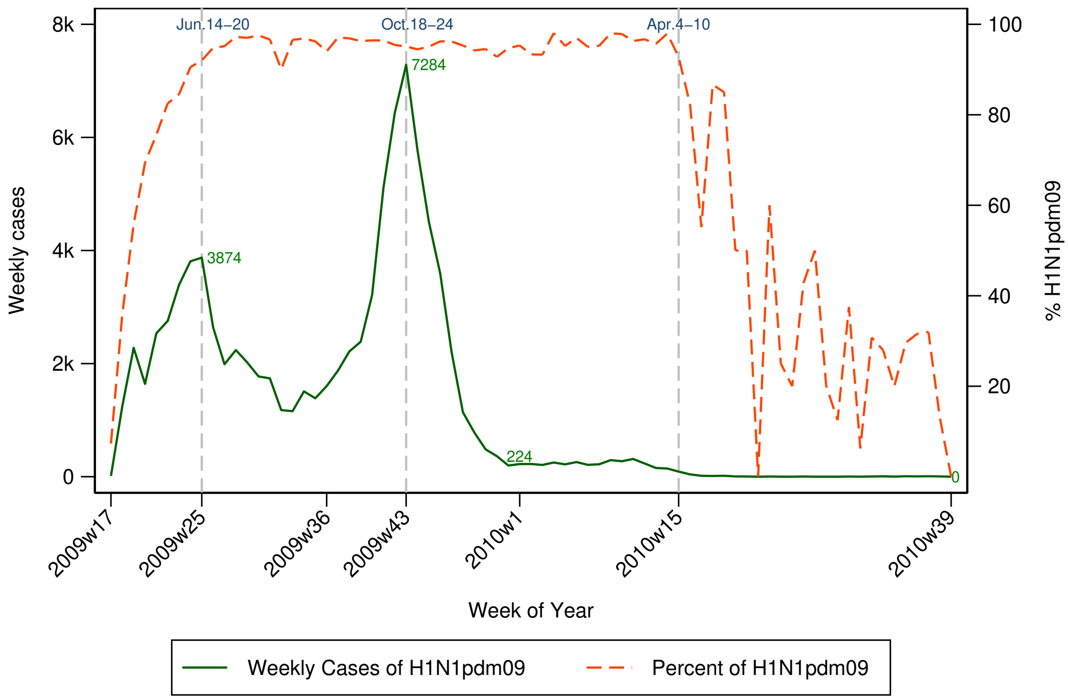
2.1 The US and the 2009 H1N1 Influenza Pandemic

The outbreak of the 2009 H1N1 influenza (informally called "swine flu") was declared by WHO as the first global flu pandemic since 1968. During the pandemic, more than 214 countries and overseas territories or communities reported cases of 2009 H1N1 infection, including more than 18,449 laboratory-confirmed deaths.[6]

The novel influenza A (H1N1) virus surfaced in the spring of 2009. It was first detected in California on April 15 and spread quickly across the US. By June 19, confirmed cases of 2009 H1N1 infection were reported by all 50 states, the District of Colombia, Puerto Rico, and the US Virgin Islands.

The 2009 H1N1 influenza virus is typically transmitted from person to person through droplets. It shares some similar symptoms to other flus: fever, cough, headache, etc. However, the disease patterns in severe cases are remarkably different from those of seasonal flus. The health of infected people can deteriorate within three to five days after they have symptoms and progress to respiratory failure. This virus differs significantly from other known H1N1 viruses at the time of the pandemic because it contains a unique segment of flu genes not identified by humans previously. As a result, children and young and middle-aged adults have almost no existing antibodies against it, while almost a third of people over 60 years old had immunity probably due to their exposure to an older H1N1 at some time in their earlier lives. It is estimated that 80% of 2009 H1N1 deaths were people less than 65 years old, while about 80–90% of typical seasonal influenza were those aged 65 or older (Dawood et al., 2012). Given the uniqueness of the novel H1N1 virus, seasonal flu vaccines offered little protection against it.

[6] See WHO pandemic (H1N1) 2009-update 112, https://www.who.int/emergencies/disease-outbreak-news/item/2010_08_06-en (accessed March 2, 2022.) Note that the number of lab-confirmed deaths, 18,499, is likely to be only a fraction of the true number and is widely considered an underestimate. For instance, Dawood et al. (2012) estimate 151,700–575,400 deaths globally.



Notes: The solid line represents the number of weekly lab-confirmed H1N1 cases, while the dashed line denotes the proportion of weekly lab-confirmed H1N1 cases in total lab-confirmed influenza cases. (Data source: WHO Collaborating Laboratories)

Figure 1. Weekly Cases of H1N1pdm09 in the US

From April 12, 2009 to April 10, 2010, the CDC estimated 43.3–89.3 million cases of the novel H1N1 virus, including 195,086–402,719 hospitalizations and 8,868–18,306 deaths in the US (Shrestha et al., 2011). Figure 1 plots the trend of the 2009 H1N1 influenza lab-confirmed cases. Specifically, the novel H1N1 flu cases in the US peaked in June and October of 2009. From June 2009 to April 2010, the (H1N1)pdm09 virus accounted for more than 90% of the total influenza cases. From then on, the H1N1 cases decreased gradually and dropped to zero by the end of August 2010.

In response to this pandemic, the US government took a series of measures. In the initial stage, schools were closed if cases were confirmed[7]. In addition, H1N1-related news were published on cdc.gov. Public health advice was also provided on these websites, including educating people to practice good hygiene, such as washing hands properly and using hand sanitizers, encouraging the public to keep social distancing, and encouraging sick people with mild symptoms to stay home from work or school until their symptoms subsided. On the other hand, CDC started working on the 2009 H1N1 flu vaccine as early as April 28, 2009.

[7]By May 5, 2009, 980 schools across the countries were closed, involving 607,778 students.

However, given the slow production process, the vaccine was not available until October 2009, when the government launched the 2009 H1N1 vaccination campaign. Only a few million were available at the beginning. Therefore, the priority of the first available vaccines was given to health care workers, children, and pregnant women. In late December 2009, free vaccines were opened up to anyone who wanted it.

In early August 2010, scientists reviewed the global epidemiological situation and made an important discovery: the H1N1 virus was circulating as a regular seasonal flu virus, and the level of pandemic flu activity had returned to normal levels that were considered typical for seasonal flu. These findings provided strong evidence that the (H1N1)pdm09 virus was transitioning to a seasonal influenza virus. As a result, the World Health Organization (WHO) declared an end to the H1N1 pandemic on August 11, 2010. From then on, the novel H1N1 virus spreads as a seasonal flu virus.

2.2 Data

2.2.1 H1N1 Data

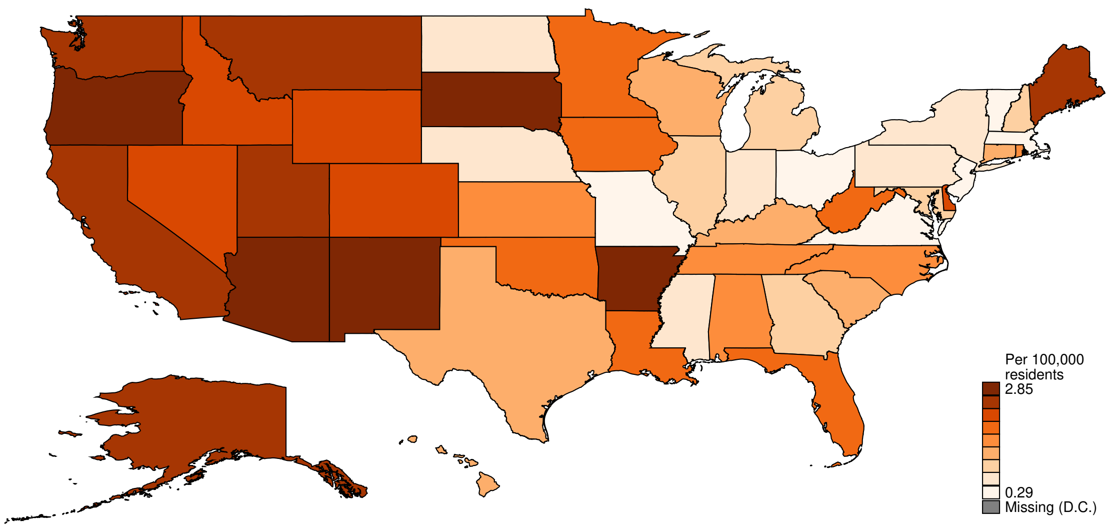
We first describe data on the severity of the H1N1 pandemic. Three potential measures are confirmed cases, hospitalizations, and deaths. The CDC publishes influenza surveillance information in a weekly report called *FluView*.[8] When the novel H1N1 virus first emerged, *FluView* reported state-level individual case counts. However, with the rapid spread of the virus, individual cases became not representative of the outbreak and were thought to be a significant underestimate of the actual number.[9] As a result, the CDC discontinued reporting confirmed cases on July 24, 2009. Nevertheless, it continued to track hospitalizations and deaths and reported the country-level hospitalizations and deaths due to the 2009 H1N1 virus. After August 30, 2009, the CDC further revised reporting criteria and asked states to report all influenza and pneumonia-related hospitalizations and deaths every week, not just those due to the 2009 H1N1 virus. From September 11, 2009 on, *FluView* published the country-level total hospitalizations and deaths (including the 2009 H1N1 and seasonal flu). Unfortunately, we can not obtain useful information from the CDC reports since the country-level figures masked the regional variations in the H1N1 outbreak.

We use data collected from *FluTrackers* (FluTrackers.com), an online forum and early warning system that has gathered information on infectious diseases since 2006. During the

[8]See www.cdc.gov/h1n1flu/updates/ for a collection of *FluView* reports on the novel H1N1 virus (accessed March 10, 2022).

[9]Many people with respiratory symptoms did not seek medical care. Only a small proportion of them saw a doctor and did an (H1N1)pdm09 test. Reed et al. (2009) find that every confirmed case reported from April 2009 to July 2009 in the US represented an estimated 79 cases.

2009 H1N1 pandemic, whenever a state health department announced the H1N1 surveillance information (usually at the state level), *FluTrackers* collected it and posted the content of the state surveillance report and the source link on the forum. As individual case counts and hospitalizations were not reported by the state in most cases, we extract the lab-confirmed H1N1 death information for each state from *FluTrackers* and compute the state-level total number of death during the pandemic (i.e., April 2009–August 2010). Then we define our main measurement for the state-level H1N1 intensity as the number of lab-confirmed death toll per 100,000 residents. We use death rates rather than death numbers because death numbers can be positively correlated with the local population. Figure 2 shows the geographic distribution of H1N1 death rates for 50 states (excluding the District of Columbia), in which a darker color implies a higher death rate. All 50 states reported deaths from the (H1N1)pdm09 virus during the pandemic. Significant variations are observed in the distribution of death rates across states, ranging from 0.29 (Missouri) to 2.85 (South Dakota) (see Appendix Table B1 for specific death rates).



Notes: The state H1N1 death rates are defined as the state-level lab-confirmed death toll per 100,000 residents during the 2009 Pandemic (April 2009–August 2010). The state-level death toll is aggregated from FluTrackers.com. The number of state residents denotes the intercensal estimate for 2009 (source: the US Census Bureau, Population Division).

Figure 2. Geographic Distribution of H1N1 Death Rates in the 2009 Pandemic

Besides the H1N1 death rate, we construct a second measure as a robustness check. Approximately 80 WHO Collaborating Laboratories are located throughout the US. They reported the total number of respiratory specimens tested and the number of positive for the influenza types A and B, including the (H1N1)pdm09, in a weekly publication called

FluView. These data were reported at the HHS region level, a broader level than a state.[10] We collect the weekly data on H1N1 case numbers via an R package called "cdcfluview." Then, we aggregate the number of confirmed cases of the 2009 H1N1 virus for each HHS region during the pandemic and calculate the H1N1 case rate (at HHS region), which is defined as the H1N1 case counts per 100,000 residents.

Examining the correlation between the H1N1 intensity and indexes for stock market performance during the pandemic is significant because stock market performance is closely related to household portfolio choices. We construct three weekly indicators of stock market performance: the weekly real S&P 500 price index, the weekly return of the real S&P 500 index, and the weekly stock market volatility.[11] We plot the time trends of these stock market indexes versus the weekly H1N1 cases during the H1N1 pandemic in Appendix Figures A1–A3. During the peaks of the first and second waves of the H1N1 pandemic, the weekly S&P price index and corresponding returns decreased to some extent. However, the correlation coefficients between these indicators and confirmed cases were all no more than 0.1 in absolute value.[12] Generally, these three indicators did not exhibit a clear uniform or contrasting trend with the confirmed cases of H1N1. In Appendix Table B3, we report the results of the Granger causality test, which suggests that the lagged values of weekly H1N1 cases do not Granger-cause the aforementioned three weekly stock market indicators at the 5% significance level. In turn, these indicators do not Granger-cause the weekly H1N1 cases either. Overall, the H1N1 pandemic had a very mild impact on the stock market, which is in distinct contrast with the case of the COVID-19 pandemic.[13]

2.2.2 PSID

Our primary data source is the PSID. It is a longitudinal and nationally representative project that tracks over 82,000 individuals from more than 9,500 families for more than 50 years. The PSID data were released annually until 1997 and became a biannual survey from then on.[14] The wealth module on asset holdings was first included in 1984, which initially repeated every five years (i.e., in 1989 and 1994). Since 1999, the wealth data have been collected in every wave. At the time of our research, due to the lack of some state-by-year-

[10] The country is divided into 10 HHS regions. For more details about HHS regions, see the website of the US Department of Health and Human Services.

[11] The data source is the Center for Research in Security Prices (CRSP) of Wharton Research Data Services. Please refer to the notes in Appendix Figures A1–A3 for details on the variable construction.

[12] The correlation between the weekly H1N1 cases and the weekly real S&P 500 price index, the weekly return of the real S&P 500 index, and weekly stock market volatility are -0.1, -0.05, -0.09, respectively.

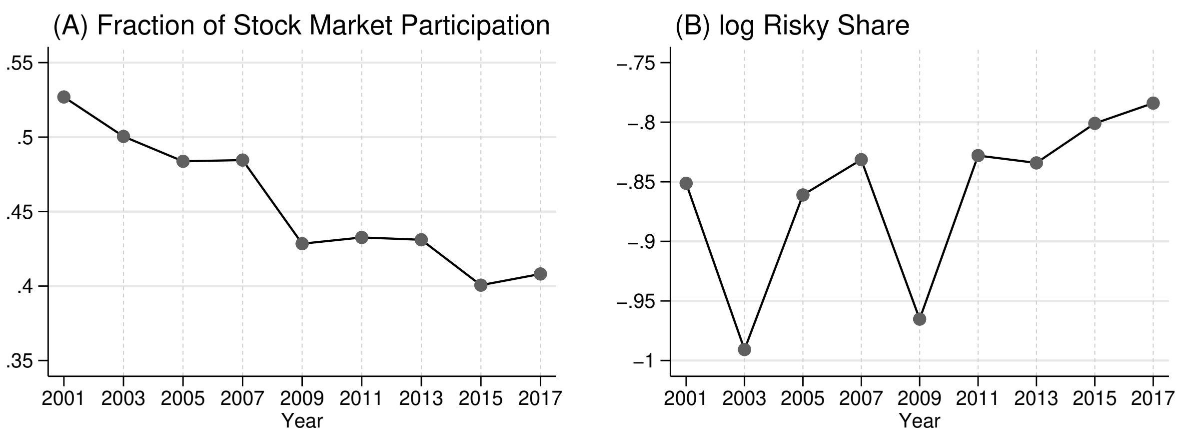
[13] The COVID-19 pandemic and the measures taken to control it caused the S&P 500 to experience a historic decline of one-third of its value in the steep drop of stock prices in February and March 2020 (Hanspal et al., 2021) and have a substantially adverse impact on stock returns (Al-Awadhi et al., 2020).

[14] The most recent available PSID survey is the 2020 wave by March 2023.

level control variables in 1999 and 2019, we use nine waves of data in the PSID (i.e., 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, and 2017).[15]

Variable Definitions.—Wealth data are collected at the household level and refer to the value at the time of the survey. Following Brunnermeier and Nagel (2008), we define risky assets as the sum of stock in publicly held corporations, stock mutual funds, and investment trusts, including stocks in the Individual Retirement Account (IRA). Risky-free assets are defined as the sum of checkings, savings, bonds, trusts, and IRA invested in interest earnings. We further denote the sum of risky and riskless assets as liquid assets. Stock market participation is defined as equal to 1 if the household has positive risky assets and zero otherwise. Following the common practice, the risky share is calculated as the proportion of the liquid assets held in risky assets, which is conditional on stock market participation.

Figure 3 plots the average changes in the household portfolio over time. In our study period (2001–2017), the fraction of households that owned risky assets displayed an overall declining trend (Panel A). In particular, it dropped substantially from 2007 to 2009 due to the financial crisis. On the other hand, the risky share revealed high volatility (Panel B).



Notes: Stock market participation is defined as owing positive risky assets. Risky share is the value of risky assets divided by liquid assets, conditional on stock market participation. (Data source: PSID, waves 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, and 2017.)

Figure 3. Aggregate Changes in Household Portfolio: 2001–2017

We proxy the household head (i.e., the "reference person" defined by PSID since 2017) as the main decision maker in a family. Therefore, the head's individual characteristics (e.g.,

[15] Most of the state-by-year control variables are missing in or before 1999, and some of them are missing in 2019. As we will introduce in Section 4.1, our rigorous causal analysis must control these variables, as they are closely related to the outcome variables and the H1N1 intensity. Therefore, we use PSID data from 2001 to 2017 such that they can be matched to the balanced panel of state-by-year characteristics.

age, gender, education, race, marital status) are used in priority.[16] All monetary values, such as wealth and income, are defined in 2017 dollar adjusted by the CPI-U index.

Sample restrictions.—We impose several sample restrictions to our analysis. Our original sample is restricted to those who have non-missing basic individual and household characteristics (introduced in detail in Section 4.1), which consists of 59,512 observations in nine waves. We then exclude observations with asset changes due to a family member moving into or out of the family, which drops 1,759 observations. We also drop observations if the household head is a student (634 observations) or retired (11,592 observations). We establish a minimum number of liquid assets of $1,000 because the asset allocation decision is not relevant for households with liquid assets less than $1,000 (Gomes and Smirnova, 2021), which leaves us with 27,739 observations. We further exclude households with a single observation to conduct a panel-data analysis. Finally, we are left with a sample with 25,947 observations from 5,049 family units. For the risky share analysis, the sample is conditional on owning risky assets and consists of 9,759 observations from 2,239 family units.

Table 1. Summary Statistic for Households

Variable	Mean	Median	Std.
Age	43.35	43.00	11.46
Male	0.83	1.00	0.37
White	0.74	1.00	0.44
Years of schooling	14.52	15.00	2.13
Stock market participation	0.41	0.00	0.49
Risky share	0.53	0.50	0.29
Number of family	5049		
Observations	25,947		

Notes: The table reports summary statistics for all households that satisfy our sample selection rule. Head information is used in priority as individual characteristics, and if head information is missing, spouse information is used instead. Stock market participation is defined as equal to 1 if the household has positive risky assets and zero otherwise. The risky share is defined as the proportion of the liquid assets held in risky assets, conditional on stock market participation. (Data source: PSID, waves 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, and 2017.)

[16] If head information is missing, we use the wife's characteristics instead, which accounts for only a trivial proportion (less than 0.1% of the sample size).

Summary Statistics—Table 1 presents pooled cross-sectional statistics for all households in our analysis sample. During our sample period, the average age of household head is 43. The head's gender is skewed to males (83%). More than 70% of the heads are white. The average number of educational years is 14.5 years. The fraction of households participating in stock market is 0.41, and the (conditional) risky share is 0.53.

2.2.3 Macroeconomic Indicators and Medical Resources

We collect a wide set of state-by-year-level variables on macroeconomic indicators and medical resources from different sources (see Appendix Table B2 for the original data and data sources). To make a fair comparison among states, we use the per capita (or per 100,000 population) basis for GDP, personal income, bankruptcy cases, assets, deposits, hospital beds, active physicians, physicians in patient care, and registered nurses.

Table 2. Balanced Checks for States

Variable	Low death-rate states (1)	High death-rate states (2)	Diff (2)-(1)
A. Macroeconomic indicators			
GDP per capita (in chained 2012 million dollars)	0.050	0.048	-0.0016*
	(0.001)	(0.001)	(0.0009)
Personal income per capita	45088.406	41851.403	-3237.0030***
	(509.401)	(374.250)	(632.1015)
Unemployment rate	5.537	5.666	0.1289
	(0.127)	(0.132)	(0.1832)
Homeownership rate	0.689	0.691	0.0021
	(0.004)	(0.003)	(0.0049)
Housing price index	189.679	214.473	24.7942***
	(2.181)	(3.464)	(4.0936)
Bankruptcy cases per 100,000 people, filed by state	416.831	414.141	-2.6898
	(12.965)	(12.664)	(18.1237)
Assets per capita (in million dollars)	0.032	0.139	0.1068***
	(0.003)	(0.030)	(0.0301)
Deposits per capita (in million dollars)	2.563	3.746	1.1828
	(0.504)	(1.163)	(1.2680)
Population density	258.404	124.507	-133.8972***
	(18.549)	(14.023)	(23.2528)

Continued on next page

Table 2 – *Continued from previous page*

Variable	Low death-rate states (1)	High death-rate states (2)	Diff (2)-(1)
B. Medical resources			
Hospital beds per 100,000 population	291.813	275.800	-16.0132**
	(5.221)	(6.089)	(8.0209)
Active physicians per 100,000 population	2.833	2.435	-0.3982***
	(0.043)	(0.029)	(0.0515)
Physicians in patient care per 100,000 population	2.614	2.260	-0.3541***
	(0.038)	(0.028)	(0.0478)
Registered nurse per 100,000 population	869.831	805.805	-64.0266***
	(8.903)	(11.443)	(14.4984)
States	25	25	
Observations	225	225	

Notes: This table reports the summary statistics by H1N1 death rates for state characteristics in 2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, and 2016 (i.e., one year before the PSID wave). States in which H1N1 death rates are below the median level of all states are defined as low death-rate states. States in which H1N1 death rates are above the median level of all states are defined as high death-rate states. Standard deviations are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are shown in parentheses. GDP per capita is in chained 2012 dollars. Homeownership rate is defined as the proportion of owner households to the total number of occupied households. The housing index price data, with the first quarter in 1991 normalized as 100, are for the fourth quarter of the year (seasonally adjusted) and reflects average price changes in repeat sales or refinancings on the same properties. Assets per capita is referred to as assets per capita in Federal Deposit Insurance Corporation (FDIC) insured financial institutions. Deposits per capita is defined as deposits per capita in FDIC insured financial institutions. Population density is defined as population per square mile of land area. Hospital beds are referred to beds in community hospitals, which are defined as all non-federal, short-term general, and other special hospitals, excluding hospitals not accessible by the general public. Except indicated, all monetary variables are in 2017 dollar, adjusted by CPI-U index. (Data sources: see Appendix Table B2.)

Table 2 reports balanced test results for these state characteristics from 2000 to 2016 (i.e., the years prior to the PSID waves). We use the data from these years to mitigate concerns regarding reverse causality. We define a state as a high death-rate state if its H1N1 death rate during the pandemic was higher than the median level of all 50 states. As shown in Table 2, high death-rate states has lower GDP per capita, personal income per capita, and population density but had higher housing price and more assets per capita in FDIC-insured financial institutions than low death-rate states. In terms of medical resources, high death-rate states tended to have fewer hospital beds, physicians, and nurses for every 100,000 population. In summary, H1N1 intensity is correlated with state macroeconomic indicators and medical resources, for which we will provide thorough analysis in Section 4.1.

3 Empirical Strategy

The primary goal of our study is to estimate the causal impact of the 2009 H1N1 pandemic on the extensive and intensive margins of stock holdings. As introduced in Section 2.2.1, we use state-level H1N1 death rates during the pandemic (i.e., April 2009–August 2010) to measure H1N1 intensity. We adopt a difference-in-differences identification strategy, in which we exploit the state-level differences in the H1N1 intensity and the differences between the pre-pandemic and post-pandemic periods. Specifically, the following equation is estimated:

$$Y_{ijt} = \beta_1 During_t \times H1N1_p + \beta_2 After_t \times H1N1_p + \alpha_t + \alpha_i + \alpha_j + \delta t\alpha_j + \gamma \boldsymbol{X_{ijt}} + \epsilon_{ijt}, \quad (1)$$

where i indexes family, t indexes year, and j indexes the state where the family resides. The outcome of interest, Y_{ijt}, denotes either an indicator variable for stock market participation or the natural log of risky share. $H1N1_p$ is the natural log of the lab-confirmed H1N1 death rate in the state p during the 2009 H1N1 pandemic. The state p is where the household resided in 2009. Our baseline analysis does not require the sample to stay in the same state. We will focus on families that did not move in the robustness analysis later. $During_t$ is an indicator equal to 1 if $t = 2009$. $After_t$ is an indicator equal to 1 if $t > 2009$. α_t, α_i, and α_j are year, family, and state fixed effects, respectively.[17] The model also includes state-specific time trends, $t\alpha_j$, to mitigate the concern that the effect of the 2009 H1N1 pandemic can be driven by preexisting state-specific trends. $\boldsymbol{X_{ijt}}$ includes a large set of household- and state-specific time-varying characteristics, which are described when introduced in the results. The inclusion $\boldsymbol{X_{ijt}}$ mainly has two advantages. On the one hand, controlling these variables helps reduce the variance of the error term and hence improves the precision of the estimate of β_1 and β_2. On the other hand, despite the unpredictability of the H1N1 pandemic, the state H1N1 death rates may be correlated with other factors that can cause the change in asset allocations, thus being correlated with household stock holdings. Including $\boldsymbol{X_{ijt}}$ may help to control for these observable differences across states. Standard errors are clustered

[17] Given that we include α_i, which controls time-invariant family characteristics, α_j captures the effect of time-invariant state-level characteristics for migrants (i.e., families that changed their residency state during our study period.)

at the family level.

In our model, $H1N1_p$ works as a continuous treatment variable. Our identification relies on the assumption that in the absence of the 2009 H1N1 pandemic, household stock holdings would have changed in a parallel way in both the treatment and pre-pandemic control group, controlling for year fixed effects, family fixed effects, state fixed effects, state-specific time trends, and other time-varying control variables. This assumption should be plausible because the outbreak of the H1N1 pandemic is unexpected and uncontrollable.

Coefficients β_1 and β_2 are our key coefficients of interests. Assuming parallel trends without treatment, we can then interpret β_1 as the average percentage change in Y_{ijt} in 2009 when the H1N1 intensity increases by 1%, relative to the pre-pandemic year. Analogously, β_2 represents the average percentage change in Y_{ijt} after 2009 when the H1N1 intensity increases by 1%, relative to the pre-pandemic year. In other words, β_1 and β_2 can be considered measurements for elasticities, that is, how sensitive stock market participation or risky share is to H1N1 intensity. We interact $H1N1_p$ with $During_t$ and $After_t$ dummy separately rather than construct the classic interaction between $H1N1_p$ and a $Post_t$ dummy ($Post_t$ is equal to 1 if $t >= 2009$). In our analysis sample, the majority of families (more than 60%) in 2009 took the PSID survey before June (i.e., the peak of the first wave in the US) (see Appendix Figure A4). As a result, these households could have had less exposure to the pandemic at the time of the 2009 survey than others who lived in the same state but took the survey later in 2009. To be conservative, we define the $During_t$ and $After_t$ dummies following Kolstad and Kowalski (2012).

We next use an event study framework to estimate year-specific treatment effects relative to the base year 2007. Formally, the model is written as:

$$Y_{ijt} = \beta_t H1N1_p + \alpha_t + \alpha_i + \alpha_j + \delta t \alpha_j + \gamma \boldsymbol{X_{ijt}} + \epsilon_{ijt}. \tag{2}$$

Notably, β is now allowed to vary by year. The estimates β_t measure the dynamics of treatment effect over time and help to examine whether pre-trends exist.

In our heterogeneity analysis, we modify Eq. (1) by allowing the treatment effect to be different in different groups. Formally, we estimate the following model:

$$Y_{ijt} = \beta_{1g} During \times H1N1_p + \beta_{2g} After \times H1N1_p + \alpha_t + \alpha_i + \alpha_j + \gamma \boldsymbol{X_{ijt}} + \epsilon_{ijt} \tag{3}$$

where β_{1g} and β_{2g} denote the treatment effect of the group g during and after the pandemic, respectively. By testing the equality of β_{1g} and $\beta_{1g'}$ (β_{2g} and $\beta_{2g'}$), we can examine whether the difference in treatment effects between different groups is significant.

4 Exposure Effect of the H1N1 Pandemic on Stock Holdings

4.1 Main Results

Table 3 shows the results of the effect of the 2009 H1N1 pandemic on stock holdings based on Eq. (1). Columns (1)–(4) and columns (5)–(8) examine the extensive margin (stock market participation) and the intensive margin (risky share), respectively.

Table 3. Impact on the 2009 H1N1 Pandemic on Household Portfolio

	Stock market participation				log risky share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
During × log(H1N1 death rate)	0.008	0.008	0.013	0.012	-0.030	-0.028	-0.078	-0.088
	(0.017)	(0.017)	(0.018)	(0.018)	(0.060)	(0.060)	(0.063)	(0.063)
After × log(H1N1 death rate)	-0.013	-0.012	0.004	-0.002	-0.209***	-0.206***	-0.228***	-0.273***
	(0.022)	(0.021)	(0.023)	(0.023)	(0.073)	(0.073)	(0.078)	(0.079)
Average of the outcome variable	0.410	0.410	0.410	0.410	-0.886	-0.886	-0.886	-0.886
Family, state and year FEs	✓	✓	✓	✓	✓	✓	✓	✓
State-specific time trend	✓	✓	✓	✓	✓	✓	✓	✓
Household features		✓	✓	✓		✓	✓	✓
Macroeconomic indicator (lag)			✓	✓			✓	✓
Medical controls (lag)				✓				✓
Number of family	5,049	5,049	5,049	5,049	2,239	2,239	2,239	2,239
Observations	25,947	25,947	25,947	25,947	9,790	9,790	9,790	9,790
Adj.R^2	0.475	0.476	0.476	0.476	0.285	0.285	0.285	0.286

Notes: This table shows baseline results on the change of stock market participation and risky share in response to the 2009 H1N1 pandemic. All regressions control for family fixed effects, year fixed effects, state fixed effects, and state-specific time trend. Columns (2) and (6) add controls for household features. Columns (3) and (7) further include time-varying state-level macroeconomic indicators. Columns (4) and (8) additionally control for time-varying state-level medical resources. See the description in Section 4.1 for the list of control variables. Standard errors are clustered at the family level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: PSID, waves 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, 2017.*)

Columns (1) and (5) control family fixed effects, year fixed effects, state fixed effects, and state-specific time trend without controlling $\boldsymbol{X_{ijt}}$. For the extensive margin, no significant change occurs in stock market participation related to H1N1 death rates during or after the pandemic. For the intensive margin, although no clear pattern is observed during the pandemic (in 2009), we find that when the H1N1 death rate increases by 1%, the risky share decreases by 0.2% after the pandemic (in 2011 and beyond).

In columns (2) and (6), we add a wide set of household characteristics, motivated by past studies on household portfolio decisions, most notably Brunnermeier and Nagel (2008). Specifically, we include the age and age square of the household head. Given that the head's race, educational attainment, and gender are time-invariant and absorbed by family fixed effects, we add their interactions with the head's age and age square. Fagereng et al. (2017)

show that there are cohort-specific patterns in stock market participation and risky share. Inspired by this finding, we include interactions between the age and cohort indicators of heads.[18] We do not include variables that can be affected by a pandemic, such as marital status, health status, income, and financial situation (e.g., whether they own mortgages, debts, and business) because these variables are bad controls. As can be shown in Table 3, for stock market participation, the coefficients of two interaction terms are still close to zero and insignificant (column (2)). While for the risky share, the effect of H1N1 intensity barely changes (column (6)).

We further control for a series of time-variant state-specific macroeconomic indicators (one-year lagged) in columns (3) and (7). These indicators include GDP per capita, personal income per capita, unemployment rate, homeownership rate, the Federal Housing Finance Agency (FHFA) housing price index (HPI), bankruptcy cases per 100,000 people, assets per capita and deposits per capita in FDIC-insured financial institutions, and population density. We control for these macroeconomic indicators for two main reasons. First, macroeconomic experiences can affect individuals' financial risk taking and hence influence household portfolio choices (Malmendier and Nagel, 2011). Second, the spread of epidemics is correlated with the macroeconomic situation and business cycles (Adda, 2016).[19] In other words, the macroeconomic variables we include may potentially be correlated with both the household portfolio choice and the H1N1 death rate. As shown in column (7), the estimated exposure effect remains stable after including these macroeconomic indicators.

Although the novel H1N1 virus outbreak is unexpected, the H1N1 death rate during the pandemic is possibly correlated with healthcare resources. As shown in Appendix Figure A5, states with fewer physicians, nurses, or hospital beds tend to have higher death rates during the pandemic (Appendix Figure A5). If unobserved time-varying confounders are correlated with the medical resources and lead to changes in household portfolio choices, our estimation strategy may suffer from biases. However, the results hold up when we additionally control for a set of medical resources (hospital beds, active physicians, physicians in patient care, and registered nurses per 100,000 people) in columns (4) and (8).

Two main conclusions can be drawn from the above analysis. First, stock market participation does not change with H1N1 intensity. Second, for risky share, we find little changes related to the H1N1 death rate in the year of the pandemic outbreak but a significant decrease after the pandemic. In our subsequent analysis, we will mainly focus on the risky

[18] Heads who were born before 1928, between 1928 and 1944, between 1945 and 1964, between 1965 and 1984, and after 1984, were defined as the "greatest generation," "silent generation," "baby boom," "baby bust," and "echo boom," respectively.

[19] Adda (2016) show that epidemics spread faster during economic booms because people are more likely to travel, which increases interpersonal connection and hence accelerate the spread of infectious diseases.

share and include year fixed effects, family fixed effects, state fixed effects, state-specific linear trend, and a full set of time-varying controls, as we have done in column (8).

4.2 Does the 2007–2008 Financial Crisis Confound Our Result?

One may have concern that the estimated exposure effect of the 2009 H1N1 pandemic on household stock holdings was confounded by the 2007–2008 financial crisis, which had a profound impact on the United States economy. The crisis was triggered by the collapse of the US housing market. As the crisis unfolded, many major financial institutions in the US faced significant losses, thus leading to a wave of bank failures and a sharp contraction in credit markets. Notably, evidence shows that the crisis could largely increase households' risk aversion and reduce the share of risky assets (e.g., Guiso et al. (2018)). Although the outbreak of the H1N1 pandemic was unexpected and uncontrollable, the H1N1 intensity in a region is likely correlated with the local severity or serious economic consequences of the financial crisis and hence creates bias in our estimation.

We develop three measures to assess the local impact of the 2007–2008 financial crisis. For each state j, we compute the change rate of GDP per capita, unemployment rate, and housing price index in 2008 compared with 2006 following this equation:

$$\%\Delta \mathrm{x}_j = (\mathrm{x}_{j,2008} - \mathrm{x}_{j,2006})/\mathrm{x}_{j,2006} \times 100,$$

where $x_{j,t}$ denotes GDP per capita, unemployment rate, or housing price index of state j in year t. The geographic distribution of the percentage changes in these indicators is shown in Appendix Figure A6. Intuitively, most states in the west (excluding Alaska) and southeast experienced larger decreases in GDP per capita and housing prices, as well as larger increases in the unemployment rate in 2008 compared with 2006. In contrast, as demonstrated in Figure 2, the western regions of the US were exposed to higher H1N1 intensity during the pandemic. We further perform a simple regression analysis to examine the relationship between H1N1 death rates during the pandemic and changes in state-level economic indicators during the financial crisis. The results, as presented in Appendix Table B5, indicate that the correlation between H1N1 intensity and changes in these economic indicators is negligible and statistically insignificant.

We now investigate whether the exposure effect of the H1N1 pandemic on the risky share persists when we control for the local impact of the 2007–2008 financial crisis. The impact of the financial crisis is captured by the interactions between year dummies and the percentage changes in GDP per capita, unemployment rate, and housing price during the financial crisis. This scenario allows us to capture the potential time-variant effect of the financial crisis on risky shares. The results are presented in Table 4. Compared with the baseline result (column (1)), the elasticity of the risky share with respect to the H1N1 death rate slightly decreases in magnitude but remains statistically significant after we control for the interactions between year dummies and GDP per capita, unemployment rate, and housing price in columns (2)–(4), respectively. In column (5), we further control for all three series of interactions. The effect of H1N1 intensity on risky share is -0.26, which is statistically significant at the 1% level. In summary, the significant exposure effect of the H1N1 pandemic on household stock holdings is quite robust even when we control for the potential impact of the financial crisis.

Table 4. Examine the Potential Bias Driven by the Financial Crisis

	Log(Risky share)				
	(1)	(2)	(3)	(4)	(5)
During × log(H1N1 death rate)	-0.088	-0.091	-0.080	-0.076	-0.098
	(0.063)	(0.064)	(0.064)	(0.065)	(0.068)
After × log(H1N1 death rate)	-0.273***	-0.269***	-0.259***	-0.263***	-0.260***
	(0.079)	(0.079)	(0.080)	(0.081)	(0.085)
Average of the outcome variable	-0.886	-0.886	-0.886	-0.886	-0.886
Family, state, year FEs	✓	✓	✓	✓	✓
State-specific time trend	✓	✓	✓	✓	✓
Household- and state-level controls	✓	✓	✓	✓	✓
%Δ in GDP per capita × year indicators		✓			✓
%Δ in unemployment rate × year indicators			✓		✓
%Δ in housing price index × year indicators				✓	✓
Number of family	2,239	2,239	2,239	2,239	2,239
Observations	9,790	9,790	9,790	9,790	9,790
Adj.R^2	0.286	0.286	0.285	0.285	0.285

Notes: The percentage change of a state-level economic indicator during the financial crisis is defined as the change rate of this economic indicator in 2008 relative to 2006. The formula is $\Delta x_j = (x_{j,2008} - x_{j,2006})/x_{j,2006} \times 100\%$, where $x_{j,t}$ is the economic indicator of state j in year t. See Appendix Table B2 for the data source of GDP per capita, unemployment rate, and housing price index. See the description in Section 5.1 in the paper for the list of other control variables. Standard errors are clustered at the family level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: PSID, waves 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, 2017.*)

4.3 Other Robustness Checks

As shown in the previous section, the H1N1 pandemic does not affect stock market participation but results in a decrease in the share of liquid assets invested in risky assets. We now examine the robustness of the findings for the risky share in Table 5.

Column (1) of Table 5 replicates the baseline result from column (8) of Table 3. In column

(2), we restrict the sample to households who always lived in the same state in our study period, dropping about 6.8% of the sample size. The state fixed effects are thus absorbed because the residence state for the same household had no variation across years. It shows that the coefficients on our two key interactions barely change.

We then check the sensitivity of our findings to the outliers. Among 50 states of the US, South Dakota and New Mexico can be treated as outliers because their H1N1 death rates are the highest, nearly three deaths per 100,000 people during the pandemic and much higher than in other states (see Appendix Table B1). As can be seen from column (3), the result remains substantively the same if we exclude these two states.

Next, we use the H1N1 case rate (i.e., the laboratory-confirmed case numbers per 100,000 people) as an alternative measure for H1N1 intensity. As has already been noted in Section 2.2.1, this measure is at the HHS region level. In column (4), the finding that risky share is negatively affected by H1N1 intensity still holds in the years after the pandemic. However, given that the H1N1 case rate is measured at the HHS region level, it may fail to capture accurate information within regions, which reduces the precision of the estimated exposure effects.

Theory models in economic epidemiology predict that agents engage in protective behavior only when the contagious disease passes a threshold prevalence (Philipson, 2000).[20] Inspired by the theory, we would like to ask whether the change in risky shares is only triggered by an unexpected and widespread public health crisis, such as the H1N1 pandemic. According to the CDC, regular seasonal influenza viruses co-circulated with the 2009 H1N1 influenza.[21] Although both the seasonal flu and the 2009 H1N1 virus posed a public health risk to people, the H1N1 outbreak was unexpected, unknown to humans, caused a large scale of infections and deaths, and invalidated the existing vaccines at the time of its onset. Therefore, we examine whether exposure to the regular seasonal flu (including (A)H1, A(H3), B, and other subtypes of influenza A viruses) has a similar impact on the risky share. We use the laboratory-confirmed number of any other flu-related cases (excluding the (H1N1)pdm09 virus) per 100,000 people during the 2009 H1N1 pandemic (i.e., April 2009–August 2010) to measure the intensity of the seasonal flu. This seasonal flu case rate is reported by WHO Collaborating Laboratories in *FluView* at the HHS region level. We estimate a model similar to Eq. (1) except that the seasonal flu case rates now interact with $During_t$ and $After_t$ dummies (column (5)).

Alternatively, we collect annual case rates of seasonal flu (excluding the novel H1N1

[20] In a study on the impact of the H1N1 pandemic on health behaviors in Mexico, Agüero and Beleche (2017) find no effect for the seasonal flu on diarrhea outcomes but a negative impact for the H1N1, which provides supporting empirical evidence for Philipson (2000)'s model.

[21] `http:/www.cdc.gov/h1n1flu/reportingqa.htm`, accessed February 2022.

virus) at the HHS region level from *FluView*. Due to data availability, this measurement only covers from 2007 to 2017 in our sample period. With this time-varying variable, we estimate the following model and present the result in column (6):

$$Y_{ijt} = \sigma Flu_{rt} + \alpha_t + \alpha_i + \alpha_j + \delta t\alpha_j + \gamma \boldsymbol{X_{ijt}} + \epsilon_{ijt}. \tag{4}$$

where Flu_{rt} denotes the natural log of laboratory-confirmed seasonal flu case rates (case numbers per 100,000 people) in the HHS region r in year t. σ captures the difference-in-differences impact of exposure to the seasonal flu. As shown in columns (5) and (6), we find little correlation between the risky share and the case rate of seasonal flu. It indicates that an expected health shock caused by the seasonal flu does not affect households' stock holdings. By contrast, an unexpected and severe health crisis, such as the H1N1 pandemic, does.

If, for some reason (e.g., policy change), families exposed to higher H1N1 death rates tended to reduce their risky share prior to the 2009 H1N1 pandemic, then the coefficients of our key interaction terms would be misunderstood as the result of the pandemic. Therefore, we conduct a falsification test by choosing a "pseudo" time of the pandemic. We assume 2007 is in the post-pandemic period and retain data from 2001 to 2007. In this way, 2001, 2003, and 2005 are hypothetical pre-treatment periods, and 2007 is the post-treatment period. We can see from column (7) that the coefficient of the post-treatment dummy ($Year2007$) interacted with the H1N1 death rate is close to zero and loses statistical significance. It suggests that in the pre-period, families in states with higher H1N1 death rates do not change with the risky share significantly. This falsification test is also used in the literature (e.g., Yurukoglu et al., 2017) as a diagnosis for the parallel trends.

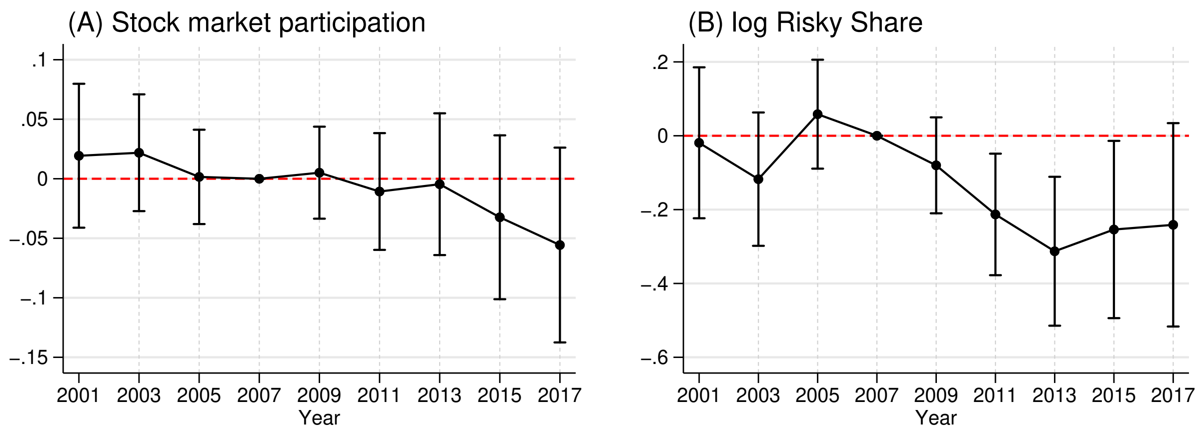
4.4 Event Study

We now estimate a more flexible functional form specified in Eq. (2). By interacting the natural log of the H1N1 death rate with year indicators, we can better understand how the treatment effect of the pandemic varies with time.

Table 5. Robustness Checks

Dependent variable	log risky share						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	Non-migrants	Drop 2 states (SD and NM)	HHS-level case rate time-invariant	HHS-level case rate time-invariant	HHS-level case rate time-varying	"Pseudo" pandemic year
During × log(H1N1 death rate)	-0.088	-0.092	-0.078				
	(0.063)	(0.067)	(0.067)				
After × log(H1N1 death rate)	-0.273***	-0.271***	-0.279***				
	(0.079)	(0.095)	(0.084)				
During × log(H1N1 case rate)				-0.123			
				(0.079)			
After × log(H1N1 case rate)				-0.157*			
				(0.093)			
During × log(Flu case rate, excluding H1N1)					-0.037		
					(0.071)		
After × log(Flu case rate, excluding H1N1)					-0.031		
					(0.082)		
log(Annual flu case rate, excluding H1N1)						-0.027	
						(0.032)	
Year2007 × log(H1N1 death rate)							-0.048
							(0.110)
Average of the outcome variable	-0.886	-0.886	-0.884	-0.886	-0.886	-0.859	-0.900
Family, state year FEs	✓	✓	✓	✓	✓	✓	✓
State-specific time trends	✓	✓	✓	✓	✓	✓	✓
Household features	✓	✓	✓	✓	✓	✓	✓
Macroeconomic index (lag)	✓	✓	✓	✓	✓	✓	✓
Medical controls (lag)		✓	✓	✓	✓	✓	✓
Number of family	2,239	2,141	2,220	2,239	2,239	1,687	1,459
Observations	9,790	9,123	9,713	9,790	9,790	5,897	4,349
Adj.R^2	0.286	0.281	0.285	0.285	0.285	0.328	0.298

Notes: See Section 4.1 for the list of variables controlled as household features, macroeconomic index, and medical resources. Column (1) replicates the result of column (8) in Table 3. Column (2) restricts the sample to family units who did not emigrant to other states during our study period. Column (3) drops families who lived in South Dakota or New Mexico in 2009. These two states are outliers that have the highest H1N1 death rate during the pandemic. Column (4) adopt the H1N1 case rate during the pandemic as the measure for H1N1 intensity. The H1N1 case rate is defined as the number of lab-confirmed case counts per 100,000 people in an HHS region from April 2009 to August 2010. Column (5) conducts a placebo test by using the constant case rate of other flu during the pandemic. The case rate of other flu is defined as the number of lab-confirmed cases of other influenza virus per 100,000 people in an HHS region from April 2009 to August 2010. Column (6) does an alternative placebo test by using the time-varying case rate of other flu. Column (7) drops data from 2009 and onward, assuming 2007 is the post-pandemic year. Standard errors are clustered at the family level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: PSID, waves 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, and 2017.*)



Notes: The figure plots the estimates of β_t in Eq. (2). The regression controls family fixed effects, state fixed effects, year fixed effects, state-specific year trend, household features, state-by-year-level macroeconomic indicators, and medical resources (the same controls as columns (4) and (8) of Table 3). The capped spikes indicate 95 percent confidence intervals, with robust standard errors clustered at the family level. (*Data source: PSID, waves 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, 2017.*)

Figure 4. Dynamic Effects of the 2009 H1N1 Pandemic on Household Portfolio

In Figure 4, we plot the estimated coefficients of β_t with 2007 as the base year. For both stock market participation and risky share, β_t is close to zero and statistically insignificant prior to 2007, thus indicating that stock holdings changed similarly in higher death-rate states and lower death-rate states prior the treatment. Relative to 2007, no immediate change is observed in either the extensive margin or the intensive margin of stock holdings during the 2009 pandemic. However, after the pandemic, we find that the risky share experienced more decreases in states with higher mortality rates than those with lower mortality rates. The estimated coefficient of β_t is about -0.21 in 2011. It then decreases to -0.31 in 2013 and stabilizes at around -0.24 by 2017. These results suggest that the exposure effect of the pandemic has a two-year lag and is long-lasting at least until 2017. Columns (1) and (3) in Table 6 report the estimates of β_t that are plotted in Figure 4. Joint F-tests show that the placebo effects in all years prior to 2007 are jointly insignificant for both the extensive and intensive margin of stock holdings, with p-values of 0.66 and 0.17, respectively. On the other hand, the treatment effects in the post-pandemic years (i.e., 2009 and onward) are jointly significant for intensive margin only, with a p-value of 0.043.

Table 6. Parallel Trends Test

	Stock market participation		log risky share	
	(1)	(2)	(3)	(4)
β_{2001}	0.019		-0.019	
	(0.031)		(0.104)	
β_{2003}	0.022		-0.118	
	(0.025)		(0.092)	
β_{2005}	0.002		0.058	
	(0.020)		(0.075)	
β_{2009}	0.005	0.014	-0.080	-0.121*
	(0.020)	(0.021)	(0.066)	(0.072)
β_{2011}	-0.011	0.006	-0.213**	-0.279***
	(0.025)	(0.028)	(0.084)	(0.097)
β_{2013}	-0.005	0.020	-0.313***	-0.399***
	(0.030)	(0.035)	(0.103)	(0.122)
β_{2015}	-0.032	0.000	-0.254**	-0.363**
	(0.035)	(0.041)	(0.122)	(0.147)
β_{2017}	-0.056	-0.015	-0.241*	-0.375**
	(0.042)	(0.047)	(0.140)	(0.168)
log(H1N1 death rate) × Survey year		-0.004		0.012
		(0.005)		(0.017)
Average of the outcome variable	0.410	0.410	-0.886	-0.886
p-value: Joint Sign. of pre-treated Coef.	0.758		0.181	
p-value: Joint Sign. of post-treated Coef.	0.427	0.587	0.048	0.028
Family, state, year FEs	✓	✓	✓	✓
State-specific time trend	✓	✓	✓	✓
Household features	✓	✓	✓	✓
Macroeconomic indicator (lag)	✓	✓	✓	✓
Medical controls (lag)	✓	✓	✓	✓
Number of family	5,049	5,049	2,239	2,239
Observations	25,947	25,947	9,790	9,790
Adj.R^2	0.476	0.476	0.286	0.285

Notes: This table presents results for parallel trend tests. Columns (1) and (3) report estimates of β_ts in Eq. (2). Columns (2) and (4) report estimates of β_ts and θ in Eq. (5). All regressions control for family fixed effects, year fixed effects, state fixed effects, and state-specific time trend, household features, and state-by-year-level macroeconomic indicators. See Section 4.1 for the list of variables controlled as household features, macroeconomic index, and medical resources. Standard errors are clustered at the family level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: PSID, waves 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, and 2017.*)

An alternative way to test parallel trends is to examine whether the differential slope between higher death rate states and lower death rate states is significantly different prior to the 2009 pandemic (e.g., Akosa Antwi et al., 2013; Muralidharan and Prakash, 2017).

Formally, we estimate the following model:

$$Y_{ijt} = \beta_t H1N1_p + \theta H1N1_p t + \alpha_t + \alpha_i + \alpha_j + \delta t \alpha_j + \gamma \boldsymbol{X_{ijt}} + \epsilon_{ijt} \tag{5}$$

where β_ts are year-specific treatment effects of the pandemic, relative to the pre-pandemic periods (i.e., 2001, 2003, 2005, and 2007). θ is our key of interest, the differential slope. If the estimate of θ is statistically insignificant (p-value greater than 0.05), we may conclude that the parallel trends existed prior to the pandemic. Different from Eq. (2), we only estimate treatment effects for the post-pandemic years (i.e., 2009 and onward). In this way, the parameter θ fits the trend difference only for the pre-pandemic period. As shown in columns (2) and (4) of Table 6, the estimates of θ are close to zero and statistically insignificant for both stock market participation and log risky share. Therefore, we can not reject the null hypothesis that higher death rate states and lower death rate states have different trends before the pandemic.

4.5 Decomposition of the Risky Share

Recall that the risky share is defined as the share of liquid assets invested in risky assets. Given this definition, a decline in the risky share can be attributed to either a decrease in risky assets or an increase in liquid assets, or both. With this in mind, we now explore which determinant plays a key role in driving the decline in risky shares in Table 7.

We first examine whether the value of risky assets changes with H1N1 intensity. As shown in column (1), we observe a decrease in the value of risky assets by approximately \$70 to \$120 per 1% increase in the H1N1 death rate. This reduction, while not statistically significant, accounts for 10% to 17% of the average value of risky assets (\$680). Contrastingly, column (2) reveals that risk-free assets exhibit a growth trend with rising H1N1 intensity. Specifically, we note a significant increase of \$207 in the value of risk-free assets for every 1% rise in the H1N1 death rate, which represents nearly a third of the mean value of these assets (\$671). We further test the exposure effect of H1N1 on liquid assets in column (3). We do not find any significant correlation between the H1N1 death rate and changes in liquid assets.[22] One potential issue with utilizing risky, risk-free, and liquid assets as dependent variables lies in that the observed changes in response to H1N1 intensity could be attributable to fluctuations in asset returns, rather than household portfolio rebalancing decisions. To address this, we

[22] In 2009, an increase of 1% in H1N1 intensity corresponded to a decline of \$53 in the value of liquid assets. This decline is statistically insignificant and represents only 3.7% of the mean value of liquid assets. Similarly, from 2011 onward, a 1% rise in H1N1 intensity results in a decrease of \$136 in the value of liquid assets. However, this reduction is not statistically significant, accounting for a mere 10% of the mean liquid assets.

examine the net purchases or sales of risky assets directly. A positive value in the net amount invested in stocks suggests net buying, while a negative value indicates net sales. Column (4) shows that when the H1N1 death rate increases by 1%, the net amount put in stocks at the household level decreases by about 37.74 dollars significantly.

Table 7. Structural Changes in Household Portfolio Choices

Dependent variable (in US$ 1000)	Risky assets	Risk-free assets	Liquid assets	Net amount put in stocks in the past 2 years
	(1)	(2)	(3)	(4)
During × log(H1N1 death rate)	-11.829	6.495	-5.335	-1.394
	(7.904)	(9.795)	(12.633)	(2.801)
After × log(H1N1 death rate)	-7.128	20.758**	13.631	-3.774**
	(10.994)	(10.460)	(15.002)	(1.801)
Average of the outcome variable	68.021	67.151	135.167	2.781
Family, state, year FEs	✓	✓	✓	✓
State-specific time trend	✓	✓	✓	✓
Household features	✓	✓	✓	✓
Macroeconomic indicator (lag)	✓	✓	✓	✓
Medical controls (lag)	✓	✓	✓	✓
Number of family	5,048	5,048	5,048	4,699
Observations	25,938	25,940	25,940	22,690
Adj.R^2	0.462	0.306	0.512	0.045

Notes: Liquid assets is the sum of risky and risk-free assets. See the description in Section 4.1 for the list of control variables. All monetary variables are adjusted in 2017 US dollar. Standard errors are clustered at the family level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (Data source: PSID, waves 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, and 2017.)

To sum up, the decrease in risky share that we have found in previous sections mainly stems from the net sales of stocks instead of the increase in liquid assets. With the value of liquid assets remaining largely unchanged, households tend to hold more risk-free assets when exposed to high H1N1 intensity. This scenario suggests that households are more likely to reduce their stock holdings and transfer their assets to safer, risk-free options in response to the pandemic.

Extensive studies have documented that a significant proportion of households do not rebalance their portfolios frequently (e.g., Brunnermeier and Nagel (2008), Calvet et al. (2009), Bilias et al. (2010)). This pattern is also evident in our analysis of the PSID 2001-2017 sample. We find that only about 20% of households have a non-zero value of net purchases or sales of stocks. This result may be due to inertia (as Brunnermeier and Nagel suggests) or measurement errors, as people may not remember their stock trading behavior precisely over the past few years. To address these concerns, we adopt Calvet et al. (2009)'s approach and decompose the change in the risky share into a passive change caused by the returns of assets and an active change that arises from household decisions to rebalance their portfolios.

We compute the *passive risky return* $\omega_{i,t}^{P}$, which is the proportion of risky assets that would have been held without any trading occurring between time $t-1$ and t. Formally,

$$\omega_{i,t}^{Passive} = \frac{\omega_{i,t-1}R_t}{\omega_{i,t-1}R_t + (1-\omega_{i,t-1})R_t^f} \tag{6}$$

where $\omega_{i,t-1}$ is the initial risky share (i.e., the risky share at t-1), R_t is the return on risky assets, and R_t^f is the return on risk-free assets.

The *passive change* is the change in the risky share, assuming that the household did not make any trades involving risky assets between $t-1$ and t:

$$\Delta\omega_{i,t}^{Passive} = \omega_{i,t}^{Passive} - \omega_{i,t-1}. \tag{7}$$

As suggested by Calvet et al. (2009), the passive change should be zero if the investor's initial investment is solely in cash or risky assets.

The *active change* refers to the change in risky share, which is not driven by realized returns but rather arises from intentional portfolio rebalancing. In other words, the active change is a result of strategic decisions aimed at achieving a desired level of risk exposure or taking advantage of market opportunities. Formally, the active change is defined as follows:

$$\Delta\omega_{i,t}^{Active} = \omega_{i,t} - \omega_{i,t}^{Passive}. \tag{8}$$

Combined with Eqs. (7) and (8), we can write the total change in the risky share as the sum of the passive and the active change:

$$\omega_{i,t} - \omega_{i,t-1} = \Delta\omega_{i,t}^{Active} + \Delta\omega_{i,t}^{Passive}. \tag{9}$$

In our empirical analysis, the return on the risk-free assets (R_t^f) is the real return on the 90-Day T-Bill. In terms of the return on the risky assets (R_t), we try five different returns from CRSP to ensure robust results: *Vwretd* (value-weighted return, including all distributions), *Vwretx* (value-weighted return, excluding dividends), *Ewretd* (equal-weighted return, including all distributions), *Ewretx* (equal-weighted return, excluding dividends), and *Sprtrn* (return on the S&P composite index). Accordingly, we compute five versions of passive changes and five versions of active changes. As we do not know the household-specific returns on risky assets (R_t), the active change ($\Delta\omega_{i,t}^{Active}$) and the passive change ($\Delta\omega_{i,t}^{Passive}$) may have measurement errors.

Appendix Figures A8 and A9 draw the scatterplots of the passive and active changes (calculated with *Vwretd*) in 2001–2017, respectively.[23] As shown in Appendix Figure A8, the passive changes in 2001, 2003, and 2009 are a U-shaped function of the initial share, as is typical in a bear market (i.e., $R_t < R_t^f$). In other years, the passive changes are a hump-shaped function of the initial share, thus indicating that $R_t > R_t^f$. The active changes plotted in Appendix Figure A9 show that the households have considerable diversity, with many exhibiting substantially positive or negative active changes. In addition, we observe that a large portion of households have trading values of risky assets close to zero, thus indicating that they either trade very infrequently or not at all throughout the year.

We investigate whether active and passive changes in stock holdings change with the H1N1 pandemic, as presented in Table 8. To facilitate the coefficient interpretation, we present the passive and active changes in the percentage form. In the first five columns, the dependent variable is the passive change. Since passive changes solely depend on the realized return on risky assets, all five types of passive changes do not change significantly with the H1N1 death rate during or after the pandemic. The next five columns (6) to (10), use the active change as the dependent variable. Consistent with our previous finding on the risky share, households do not actively trade their risky assets during the pandemic (i.e., in 2009). However, since 2011, the active change declines by about 0.07 percentage points if the H1N1 intensity increases by 1%. In other words, people tend to sell their stocks actively in response to an increase in the H1N1 death rate.

[23] The scatterplots of the passive and active changes computed with *Vwretd*, *Vwretx*, *Ewretd*, *Ewretx*, and *Sprtrn* are similar to the ones computed with *Vwretd*. The summary statistics of active and passive changes using five different returns on risky assets are presented in Appendix Table B6.

Table 8. Active and Passive Changes in Household Portfolio Choices

Dependent variable	$\Delta\omega_{i,t}^{Passive} \times 100\%$					$\Delta\omega_{i,t}^{Active} \times 100\%$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Return on risky assets	*Vwretd*	*Vwretx*	*Ewretd*	*Ewretx*	*Sprtrn*	*Vwretd*	*Vwretx*	*Ewretd*	*Ewretx*	*Sprtrn*
During × log(H1N1 death rate)	-0.209	-0.261	-0.284	-0.321	-0.269	-0.620	-0.569	-0.556	-0.519	-0.561
	(0.332)	(0.344)	(0.380)	(0.389)	(0.351)	(3.293)	(3.296)	(3.291)	(3.293)	(3.296)
After × log(H1N1 death rate)	0.077	0.078	-0.100	-0.080	0.078	-6.945*	-6.946*	-6.768*	-6.789*	-6.947*
	(0.339)	(0.317)	(0.441)	(0.419)	(0.321)	(3.827)	(3.832)	(3.816)	(3.821)	(3.832)
Average of the outcome variable	1.413	0.732	2.758	2.127	0.699	-1.258	-0.577	-2.603	-1.973	-0.544
Family, state, year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State-specific time trend	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Household features	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Macroeconomic indicator (lag)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Medical controls (lag)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Number of family	1,497	1,497	1,497	1,497	1,497	1,497	1,497	1,497	1,497	1,497
Observations	6,559	6,559	6,559	6,559	6,559	6,559	6,559	6,559	6,559	6,559

Notes: As introduced in the main text, we compute five types of passive and active changes. The return on risk-free assets is the real return on the 90-Day T-bill. The return on risky assets is computed with *Vwretd* (the value-weighted return, including all distributions), *Vwretx* (the value-weighted return, excluding dividends), *Ewretd* (the equal-weighted return, including all distributions), *Ewretx* (the equal-weighted return, including all distributions), *Sprtrn* (Return on the S&P Composite Index), respectively. Both the passive and active changes are expressed in percentages. Standard errors are clustered at the family level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (Data source: PSID, waves 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, and 2017.)

5 Heterogeneity Analysis

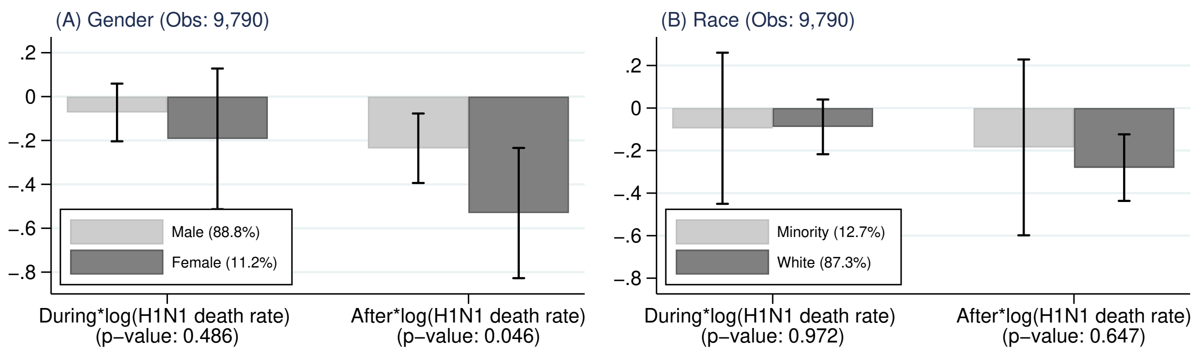
We now turn to the heterogeneous effect of the H1N1 pandemic on the risky share by estimating Eq. (3). We visualize the estimates of β_{1g} and β_{2g} in Figures 5 and 6.[24] Capped spikes represent the 95 percent confidence interval for each coefficient. In each panel of the figures, the p-value in the parentheses below the x-axis comes from a Wald test, where the null hypothesis is that the estimates of the H1N1 impact for groups g and g' are equal to each other.

In general, the estimates of β_{1g}s, which capture the change in the risky share for group g in 2009, are statistically insignificant (at the 5% level) and close to zero, which is consistent with our main results that no immediate change occurs in the risky share during the pandemic. In contrast, we find some interesting heterogeneous changes in risky shares after the pandemic. Therefore, we now focus on discussing the estimates of β_{2g}s.

[24]We report the estimates of β_{1g} and β_{2g} in Appendix Tables B7 and B8.

5.1 Heterogeneity by Demographics

We first display in Figure 5 the heterogeneous patterns in terms of demographic features, including the heads' gender, race, marital status, and education.



Notes: This figure plots the estimates of β_{1g} and β_{2g} in Eq. (3). We mainly use household heads' gender, race, marital status, and education. In rare cases when heads' information is missing, we use spouses' instead. Particularly, marital status is measured in 2007 to avoid potential endogeneity. Capped spikes represent the 95 percent confidence interval for each coefficient. In each panel of the figures, the p-value in the parentheses below the x-axis comes from a Wald test, where the null hypothesis is that the estimates of the H1N1 impact for groups g and g' are equal to each other. (*Data source: PSID, waves 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, and 2017.*)

Figure 5. Heterogeneous Effects of the 2009 H1N1 Pandemic, by Demographic Features

Gender.—On average, when the H1N1 death rate increases by 1%, families with male heads reduce by nearly 0.25% of the risky share, while families with female heads reduce more than 0.5% of the risky share (Panel A). The p-value of the difference between males and females is less than 0.05. This finding suggests that the portfolio choice of households whose head is female is more affected by the pandemic. This result may have several possible explanations. First, women are more risk-averse than men (Borghans et al., 2009) and less willing to take financial risks (Charness and Gneezy, 2012). Second, female heads are more likely to be single than male heads. In our sample, almost all female heads are single (about 99.4%), while only one-fifth of the male heads are single.[25] It is difficult for single females to share risks with others. Hence, they tend to reduce their risky shares more than males. This scenario is consistent with our subsequent analysis of marital status. Third, females earn more volatile income than males. Based on our calculation, the standard deviation of female income is larger than that of male income, and the difference is significant at the 1% level.[26] This accords with our later heterogeneous results by income fluctuation, which demonstrate that the exposure effect of a pandemic is stronger for those with more fluctuated income.

Race.—For the minority and the white, when the H1N1 death rate increases by 1%, risky share decreases by about 0.2% and 0.3%, respectively (Panel B).[27] The large p-value (0.65) suggests that no significant difference exists between the minority and the white.

Marital status.—In case that marital status in the post-pandemic year is correlated with the H1N1 intensity, we use the marital status of the household head in 2007. According to Panel C, the H1N1 effect for households whose heads are not married is more than twice that for those whose heads are married. Moreover, the difference is statistically significant, with a p-value of 0.023. Intuitively, a married individual carries less risk than a single one because a couple can share risk. As a result, households whose heads are married can be less sensitive to the pandemic.

Education.—As shown in Panel D, no significant difference exists in the risky-share elasticity of H1N1 intensity between people with high school degrees or below and those with college degrees or above. For both groups, the H1N1-intensity elasticity is about -0.27.

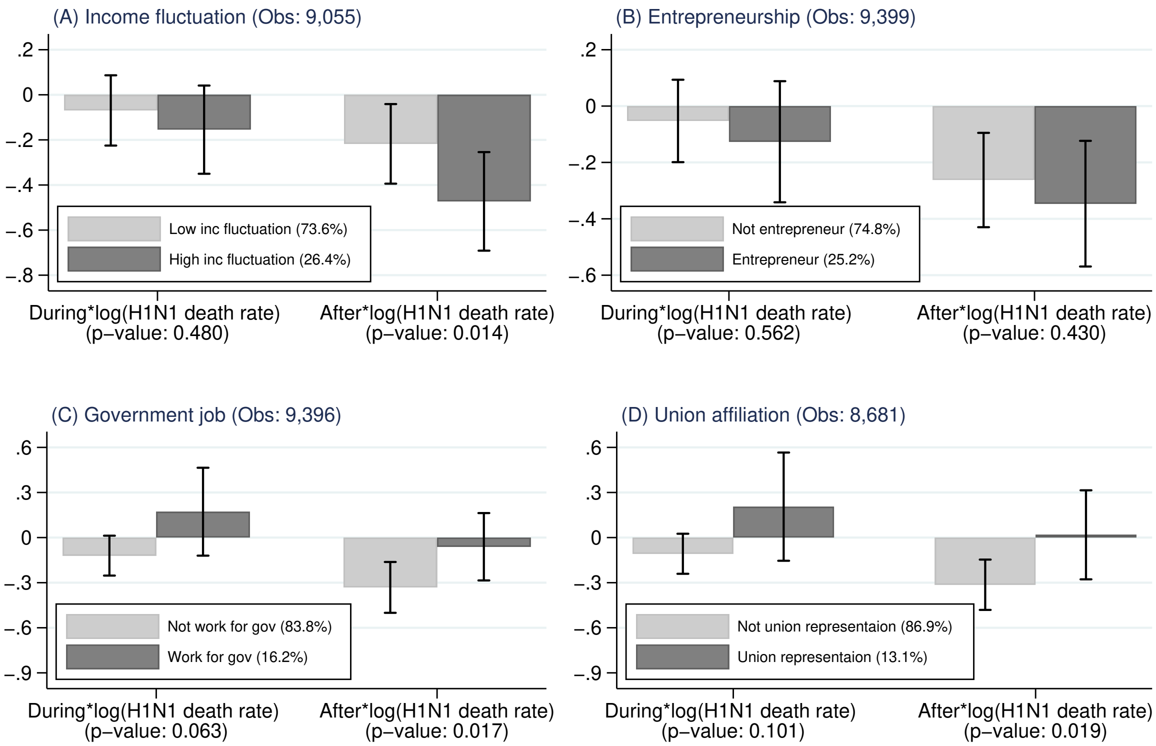
5.2 Heterogeneity by Labor Market Characteristics

We next discuss the heterogeneity related to job features of the head in Figure 6, including income fluctuation, entrepreneurship, government employment, and union affiliation.

[25] To alleviate endogeneity, marital status is measured in the PSID 2007 wave.

[26] The standard deviations of female and male income are 0.31 and 0.27, respectively. For more details about how to compute the standard deviations, see descriptions of the heterogeneous analysis by income fluctuation.

[27] Note that the estimate for the minority is insignificant and imprecise, which may be due to the small sample size of the minority.



Notes: This figure plots the estimates of β_{1g} and β_{2g} in Eq. (3). We mainly use household heads' information on income fluctuation, entrepreneurship, whether have a government job, and whether have union representation. In rare cases when heads' information is missing, we use spouses' instead. To deal with the endogenous concern, a Mincer regression of income on age, age square, education, race, gender, and state fixed effects is estimated, using the data before 2009. A family is defined as being high (low) income-fluctuated if the standard deviation of the Mincer residual is above (below) the average level. Similarly, the information on entrepreneurship, whether have a government job, and whether have union representation is related to 2007. Capped spikes represent the 95 percent confidence interval for each coefficient. In each panel of the figures, the p-value in the parentheses below the x-axis comes from a Wald test, where the null hypothesis is that the estimates of the H1N1 impact for groups g and g' are equal to each other. (*Data source: PSID, waves 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, and 2017.*)

Figure 6. Heterogeneous Effects of the 2009 H1N1 Pandemic on Risky Share, by Job Features

Income fluctuation.—To address the endogeneity concern that income stability can be affected by H1N1 intensity, we use the fluctuation of income before the pandemic as a proxy. Specifically, we run a Mincer regression using data before the pandemic (i.e., data in 2001, 2003, 2005, and 2007) and obtain residuals.[28] Then, we calculate the standard deviation of

[28] The Mincer equation includes age, age square, educational attainment, race, gender, and state fixed

the residual for each household before the pandemic. In particular, a family is defined as being high-(low-)income fluctuating if the standard deviation of the Mincer residual is above (below) the average level. Panel A shows that families with more fluctuating income have a risky share elasticity of -0.46, which is significantly different from that of the low-income fluctuating ones, which is -0.24.

Entrepreneurship.—Panel B examines whether heterogeneous responses by entrepreneurship exist. Entrepreneurs are defined as owning part or all of a farm or business, which account for 25% of our sample size. Considering that entrepreneurship can be time-varying and associated with the H1N1 pandemic, we define entrepreneurship using the information in 2007, the year prior to the pandemic.[29] When the H1N1 death rate increases by 1%, entrepreneurs reduce their risky shares by about 0.35%, while households without a farm or business reduce risky shares by 0.26%. However, the difference between entrepreneurs and employees is statistically insignificant.

Government job.—Government jobs are defined as working for the federal, state, or local government or in a public school system. Relative to a private sector job, a government job is more stable. It comes with a lot of benefits, including competitive pay, health insurance, allowances, housing benefits, social security, job security, etc. About 16% of the participants in our sample work for the government. Panel C shows that for people working for the government, their risky shares barely change after the pandemic. By contrast, for those not working for the government, their risky shares decrease by almost 0.35% if the H1N1 mortality rate increases by 1%.

Union contract.—According to the US Bureau of Labor Statistics (BLS), in 2021, workers represented by a union had median weekly earnings of $1,158, while nonunion workers had median weekly earnings of $975.[30] Union workers are better protected and harder to be laid off. Unions not only provide workers with higher earnings but also offer them better fringe benefits, including paid leave and health care. In our sample, workers represented by a union account for about 13%. As shown in Panel D, when the H1N1 death rate increases by 1%, workers represented by a union do not change risky shares. By contrast, people not

effects.

[29]Likewise, due to the endogeneity concern, we use the information from 2007 to define working for the government and having a job covered by the union contract.

[30]The median weekly earnings are reported by BLS based on the data from the Current Population Survey (see https://www.bls.gov/news.release/pdf/union2.pdf). According to BLS, workers represented by unions refer to both union members and workers who have no union affiliation but whose jobs are covered by a union contract.

represented by a union decrease their risky shares by 0.33%.

Overall, we find that the effect of H1N1 on risky shares differs between males and females, married and unmarried individuals, those with lower income stability and those with higher income stability, those employed in government versus non-government positions, and those represented by unions versus those who are not. Our results suggest that households with greater income risk are more vulnerable to the pandemic shock.

5.3 Life-cycle Effects of the H1N1 Pandemic

We now examine how the H1N1 pandemic affects the risky share differentially for people of different age groups. Before proceeding to the result, it is necessary to get a picture of the life-cycle profile of risky shares. We plot the 25th percentile, the median, and the 75th percentile of risky shares in Appendix Figure A7.[31] For people aged 20 to 69, the risky share increases with age, and it increases faster at an early age. Generally, older people tend to invest more in risky assets and hold a higher risky share.[32]

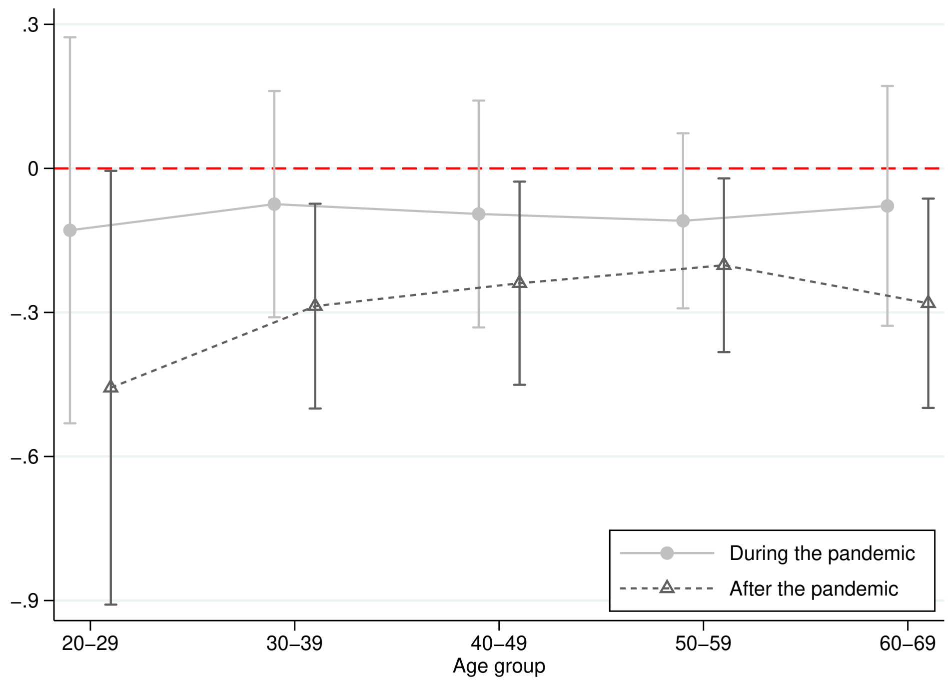
To evaluate the life-cycle impact of the pandemic on stock holdings, we estimate Eq. (3), with the log risky share as the outcome of interest, to measure the age-specific elasticity during and after the pandemic. The index g in Eq. (3) now represents an age group (i.e., 20–29, 30–39, 40–49, 50–59, or 60–69). The estimated coefficients of β_{1g}s and β_{2g}s are plotted in Figure 7.[33] Consistent with our previous findings in Section 4.1, the age profile of changes in risky share in 2009 is insignificant and pretty flat. By contrast, the life-cycle profile after the pandemic delivers a hump-shaped pattern. The risky share elasticity decreases in magnitude from around 0.45 at ages 20–29, to 0.2 at ages 50–59, and then increases to about 0.3 at ages 60–69. While interpreting the coefficients for different age groups, it is important to exercise caution as their differences lack statistical significance. Intuitively, young investors are faced with higher background risk when they have just entered the labor market and have very little buffer savings (Guiso and Sodini, 2013). The outbreak of a pandemic may lead to large uncertainty in their jobs and income. As a result, they tend to hold fewer risky assets but more conservative portfolios relative to older people. For those aged 60–69, they are getting close to retirement and are faced with deductions in their stock of human wealth. As suggested by Fagereng et al. (2017), these people should lower their exposure

[31] In case that the age profile is affected by the pandemic, we drop the data starting from 2009 and only use the data in 2001, 2003, 2005, and 2007.

[32] This pattern broadly supports Guiso and Paiella (2008)'s finding. Using a household survey in Italy, they show that for people less than 61 years, the risky share increases by 2% on average when the age increases by 10 years.

[33] The estimates of β_{1g}s and β_{2g}s are reported in Appendix Table B9.

to the stock market as compensation. With an exogenous shock from the H1N1 pandemic, people approaching retirement are more susceptible and reduce their risky share more when exposed to a higher H1N1 mortality rate.



Notes: This figure plots the age profiles of the H1N1-intensity elasticities for the risky share by estimating Eq. (3). Capped spikes represent the 95 percent confidence interval for each coefficient. (*Data source: PSID, waves 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, and 2017.*)

Figure 7. Life-cycle Impact of the 2009 H1N1 Pandemic on Risky Share

6 Exposure Effect of the H1N1 Pandemic on Illiquid Assets

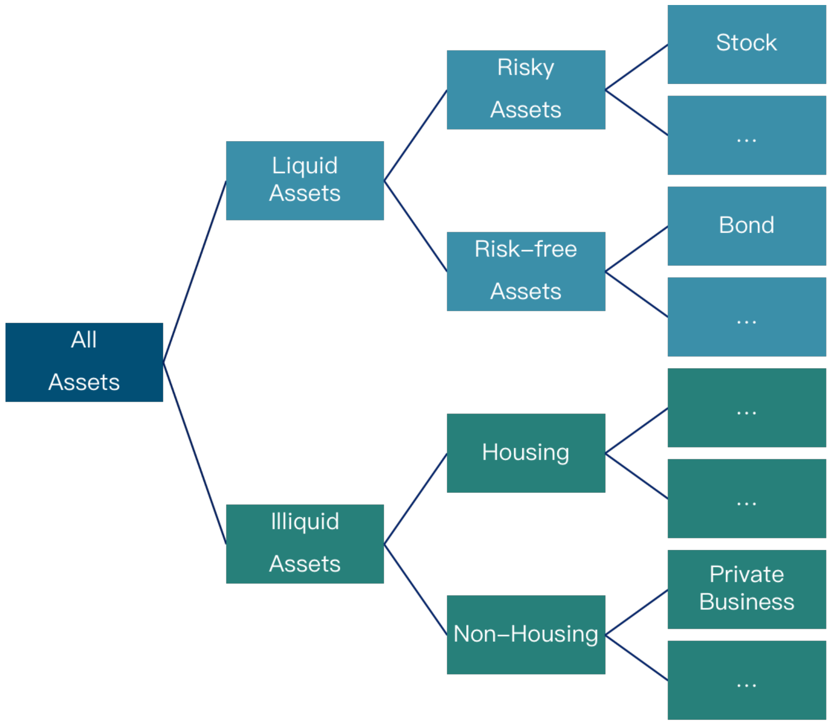


Figure 8. Portfolio Composition Chart

As illustrated in Figure 8, a household can have liquid and illiquid assets. In previous sections, our analysis of the exposure effect of the H1N1 pandemic concentrates on the liquid assets holding. In this section, we turn to explore the change in illiquid assets in response to the H1N1 pandemic.

In columns (1) and (2), we first report the results on two types of business owners. After the pandemic, the probability of being an incorporated business (IB) owner falls statistically significantly. A 1 percent increase in H1N1 intensity decreases the probability of owning an IB by 0.028%. By contrast, we do not find a significant change in the probability of owning an unincorporated business (UB). Even so, the exposure effect of H1N1 on UB is positive. Rubinstein and Levine (2020) show that entrepreneurship is procyclical, while other self-employment is countercyclical. Our result provides suggestive evidence that a pandemic can act as a recession, during which the incorporated self-employed are "procyclical," and the unincorporated self-employed are "countercyclical."

In addition to business, we also examine non-business outcomes, such as owning housing and cars, in columns (3) and (4) in Table 9. However, no significant exposure effect on being a home or car owner exists. As shown in this table, more than 70% and over 90% of the households in our sample own housing or cars, respectively. Housing and cars are somewhat analogous to necessities in most American families. Hence, the H1N1 pandemic has little impact on the household holding of these assets.

Table 9. Exposure Effect of H1N1 Pandemic on Illiquid Assets

Outcome variables	Business		Housing	Car
	(1) IB	(2) UB	(3)	(4)
During × log(H1N1 death rate)	-0.015	0.019	0.005	-0.001
	(0.010)	(0.012)	(0.014)	(0.011)
After × log(H1N1 death rate)	-0.028**	0.021	0.006	0.012
	(0.013)	(0.016)	(0.024)	(0.015)
Average of the outcome variable	0.074	0.096	0.740	0.921
Family, state, year FEs	✓	✓	✓	✓
State-specific time trend	✓	✓	✓	✓
Household- and state-level time-variant features	✓	✓	✓	✓
%Δ in GDP, unemployment, HPI, bankruptcy rate during the financial crisis	✓	✓	✓	✓
Medical controls (lag)	✓	✓	✓	✓
Number of family	5,095	5,095	5,100	5,100
Observations	26,711	26,711	26,846	26,846
Adj.R^2	0.552	0.415	0.639	0.314

Notes: IB denotes incorporated business owner. UB denotes unincorporated business owner. See the description in Section 4.1 for the list of control variables. Standard errors are clustered at the family level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: PSID, waves 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, and 2017.*)

7 Discussions of Potential Mechanisms

We now move to a primary investigation into why the H1N1 pandemic affects household portfolio choices. Different channels can explain the exposure effect. First, a pandemic may have a profound impact on people's health. It can cause respiratory symptoms that range from mild to severe and may require hospitalization or even lead to death. Stress and anxiety associated with a pandemic can also take a toll on one's mental health. Second, a pandemic can affect demographic features in a variety of ways. On the one hand, it can lead to changes in the number of children within a family, as economic uncertainties and concerns about health and safety may lead some couples to postpone having children or even opt to have fewer children. On the other hand, extended periods of isolation and stress can exacerbate existing marital issues, thus potentially leading to divorce or separation. Furthermore, a pandemic can cause shocks to the labor market. It can lead to a decrease in economic activity as businesses shut down or scale back their operations, thereby causing reduced earnings and even job losses.

In Appendix Table B11, we examine whether the H1N1 pandemic has an impact on various factors, such as people's health, marital status, number of children, earnings, and employment status. We did not observe any significant changes in response to the H1N1 intensity for most of the outcomes. However, significant evidence shows that the unemployment rate increases with the H1N1 death rate during and after the pandemic, which coincides with our earlier finding in Section 6 that the H1N1 pandemic can affect labor market risks by reducing the probability of being an IB owner.

We then additionally control for these aforementioned possible channels. We expect that if any channel is effective in explaining this relationship, we will observe a significant change in the exposure effect of the H1N1 pandemic (i.e., coefficients β_1 and β_2 in Eq. (1)). However, as presented in Appendix Table B12, the estimate of the exposure effects remains significant at -0.27 in columns (2)–(6) compared with the baseline case (column (1)). Therefore, we conclude that these channels (i.e., health, marital status, number of children, earnings, and employment status) do not provide a satisfactory explanation for why the H1N1 pandemic affected the intensive margin of stock holdings.

Several studies, such as Calvet et al. (2009) and Calvet and Sodini (2014), suggest that households tend to invest in a greater proportion of risky assets when their overall family wealth increases. It is plausible that the H1N1 pandemic might diminish family wealth, resulting in a corresponding decrease in this risky investment share. Therefore, we analyze the impact of the H1N1 pandemic's mortality rate on two versions of total family wealth calculations: one that excludes home equity and another that includes it. Our findings, as outlined in the first two columns of Appendix Table B13, indicate a minor rise in family wealth associated with the H1N1 death rate. However, the effect of this exposure is statistically negligible. In the last two columns in Appendix Table 3 B13, we add the control of total wealth in Eq. (1) but we do not observe a notable shift in the log risky share in relation to total wealth.[34] Consequently, it seems less likely that the decrease in risky share in response to H1N1 intensity is primarily driven by changes in family wealth.

8 Conclusion

Taking advantage of the exogenous nature of the 2009 H1N1 pandemic and the state-level variation in the H1N1 death rate, we examine the extent to which the H1N1 intensity influences the allocation of household portfolios in a difference-in-differences framework.

[34] This observation aligns with several studies, including those by Brunnermeier and Nagel (2008) and Chiappori and Paiella (2011), which suggest a lack of significant correlation between risky investment shares and family wealth.

Using nine waves of the PSID (2001–2017), we find that the exposure of the pandemic affects the intensive margin (risky share) but not the extensive margin (stock market participation). During the pandemic in 2009, we do not observe changes due to the H1N1 death rate in the risky share. After the pandemic, however, the risky share is reduced by approximately 0.26 percent if the death number per 100,000 people increases by 1%. The exposure effect is relatively stable and long-lasting until the end of our sample. Our decomposition analysis suggests that this change is driven by a change in risky assets rather than a change in liquid assets. Specifically, the active change, as opposed to the passive change, appears to be the driving force behind this shift. We also conduct a rich analysis on heterogeneity in terms of demographics and job features. The effect of the pandemic is more substantial for households whose heads are females and single, earn more unstable income, do not work for the government, and are not represented by a union. Besides, our result suggests that the age profiles of the exposure effect display a hump-shaped pattern.

The interesting patterns shown in our heterogeneity analysis suggest that more risk-averse people and those who have more volatile income and unstable jobs are more susceptible to the pandemic. Our preliminary investigation suggests that family wealth and a range of factors related to health, demographic features, and labor market outcomes can not help us understand the relationship between the H1N1 pandemic and risky assets. Given that the risky share does not change immediately during the pandemic, the impact of the pandemic is unlikely to be driven by the background-risk theory.

References

Adda, Jérôme, "Economic activity and the spread of viral diseases: Evidence from high frequency data," *The Quarterly Journal of Economics*, 2016, *131* (2), 891–941.

Agarwal, Sumit, Keyang Li, Yu Qin, Jing Wu, and Jubo Yan, "Household Asset Portfolios during the Covid-19 Pandemic," *Available at SSRN 3674702*, 2020.

Agüero, Jorge M and Trinidad Beleche, "Health shocks and their long-lasting impact on health behaviors: Evidence from the 2009 H1N1 pandemic in Mexico," *Journal of Health Economics*, 2017, *54*, 40–55.

Al-Awadhi, Abdullah M, Khaled Alsaifi, Ahmad Al-Awadhi, and Salah Alhammadi, "Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns," *Journal of Behavioral and Experimental Finance*, 2020, *27*, 100326.

Albanesi, Stefania and Jiyeon Kim, "Effects of the COVID-19 recession on the US labor market: Occupation, family, and gender," *Journal of Economic Perspectives*, 2021, *35* (3), 3–24.

Almond, Douglas and Bhashkar Mazumder, "The 1918 influenza pandemic and subsequent health outcomes: an analysis of SIPP data," *American Economic Review*, 2005, *95* (2), 258–262.

Angerer, Xiaohong and Pok-Sang Lam, "Income risk and portfolio choice: An empirical study," *The Journal of Finance*, 2009, *64* (2), 1037–1055.

Antwi, Yaa Akosa, Asako S Moriya, and Kosali Simon, "Effects of federal policy to insure young adults: evidence from the 2010 Affordable Care Act's dependent-coverage mandate," *American Economic Journal: Economic Policy*, 2013, *5* (4), 1–28.

Baker, Scott R, Robert A Farrokhnia, Steffen Meyer, Michaela Pagel, and Constantine Yannelis, "How does household spending respond to an epidemic? Consumption during the 2020 COVID-19 pandemic," *The Review of Asset Pricing Studies*, 2020, *10* (4), 834–862.

Betermier, Sebastien, Thomas Jansson, Christine Parlour, and Johan Walden, "Hedging labor income risk," *Journal of Financial Economics*, 2012, *105* (3), 622–639.

Bilias, Yannis, Dimitris Georgarakos, and Michael Haliassos, "Portfolio inertia and stock market fluctuations," *Journal of Money, Credit and Banking*, 2010, *42* (4), 715–742.

Bogan, Vicki L and Angela R Fertig, "Portfolio choice and mental health," *Review of Finance*, 2013, *17* (3), 955–992.

Borghans, Lex, James J Heckman, Bart HH Golsteyn, and Huub Meijers, "Gender differences in risk aversion and ambiguity aversion," *Journal of the European Economic Association*, 2009, *7* (2-3), 649–658.

Brunnermeier, Markus K and Stefan Nagel, "Do wealth fluctuations generate time-varying risk aversion? Micro-evidence on individuals," *American Economic Review*, 2008, *98* (3), 713–36.

Calvet, Laurent E and Paolo Sodini, "Twin picks: Disentangling the determinants of risk-taking in household portfolios," *The Journal of Finance*, 2014, *69* (2), 867–906.

_ , John Y Campbell, and Paolo Sodini, "Fight or flight? Portfolio rebalancing by individual investors," *The Quarterly journal of economics*, 2009, *124* (1), 301–348.

Charness, Gary and Uri Gneezy, "Strong evidence for gender differences in risk taking," *Journal of Economic Behavior & Organization*, 2012, *83* (1), 50–58.

Chetty, Raj, John N Friedman, Nathaniel Hendren, Michael Stepner, and The Opportunity Insights Team, *How did COVID-19 and stabilization policies affect spending and employment? A new real-time economic tracker based on private sector data*, Vol. 27431, National Bureau of Economic Research Cambridge, MA, 2020.

_ , László Sándor, and Adam Szeidl, "The effect of housing on portfolio choice," *The Journal of Finance*, 2017, *72* (3), 1171–1212.

Chiappori, Pierre-André and Monica Paiella, "Relative risk aversion is constant: Evidence from panel data," *Journal of the European Economic Association*, 2011, *9* (6), 1021–1052.

Christelis, Dimitris, Tullio Jappelli, and Mario Padula, "Cognitive abilities and portfolio choice," *European Economic Review*, 2010, *54* (1), 18–38.

Cocco, Joao F, "Portfolio choice in the presence of housing," *The Review of Financial Studies*, 2005, *18* (2), 535–567.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber, "The cost of the covid-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending," Technical Report, National Bureau of Economic Research 2020.

Dawood, Fatimah S, A Danielle Iuliano, Carrie Reed, Martin I Meltzer, David K Shay, Po-Yung Cheng, Don Bandaranayake, Robert F Breiman, W Abdullah Brooks, Philippe Buchy et al., "Estimated global mortality associated with the first 12 months of 2009 pandemic influenza A H1N1 virus circulation: a modelling study," *The Lancet Infectious Diseases*, 2012, *12* (9), 687–695.

Eeckhoudt, Louis, Christian Gollier, and Harris Schlesinger, "Changes in background risk and risk taking behavior," *Econometrica: Journal of the Econometric Society*, 1996, pp. 683–689.

Fagereng, Andreas, Charles Gottlieb, and Luigi Guiso, "Asset market participation and portfolio choice over the life-cycle," *The Journal of Finance*, 2017, *72* (2), 705–750.

Fan, Elliott and Ruoyun Zhao, "Health status and portfolio choice: Causality or heterogeneity?," *Journal of Banking & Finance*, 2009, *33* (6), 1079–1088.

Gomes, Francisco and Oksana Smirnova, "Stock Market Participation and Portfolio Shares Over the Life-Cycle," *Available at SSRN 3808350*, 2021.

Guiso, Luigi and Monica Paiella, "Risk aversion, wealth, and background risk," *Journal of the European Economic association*, 2008, *6* (6), 1109–1150.

_ **and Paolo Sodini**, "Household finance: An emerging field," in "Handbook of the Economics of Finance," Vol. 2, Elsevier, 2013, pp. 1397–1532.

_ **, Paola Sapienza, and Luigi Zingales**, "Time varying risk aversion," *Journal of Financial Economics*, 2018, *128* (3), 403–421.

_ **, Tullio Jappelli, and Daniele Terlizzese**, "Income risk, borrowing constraints, and portfolio choice," *The American Economic Review*, 1996, pp. 158–172.

Hanspal, Tobin, Annika Weber, and Johannes Wohlfart, "Exposure to the COVID-19 stock market crash and its effect on household expectations," *Review of Economics and Statistics*, 2021, *103* (5), 994–1010.

Heaton, John and Deborah Lucas, "Portfolio choice and asset prices: The importance of entrepreneurial risk," *The Journal of Finance*, 2000, *55* (3), 1163–1198.

Hong, Harrison, Jeffrey D Kubik, and Jeremy C Stein, "Social interaction and stock-market participation," *The Journal of Finance*, 2004, *59* (1), 137–163.

Hurwitz, Abigail, Olivia S Mitchell, and Orly Sade, "Longevity perceptions and saving decisions during the COVID-19 outbreak: An experimental investigation," in "AEA Papers and Proceedings," Vol. 111 2021, pp. 297–301.

Kelly, Heath, Heidi A Peck, Karen L Laurie, Peng Wu, Hiroshi Nishiura, and Benjamin J Cowling, "The age-specific cumulative incidence of infection with pandemic influenza H1N1 2009 was similar in various countries prior to vaccination," *PloS one*, 2011, *6* (8), e21828.

Kolstad, Jonathan T and Amanda E Kowalski, "The impact of health care reform on hospital and preventive care: evidence from Massachusetts," *Journal of Public Economics*, 2012, *96* (11-12), 909–929.

Larrimore, Jeff, Jacob Mortenson, and David Splinter, "Earnings Shocks and Stabilization During COVID-19," *Journal of Public Economics*, 2022, p. 104597.

Lau, Joseph TF, Xilin Yang, HY Tsui, and Jean H Kim, "Impacts of SARS on health-seeking behaviors in general population in Hong Kong," *Preventive Medicine*, 2005, *41* (2), 454–462.

Li, Jianjun, Qize Li, and Xu Wei, "Financial literacy, household portfolio choice and investment return," *Pacific-Basin Finance Journal*, 2020, *62*, 101370.

Liang, Pinghan and Shiqi Guo, "Social interaction, Internet access and stock market participation—An empirical study in China," *Journal of Comparative Economics*, 2015, *43* (4), 883–901.

Malmendier, Ulrike and Stefan Nagel, "Depression babies: do macroeconomic experiences affect risk taking?," *The Quarterly Journal of Economics*, 2011, *126* (1), 373–416.

Muralidharan, Karthik and Nishith Prakash, "Cycling to school: Increasing secondary school enrollment for girls in India," *American Economic Journal: Applied Economics*, 2017, *9* (3), 321–50.

Philipson, Tomas, "Economic epidemiology and infectious diseases," *Handbook of Health Economics*, 2000, *1*, 1761–1799.

Rasul, Imran, "The economics of viral outbreaks," in "AEA Papers and Proceedings," Vol. 110 2020, pp. 265–68.

Reed, Carrie, Frederick J Angulo, David L Swerdlow, Marc Lipsitch, Martin I Meltzer, Daniel Jernigan, and Lyn Finelli, "Estimates of the prevalence of pandemic (H1N1) 2009, United States, April–July 2009," *Emerging Infectious Diseases*, 2009, *15* (12), 2004.

Restrepo, Brandon J and Eliana Zeballos, "The effect of working from home on major time allocations with a focus on food-related activities," *Review of Economics of the Household*, 2020, *18* (4), 1165–1187.

Rubinstein, Yona and Ross Levine, "Selection into entrepreneurship and self-employment," 2020.

Schooley, Diane K and Debra Drecnik Worden, "Risk aversion measures: Comparing attitudes and asset allocation," *Financial Services Review*, 1996, *5* (2), 87–99.

Shrestha, Sundar S, David L Swerdlow, Rebekah H Borse, Vimalanand S Prabhu, Lyn Finelli, Charisma Y Atkins, Kwame Owusu-Edusei, Beth Bell, Paul S Mead, Matthew Biggerstaff et al., "Estimating the burden of 2009 pandemic influenza A (H1N1) in the United States (April 2009–April 2010)," *Clinical Infectious Diseases*, 2011, *52* (suppl_1), S75–S82.

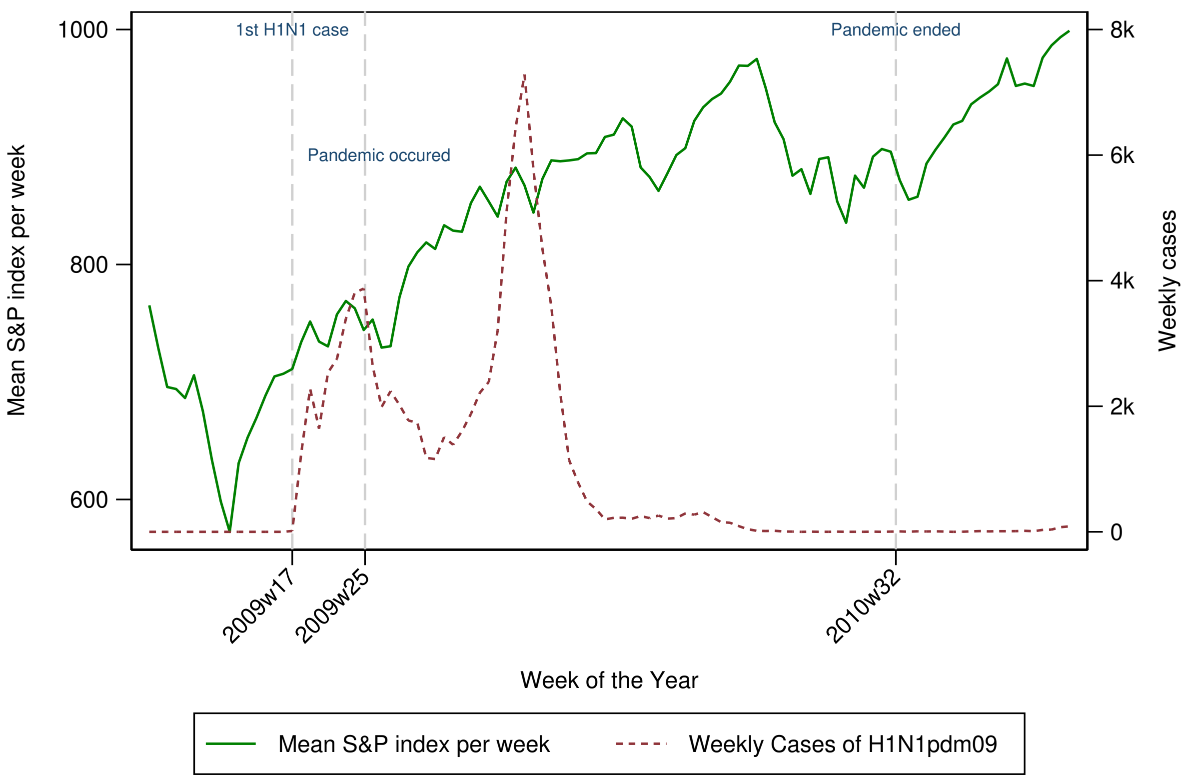
Taubenberger, Jeffery K and David M Morens, "1918 Influenza: the mother of all pandemics," *Revista Biomedica*, 2006, *17* (1), 69–79.

Yue, Pengpeng, Aslihan Gizem Korkmaz, and Haigang Zhou, "Household financial decision making amidst the COVID-19 pandemic," *Emerging Markets Finance and Trade*, 2020, *56* (10), 2363–2377.

Yurukoglu, Ali, Eli Liebman, and David B Ridley, "The role of government reimbursement in drug shortages," *American Economic Journal: Economic Policy*, 2017, *9* (2), 348–82.

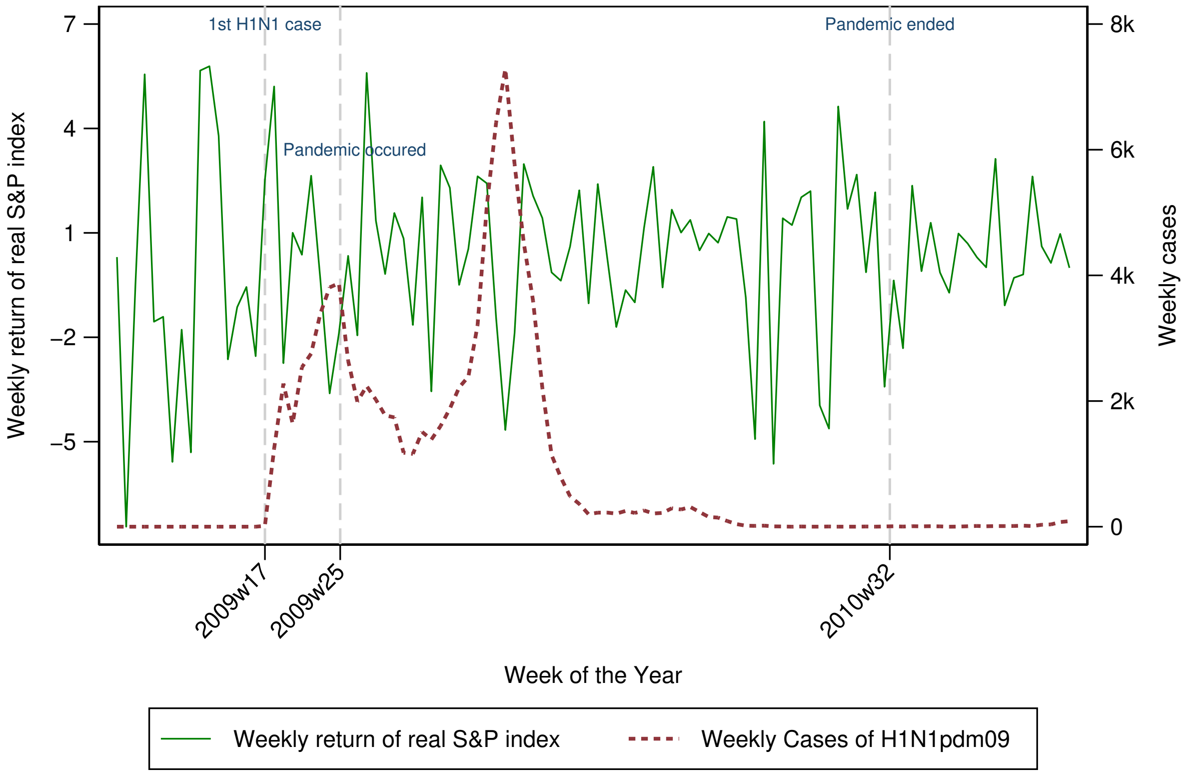
Appendix

A Figures



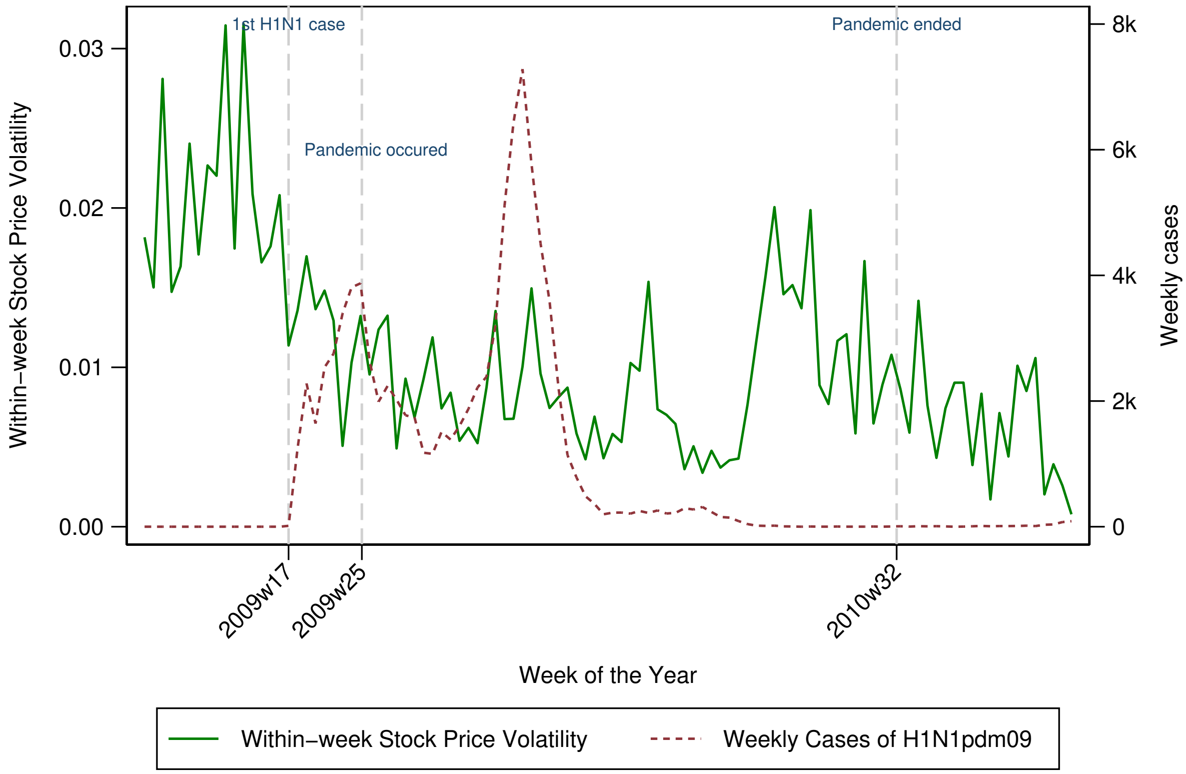
Notes: The weekly lab-confirmed cases of H1N1 flu are obtained from the World Health Organization (WHO) Collaborating Laboratories. The weekly S&P index is the average of real S&P price index between Monday and Friday in a week. The S&P 500 Index is computed by adjusting the nominal S&P 500 Index using the daily Consumer Price Index (CPI). The daily CPI is calculated by interpolating the monthly CPI, which, along with the nominal S&P 500 Index, is sourced from CRSP.

Figure A1. Time Trends of Weekly Real S&P 500 Price Index



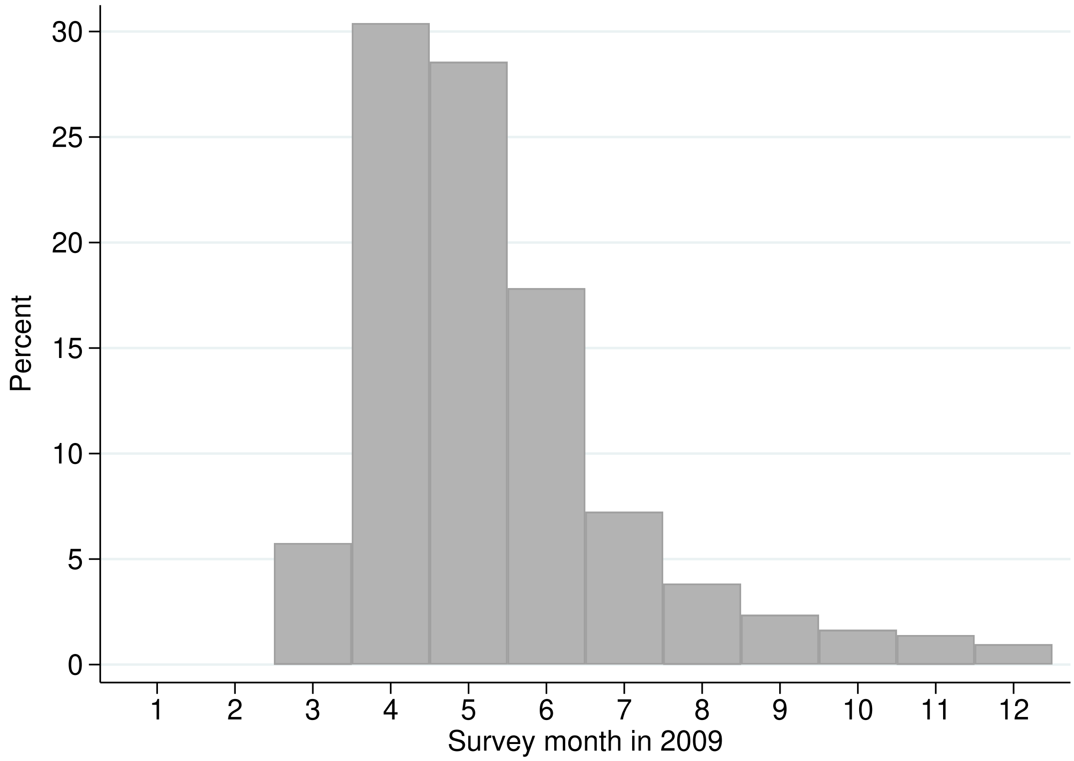
Notes: The weekly lab-confirmed cases of H1N1 flu are obtained from the World Health Organization (WHO) Collaborating Laboratories. The weekly return for the real S&P 500 Index is computed as: $R_\omega = [(P_{Fri,\omega} - P_{Mon,\omega})/P_{Mon,\omega}] \times 100\%$, where $P_{Fri,\omega}$ is the real S&P 500 index on the Friday of week ω, and $P_{Mon,\omega}$ is the real S&P 500 index on the Monday of week ω. The real S&P 500 index is adjusted with the daily CPI, which is calculated by interpolating the monthly CPI. The monthly CPI, along with the nominal S&P 500 Index, is sourced from CRSP.

Figure A2. Time Trends of Weekly Real Return for S&P 500 Index



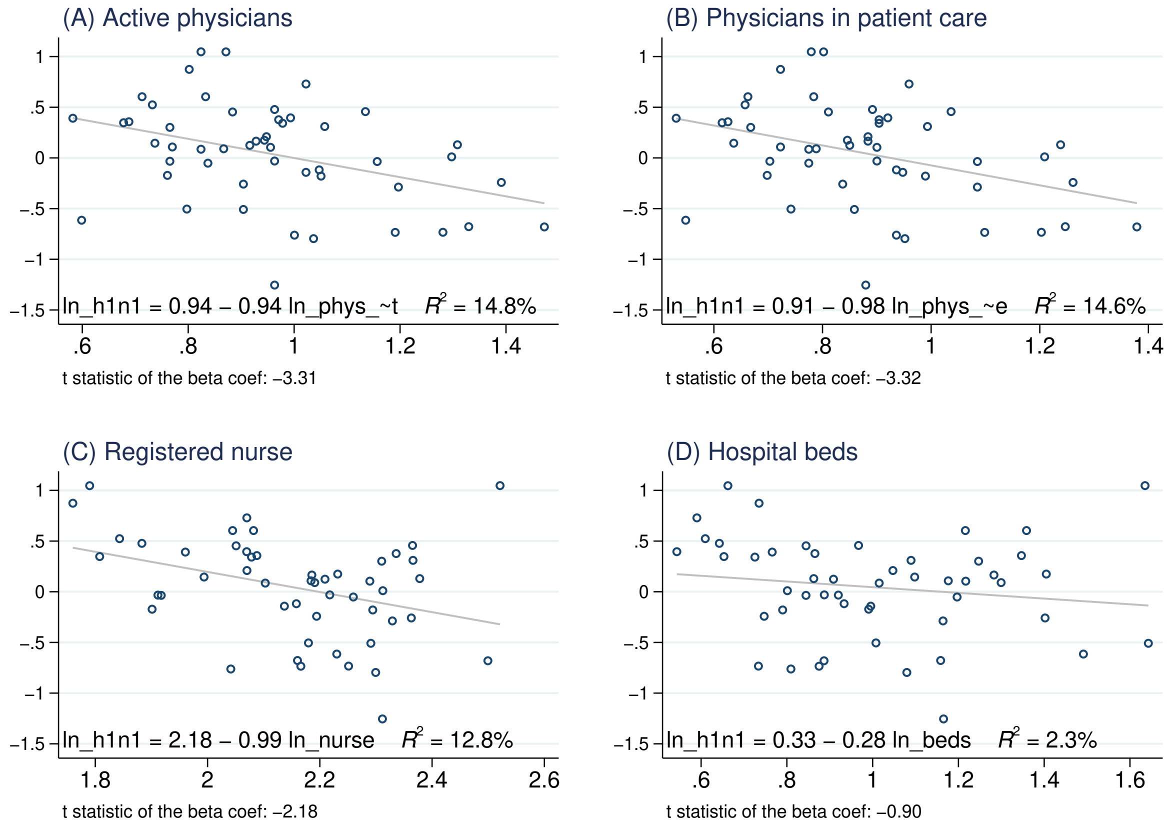
Notes: The weekly lab-confirmed cases of H1N1 flu are obtained from the World Health Organization (WHO) Collaborating Laboratories. The within-week stock price volatility is defined as the weekly standard deviation of the return for the S&P price index. The return for the real S&P 500 Index is computed as: $R(t) = [(P(t) - P(t-1))/P(t-1)] \times 100\%$, where $P(t)$ is the real S&P 500 index on day t. The daily CPI is calculated by interpolating the monthly CPI, which, along with the nominal S&P 500 Index, is sourced from CRSP.

Figure A3. Time Trends of Within-week Stock Price Volatility



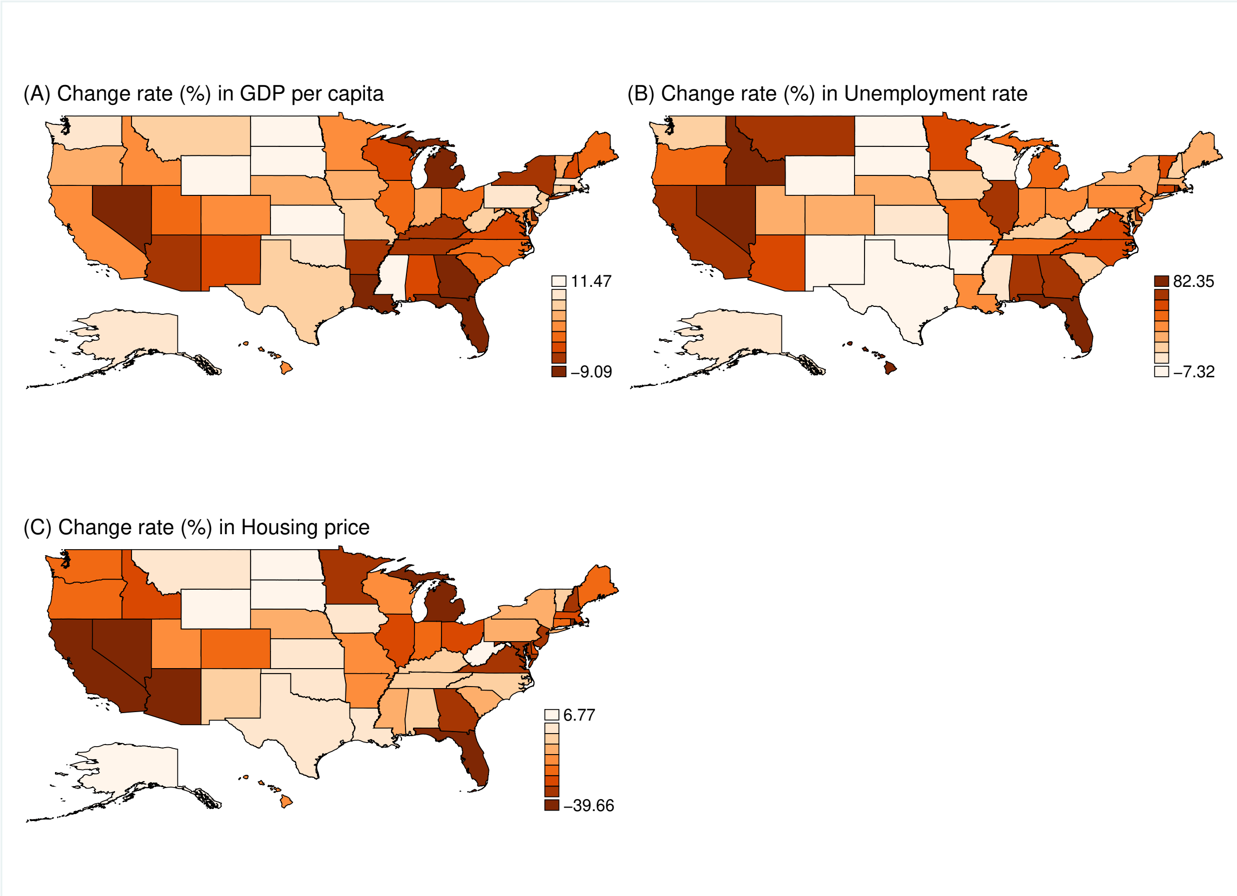
Data source: PSID wave 2009.

Figure A4. Proportion of Survey Month in 2009



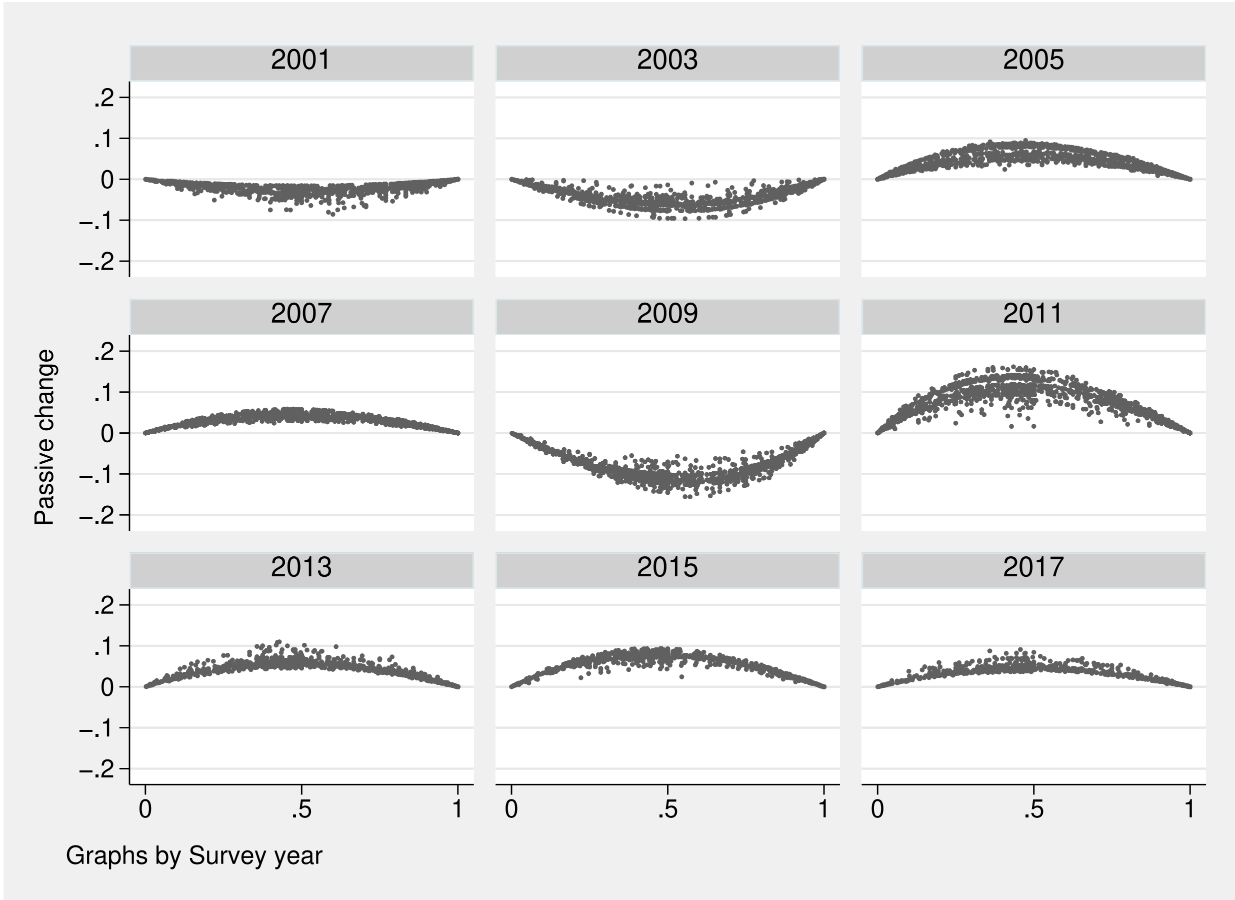
Notes: This figure plots the relationship between lab-confirmed H1N1 death rate and medical resources of 50 states. In each panel, the vertical axis is log H1N1 death rate during the pandemic and the horizontal axis denotes medical resources in 2008. In Panel (A), the horizontal axis is active physicians per 100,000 population. In Panel (B), the horizontal axis is physicians in patient care per 100,000 population. In Panel (C), the horizontal axis is registered nurse per 10 million population. In Panel (D), the horizontal axis is hospital beds per 10 million population.

Figure A5. Relationship between H1N1 Death Rate and Medical Resources in 2008



Notes: The percentage change of a state-level economic indicator during the financial crisis is defined as the change rate of this economic indicator in 2008 relative to 2006. The formula is $\Delta x_j = (x_{j,2008} - x_{j,2006})/x_{j,2006} \times 100\%$, where $x_{j,t}$ is the economic indicator of state j in year t. See Appendix Table B2 for the data source of GDP per capita, unemployment rate, and housing price index.

Figure A6. Percentage Changes of GDP Per Capita, Unemployment Rate, and Housing Price, During the 2007-2008 Crisis

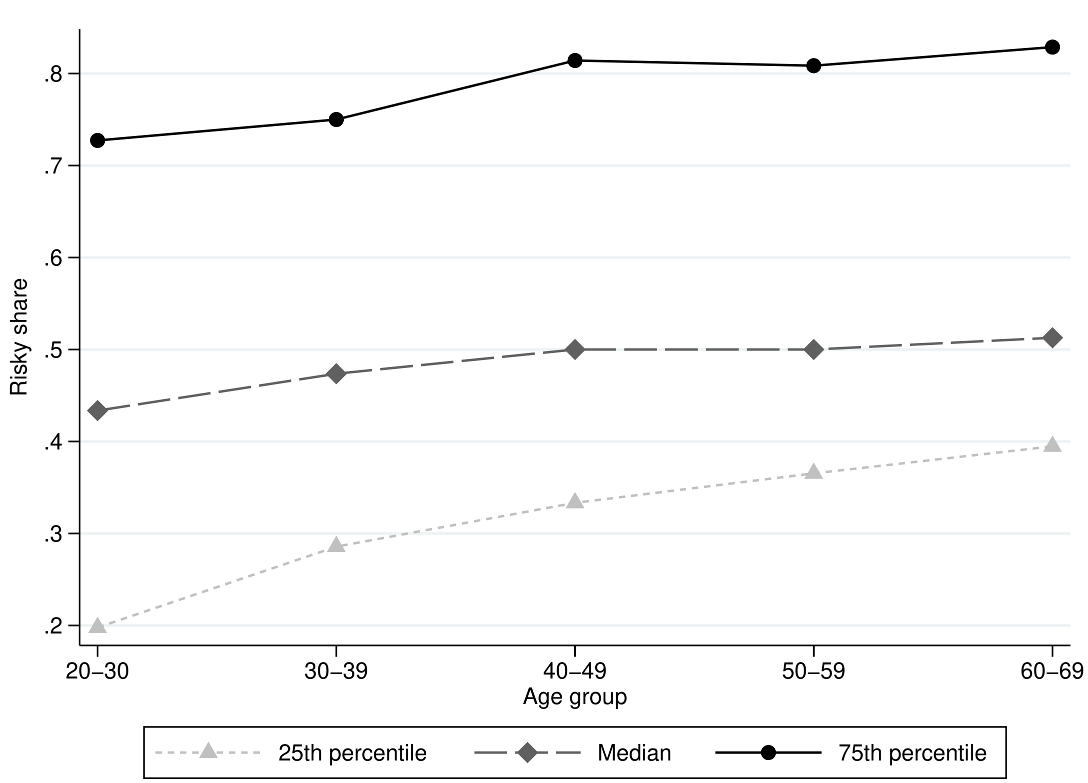


Notes: This figure illustrates the passive change versus the initial risky share using our analysis sample in PSID 2001–2017. The return on risk-free assets is the real return on the 90-Day T-bill. The return on risky assets is computed with *Vwretd* (the value-weighted return, including all distributions). Data source: CRSP.

Figure A8. Scatterplots of Passive Change versus the Initial Risky Share

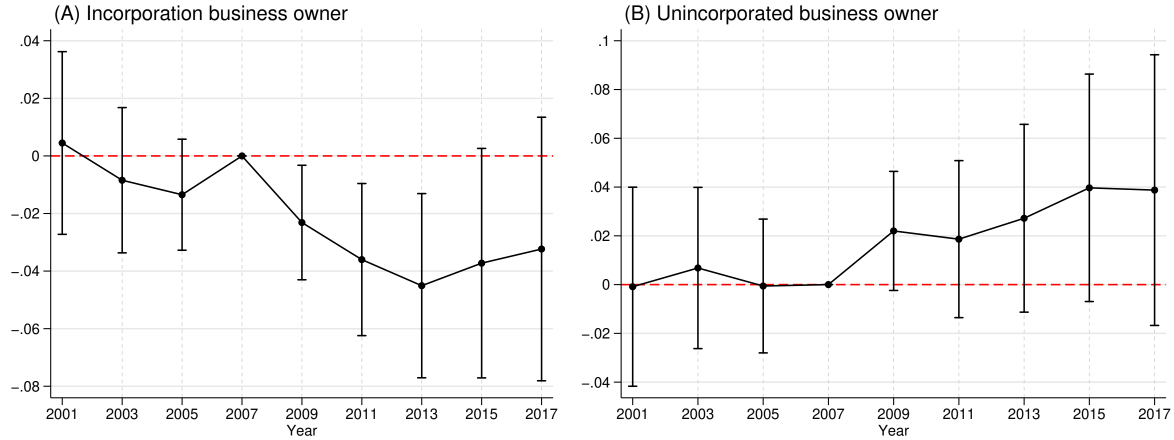
Notes: This figure illustrates the active change versus the initial risky share using our analysis sample in PSID 2001–2017. The return on risk-free assets is the real return on the 90-Day T-bill. The return on risky assets is computed with *Vwretd* (the value-weighted return, including all distributions). Data source: CRSP.

Figure A9. Scatterplots of Active Change versus the Initial Risky Share



Notes: This figure plots the age profiles of the 25^{th} percentile, the median, and the 75^{th} percentile of risky share, respectively. The risky share is defined as the share of risky assets (stock in publicly-held corporations, stock mutual funds, investment trusts, including stocks in IRA) in liquid financial assets of stock markets participants. (Data sources: PSID waves 2001, 2003, 2005, 2007.)

Figure A7. Cross-sectional Risky Share Across Age Groups



Notes: The figure plots the estimates of $\hat{\beta}_t$ in Eq. (2). In Panel A, the dependent variable is a dummy variable that indicates whether the household owns an incorporation business. In Panel B, the dependent variable is a dummy variable that indicates whether the household owns an unincorporated business. The capped spikes indicate 95 percent confidence intervals, with robust standard errors clustered at the family level.

Figure A10. Exposure Effect of the 2009 H1N1 Pandemic on Entrepreneurship

B Tables

Table B1. H1N1 Death Rate During the 2009 H1N1 Pandemic

	State	Deaths per 100,000 people		State	Deaths per 100,000 people
1	Missouri	0.285	26	Alabama	1.114
2	Ohio	0.451	27	North Carolina	1.132
3	Virginia	0.467	28	Rhode Island	1.139
4	New Jersey	0.480	29	Oklahoma	1.157
5	Vermont	0.480	30	Louisiana	1.180
6	Massachusetts	0.506	31	West Virginia	1.191
7	New York	0.508	32	Florida	1.233
8	Mississippi	0.541	33	Iowa	1.352
9	North Dakota	0.602	34	Minnesota	1.363
10	Indiana	0.604	35	Colorado	1.408
11	Pennsylvania	0.750	36	Nevada	1.415
12	Nebraska	0.772	37	Wyoming	1.429
13	Maryland	0.785	38	Delaware	1.458
14	New Hampshire	0.836	39	Idaho	1.480
15	Georgia	0.842	40	Washington	1.485
16	Illinois	0.867	41	Alaska	1.574
17	Michigan	0.889	42	Maine	1.580
18	Kentucky	0.950	43	California	1.613
19	Hawaii	0.965	44	Utah	1.689
20	Texas	0.968	45	Montana	1.829
21	Wisconsin	0.970	46	Arkansas	1.830
22	Connecticut	1.011	47	Oregon	2.074
23	South Carolina	1.089	48	Arizona	2.340
24	Kansas	1.094	49	New Mexico	2.848
25	Tennessee	1.110	50	South Dakota	2.850

Notes: This table presents the state-level lab-confirmed H1N1 death rates from April 2009 to August 2010 in the US. Death numbers for 50 states are collected from the website of https://FluTrackers.com.

Table B2. Data Sources for State-by-year Level Characteristics

Original data	Data source
Macroeconomic indicators	
GDP (in chained (2012) billions of dollars)	Bureau of Economic Analysis (BEA), "Regional Economic Accounts", http://www.bea.gov
Personal income per capita	BEA, "Regional Economic Accounts, State Annual Personal Income and Employment", http://www.bea.gov
Unemployed rate	Bureau of Labor Statistics (BLS), "Local Area Unemployment Statistics", http://www.bls.gov
Homeownership rate	Census Bureau, "Housing Vacancies and Home Ownership", http://www.census.gov
Housing price index	Federal Housing Finance Agency, "House Price Index Datasets, Quarterly Data, Purchase-Only Indexes", http://www.fhfa.gov
Bankruptcy cases (in 1,000) filed by state	Administrative Office of the United States Courts, "Caseload Statistics Data", http://www.uscourts.gov
Assets (in billion dollars) in FDIC-insured financial institutions	Federal Deposit Insurance Corporation, http://www.fdic.gov
Deposits (in billion dollars) in FDIC-insured financial institutions	Federal Deposit Insurance Corporation, http://www.fdic.gov
Population density	Census Bureau, http://www.census.gov
Medical controls	
Beds (1,000) in community hospital	American Hospital Association, http://www.ahadata.com
Active physicians per 10,000 resident population	National Center for Health Statistics. (2003–2019).
Physicians in patient care per 10,000 resident population	National Center for Health Statistics. (2003–2019).
Registered nurse per 100,000 residents	Bureau of Labor Statistics, "Occupational Employment Statistics", http://www.bls.gov

Table B3. Results of Granger Causality Test

Equation	Excluded	F statistics	p-value
Panel A: Weekly S&P index price and Weekly H1N1 cases			
FD of S&P index price	FD of H1N1 cases	.069	.793
FD of H1N1 cases	FD of S&P index price	.012	.914
Panel B: Weekly return of S&P index and Weekly H1N1 cases			
S&P index return	FD of H1N1 cases	3.539	.063
FD of H1N1 cases	S&P index return	3.615	.060
Panel C: Within-week stock market volatility and Weekly H1N1 cases			
Within-week stock market volatility	FD of H1N1 cases	.734	.483
FD of H1N1 cases	Within-week stock market volatility	.320	.727

Notes: FD denotes “first-difference”. The table reports results of pairwise Granger causality tests for vector autoregressive (VAR) models, using the *vargranger* command. The unit-root tests (Appendix Table B4) show that the FD of S&P index price, the FD of H1N1 cases, the weekly S&P index return, and the within-week stock market volatility are stationary. We select the lag order for VAR models based on the final prediction error (FPE), Akaike’s information criterion (AIC), Schwarz’s Bayesian information criterion (SBIC), and the Hannan and Quinn information criterion (HQIC) lag-order selection statistics. In Panel A and Panel B, the selected lag order is 1. In Panel C, the selected lag order is 1 and 2 (the result barely changes if we choose lag order 2). F statistics is the small-sample F statistics. The null hypothesis is that the lagged variable (the excluded ones) does not Granger cause the variable in the column of “Equation”.

Table B4. Results of Unit-root Test

	MacKinnon approximate p-value	
	(1) Augmented Dickey-Fuller unit-root test	(2) Phillips-Perron unit-root test
Weekly S&P index price	.887	.849
FD of Weekly S&P index price	0.000	0.000
Weekly return for S&P index	0.000	0.000
Within-week stock market volatility	0.000	0.000
Weekly cases of H1N1 cases	.503	.170
FD of Weekly cases of H1N1 cases	0.000	0.000

Notes: Columns (1) and (2) report the p-value of Augmented Dickey-Fuller unit-root test and Phillips-Perron unit-root test, respectively. The null hypothesis is that the data are non-stationary.

Table B5. Correlation between H1N1 Intensity During the Pandemic and Percentage Change of State-level Economic Indicators During the Financial Crisis

Outcome variable	State-level H1N1 death rate		
	(1)	(2)	(3)
%Δ in GDP per capita	-0.010		
	(0.021)		
%Δ in unemployment rate		-0.002	
		(0.004)	
%Δ in housing price			-0.004
			(0.008)
Observations	50	50	50
Adj.R^2	-0.016	-0.018	-0.017

Notes: The percentage change of a state-level economic indicator during the financial crisis is defined as the change rate of this economic indicator in 2008 relative to 2006. The formula is $\Delta x_j = (x_{j,2008} - x_{j,2006})/x_{j,2006} \times 100\%$, where $x_{j,t}$ is the economic indicator of state j in year t. See Appendix Table B2 for the data source of GDP per capita, unemployment rate, and housing price index. The state-level H1N1 death rate is assessed during the H1N1 pandemic.

Table B6. Summary Statistics of Passive Risky share, Active and Passive Changes

	N	mean	sd	min	p25	p50	p75	max
Panel A: Passive risky share								
Vwretd	9,792	0.549	0.290	0.000	0.326	0.542	0.814	1.000
Vwretx	9,792	0.542	0.290	0.000	0.317	0.532	0.808	1.000
Ewretd	9,792	0.562	0.289	0.000	0.339	0.558	0.827	1.000
Ewretx	9,792	0.556	0.289	0.000	0.330	0.548	0.822	1.000
Sprtrn	9,792	0.542	0.291	0.000	0.316	0.531	0.807	1.000
Panel B: Passive change								
Vwretd	9,792	0.014	0.056	-0.156	-0.021	0.021	0.051	0.162
Vwretx	9,792	0.007	0.056	-0.166	-0.025	0.017	0.042	0.150
Ewretd	9,792	0.027	0.062	-0.181	0.000	0.030	0.060	0.219
Ewretx	9,792	0.020	0.062	-0.190	-0.001	0.024	0.052	0.208
Sprtrn	9,792	0.006	0.057	-0.170	-0.026	0.017	0.042	0.153
Panel C: Active change								
Vwretd	7,110	-0.011	0.305	-1.000	-0.179	-0.011	0.160	0.971
Vwretx	7,110	-0.005	0.306	-1.000	-0.172	-0.006	0.167	0.971
Ewretd	7,110	-0.025	0.304	-1.000	-0.194	-0.020	0.142	0.970
Ewretx	7,110	-0.019	0.305	-1.000	-0.187	-0.016	0.150	0.970
Sprtrn	7,110	-0.004	0.306	-1.000	-0.172	-0.006	0.168	0.971

Notes: This table reports summary statistics of passive risky share, active changes, and passive changes in our study period, 2001–2017. The return on risk-free assets is the real return on the 90-Day T-bill. The return on risky assets is computed with *Vwretd* (the value-weighted return, including all distributions), *Vwretx* (the value-weighted return, excluding dividends), *Ewretd* (the equal-weighted return, including all distributions), *Ewretx* (the equal-weighted return, including all distributions), *Sprtrn* (Return on the S&P Composite Index), respectively. Data source: CRSP.

Table B7. Heterogeneous Effects of the H1N1 Pandemic by Demographic Features

Dependent variable	log risky share			
	(1) Gender	(2) Race	(3) Marital status	(4) Education
Male × During × log(H1N1 death rate)	-0.072			
	(0.067)			
Female × During × log(H1N1 death rate)	-0.193			
	(0.163)			
Male × After × log(H1N1 death rate)	-0.236***			
	(0.081)			
Female × After × log(H1N1 death rate)	-0.531***			
	(0.151)			
Minority × During × log(H1N1 death rate)		-0.095		
		(0.181)		
White × During × log(H1N1 death rate)		-0.088		
		(0.066)		
Minority × After × log(H1N1 death rate)		-0.185		
		(0.211)		
White × After × log(H1N1 death rate)		-0.280***		
		(0.080)		
Not married × During × log(H1N1 death rate)			-0.166	
			(0.126)	
Married × During × log(H1N1 death rate)			-0.047	
			(0.070)	
Not married × After × log(H1N1 death rate)			-0.481***	
			(0.117)	
Married × After × log(H1N1 death rate)			-0.228***	
			(0.085)	
High school or below × During × log(H1N1 death rate)				-0.171
				(0.113)
College or above × During × log(H1N1 death rate)				-0.061
				(0.072)
High school or below × After × log(H1N1 death rate)				-0.275**
				(0.118)
College or above × After × log(H1N1 death rate)				-0.271***
				(0.083)
Average of the outcome variable	-0.886	-0.886	-0.881	-0.886
Family FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
State-specific time trend	✓	✓	✓	✓
Household features	✓	✓	✓	✓
Macroeconomic indicator (lag)	✓	✓	✓	✓
Medical controls (lag)	✓	✓	✓	✓
Number of family	2,239	2,239	2,113	2,239

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Table B7 – *Continued from previous page*

Dependent variable	log risky share			
	(1) Gender	(2) Race	(3) Marital status	(4) Education
Observations	9,790	9,790	9,406	9,790
Adj.R^2	0.286	0.285	0.283	0.286

Notes: This table reports the heterogenous effects of the H1N1 pandemic on the risky share by estimating Eq. (3). All regressions control for family fixed effects, year fixed effects, state fixed effects, and state-specific time trend, household features, and state-by-year-level characteristics. See Section 4.1 for the list of variables controlled as household features, macroeconomic index, and medical resources. We mainly use household heads' gender, race, marital status, and education. In rare cases when heads' information is missing, we use spouses' instead. Particularly, marital status is measured in 2007 to avoid potential endogeneity. Standard errors are clustered at the family level and shown in parentheses. (*Data source: PSID, waves 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, and 2017.*)

Table B8. Heterogeneous Effects of the H1N1 Pandemic by Job Features

Dependent variable	log risky share			
	(1) Income fluctuation	(2) Entrepre-neurship	(3) Government job	(4) Union affiliation
Low inc fluctuation × During × log(H1N1 death rate)	-0.074			
	(0.075)			
High inc fluctuation × During × log(H1N1 death rate)	-0.155			
	(0.115)			
Low inc fluctuation× After × log(H1N1 death rate)	-0.238***			
	(0.090)			
High inc fluctuation × After × log(H1N1 death rate)	-0.464***			
	(0.116)			
Not entrepreneur × During × log(H1N1 death rate)		-0.053		
		(0.075)		
Entrepreneur × During × log(H1N1 death rate)		-0.127		
		(0.110)		
Not entrepreneur × After × log(H1N1 death rate)		-0.262***		
		(0.085)		
Entrepreneur × After × log(H1N1 death rate)		-0.346***		
		(0.114)		
Not work for gov × During × log(H1N1 death rate)			-0.120*	
			(0.068)	
Work for gov × During × log(H1N1 death rate)			0.172	
			(0.149)	
Not work for gov × After × log(H1N1 death rate)			-0.331***	
			(0.086)	
Work for gov × After × log(H1N1 death rate)			-0.061	
			(0.114)	
No union contract × During × log(H1N1 death rate)				-0.106
				(0.067)
A union contract × During × log(H1N1 death rate)				0.179
				(0.178)
No union contract × After × log(H1N1 death rate)				-0.327***
				(0.083)
A union contract × After × log(H1N1 death rate)				-0.006
				(0.144)
Average of the outcome variable	-0.879	-0.881	-0.882	-0.881
Family FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
State-specific time trend	✓	✓	✓	✓
Household features	✓	✓	✓	✓
Macroeconomic indicator (lag)	✓	✓	✓	✓
Medical controls (lag)	✓	✓	✓	✓
Number of family	2,013	2,111	2,111	2,102

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Table B8 – *Continued from previous page*

Dependent variable	log risky share			
	(1) Income fluctuation	(2) Entrepre- neurship	(3) Government job	(4) Union affiliation
Observations	9,055	9,399	9,396	9,377
Adj.R^2	0.282	0.283	0.284	0.284

Notes: This table reports the heterogenous effects of the H1N1 pandemic on the natural log of risky share by estimating Eq. (3). All regressions control for family fixed effects, year fixed effects, state fixed effects, and state-specific time trend, household features, and state-by-year-level characteristics. See Section 4.1 for the list of variables controlled as household features, macroeconomic index, and medical resources. We mainly use household heads' information on income fluctuation, entrepreneurship, whether have a buffer, and whether have union representation. In rare cases when heads' information is missing, we use spouses' instead. To deal with the endogeneous concern, a Mincer regression of income on age, age square, education, race, gender, and state fixed effects is estimated, using the data before 2009. A family is defined as being high (low) income-fluctuated if the standard deviation of the Mincer residual is above (below) the average level. Similarly, the information on entrepreneurship, whether have a buffer, and whether have union representation is related to 2007. Standard errors are clustered at the family level and shown in parentheses. (*Data source: PSID, waves 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, and 2017.*)

Table B9. Life-cycle Impact of the H1N1 Pandemic on Risky Share

Dependent variable	log risky share
	(1)
20-30 × During × log(H1N1 death rate)	-0.129
	(0.205)
30-39 × During × log(H1N1 death rate)	-0.074
	(0.120)
40-49 × During × log(H1N1 death rate)	-0.095
	(0.120)
50-59 × During × log(H1N1 death rate)	-0.109
	(0.093)
60-69 × During × log(H1N1 death rate)	-0.078
	(0.127)
20-30 × After × log(H1N1 death rate)	-0.457**
	(0.230)
30-39 × After × log(H1N1 death rate)	-0.287***
	(0.109)
40-49 × After × log(H1N1 death rate)	-0.239**
	(0.108)
50-59 × After × log(H1N1 death rate)	-0.202**
	(0.092)
60-69 × After × log(H1N1 death rate)	-0.281**
	(0.111)
Average of the outcome variable	-0.887
Family FE	✓
Year FE	✓
State-specific time trend	✓
Household features	✓
Macroeconomic indicator (lag)	✓
Medical controls (lag)	✓
Number of family	2,218
Observations	9,661
Adj.R^2	0.281

Notes: This table reports the age profiles of the H1N1-intensity elasticities for the natural log of risky share by estimating Eq. (3). All regressions control for family fixed effects, year fixed effects, state fixed effects, and state-specific time trend, household features, and state-by-year-level characteristics. See Section 4.1 for the list of variables controlled as household features, macroeconomic index, and medical resources. Standard errors are clustered at the family level and shown in parentheses. (*Data source: PSID, waves 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, and 2017.*)

Table B10. Available Information on Consumption in PSID 2001–2017

Domains	Items	Waves available
Food	Food at home, food away from home, food stamps	2001–2017
Transportation	Including gasoline, parking and carpool, bus fares and train fares, taxicabs, other transportation, carpyments	
Health care	Including payment for nursing home and hospital bills, payment for doctor, outpatient surgery, and dental bills, payment for prescriptions, in-home medical care, special facilities, and payment for health insurance premiums	
Housing	Including rent, monthly loan payments, heating, water and sewer, housing insurance premium, housing property taxes, electricity, and other utility expenses	
Education	Including tuition or tutoring expenses and other school-related expenses	
Child Care	Payment for child care	
Home Repairs & Maintenance	Including materials plus any costs for hiring a professional	2005–2017
Household Furnishings & Equipment	Including household textiles, furniture, floor coverings, major appliances, small appliances and miscellaneous housewares	
Clothing & Apparel	Including footwear, outerwear, and products such as watches or jewelry	
Trips & Vacations	Including transportation, accommodations, and recreational expenses on trips	
Recreation & Entertainment	Including performing arts and hobbies	
Telephone & Internet expenses	Payment for telephone, including cellphone, cable or satellite TV, Internet service	

Table B11. Mediation Analysis (First Stage)

Outcome variable	Poor health (dummy) (1)	Married (dummy) (2)	Have children (dummy) (3)	log of total income (4)	Unemployed (dummy) (5)
During × log(H1N1 death rate)	-0.016	0.003	-0.004	-0.001	0.019*
	(0.010)	(0.009)	(0.014)	(0.022)	(0.011)
After × log(H1N1 death rate)	-0.013	0.005	0.013	-0.014	0.023*
	(0.014)	(0.014)	(0.020)	(0.032)	(0.014)
Average of the outcome variable	0.072	0.714	0.484	11.372	0.056
Family, year, state FEs	✓	✓	✓	✓	✓
State-specific time trend	✓	✓	✓	✓	✓
Household features	✓	✓	✓	✓	✓
Macroeconomic indicator (lag)	✓	✓	✓	✓	✓
Medical controls (lag)	✓	✓	✓	✓	✓
Number of family	5,100	5,099	5,100	5,097	5,100
Observations	26,846	26,844	26,846	26,830	26,846
Adj.R^2	0.397	0.835	0.644	0.588	0.142

Notes: "Poor health" is a dummy variable that is equal to 1 if the household head reports his/her health status is poor or fair. "Have children" is a dummy variable that is equal to 1 if the household has children aged between 0–17. Income is defined in 2017 dollar adjusted by the CPI-U index. All regressions control for family fixed effects, year fixed effects, state fixed effects, and state-specific time trend, household features, and state-by-year-level macroeconomic indicators. See Section 4.1 for the list of variables controlled as household features, macroeconomic index, and medical resources. Standard errors are clustered at the family level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: PSID, waves 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, and 2017.*)

Table B12. Exposure Effect of H1N1 Pandemic on Risky Share

Outcome variable	log(Risky share)					
Additional controls	Baseline	Health status	Family structure	Labor market outcomes		All
	(1)	(2)	(3)	(4)	(5)	(6)
During × log(H1N1 death rate)	-0.088	-0.087	-0.089	-0.087	-0.087	-0.086
	(0.063)	(0.064)	(0.064)	(0.063)	(0.063)	(0.064)
After × log(H1N1 death rate)	-0.273***	-0.273***	-0.274***	-0.274***	-0.271***	-0.273***
	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)
Poor health		0.024				0.022
		(0.062)				(0.062)
Have children 0–17			0.008			0.008
			(0.034)			(0.035)
Married			-0.110**			-0.092
			(0.055)			(0.056)
Log total income				-0.043**		-0.041**
				(0.020)		(0.020)
Unemployed					-0.059	-0.069
					(0.049)	(0.049)
Average of the outcome variable	-0.886	-0.886	-0.886	-0.886	-0.886	-0.886
Family, year, state FEs	✓	✓	✓	✓	✓	✓
State-specific time trend	✓	✓	✓	✓	✓	✓
Household features	✓	✓	✓	✓	✓	✓
Macroeconomic indicator (lag)	✓	✓	✓	✓	✓	✓
Medical controls (lag)	✓	✓	✓	✓	✓	✓
Number of family	2,239	2,239	2,239	2,239	2,239	2,239
Observations	9,790	9,790	9,790	9,789	9,790	9,789
Adj. R^2	0.286	0.286	0.286	0.286	0.286	0.286

Notes: "Poor health" is a dummy variable that is equal to 1 if the household head reports his/her health status is poor or fair. "Have children" is a dummy variable that is equal to 1 if the household has children aged between 0–17. Income is defined in 2017 dollar adjusted by the CPI-U index. All regressions control for family fixed effects, year fixed effects, state fixed effects, and state-specific time trend, household features, and state-by-year-level macroeconomic indicators. See Section 4.1 for the list of variables controlled as household features, macroeconomic index, and medical resources. Standard errors are clustered at the family level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: PSID, waves 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, and 2017.*)

Table B13. Exposure Effect of H1N1 Pandemic on Family Wealth

Outcome variable	Total wealth (exc. home equity)) (in 10k US$))	Total wealth (inc. home equity) (in 10k US$)	log risky share	
	(1)	(2)	(3)	(4)
During × log(H1N1 death rate)	0.262	0.256	-0.090	-0.090
	(1.020)	(1.036)	(0.063)	(0.063)
After × log(H1N1 death rate)	0.286	0.371	-0.274***	-0.274***
	(1.156)	(1.175)	(0.079)	(0.079)
Total wealth (exc. home equity)			-0.000	
			(0.001)	
Total wealth (inc. home equity)				-0.000
				(0.001)
Average of the outcome variable	5.466	7.292	-0.886	-0.886
Family, state, year FEs	✓	✓	✓	✓
State-specific time trend	✓	✓	✓	✓
Household features	✓	✓	✓	✓
Macroeconomic indicator (lag)	✓	✓	✓	✓
Medical controls (lag)	✓	✓	✓	✓
Number of family	2,239	2,239	2,239	2,239
Observations	9,790	9,790	9,790	9,790
Adj.R^2	0.591	0.648	0.285	0.285

Notes: Following PSID's definition, We define *Total wealth (exc. home equity)* as the aggregate value of all types of assets — encompassing risky assets, risk-free assets, business or farm ownership, other real estate, and vehicles — minus the total debt value, with home equity expressly excluded from this calculation. On the other hand, *Total wealth (inc. home equity)* follows the same summation of assets as *Total wealth (exc. home equity)*, with the distinction being the inclusion of home equity in the total, which is then deducted by the overall debt value. Wealth variables (in 10k US$) are defined in 2017 dollar adjusted by the CPI-U index. All regressions control for family fixed effects, year fixed effects, state fixed effects, and state-specific time trend, household features, and state-by-year-level macroeconomic indicators. See Section 4.1 for the list of variables controlled as household features, macroeconomic index, and medical resources. Standard errors are clustered at the family level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: PSID, waves 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, and 2017.*)