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From Pandemics to Portfolios: Long-Term Impacts of the 2009 H1N1 Outbreak on Household Investment Choices

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This study examines how experiencing a pandemic affects household investment behaviors. By leveraging cross-state variations in the H1N1 mortality rate in 2009, our difference-in-differences analysis reveals interesting findings. Although the pandemic does not significantly affect stock market participation, it depresses the proportion of liquid assets invested in risky assets among households who participate in the stock market. This effect persists for up to eight years after the pandemic and is particularly pronounced among households characterized by higher risk aversion and greater income volatility. Analysis conducted using different datasets consistently suggests that the pandemic primarily influences portfolio choices through a shift in risk attitudes.

Keywords: pandemic, portfolio choice, rational inattention, risky share, risk attitude

JEL Codes: D10, G11, I10

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1 Introduction

Over the last century, viruses have taken more lives than all armed conflicts (Adda 2016).[1] Beyond their health impact, viral outbreaks also incur substantial economic damage.[2] Furthermore, viral public health crises expose people to great risks and prompt behavioral responses (Rasul 2020). Specifically, pandemics can limit inter-person interactions (Ghent, Rowberry, and Spiegel 2024), change health behaviors (Agüero and Beleche 2017), alter household consumption (Chetty et al. 2020) and savings (Hurwitz, Mitchell, and Sade 2021), affect time allocation decisions (Restrepo and Zeballos 2020), human capital investment (Hanushek 2023), and shape people's expectations (Hanspal, Weber, and Wohlfart 2021; Chen et al. 2023).

Households, as the ultimate owners of property, financial, and business assets, directly manage one-third of these assets in the US (Koijen and Yogo 2019). While extensive research exists on pandemics, their impact on financial behavior, particularly household portfolio choices, is less understood. This study aims to fill this gap by examining how a pandemic influences these decisions.

A pandemic can affect household finance through several channels. First, pandemics can alter subjective perceptions, such as risk preference, subjective life expectancy, and degree of impatience, temporarily or permanently, thus affecting portfolio decisions. As noted by Shachat, Walker, and Wei (2021), the emergence of a public health crisis can unpredictably change individuals' economic preferences, which are crucial in economic decision-making. Second, a pandemic can increase background risks,[3] which subsequently alter portfolio decisions (Guiso, Jappelli, and Terlizzese 1996; Heaton and Lucas 2000). This can manifest through changes in household finance due to shocks in health status (Almond and Mazumder 2005; Fan and Zhao 2009), wealth (Pool et al. 2019),

1. 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 August 2024, has infected 775 million people and caused over 7 million deaths (Source: the World Health Organization website, `https://covid19.who.int/`, accessed August 5, 2024).

2. The annual global cost of moderately severe to severe pandemics accounts for 0.7% of global income (Source: World Report in 2017, accessed August 17, 2024).

3. The background risk is referred to as the exogenous risks that are not under the agent's control (Eeckhoudt, Gollier, and Schlesinger 1996).

and labor market outcomes, such as employment, occupational choice, and earnings (Albanesi and Kim 2021; Larrimore, Mortenson, and Splinter 2022).

This study delves into the immediate and enduring effects of the 2009 H1N1 pandemic on US household portfolio choices and examines the risk preference and the background risk channels. The H1N1 pandemic, occurring from April 2009 to August 2010, was caused by a novel human-to-human transmissible H1N1 virus, also known as the "swine flu".[4] The swine flu garnered significant public attention in the US, which experienced the highest number of H1N1 cases and fatalities globally during the pandemic.[5] The unforeseen H1N1 pandemic provides a natural experiment on how households adjust their portfolios in response to an exogenous shock.[6]

We utilize data from four sources. First, we manually collect state-level H1N1 death data during the pandemic from an online forum *FluTracker*, calculating the death rate for each state as a measure of H1N1 intensity. Second, we gather data from nine waves of the Panel Study of Income Dynamics (PSID) (2001–2017, in odd-numbered years). We construct two portfolio choice measures: stock market participation and risky share (the share of risky assets in liquid assets, conditional on stock market participation). Third, we collect state-level macroeconomic indicators and medical resources to account for potential confounding factors related to H1N1 intensity. Last, we draw data from four waves (2009, 2012, 2015, and 2018) of the National Financial Capability Study State-by-state Survey (NFCS), which elicits respondents' risk attitudes, to explore the risk attitude mechanism.

4. The name "swine flu" comes from the fact that its gene components are similar to viruses known to infect pigs, even though it cannot be transmitted through the consumption of pork products. In the epidemiological literature, the 2009 H1N1 influenza virus is formally referred to as the "(H1N1)pdm09 virus" or the "novel H1N1 virus."

5. Data from 2009 Google searches originated in the US reveals that the term "Swine influenza" even exceeded the popularity of "Barack Obama," the first African-American US president who took office in 2009, and "unemployment," which had hit a peak rate of 10% in 2009 for the first time since 1983 (Appendix Figure A1). See Section 2.1 for an overview of the H1N1 pandemic.

6. Compared to COVID-19, studying the impact of the H1N1 pandemic on portfolio choices offers several advantages. Firstly, the H1N1 pandemic occurred over a decade ago, providing a longer time frame to assess its long-term effects. Secondly, the government response to COVID-19, including quarantines, business closures, cash distributions, and the widespread adoption of remote work, introduces additional variables that can confound the analysis of portfolio decisions. In contrast, the simpler response to the H1N1 pandemic allows for a clearer and more straightforward examination of its impact on household financial behavior.

We use a difference-in-differences (DID) approach to study the impact of the H1N1 pandemic on household portfolio choices. This method utilizes state-level variations in H1N1 intensity and differences between pre- and post-pandemic periods *within households*. The panel data enables us to account for time-invariant unobserved heterogeneity at the household level and examine the long-term effect of the pandemic.

We find that the 2009 pandemic does not influence stock market participation (the extensive margin of stock holdings). However, the risky share (the intensive margin) decreases with the H1N1 intensity in the post-pandemic period. Specifically, a 1 percent increase in the 2009 H1N1 death rate leads to an average decrease in the risky share by 0.3 percent. Additionally, our decomposition analysis suggests that this decline in the risky share is primarily due to a decrease in net investment in stocks, rather than an increase in liquid assets.

Our findings are robust to several concerns. To address the possibility of omitted variable bias, we include interactions between year dummies and a set of pre-pandemic state-level covariates that may correlate with H1N1 intensity, stock holdings, or both. We also address the potential confounding effect of the 2007–2008 financial crisis by controlling for economic indicators that reflect the impact of the financial crisis. In addition, our results are robust to different sample selection criteria, alternative measures of the H1N1 intensity, and discretizing the H1N1 death rate. Furthermore, we perform placebo tests by examining the effect of exposure to seasonal influenza on risky shares and using the hypothetical pandemic year.

An event study framework reveals the *time-varying* impact of the H1N1 pandemic on portfolio choices. In line with the parallel trend assumption, the difference in risky share is small and statistically insignificant prior to 2009. The initial exposure impact in 2009 is negligible. However, from 2011 onwards, the exposure effect on the risky share becomes significantly negative and remains stable, suggesting a delayed but prolonged impact of the H1N1 pandemic.

To explain these findings, we use NFCS data to explore the risk preference mechanism. We find that an increase in H1N1 intensity significantly decreases an individual's risk tolerance during the *post-pandemic* period. This suggests that living in a state with a higher H1N1 death rate amplifies risk aversion, which results in more conservative financial behavior, such as reducing exposure to risky assets in favor of safe alternatives. Moreover, the effect is particularly pronounced for women and unmarried individuals.

Additionally, analysis using PSID data indicates that alternative factors such as health, demographics, labor market outcomes, and family wealth, which might affect household portfolio choices through the background-risk channel, are unlikely to account for our results.

Our heterogeneity analysis shows that the impact of H1N1 is stronger for households headed by women or single individuals. This supports the risk attitude channel, showing that households with higher risk aversion and greater income volatility are more susceptible to the pandemic's adverse effects. The impact is also stronger for those with heads experiencing unstable income, including those not working for a government and those not represented by a union. Using a risk tolerance measure from the 1996 PSID, we find that risk-averse individuals reduce their risky share more than risk-loving individuals in response to the H1N1 pandemic. Additionally, the exposure effect follows a hump-shaped pattern over the life cycle, with young individuals (who have lower accumulated wealth) and older workers (nearing retirement with declining labor income) reducing their risky asset holdings most significantly.

This study makes three key contributions to the literature. Firstly, it enriches the body of work examining the socioeconomic consequences of pandemics, particularly their impact on household portfolio choices. While existing studies predominantly focus on the *short-term* correlation between the COVID-19 pandemic and the *intensive margin* of asset holding,[7] this study shifts the focus to the 2009 H1N1 pandemic. Using long panel data from 2001 to 2017, we identify both the immediate

7. For instance, Coibion, Gorodnichenko, and Weber (2020) show that COVID-19 exposure is negatively associated with household investments.

and *long-term* effects of the H1N1 pandemic on stock market participation and risky shares.[8] In addition, our DID framework provides more rigorous causal evidence of the pandemic impact.

Secondly, this study contributes to the literature on the determinants of household portfolio choices. Previous factors identified include cognitive ability (Christelis, Jappelli, and Padula 2010; Agarwal and Mazumder 2013; Breunig et al. 2021), financial literacy (Gaudecker 2015), housing (Cocco 2005; Chetty, Sándor, and Szeidl 2017), income risk (Angerer and Lam 2009; Betermier et al. 2012), social interaction (Hong, Kubik, and Stein 2004; Liang and Guo 2015), physical health (Fan and Zhao 2009), mental health (Bogan and Fertig 2013), and emotional status (Kuhnen and Knutson 2011). We add to this literature by highlighting the role of pandemics in household asset allocations and emphasizing the shift in risk preference as a potential mechanism.

Thirdly, this study contributes to the broader literature on how aggregate shocks influence preferences and beliefs. There is substantial evidence that aggregate shocks can shift risk preferences and alter risk-taking behavior.[9] For instance, Malmendier and Nagel (2011) find that economic fluctuations reduce stock market participation and risky asset allocations, while Cameron and Shah (2015) show that non-economic shocks, such as earthquakes or floods, decrease risk-taking behavior. As comprehensively reviewed by Giuliano and Spilimbergo (2024), the existing literature on pandemics primarily focuses on trust and political preferences. Limited research studies how the pandemic, a key type of non-economic shock, affects preferences. This study fills the gap by providing novel evidence that pandemics can reshape risk preferences and influence investment decisions.

This paper is organized as follows. Section 2 introduces the background of the 2009 H1N1 pandemic and describes the data. Section 3 discusses our DID empirical strategy and Section

8. This is in sharp contrast to the earlier studies which focus on how pandemic may affect people's perception in the short run, such as Ibuka et al. (2010). Almond (2006) explores the long-term consequences of the 1918 influenza pandemic, but does not relate to the financial market.

9. The direction of these effects is debated. See Chuang and Schechter (2015) and Schildberg-Hörisch (2018) for detailed reviews on how economic shocks, natural disasters, and conflicts affect risk preferences.

4 reports the findings on how exposure to the H1N1 pandemic affects household stock holdings. Section 5 discusses the possible channels through which the H1N1 pandemic affects household portfolio choices, followed by the heterogeneity analysis in Section 6. The last section concludes.

2 Background and Data

2.1 The US and the 2009 H1N1 Influenza Pandemic

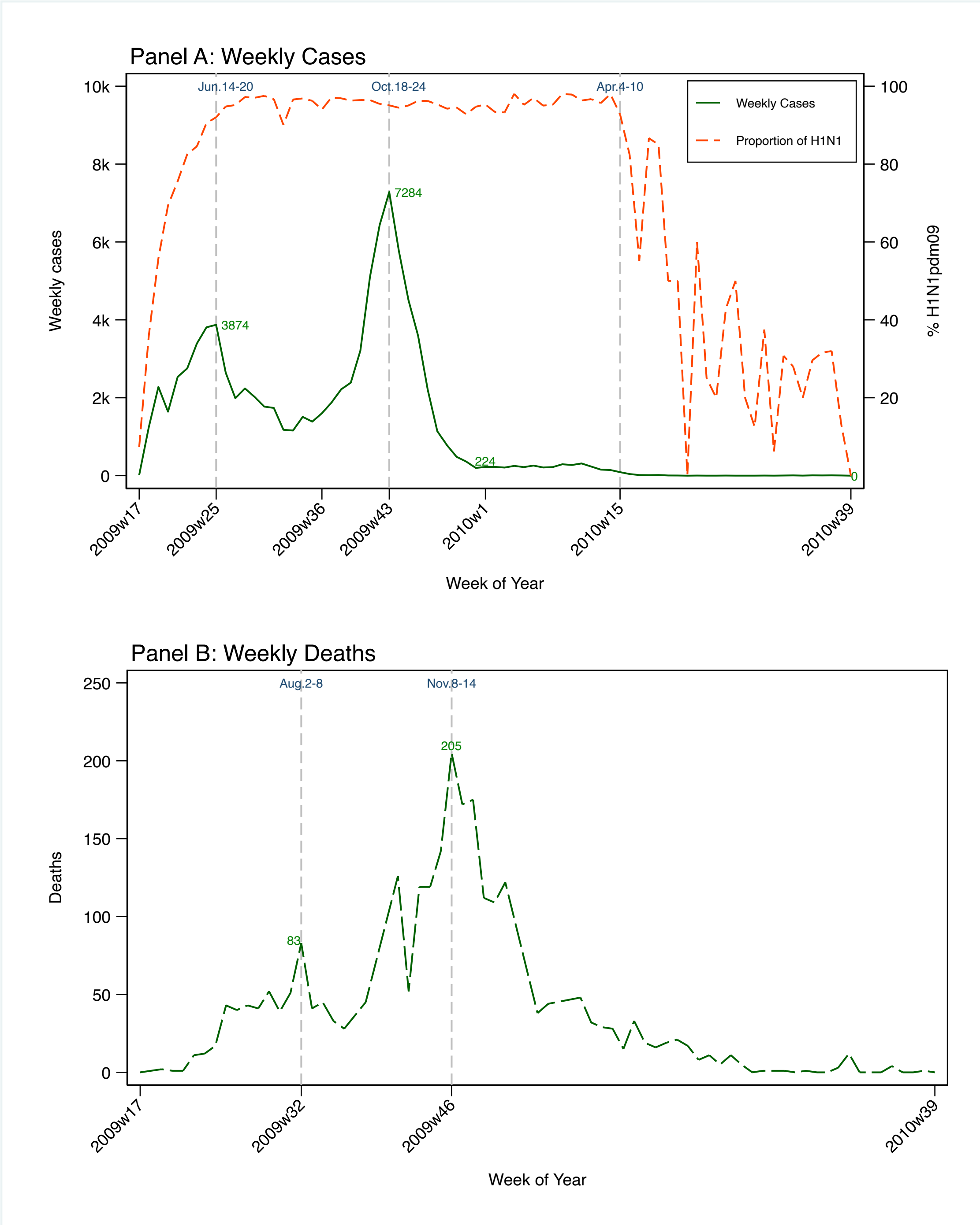
The 2009 outbreak of the novel A (H1N1) influenza (informally called "swine flu") was declared by WHO as the first global pandemic since the 1968 flu pandemic. During the pandemic, more than 214 countries and overseas territories or communities reported cases of 2009 H1N1 infection, which accounts for 11 to 21 percent of the world population at the time (Kelly et al. 2011). In the US, the novel H1N1 virus was first detected in California on April 15, 2009, and spread quickly across 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 illustrates the weekly trends of lab-confirmed cases and deaths associated with the 2009 H1N1 influenza in the United States. The data reveal that H1N1 cases peaked in June and October, while related deaths followed slightly later, reaching their highest levels in August and November of 2009.

The (H1N1)pdm09 virus is typically transmitted from person to person through droplets. It shares symptoms similar to other flu: fever, cough, headache, etc. However, the disease patterns in severe cases are remarkably different from seasonal flu. 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 during 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. By contrast, 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.

The US government took a series of measures in response to this pandemic. In the initial stage, schools were closed if cases were confirmed.[10] In addition, H1N1-related news was published on cdc.gov and the official websites of state health departments every week. Public health advice was also provided on these websites, including 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 in April. However, given the slow production process, the vaccine was unavailable until October 2009.

In early August 2010, scientists found that the pandemic flu activity had returned to normal levels that were considered typical for seasonal flu, which 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.

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



Notes: In Panel A, 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. In Panel B, the long-dashed line denotes the number of weekly lab-confirmed H1N1 deaths. (*Data source: WHO Collaborating Laboratories.*)

Figure 1. Weekly Cases and Cumulative Deaths of H1N1pdm09 in the US

2.2 Data

2.2.1 H1N1 Data

We first describe the data on the severity of the H1N1 pandemic. We use data collected from *FluTrackers* (FluTrackers.com), an online forum and early warning system that has gathered information on infectious diseases since 2006.[11] *FluTrackers* collected in real time the state-level H1N1 surveillance information from each state health department and posted the content as well as the source link. We extract the lab-confirmed H1N1 death information of each state from *FluTrackers* during the pandemic (i.e., April 2009–August 2010). Our main measurement for the state-level H1N1 intensity is the number of lab-confirmed death tolls per 100,000 residents. We use death rates rather than death numbers because death numbers can be positively correlated with the local population. To our knowledge, this state-level data is the most granular geographical unit that can be publicly accessible. Figure 2 shows the geographic distribution of H1N1 death rates for 50 states (excluding the District of Columbia), where a darker color implies a higher death rate, ranging from 0.29 (Missouri) to 2.85 (South Dakota).

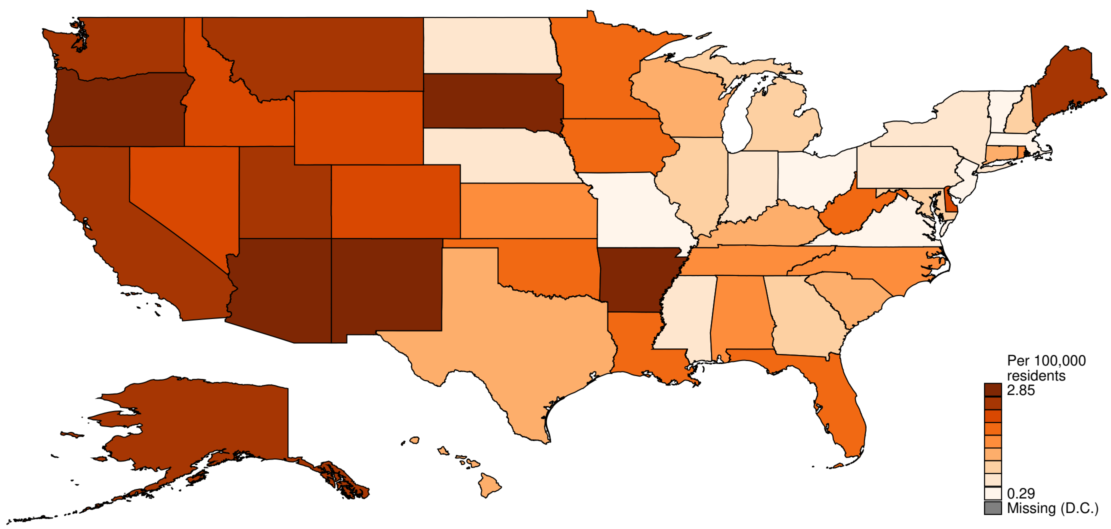
Given the impact of H1N1 on casualties, it is natural to inquire whether the stock market mirrors the prevalence of the pandemic and drives the adjustments in household portfolios. We conduct several analyses and reserve the details in Figures A2–A4 and Table B2 in Appendix. Overall, the H1N1 pandemic has a negligible impact on the stock market, which is in distinct contrast with the case of the COVID-19 pandemic.[12]

In addition to the state-level H1N1 death rate, we develop a measure of the H1N1 case rate. However, the state-level number of H1N1 cases is unavailable during the pandemic. To address

11. The CDC publishes influenza surveillance information in a weekly report called *FluView*. When the novel H1N1 virus emerged, *FluView* reported state-level individual case counts. However, the CDC discontinued reporting confirmed cases on July 24, 2009, and only reported the country-level hospitalizations and deaths due to the 2009 H1N1 virus. Unfortunately, we can not obtain useful information from the CDC reports since the country-level figures mask the regional variations in the H1N1 outbreak.

12. he 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 February and March 2020 (Hanspal, Weber, and Wohlfart 2021) and have a substantially adverse impact on stock returns (Al-Awadhi et al. 2020).

this limitation, we compile data on H1N1 cases from a broader geographic level. Specifically, approximately 80 WHO Collaborating Laboratories across the United States report weekly data on the total number of respiratory specimens tested and the number testing positive for influenza types A and B, including (H1N1)pdm09. These data are aggregated at the Health and Human Services (HHS) region level, which encompasses multiple states.[13] We utilized an R package named "cdcfluview" to gather this weekly HHS-level data on H1N1 case numbers. We aggregate the number of confirmed H1N1 cases for *each HHS region* during the pandemic to calculate the H1N1 case rate, i.e., the number of H1N1 case counts per 100,000 residents.



Notes: The state-level H1N1 death rate is 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 is the intercensal estimate for 2009, drawn from the Population Division of the US Census Bureau. See Appendix Table B1 for specific death rates of each state.

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

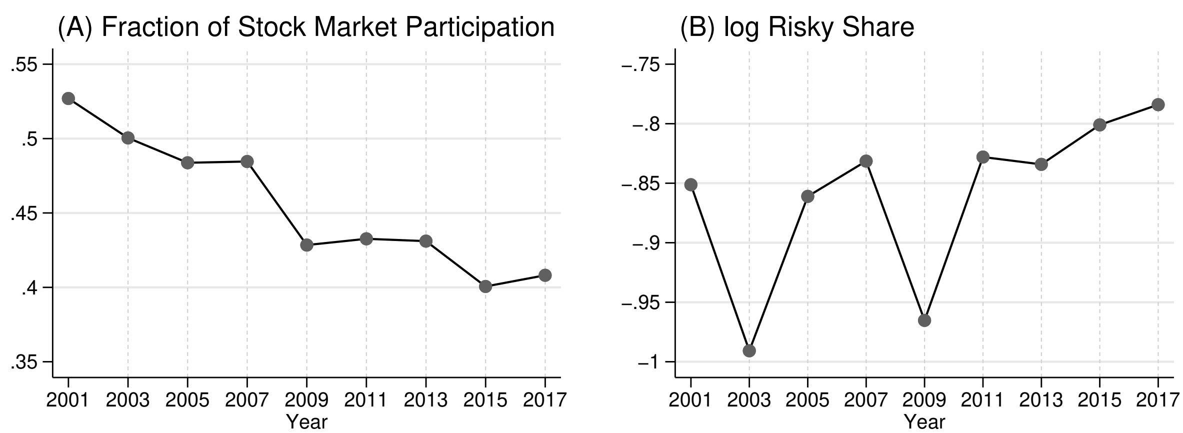
2.2.2 PSID

Our primary data source for household information is the PSID. It is a longitudinal and nationally representative survey that tracks over 82,000 individuals from more than 9,500 families for over 50 years. The PSID data were released annually until 1997 and became a biannual survey. At

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

the time of our research, due to the lack of some state-by-year-level control variables in 1999 and 2019, we used nine waves of data in the PSID (i.e., 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, and 2017).[14]

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), *risky assets* is defined 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 the sum of checkings, savings, bonds, trusts, and IRAs invested in interest earnings. We further denote the sum of risky and riskless assets as liquid assets. *Stock market participation* equals one if the household has positive risky assets and zero otherwise. The *risky share* is the proportion of the liquid assets held in risky assets, conditional on stock market participation.



Notes: Stock market participation is defined as owning positive risky assets. Risky share is the value of risky assets divided by liquid assets, conditional on stock market participation. (*Data source: PSID, waves 2001–2017, in odd-numbered years.*)

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

Figure 3 plots the average changes in the household portfolios over time. Since 2001, the fraction of households owning risky assets displays an overall declining trend (Panel A).[15] In particular, it

14. Most state-by-year control variables are missing in or before 1999, and some are missing in 2019. As we will introduce in Section 4.1, controlling these variables in causal analysis is essential since they are closely related to the outcome variables and the H1N1 intensity. Therefore, we use PSID data from 2001 to 2017 for a balanced panel of state-by-year characteristics.

15. This downward trend aligns with the pattern presented with the Survey of Consumer Finances data in the same

dropped substantially during the financial crisis period (2007–2009). On the other hand, the risky share displayed high volatility between 2001 and 2017 (Panel B).[16]

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 characteristics (e.g., age, gender, education, race, marital status) are used as a priority. All monetary values, such as wealth and income, are defined in the 2017 dollar adjusted by the CPI-U index.

Sample restrictions. — Appendix Figure A5 provides a step-by-step illustration of the sample size and the selection criteria applied for both the stock market participation and the risky asset share. Our original sample is restricted to those who have non-missing basic individual and household characteristics (introduced in detail in Section 4.1). We then exclude households with asset changes due to a family member moving into or out of the family. We also drop observations if the household head is either a student or retired.[17] Households with liquid assets less than $1,000 are also excluded because the asset allocation decision is irrelevant for households with little wealth (Gomes and Smirnova 2021). To facilitate panel-data analysis, we further remove households with only one observation. After applying these criteria, the final sample for stock market participation includes 25,947 observations from 5,049 family units. For the analysis of risky asset allocation, we focus on households owning risky assets, resulting in a sample of 9,790 observations from 2,239 family units.

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

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period, as described by Gomes and Smirnova (2021).
Gomes and Smirnova (2021) notes that the stock market participation rate increased during the "dotcom bubble" in the late 1990s, and then gradually reverted to its prior level in the early 2000s.

16. Since 2011, the proportion of risky shares has actually increased, which contradicts the hypothesis of a general rise in risk aversion. Conversely, the proportion of stock market investors has declined, suggesting heterogeneous responses to market shocks. This point will be further explored in a later section of the analysis.

17. Household investment decisions usually change significantly during the transition into retirement (Addoum 2017; Fagereng, Gottlieb, and Guiso 2017). As a result, we exclude retired households following Brunnermeier and Nagel (2008).

years of education is 14.5 years. The fraction of households participating in the stock market is 0.41, and the (conditional) risky share is 0.53.

Table 1. Summary Statistic for the PSID 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	5,049		
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* equals unity if the household has positive risky assets and zero otherwise. *Risky share* is the proportion of the liquid assets held in risky assets, conditional on stock market participation. (*Data source: PSID, waves 2001–2017, in odd-numbered years.*)

2.2.3 Macroeconomic Indicators and Medical Resources

We collect a comprehensive set of state-level variables in 2008 on macroeconomic indicators and medical resources from different sources (see Appendix Table B4 for the data sources). To compare various states fairly, 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.

Appendix Table B5 reports balanced test results for these state characteristics in 2008, the year preceeding the H1N1 pandemic. A state is classified as high death-rate (HDR) if its H1N1 death rate during the pandemic exceeded the median level observed across all 50 states. As shown in the table, H1N1 intensity correlates with state macroeconomic indicators, such as housing price, asset per capita, population density, and medical resources, including physicians and nurses. To account for potential confounding factors that might influence both a state's response to the H1N1 pandemic and its H1N1 intensity, our robustness checks include interactions between all observed pre-pandemic macroeconomic and medical covariates and year indicators.[18]

2.2.4 Risk Attitude

In Section 5.1, we investigate whether changes in risk attitude can explain why the H1N1 pandemic affects stock holdings. Since PSID only surveyed risk attitude in the 1996 wave, we employ the NFCS data, which contains risk attitude data across waves. Initiated in 2009 and conducted triennially, the NFCS surveys a sample of over 25,000 adults in each wave, with approximately 500 respondents per state.

We pool four waves of NFCS (2009, 2012, 2015, and 2018) and obtain a sample of over 93,000 observations. The weighted summary statistics of this NFCS sample are presented in Appendix Table B8. The survey question on risk tolerance in the NFCS inquires: "When thinking of your financial investments, how willing are you to take risks? Please use a 10-point scale, where 1 means 'Not At All Willing' and 10 means 'Very Willing.' " A lower score corresponds to greater risk aversion. As shown in Table B8, the average risk score of the NFCS sample is 4.77.

3 Empirical Strategy

Our primary goal 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 DID identification strategy and exploit the state-level differences in the H1N1 intensity and the differences between the pre-pandemic and post-pandemic periods. Specifically, the following

18. Since the results of the balanced test could be influenced by states near the "cut-off" between the low and high death-rate groups, we perform a robustness check by dropping states with mid-level death rates (Appendix Table B6). Another potential issue arises from states with extreme H1N1 death rates, which could skew the balance test. So we execute another test by excluding states with the lowest and highest death rates (Appendix Table B7). The findings from both robustness checks align with those presented in Table B5.

equation is estimated:

$$\begin{aligned} Y_{ijt} = {} & \beta_1 During_t \times H1N1_s + \beta_2 After_t \times H1N1_s \\ & + \alpha_t + \alpha_i + \alpha_j + \delta t\alpha_j + \gamma \boldsymbol{X_{it}} + \epsilon_{ijt}, \end{aligned} \tag{1}$$

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. $H1N1_s$ is the natural log of the lab-confirmed H1N1 death rate in the state s during the 2009 H1N1 pandemic. The state s is where the household resided in 2009.[19] $During_t$ 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. Note that we can still identify state fixed effects (α_j) even when we include family fixed effects (α_i) since there are families who move across states.[20] The model also includes state-specific time trends, $t\alpha_j$, to mitigate the concern that the effect of the pandemic can be driven by preexisting state-specific trends. Including these trends in a DID framework is a more conservative specification, as it relaxes the standard assumption that all unit-specific trends are zero (Downey 2024).[21] $\boldsymbol{X_{it}}$ includes household characteristics, which are described in Section 4.1. 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. Standard errors are clustered at the state level, aligning with the level at which the treatment is defined (Abadie et al. 2023).

We interact $H1N1_s$ with $During_t$ and $After_t$ dummy separately rather than construct the classic interaction between $H1N1_s$ and a $Post_t$ dummy ($Post_t$ is equal to 1 if $t \geq 2009$). This is because more than 60% of the families in 2009 took the PSID survey before June (i.e., the peak of the first wave in the US), as shown in Appendix Figure A6. Therefore, to be conservative, we define $During_t$ and $After_t$ dummies following Kolstad and Kowalski (2012).

19. Our baseline analysis does not require the sample to stay in the same state. Later, we will focus on families that did not move in the robustness analysis.

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

21. It is crucial to include state-specific time trends in our regressions. Omitting these trends could violate the parallel trends assumption, particularly for the intensive margin of stock investment.

Our DID setting aligns with the case without untreated units, as all states in our sample were exposed to the H1N1 pandemic and reported H1N1-related deaths. Therefore, the continuous variation in the H1N1 intensity can be used to recover the average causal response (ACR) (Callaway, Goodman-Bacon, and Sant'Anna 2024), i.e., the average treatment effect with respect to an increase in the H1N1 death rate.[22]

With a continuous treatment variable in our DID framework, the traditional parallel trends assumption, which consider untreated potential outcomes, is not strong enough to identify the average treatment effect.[23] This limitation arises because selection bias may occur if different states experience different treatment effects of the same H1N1 intensity. As emphasized by Callaway, Goodman-Bacon, and Sant'Anna (2024), identifying ACR with a continuous treatment requires a stronger parallel trends assumption, which involves potential outcomes under different treatment intensities. The stronger assumption stipulates that changes in household stock holdings for states with lower death rates should provide a good counterfactual for the changes in household stock holdings that would have been observed for states with higher death rates.[24] In other words, the stronger assumption assumes there is no heterogeneous treatment effect. As a robustness check, we discretize the H1N1 death rate to generate a discrete treatment variable, which allows identification under the standard parallel trends assumption. We then assess whether the exposure effect remains significant (see Appendix C for details).

Downey (2024) highlights that the introduction of unit-specific trends in Equation (1) can lead to inconsistency in the pooled post-treatment coefficient, $\hat{\beta}_2$. This bias arises from two main issues. First, short-term treatment effects are given disproportionately larger weights compared to

22. ACR, as defined by Callaway, Goodman-Bacon, and Sant'Anna (2024), is the derivative of the average treatment effect with respect to the treatment does, expressed as $ACR(d) = \frac{\partial ATE(d)}{\partial d}$.

23. The traditional parallel trends assumption is expressed as $\mathbb{E}\left[Y_{post}(0) - Y_{pre}(0) \mid D = d\right] = \mathbb{E}\left[Y_{post}(0) - Y_{pre}(0) \mid D = 0\right]$, which says that the average counterfactual outcome evolution, for units with any dose d in the absence of treatment, is identical to the outcome evolution observed for units in the untreated group.

24. The strong parallel trends assumption is expressed as: $\mathbb{E}\left[Y_{post}(d) - Y_{pre}(0)\right] = \mathbb{E}\left[Y_{post}(d) - Y_{pre}(0) \mid D = d\right]$, which says that the average outcome evolution for the entire population, if all units received dose d, is equal to the actual outcome path experienced by the units in dose group d.

long-term effects. Second, some weights may be negative. In the worst-case scenario, these issues combined could result in a pooled post-treatment effect with a sign opposite to that of all individual dynamic treatment effects. To address this problem, Downey recommends estimating Equation (2) and calculating a consistent estimate of the average treatment effect, $\bar{\beta}_{post}$, which is our preferred estimate. This estimate is derived as the average of the dynamic treatment effects (i.e., separate effects for each post-treatment time period), $\hat{\beta}_{2011}$, $\hat{\beta}_{2013}$, $\hat{\beta}_{2015}$, and $\hat{\beta}_{2017}$. In our analysis, we will report both $\hat{\beta}_2$ and $\bar{\beta}_{post}$ for comparison.

$$\begin{aligned} Y_{ijt} = {} & \beta_1 During_t \times H1N1_s + \beta_{2011} H1N1_s + \beta_{2013} H1N1_s + \beta_{2015} H1N1_s + \beta_{2017} H1N1_s \\ & + \alpha_t + \alpha_i + \alpha_j + \delta t \alpha_j + \gamma \boldsymbol{X_i} + \epsilon_{ijt}, \end{aligned} \tag{2}$$

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:

$$Y_{ijt} = \beta_t H1N1_s + \alpha_t + \alpha_i + \alpha_j + \delta t \alpha_j + \gamma \boldsymbol{X_{it}} + \epsilon_{ijt}. \tag{3}$$

The estimates β_ts measure the dynamic treatment effects over time and help to examine whether pre-trends exist.[25]

In our heterogeneity analysis, we modify Eq. (1) to allow for varying treatment effects across different groups. The modified model is expressed as:

$$Y_{ijt} = \beta_{1g} During \times H1N1_s + \beta_{2g} After \times H1N1_s + \alpha_t + \alpha_i + \alpha_j + \delta t \alpha_j + \gamma \boldsymbol{X_{it}} + \epsilon_{ijt}, \tag{4'}$$

where β_{1g} and β_{2g} denote the treatment effect of the group g during and after the pandemic, respectively. As discussed in the baseline specification, the inclusion of $t\alpha_j$ in Eq. (4') may lead to an inconsistent estimate of the pooled post-treatment effect $\hat{\beta}_{2g}$. To address this, we estimate dynamic treatment effects for 2011, 2013, 2015, and 2017 using Equation (4), and compute the consistent estimator $\bar{\beta}_{post,g}$, which is the average of $\hat{\beta}_{2011,g}$, $\hat{\beta}_{2013,g}$, $\hat{\beta}_{2015,g}$, and $\hat{\beta}_{2017,g}$). We then test the equality of $\hat{\beta}_{1g}$ and $\hat{\beta}_{1g'}$ (or $\bar{\beta}_{post,g}$ and $\bar{\beta}_{post,g'}$) to assess whether the treatment effects differ

25. Although we include the state-specific time trends in Eq (3), the consistency of $\hat{\beta}_t$ is not a concern. This is because the event study approach estimates year-specific treatment effects rather than a pooled average treatment effect (Downey 2024).

significantly between groups g and g'.

$$
\begin{aligned}
Y_{ijt} = {} & \beta_{1,g} During_t \times H1N1_s + \beta_{2011,g} H1N1_s + \beta_{2013,g} H1N1_s + \beta_{2015,g} H1N1_s \\
& + \beta_{2017,g} H1N1_s + \alpha_t + \alpha_i + \alpha_j + \delta t \alpha_j + \gamma \boldsymbol{X_{it}} + \epsilon_{ijt},
\end{aligned}
\tag{4}
$$

4 Exposure Effect of the H1N1 Pandemic on Stock Holdings

This section presents our main empirical findings. We begin by presenting baseline results that illustrate the impact of the H1N1 pandemic on both the extensive and intensive margins of stock holdings. Following this, we perform an event study analysis to estimate the year-specific effects of exposure to the pandemic. To ensure the robustness of our findings regarding the risky share, we conduct a comprehensive set of tests. Lastly, we undertake a decomposition analysis for the risky share.

4.1 Main Results

Table 2 shows the results of the effect of the 2009 H1N1 pandemic on the extensive margin and the intensive margin of stock holdings. Columns (1) and (5) control family fixed-effects on family, year, and state, and state-specific time trends. In columns (2) and (6), we add a wide set of household characteristics, motivated by past studies on household portfolio decisions, including the age and squared age of the household head, along with their interactions with the head's race, educational level, and gender. We also include interactions between the age and cohort indicators of heads.[26] Our results barely change with these household-level controls. Stock market participation does not change with H1N1 intensity, possibly suggesting the fixed participation costs associated

26. Fagereng, Gottlieb, and Guiso (2017) show cohort-specific patterns in stock market participation and risky share. 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. Note that we do not include marital status, health status, income, and financial situation (e.g., whether they own mortgages, debts, or business), since these variables can be affected by the pandemic.

with the H1N1 pandemic remain unchanged.[27] For risky share, we find little changes related to the H1N1 death rate in the year of the pandemic outbreak.[28] In contrast, we show a significant decrease after the pandemic. The estimated coefficients in columns (4) and (5), are around -0.21, indicating that a 1 percent rise in the H1N1 mortality rate corresponds to a decrease of 0.21 percent in the risky share.

Table 2. Impact on the 2009 H1N1 Pandemic on Household Portfolio

	Stock market participation			log risky share		
	(1)	(2)	(3)	(4)	(5)	(6)
During × log(H1N1 death rate)	0.008	0.008	-0.002	-0.030	-0.030	-0.068
	(0.017)	(0.017)	(0.018)	(0.051)	(0.051)	(0.054)
After × log(H1N1 death rate)	-0.013	-0.013		-0.209***	-0.209***	
	(0.026)	(0.026)		(0.058)	(0.058)	
β_{2011}			-0.023			-0.186***
			(0.028)			(0.068)
β_{2013}			-0.014			-0.321***
			(0.029)			(0.064)
β_{2015}			-0.041			-0.332***
			(0.030)			(0.081)
β_{2017}			-0.058			-0.365***
			(0.037)			(0.100)
$\bar{\beta}_{post}$			-0.034			-0.301***
			(0.029)			(0.069)
Average of the outcome variable	0.410	0.410	0.410	-0.886	-0.886	-0.886
Family FE, State FE, Year FE	✓	✓	✓	✓	✓	✓
State-specific time trends	✓	✓	✓	✓	✓	✓
Family controls		✓	✓		✓	✓
Observations	25,947	25,947	25,947	9,790	9,790	9,790
Adj.R^2	0.475	0.475	0.475	0.285	0.285	0.285

Notes: All specifications include fixed effects of family, state, and year. Columns (1), (2), (4), and (5) estimate Eq. (1). Columns (3) and (6) estimate Eq. (2). $\bar{\beta}_{post}$ is the average of estimated dynamic treatment effects in 2011, 2013, 2015, and 2017 (i.e., $\hat{\beta}_{2011}$, $\hat{\beta}_{2013}$, $\hat{\beta}_{2015}$, and $\hat{\beta}_{2017}$ in Eq. (2)). See the description in Section 4.1 for the list of family controls. Standard errors are clustered at the state level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: PSID, waves 2001–2017, in odd-numbered years.*)

As discussed in Section 3, the pooled post-treatment coefficient (β_2) in Eq (1) may be inconsistent if we introduce the unit-specific time trends in the DID specification. Following the

27. As noted by Fagereng, Guiso, and Pistaferri (2016), the fixed entry cost can affect stock market entry and exit but not affect the conditional risky share.

28. The absence of a significant change in the risky share in 2009 may be partially explained by the timing of the data collection. As shown in Appendix Figure A6, more than 60% of the data in 2009 were collected before June, i.e., the peak of the first wave in the US. Therefore, the limited exposure to the H1N1 pandemic within our 2009 sample likely accounts for the null effect on the risky share that year. To address this, we conduct a robustness check by excluding the 2009 sample and re-estimating the exposure effect for the post-pandemic periods only. The details of this analysis are provided in Appendix C.

approach in Downey (2024), we calculate the weights on underlying dynamic treatment effects for β_2. Appendix Figure A7 shows that these weights are downward sloping, indicating that the pooled post-treatment effect disproportionately emphasizes short-term treatment effects. In addition, the weight for 2017 is slightly negative. To address this potential bias, we estimate dynamic treatment effects for 2011, 2013, 2015, and 2017 using Eq. (2), with results reported in columns (3) and (6) in Table 2. At the bottom of table, we compute the sample mean of the year-specific estimates, $\bar{\beta}_{post} = (\hat{\beta}_{2011} + \hat{\beta}_{2013} + \hat{\beta}_{2015} + \hat{\beta}_{2017})/4$, which serves as the consistent estimator of the pooled post-treatment effect. For stock market participation, $\bar{\beta}_{post}$ is close to zero and statistically insignificant. For risky share, $\bar{\beta}_{post}$ is statistically significant at the 1% level. A 1 percent increase in the H1N1 intensity leads to a decrease of 0.3 percent in the risky share. Alternatively, a standard deviation above the mean of the H1N1 death rate leads to a decrease of 14.48% of the mean of the risky share.[29]

Although the estimated coefficient of $After \times log(H1N1\ death\ rate)$ (β_2) in column (5) is smaller in magnitude than the sample mean of the year-specific estimates ($\bar{\beta}_{post}$) in column (6), the difference between these estimates is not statistically significant.[30] Downey (2024) suggests that the bias of the pooled post-treatment effect might be negligible in cases where treatment effects are roughly constant across time, which could explain our results. As shown in column (6) of Table 2, the year-specific treatment effects increases between 2011 and 2013, but remain relatively constant from 2013 to 2017. In our subsequent analysis, we mainly focus on the risky share, adopt the specification that includes household-level characteristics, and report both the pooled post-treatment effect β_2 and the mean of year-specific estimates $\bar{\beta}_{post}$.

29. The mean and standard deviation of state death rate during the H1N1 pandemic are 1.16 and 0.56, respectively. So the percentage change in the H1N1 death rate due to a 1 standard deviation above the mean is 48.28% (0.56/1.16*100%). Applying this percentage change to the elasticity coefficient β_2, we get the percentage decrease in risky share, equal to 14.48% (0.3*48.28%).

30. Assuming these two estimates are independent, the t statistic is computed as $t = \frac{\hat{\beta}_{pool} - \bar{\beta}_{post}}{\sqrt{SE(\hat{\beta}_{pool})^2 + SE(\bar{\beta}_{post})^2}} = \frac{-0.206-(-0.299)}{\sqrt{0.058^2+0.070^2}} \approx 1.023$, which is well below the threshold of 2.

Our finding that the year-specific treatment effect is non-decreasing over time may initially seem at odds with rational expectation theory, but it may align more closely with rational inattention theory (RIT) (Sims (2003), Miao, Wu, and Young (2022), and Maćkowiak, Matějka, and Wiederholt (2023). According to RIT, economic agents have limited attention and must rationally ignore lower-priority items. During the pandemic, agents naturally shifted their focus to preventing illness and caring for friends and family who were infected, temporarily sidelining financial portfolios. As vaccines and treatments became available over time, these agents would begin to reallocate their attention from medical concerns to financial considerations. Consequently, economic agents would actively adjust their portfolios, resulting in a year-specific treatment effect that appears non-decreasing over time.

Our definition of risky assets includes both IRA and non-IRA stocks. Although IRA stocks are often managed by institutions, individuals can adjust the portfolio annually. Individuals can also hold multiple IRA accounts, provided that the total annual contribution to all IRAs does not exceed the contribution limits.[31] To address the concern that the observed decrease in risky asset share may reflect institutional trading rather than household decisions, we exclude IRA and private annuity investments and construct alternative measures.[32] The results are reported in Appendix Table B10. The reduction in the risky asset share remains robust compared to our main results. Unlike the null results with IRA stocks included, stock market participation is now significantly reduced. This is because adjusting investments in non-IRA stocks is more flexible than in IRA stocks, which are subject to withdrawal restrictions.[33] Nonetheless, we retain our original definition of risky assets, including IRA stocks, consistent with common practice in household finance literature (e.g.,

31. There are different kinds of IRAs, each with different contribution limits (https://www.iraresources.com/ira-contribution-limits).

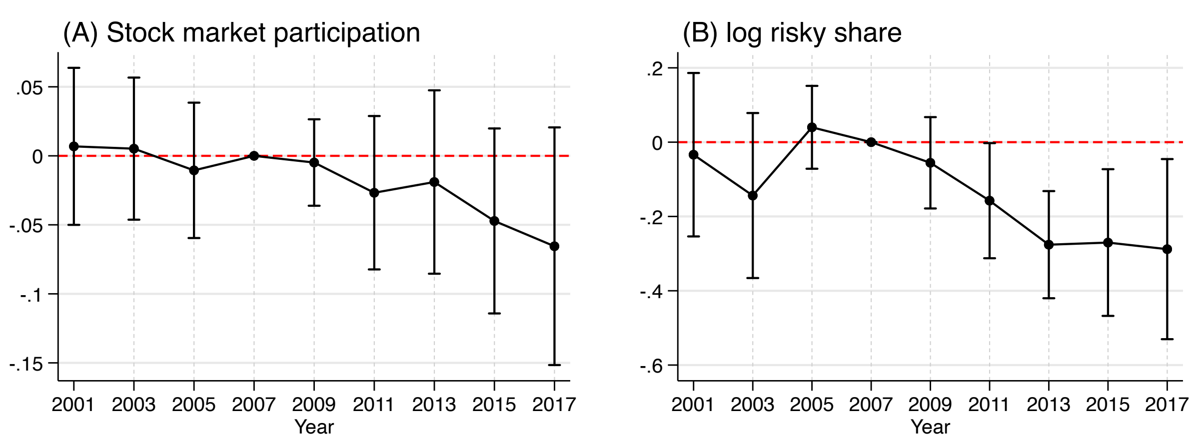
32. The PSID does not distinguish between personally traded IRA stocks and institutionally traded ones, nor does it differentiate between IRAs and private annuities.

33. Withdrawing from an IRA before age 59.5 will incur an early withdrawal penalty in addition to taxes on the withdrawal (https://www.investopedia.com/articles/personal-finance/121115/how-ira-works-after-retirement.asp).

Guvenen (2007), Brunnermeier and Nagel (2008), Malmendier and Nagel (2011), Atella, Brunetti, and Maestas (2012), Palia, Qi, and Wu (2014)).

4.2 Event Study

We now estimate a more flexible functional form specified in Eq. (3). 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. These results justify the parallel trend assumption imposed in the DID analysis.[34] In addition, no immediate change associated with the H1N1 death rate is observed in the extensive margin or the intensive margin of stock holdings in 2009. However, after the pandemic, the risk share in states with higher mortality rates decreases more than in those with lower mortality rates. The estimated coefficient of β_t is about -0.16 in 2011, then reduces to -0.28 in 2013 and stabilizes at around -0.29 by 2017, suggesting that the exposure effect exhibits a two-year lag and persists at least until 2017.



Notes: The figure plots the estimates of β_t in Eq. (3). Appendix Table B9 reports the estimates of β_t. The regression controls fixed-effects of family, state, year, state-specific year trend, and household features. The capped spikes indicate 95 percent confidence intervals, with robust standard errors clustered at the state level. (*Data source: PSID, waves 2001–2017, in odd-numbered years.*)

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

34. One important implication from Callaway, Goodman-Bacon, and Sant'Anna (2024) is that we can not distinguish between the standard and strong parallel trends assumption using the conventional tests of pre-trends. This limitation arises because only untreated potential outcomes are observed in pre-treatment periods, making it impossible to test the additional component of the strong parallel trends assumption, which involves treated potential outcomes. Consequently, as they suggest, the results of pre-trend tests should be interpreted with caution.

4.3 Robustness Checks

We now examine the robustness of our findings on risky share in Table B11.

Add pre-pandemic state-level controls. — In column (1), we control for the interactions of observed pre-pandemic macroeconomic characteristics and year dummies. 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, deposits per capita in FDIC-insured financial institutions, and population density. These macroeconomic indicators capture factors that may affect individuals' financial risk-taking and influence household portfolio choices (Malmendier and Nagel 2011). Moreover, as discussed in Section 2.2.3, the H1N1 death rates can be correlated with the macroeconomic situation and business cycles.[35] We find that the exposure effect of the H1N1 pandemic barely changes.

Although the outbreak of the novel H1N1 virus was unforeseen, states with fewer medical resources generally experienced higher death rates during the pandemic (Section 2.2.3). In column (2), we further add the interactions of pre-pandemic medical controls (hospital beds, active physicians, physicians in patient care, and registered nurses per 100,000 people) and year dummies. The result confirms that the effect of H1N1 intensity on risky share remains robust.

Examine whether the financial crisis confounds the results. — One may be concerned that the exposure effect of the 2009 H1N1 pandemic on household stock holdings is confounded by the 2007–2008 financial crisis, which profoundly impacted the US economy.[36] If the H1N1 intensity in a region is correlated with the local severity of the financial crisis, our estimation would be biased.

To assess the local impact of the 2007–2008 financial crisis, we compute the state-level change rate of GDP per capita, unemployment rate, and housing price index in 2008 compared with 2006

35. Adda (2016) shows that epidemics spread faster during economic booms because people are more likely to travel, which increases interpersonal connection and hence accelerates the spread of infectious diseases.

36. Among others, see Agarwal and Varshneya (2022) and Piskorski and Seru (2021) for more discussion of the financial crisis.

following this equation:

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

where $x_{j,t}$ represents 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 A8. 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. As presented in Appendix Table B13, the correlation between H1N1 intensity and changes in these economic indicators is negligible and statistically insignificant.

We further incorporate the local impact of the 2007–2008 financial crisis in our main regression to examine whether the exposure effect of the H1N1 pandemic on the risky share persists. 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 prices during the financial crisis. Column (3) of Appendix Table B11 presents the results. The elasticity of the risky share concerning the H1N1 death rate barely changes and remains statistically significant after we control for these interactions.

Other robustness checks. — More robustness checks are presented in Appendix C. Specifically, we examine whether migration decisions are correlated with the H1N1 death rate and exclude migrants from the sample, focusing only on households that have always lived in the same state. We also drop outlier states with unusually high H1N1 death rates, South Dakota and New Mexico. To address potential timing issues, we exclude the 2009 sample and re-estimate the key coefficients. We use an alternative measure of H1N1 intensity based on HHS-level case rates and conduct placebo tests using seasonal flu case rates from 2009 to 2010 to assess the specificity of the results to the H1N1 pandemic. Furthermore, we discretize the H1N1 death rates into two or three groups based on death rate distributions. A falsification test using pre-2009 data helps verify the parallel trends assumption. Lastly, we examine the exposure effect of the H1N1 pandemic on illiquid assets, including business ownership and non-business assets like housing and cars. The findings from these robustness checks confirm that households in states with higher H1N1 death rates significantly reduce their risky asset holdings and the ownership of incorporated businesses in the post-pandemic periods, consistent with our main results.

4.4 Decomposition of the Risky Share

As our measure of the risky share is the proportion of liquid assets invested in risky assets, a decrease in the risky share can stem from a reduction in risky assets, an augmentation in liquid assets, or a combination of both factors. Therefore, we now explore what factors drive the decline in risky shares in Table 3.

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 percent increase in the H1N1 death rate. While not statistically significant, this reduction 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 percent increase in the H1N1 death rate, representing 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) but do not find any significant correlation between the H1N1 death rate and changes in liquid assets.[37]

37. In 2009, an increase of 1 percent 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 percent 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.

Table 3. 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)	-10.255	14.826*	4.571	3.400
	(7.151)	(8.348)	(11.044)	(2.961)
After × log(H1N1 death rate)	-10.229	11.313	1.084	-2.494***
	(9.560)	(7.596)	(9.547)	(0.723)
$\bar{\beta}_{post}$	-14.769	25.841***	11.072	-2.517***
	(12.679)	(7.540)	(12.236)	(0.686)
Average of the outcome variable	68.016	67.151	67.151	2.781
Family, state, year FEs	✓	✓	✓	✓
State-specific time trend	✓	✓	✓	✓
Family controls	✓	✓	✓	✓
State-level controls 2008 × year dummies	✓	✓	✓	✓
Observations	25,940	25,940	25,940	22,690
Adj. R^2	0.462	0.306	0.511	0.043

Notes: Liquid assets are the sum of risky and risk-free assets. See the description in Section 4.1 for the list of family controls and state-level controls. $\bar{\beta}_{post}$ is the average of estimated dynamic treatment effects in 2011, 2013, 2015, and 2017 (i.e., β_{2011}, β_{2013}, β_{2015}, and β_{2017}). Standard errors are clustered at the state level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: PSID, waves 2001–2017, in odd-numbered years.*)

Since observed changes in risky shares in response to H1N1 intensity could be attributable to fluctuations in asset returns rather than household portfolio rebalancing decisions, we directly examine the net purchases of risky assets, where a positive (negative) value indicates net buying (selling) of stocks. Column (4) shows that when the H1N1 death rate increases by 1 percent, the net amount put in household stocks decreases significantly by about 37.74 dollars.

Only about 20% of our PSID sample report non-zero net purchases or sales of stocks. This result may be due to inertia (Brunnermeier and Nagel 2008) since people do not rebalance portfolios frequently.[38] In Appendix D, we adopt the approach of Calvet, Campbell, and Sodini (2009) and decompose the change in the risky share into a passive change caused by the returns of assets and an active change arising from household decisions to rebalance their portfolios. The decomposition analysis collaborates with our previous finding that the decline in the risky share can be attributed

38. Another explanation can be measurement errors, as people may not be able to remember their stock trading behavior precisely over the past few years. In addition, people tend to incorporate information consistent with their previous portfolio choices, resulting in sticky portfolios across time (Kuhnen, Rudorf, and Weber 2017).

mainly to an active rebalancing strategy.

5 Why Did the H1N1 Pandemic Lead People to Hold a Lower Risky Share?

5.1 Increased Risk Aversion

From April 2009 to November 2009, the percentage of Americans worrying about getting H1N1 rose steadily from about 30% to as high as 80% (Appendix Figure A13). This suggests that with the outbreak of the swine flu, public concern about infection increased progressively. Since the H1N1 pandemic is caused by a new and unexpected virus, posing significant health risks, such concerns could potentially alter individuals' risk attitudes, which could explain why people reallocate their portfolios toward less risky assets in response to the pandemic.[39]

The PSID provides risk-tolerance information only in its 1996 wave, making it unsuitable for examining changes in risk attitudes in response to the 2009 H1N1 pandemic. Instead, we utilize data from the 2009–2018 NFCS, which includes risk attitude scores across multiple waves, to analyze this mechanism. Our regression model is specified as follows:

$$Y_{ijt} = \theta After_t \times H1N1_j + \alpha_t + \alpha_j + \gamma \boldsymbol{X_{ijt}} + \epsilon_{ijt}. \tag{5}$$

Here, Y_{ijt} denotes the risk attitudes towards financial investments of individual i who lives in state j in year t. Specifically, Y equals 1 if the individual is unwilling to take any financial risks (risk-averse) and 0 otherwise. $After_t$ is a binary indicator, assigned a value of 0 for 2009 and 1 for subsequent years. $H1N1_j$ is log of H1N1 death rate in state j during the pandemic. Since the NFCS data set is pooled cross-sectional, we only control for the fixed effects for years (α_t) and states (α_j), not individual fixed effects. Additionally, because the NFCS was first collected in 2009, coinciding with the H1N1 outbreak, we cannot control for the state-specific pre-trends ($t\alpha_j$) in the regression. The vector $\boldsymbol{X_{ijt}}$ encompasses household controls and the interactions between the

39. Previous literature has highlighted a systematic relationship between risk attitude and portfolio choice. Specifically, financial risk attitude is a significant positive predictor of the willingness to invest in stocks (Keller and Siegrist 2006) and plays a crucial role in determining portfolio choices (Frijns, Koellen, and Lehnert 2008).

pre-pandemic state-level characteristics and year dummies, aligning with the covariates in column (2) of Appendix Table B11. Standard errors ϵ_{ijt} are clustered at the state level.

We also perform an event study analysis, allowing the exposure effect of the pandemic (θ) to vary over time, with 2009 as the base year. We estimate the following equation for this analysis:

$$Y_{ijt} = \theta_t H1N1_j + \alpha_t + \alpha_j + \gamma \boldsymbol{X_{ijt}} + \epsilon_{ijt}. \tag{6}$$

In addition, we examine whether there exist heterogeneous effects of the pandemic on risk aversion by estimating the following equation:

$$Y_{ijt} = \theta_g After \times H1N1_s + \alpha_t + \alpha_j + \gamma \boldsymbol{X_{ijt}} + \epsilon_{ijt}, \tag{7}$$

where θ_g is the exposure effect of the H1N1 intensity on risk attitude for group g.

The related results are presented in Table 4. Column (1) shows the baseline results based on Eq. (5) while column (2) presents the event study results estimated through Eq. (6). Using both specifications, we find a significant increase in the probability of being risk-averse in response to the H1N1 pandemic in the post-pandemic periods.

Table 4. The Effect of H1N1 Pandemic on Risk Attitude

Outcome variable	Risk aversion (binary variable)			
	(1)	(2)	(3)	(4)
After × log(H1N1 death rate)	0.017*			
	(0.008)			
θ_{2012}		0.010		
		(0.008)		
θ_{2015}		0.022**		
		(0.010)		
θ_{2018}		0.017*		
		(0.009)		
Male×After × log(H1N1 death rate)			0.007	
			(0.014)	
Female×After × log(H1N1 death rate)			0.026*	
			(0.016)	
Unmarried×After × log(H1N1 death rate)				0.029*
				(0.015)
Married×After × log(H1N1 death rate)				0.006
				(0.011)
Average of the outcome variable	0.170	0.170	0.170	0.170
Family FE, State FE, Year FE	✓	✓	✓	✓
Family and state-level controls	✓	✓	✓	✓
Observations	90,276	90,276	90,276	90,276
Adj.R^2	0.067	0.067	0.053	0.068

Notes: Risk aversion is a binary variable set to 1 when the risk score is 1, indicating the respondent's unwillingness to take any risks in financial investments. The covariates include family-level controls and interactions between pre-pandemic state-level controls and year dummies. Column (1) shows the result based on Eq. (5). Column (2) shows the results using Eq. (6). Columns (3) and (4) report the results using Eq. (7). Standard errors are clustered at the state level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: NFCS, waves 2009, 2012, 2015 and 2018.*)

We now move to investigate whether the H1N1 pandemic differentially affects people's risk attitude by running the regression (7). As presented in columns (3) and (4) in Table 4, we find that women and unmarried individuals become more risk-averse after the H1N1 pandemic. By contrast, the willingness of men and married individuals to take financial risks remains largely unaffected. In addition, our heterogeneity analysis in Section 6 offers further evidence, showing that households with female or unmarried heads significantly reduce their risky asset share after the pandemic, compared to households with male or married heads. This implies that women and unmarried individuals may be more susceptible to the pandemic's impact, leading to a shift in their risk preferences and subsequent adjustment in their risky asset allocation.

Additionally, we provide evidence related to health consumption to corroborate the risk-averse mechanism. In each wave, the PSID collects the consumption information of the preceding year.[40] As shown in Appendix Figure A14, while the overall household consumption remains unaffected by the H1N1 death rate, both health consumption and the proportion of total consumption allocated to health increase, especially in 2014 and 2016.[41] Delving deeper, we examine different components of health consumption in Appendix Figure A15. Interestingly, although the share of expenditures on doctors, hospitals/nursing homes, and prescriptions do not show significant changes, the share of health insurance premiums paid by families notably *rises* with the intensity of H1N1, in line with our earlier findings from the NFCS data that people become more risk-averse in response to the pandemic.

5.2 Background Risks

Factors such as health, demographics, and labor market outcomes may affect household portfolio decisions are often refereed as background risks. In Appendix Table B16, we examine whether the H1N1 pandemic affects people's health, marital status, having young children or not, earnings, and employment status. We observe no significant changes in most outcomes in response to the H1N1 intensity. However, we do find an increase in the probability of having children under 18 and the probability of being unemployed after the pandemic. In particular, the finding on the unemployment rate coincides with our earlier finding in Appendix C that the H1N1 pandemic *reduces* the likelihood of being an incorporation business owner, suggesting that the H1N1 pandemic discourage risk-taking.

We then formally control for these possible channels in Eq. (1). If any of these channels are essential, we would observe a significant change in the exposure effect of the H1N1 pandemic. However, Appendix Table B17 shows that the estimate of the exposure effects ($\bar{\beta}_{post}$) remains -0.3

40. For instance, the 2017 wave documents the consumption of 2016.

41. The PSID documents a range of domains of consumption. However, several domains were not recorded prior to 2005. To approximate the total consumption of a household, we use the method proposed by Attanasio and Pistaferri (2014). The details about this approach can be found in Appendix F.

significantly in columns (2)–(6), as in the baseline case (column (1)). Therefore, we conclude that these channels do not provide a satisfactory explanation for why the H1N1 pandemic affects the intensive margin of stock holdings.

Several studies suggest that households increase their risky assets when their overall family wealth increases (e.g., Calvet, Campbell, and Sodini 2009). It is plausible that the H1N1 pandemic might diminish family wealth, resulting in a corresponding decrease in the risky share. Our findings indicate an insignificant change in family wealth associated with the H1N1 death rate (the first two columns of Appendix Table B18). Even after we add the control of total wealth in Eq. (1), we do not observe a notable shift in the exposure effect (the last two columns in Appendix Table B18). Hence, changes in family wealth are unlikely to be a driver of the result that risky shares decline with H1N1 intensity.[42]

5.3 Discussions on Other Possible Mechanisms

In addition to a shift in risk preference, other changes in subjective perceptions may also explain the impact of a pandemic on household portfolio choices. For example, investors with longer subjective life horizons tend to increase their equity investments on both the extensive and intensive margin (Spaenjers and Spira 2015).[43] Due to data limitations in the PSID, we cannot directly test whether the H1N1 pandemic reduced subjective life expectancy. However, we believe that subjective life expectancy is less likely to change, as self-reported health status does not significantly vary with H1N1 intensity (see column (1) in Appendix Table B16).

Another possible mechanism is a change in the degree of impatience. When people have a large discount rate, they tend to put more weights on current consumption rather than future utility. Those exposed to higher H1N1 intensity might become less patient, placing more importance on

42. Similarly, Brunnermeier and Nagel (2008) and Chiappori and Paiella (2011) suggest a lack of significant correlation between risky investment shares and family wealth.

43. This could be because stocks are considered safer in the long run (Campbell and Viceira 2002) or because the optimal stock exposure can rise with a longer investment horizon (Benartzi and Thaler 1995).

the present and devaluing the future. This could lead to a reduction in risky investments and an increase in immediate consumption. However, our data shows no significant changes in total household consumption in response to the H1N1 pandemic (Panel A of Appendix Figure A14), suggesting little change in the degree of impatience among individuals.

6 Heterogeneity Analysis

This section presents evidence of how the H1N1 pandemic affects the risky share of various groups differently. Our findings show that such heterogeneous effects are related to risk attitude and income volatility. In particular, household heads who are more risk-averse tend to reduce their risky shares, which supporting our proposed risk attitude mechanism in Section 5.1. In addition, household heads experiencing greater income volatility or job instability are more likely to decreases their share of stock holdings after the pandemic.

We estimate Eq. (4) and visualize the estimates of β_{1g} and β_{2g} in Figures 5 and 6. Since the estimates of β_{1g}s, which capture the *contemporary* change (i.e., the change in 2009) in the risky share for group g, are close to zero and statistically insignificant, we focus on the estimates of β_{2g}s, i.e., the *post-pandemic* change of the risky share.

6.1 Heterogeneous Effects by Groups

We first illustrate the heterogeneous patterns regarding demographic features, job features, and risk attitude in Figure 5.

Gender. — On average, when the H1N1 death rate increases by 1 percent, families with male heads reduce the risky share by 0.26%, while families with female heads reduce the risky share by 0.55% (Panel A of Figure 5). The portfolio choice of households with female heads is more affected by the pandemic, and the difference is statistically significant, with a p-value of 0.064.[44]

44. This result may have several possible explanations. First, women are more risk-averse than men (Borghans et al. 2009) and are less willing to take financial risks (Charness and Gneezy 2012). Second, female heads are more

Marital status. — We divide our sample into single and married subsamples according to the marital status of the household head in 2007. Panel B shows that the exposure effect of the pandemic for households whose heads are single is nearly twice that for those whose heads are married. Moreover, the difference is statistically significant, with a p-value of 0.016. Intuitively, a married individual carries less risk than a single one because a couple can share risk. As a result, households with married heads are less sensitive to the pandemic.

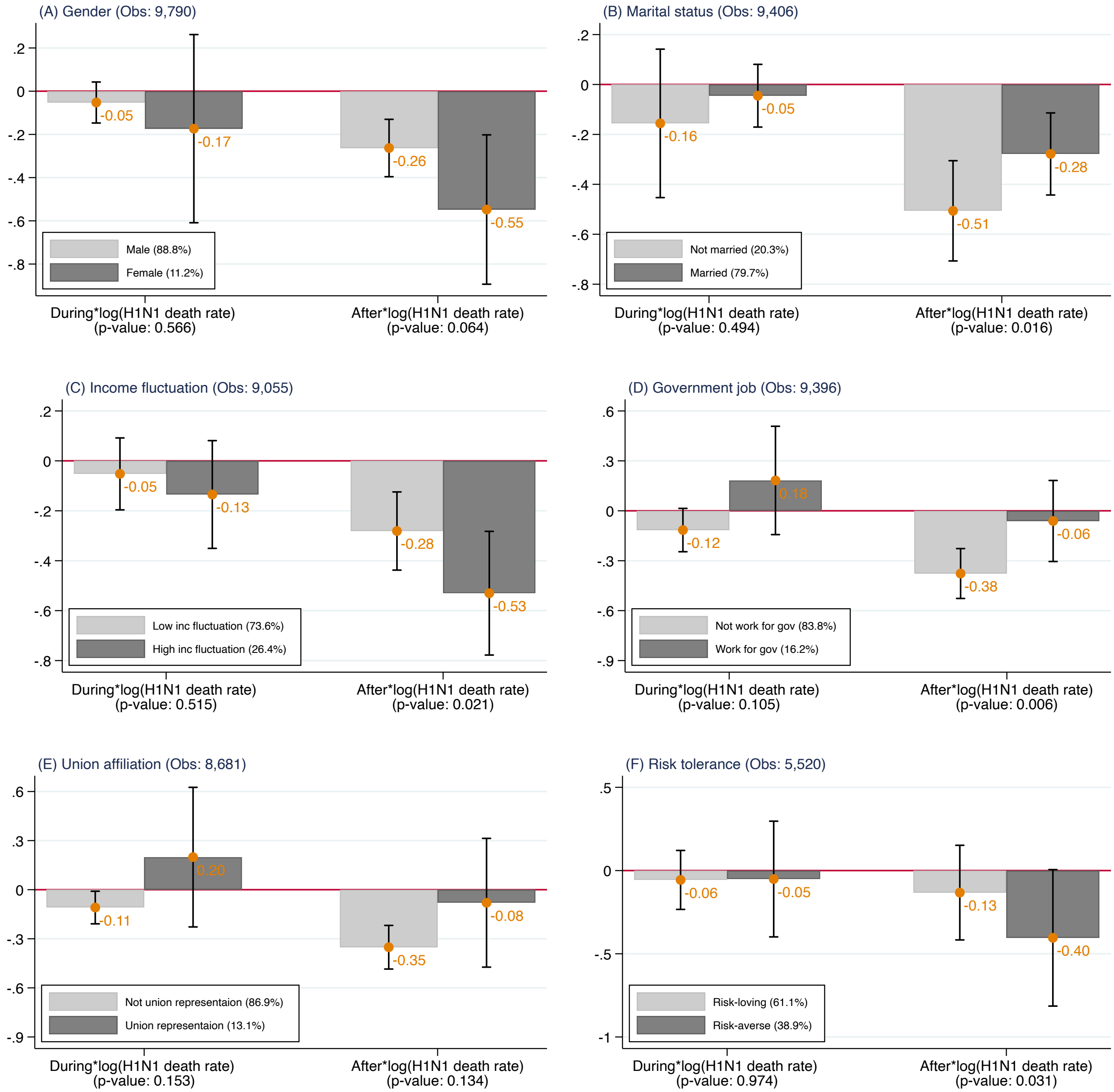
Income fluctuation. — To address the endogeneity concern that income stability can be affected by H1N1 intensity, we use the fluctuation of income before the pandemic as a proxy.[45] Panel C illustrates that families with more volatile income exhibit a risky share elasticity of -0.53, nearly double that of families with less volatile income, which stands at -0.28. The difference between these two groups is statistically significant at the 5% level.

Government job and Union contract. — Government jobs in PSID are defined as working for the federal, state, or local government or in a public school system. Compared to private sector jobs, government jobs are more stable (Kopelman and Rosen 2016). Panel D shows that government workers' risky shares barely changed after the pandemic. By contrast, the risky shares of private sector workers decrease by 0.38% if the H1N1 mortality rate increases by 1%.

Panel E shows that union workers, who are more protected from layoffs and with better health benefits, behave like government workers. When the H1N1 death rate increases by 1 percent, workers represented by a union do not change risky shares. By contrast, people not represented by a union decrease their risky shares by 0.35%.

likely to be single than male heads. In our sample, nearly all female heads are single (approximately 99.4%), whereas only one-fifth of the male heads share this marital status (marital status is elicited from the PSID 2007 wave to address endogeneity concerns). It is difficult for single to share risks with others, so they tend to reduce their risky shares more than married couples. Third, females earn more volatile income than males. Based on our calculation, the standard deviation of female income is 0.31, significantly larger than that of male income, 0.27.

45. Specifically, we run a Mincer regression of income on age, age square, educational attainment, race, gender, and state fixed effects, using data prior to the pandemic (i.e., data in 2001, 2003, 2005, and 2007) and obtain residuals. Then, we calculate the standard deviation of the residual for each household before the pandemic. A family has *high-income (low-income)* fluctuation if the standard deviation of the Mincer residual is *above (below)* the average level.



Notes: This figure plots the estimates of β_{1g} and β_{2g} in Eq. (4). 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. (*Data source: PSID, waves 2001–2017, in odd-numbered years.*)

Figure 5. Heterogeneous Effects of the 2009 H1N1 Pandemic

Risk aversion. — The 1996 PSID elicits respondents' risk preferences using income-related gambling questions. When answering these questions, respondents have to choose between a job with a certain income and one with a risky income. In the latter option, they face equal chances of either doubling their income or having it decreased by a specific percentage. The detailed gamble questions are described in Appendix E. Based on their responses, respondents are sorted into six risk-tolerance categories, with Category 1 (Category 6) being the most (least) risk-averse.[46] 20.8 percent of the respondents decline all the risky job options, while 7.7 percent accept all of them (Appendix Table B14).

To exploit the risk tolerance measure, we limit our subsequent heterogeneity analysis to household heads who answered the gamble questions in 1996, leaving us a subsample comprising 56.4 percent of our initial sample. Respondents in Category 1 or 2 are categorized as *risk-averse* and the others are *risk-loving*. We estimate Eq. (4) and plot the estimated effect of the pandemic in Panel F of Figure 5. When the H1N1 death rate increases by 1 percent, the risk-averse respondents decrease their risky shares by 0.33%, while the risk-loving respondents show no significant adjustment in their risky shares. Such a difference in the exposure effect is statistically significant, with a p-value of 0.046. This result implies that risk-averse respondents exhibit greater sensitivity to the H1N1 pandemic exposure.

In Appendix G, we present additional analyses examining heterogeneity by race, education, and entrepreneurship. However, these analyses do not reveal significant heterogeneous effects across these groups.

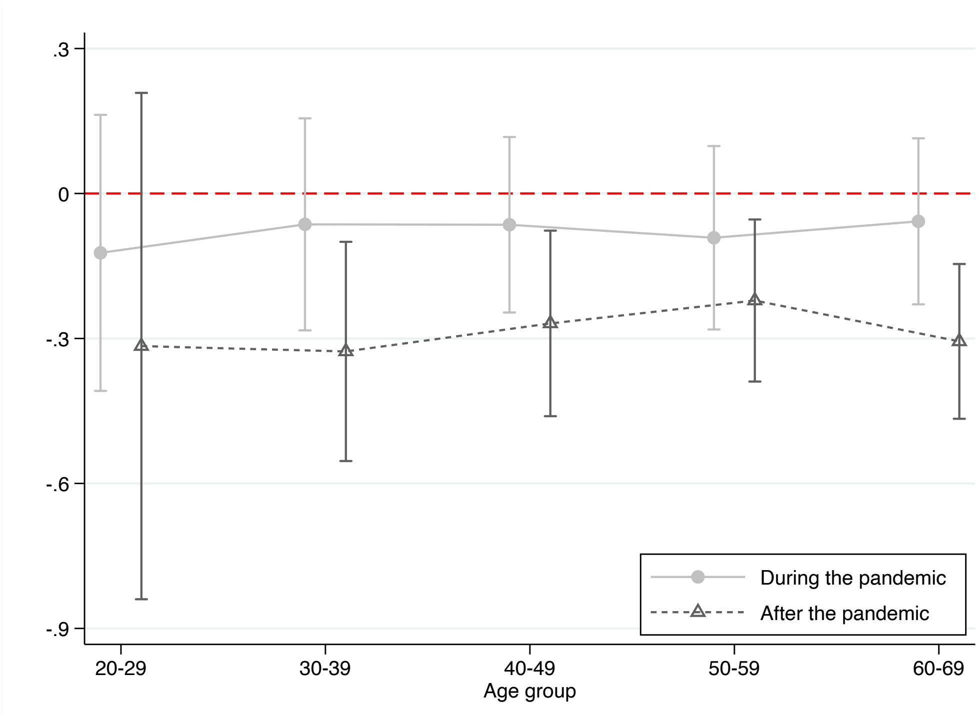
6.2 Life-cycle Effects of the H1N1 Pandemic

We now examine how the H1N1 pandemic might differentially impact the risky share among various age groups. We estimate Eq. (4) to measure the age-specific elasticity during and after the pandemic. The index g in Eq. (4) now represents an age group (i.e., 20–29, 30–39, 40–49, 50–59,

46. It is important to acknowledge that risk preferences may shift due to events like natural catastrophes (Hanaoka, Shigeoka, and Watanabe 2018) and macroeconomic shocks (Dohmen, Lehmann, and Pignatti 2016). Ideally, an index reflecting risk tolerance just prior to the H1N1 pandemic outbreak would be used. However, the PSID contains risk attitudes only in the 1996 wave. Hence, we assume the risk-tolerance categories recorded in the 1996 PSID remain constant until the 2009 pandemic.

or 60–69).

As shown in Figure 6, while the life-cycle profile of H1N1 effect *during* the pandemic is insignificant and relatively flat, the *post*-pandemic counterpart delivers a hump-shaped pattern. However, the differences across age groups lack statistical significance. Numerically, the risky share elasticity decreases from around 0.45 at ages 20–29, to 0.2 at ages 50–59, and then slightly increases to 0.3 at ages 60–69. Intuitively, young investors (aged 20–29) who have just entered the labor market have very little buffer savings and hence may bear higher background risk (Guiso and Sodini 2013). The pandemic outbreak may lead to large uncertainty in their jobs and income. As a result, they would reduce their risky investment more than others. For older investors (aged 60–69), they are approaching retirement and should compensate for the anticipated decline in labor income by reducing risky share (Fagereng, Gottlieb, and Guiso 2017). Consequently, these people tend to decrease more risky share when they are exposed to higher H1N1 intensity.



Notes: This figure plots the age profiles of the H1N1-intensity elasticities for the risky share by estimating Eq. (4). Capped spikes represent the 95 percent confidence interval for each coefficient. The estimated coefficients for each age group are reported in Appendix Table B15. (*Data source: PSID, waves 2001–2017, in odd-numbered years.*)

Figure 6. Life-cycle Impact of the 2009 H1N1 Pandemic on Risky Share

Overall, our findings indicate that the impact of H1N1 on risky investments is more significant for households with female, single, and young heads. Additionally, this effect is more pronounced for household heads experiencing greater income fluctuations, those who are non-government employees and not represented by unions, and heads who exhibit higher levels of risk aversion. These results suggest that households facing greater income volatility and displaying higher risk aversion are more susceptible to the adverse effects of the pandemic.

7 Conclusion

To examine the potential impact of pandemic exposure on household portfolio allocation in subsequent years, we utilize the exogenous nature of the 2009 H1N1 pandemic and the corresponding variation in death rates across states. By analyzing nine waves of the PSID from 2001 to 2017 through a DID framework, we have made several significant observations.

Firstly, we find that exposure to the pandemic influences the composition of household portfolios in terms of risky assets (intensive margin), but it does not affect stock market participation (extensive margin). Specifically, we do not observe any changes in stock holdings during the 2009 pandemic. However, conditioning on the stock market participation, we observe that a 1 percent increase in the H1N1 death rate leads to a subsequent 0.3 percent reduction in the proportion of risky assets held in portfolios. This exposure effect remains stable over time and *persists* until the end of our sample period. Our decomposition analysis further reveals that this exposure effect primarily arises from *adjustments in risky assets* rather than liquid assets.

To further validate these findings, we utilize multiple waves of the National Financial Capability Study (NFCS), which confirm that higher H1N1 intensity decreases people's willingness to take financial investment risks following the pandemic. Notably, neither family wealth nor a range of factors related to health, demographic characteristics, and labor market outcomes can fully account for the relationship between the H1N1 pandemic and portfolio choices.

Additionally, we find that the impact of the pandemic varies across different household characteristics. Specifically, the effect of the pandemic is more pronounced for households with female or single heads, those experiencing greater income volatility, individuals not employed in government positions, those not represented by a union, and those with a risk-averse attitude. Furthermore, the age profiles of the exposure effect exhibit a hump-shaped pattern, indicating that middle-aged individuals exhibit a relatively smaller adjustment in their portfolios compared to other age groups. These findings collectively suggest that individuals who are more risk-averse and face greater income volatility and job instability are more susceptible to the effects of the pandemic.

Our study indicates that the recollection of significant events, like a pandemic, can profoundly influence our risk attitudes. This finding holds crucial implications for the finance industry. Financial institutions may need to reassess their risk management strategies, recognizing that exposure to a pandemic can lead to changes in investment behavior and market dynamics. Additionally, understanding these behavioral shifts can aid policymakers and regulators in designing interventions that stabilize markets during periods of heightened uncertainty. Furthermore, although our analysis centers on household portfolio decisions, future research should investigate whether these shifts in risk attitudes could also surface in other domains.

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Online Appendix

Online publication Only.

Appendix A contains more figures.

Appendix B contains more tables.

Appendix C introduces additional robustness checks

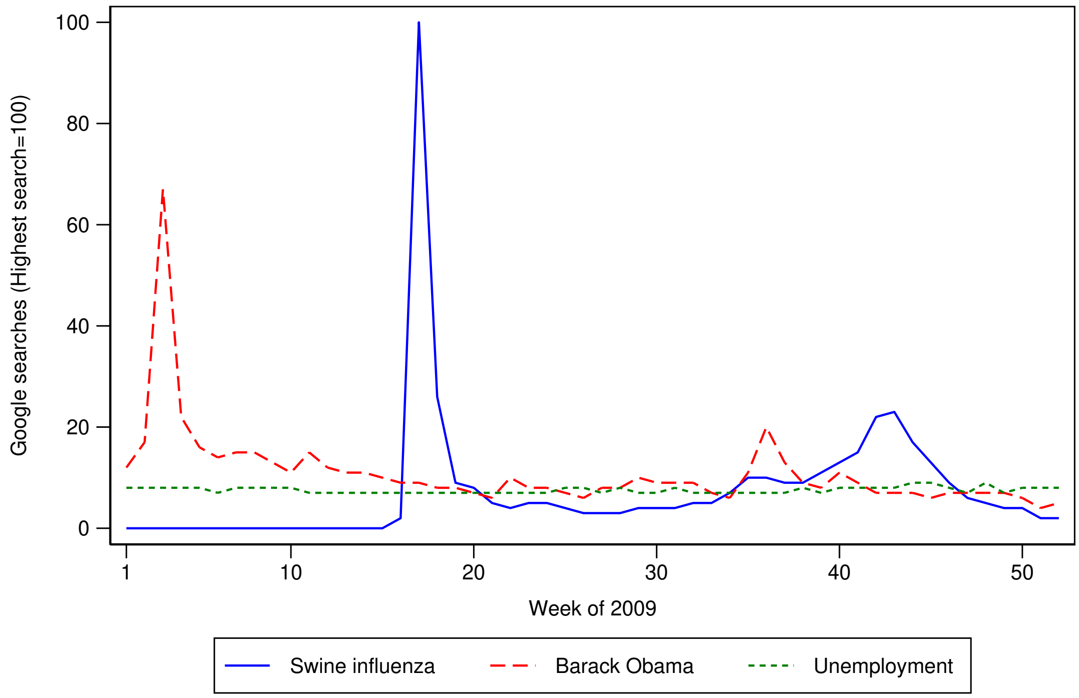
Appendix D introduces the decomposition analysis.

Appendix E introduces risk-tolerance measures in the 1996 PSID.

Appendix F describes the imputation of total consumption.

Appendix G conducts additional heterogeneous analysis.

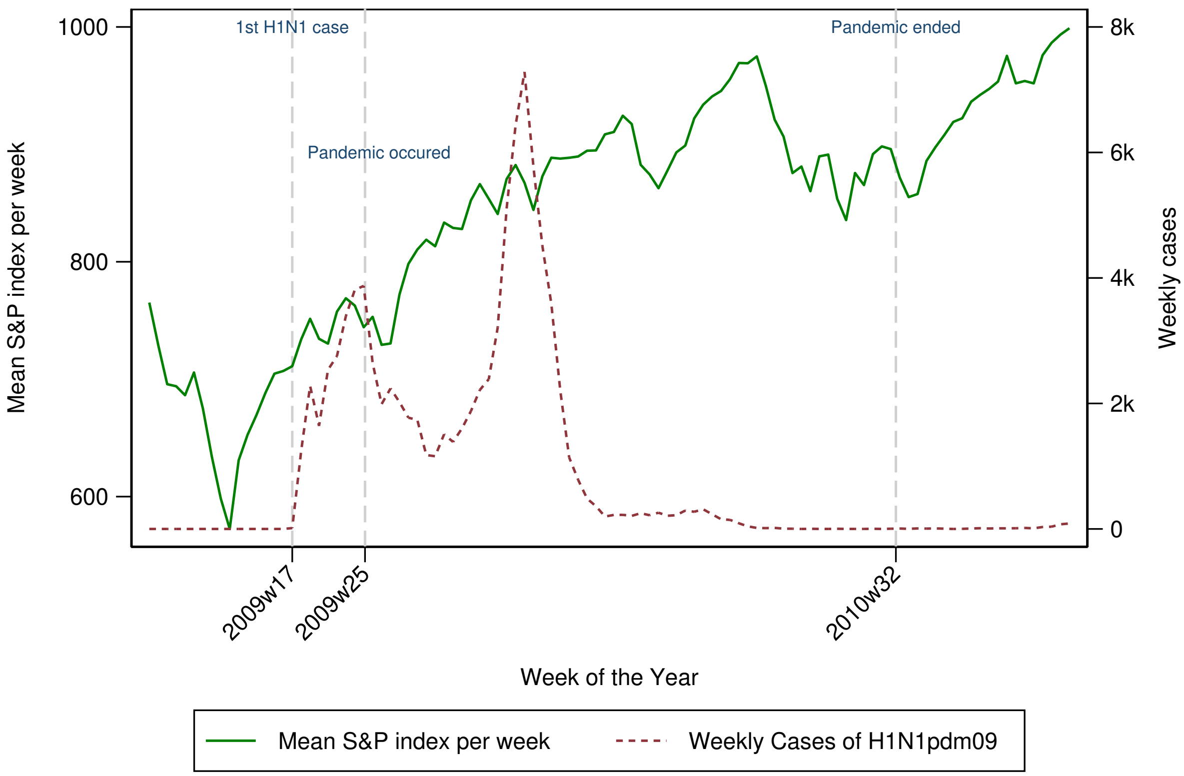
A Figures



Notes: The number on the y axis shows how much interest there is in a particular search term for the given region and time, compared to the highest point. A value of 100 means it is the highest level of popularity. A value of 0 means there is not enough data. (Data source: Authors' analysis of data on Google searches for the words "Swine influenza," "Barack Obama," and "Unemployment" from GoogleTrends (https://trends.google.com/trends/).)

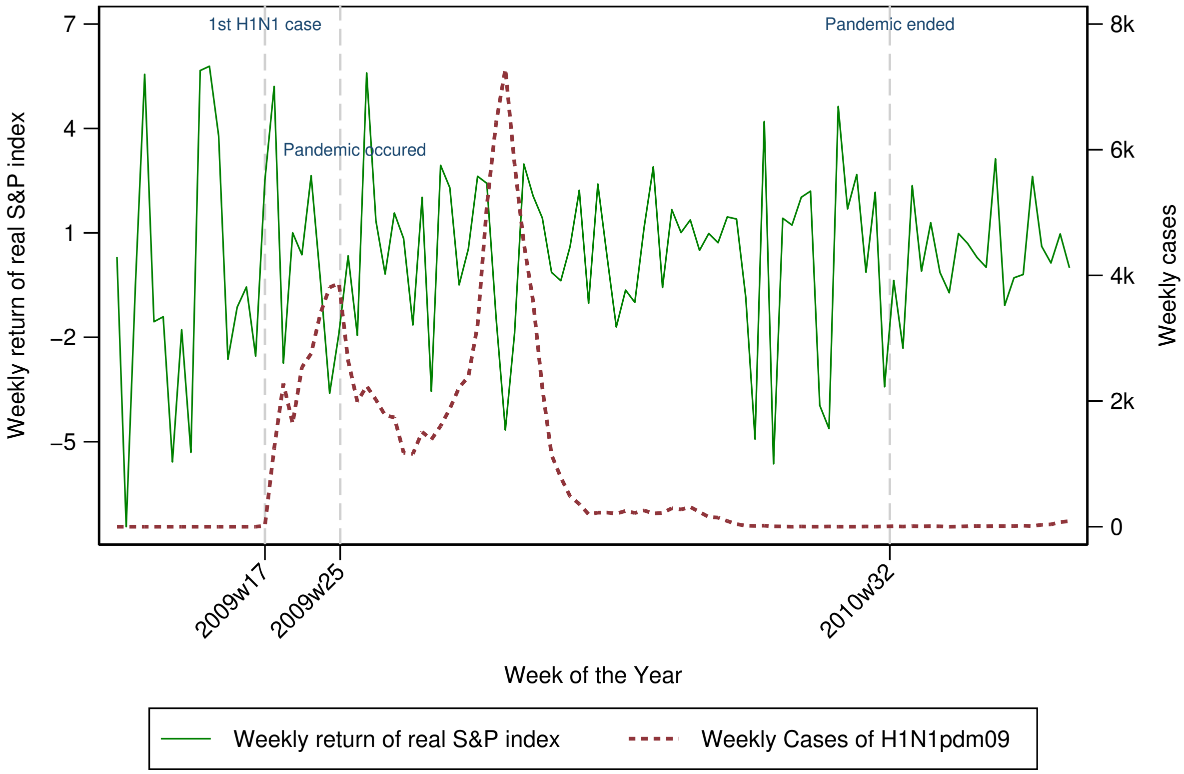
Figure A1. Google Searches for Swine Flu and Focus in the US in 2009

In Appendix Figures A2–A4, we plot the time trends of the weekly H1N1 cases during the pandemic years (2009–2010) versus different weekly stock market indicators in the same period. Generally, these stock market indexes do not exhibit a consistent or contrasting trend with the confirmed cases of H1N1. 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 (Appendix Figures A2 and A3). However, the relationship between these indicators and confirmed cases appears weak. Specifically, the correlation coefficients between the weekly H1N1 cases and the weekly real S&P price 500 price index, the weekly return of the real S&P price 500 index, and weekly stock market volatility are –0.1, –0.05, and –0.09, respectively. Moreover, extending the analysis to a longer period (2009-2017), the lagged values of weekly H1N1 cases do not Granger-cause the weekly stock market indicators, and vice versa (refer to Appendix Table B2 for details). This further indicates that the H1N1 pandemic cannot affect or predict stock market performances.



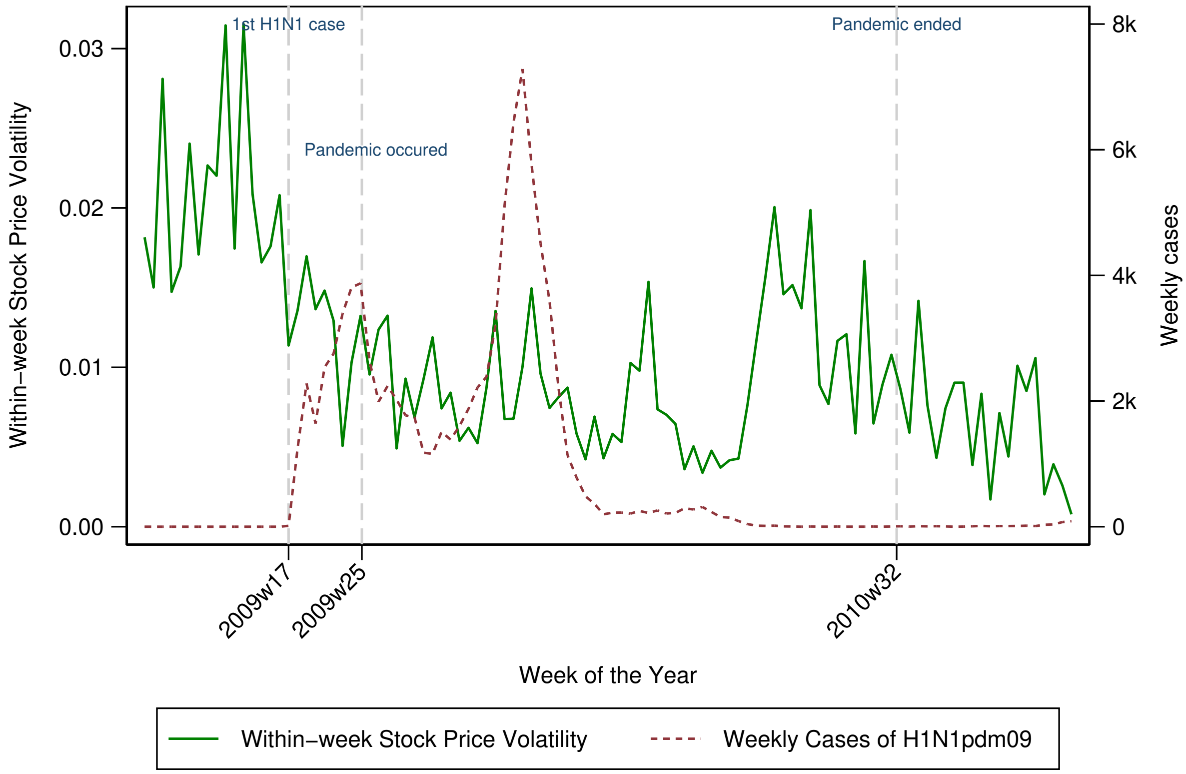
Notes: The weekly lab-confirmed cases of H1N1 flu are obtained from the World Health Organization (WHO) Collaborating Laboratories. The weekly S&P index is the average of the real S&P price index between Monday and Friday in a week. The S&P 500 Index is computed by adjusting the nominal S&P 500 Index 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 the Center for Research in Security Prices (CRSP).

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



Notes: The weekly lab-confirmed cases of H1N1 flu are obtained from the 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 and the nominal S&P 500 Index, is sourced from CRSP.

Figure A3. Time Trends of Weekly Real Return for S&P 500 Index



Notes: The weekly lab-confirmed cases of H1N1 flu are obtained from the 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 A4. Time Trends of Within-week Stock Price Volatility

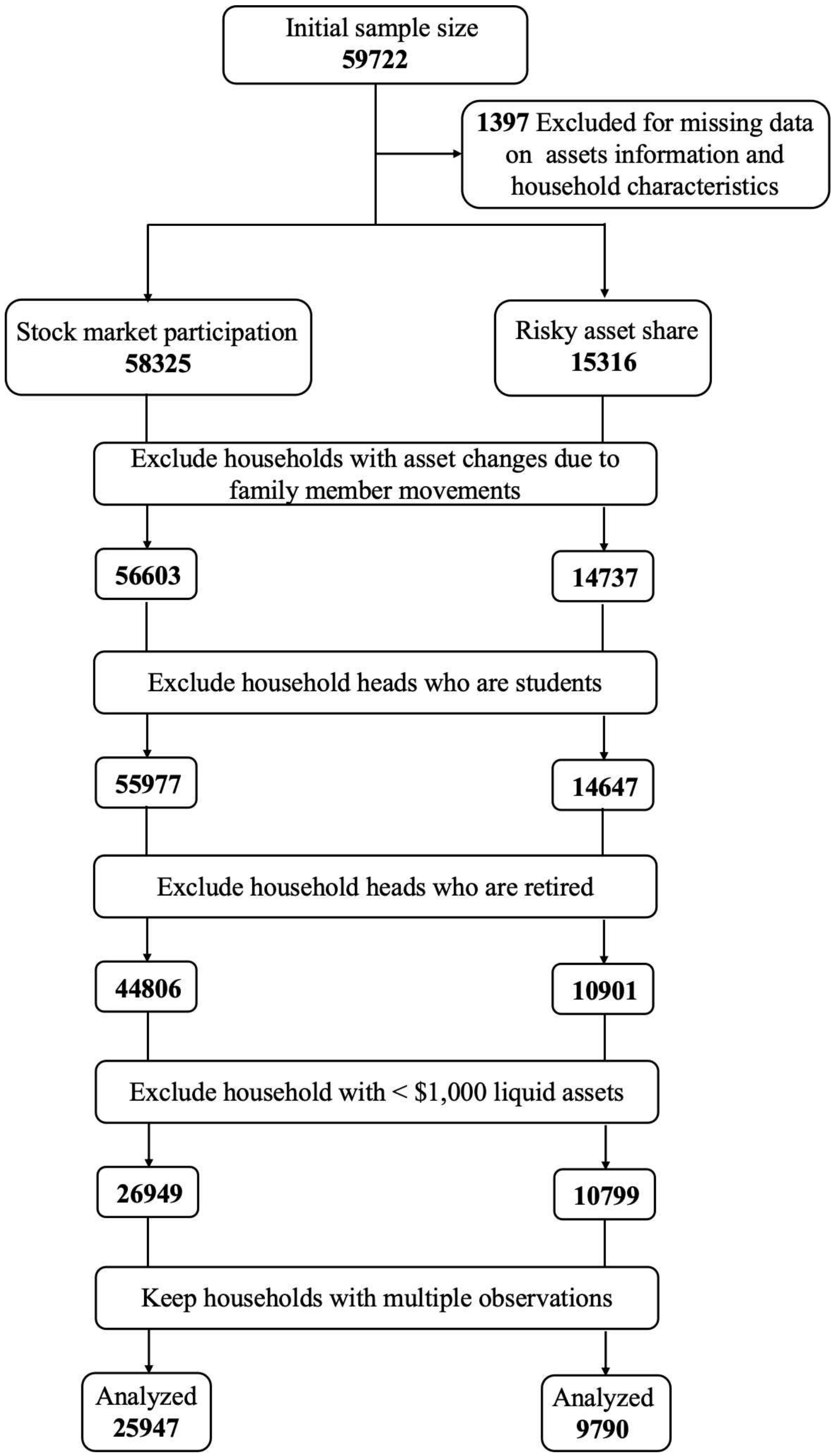
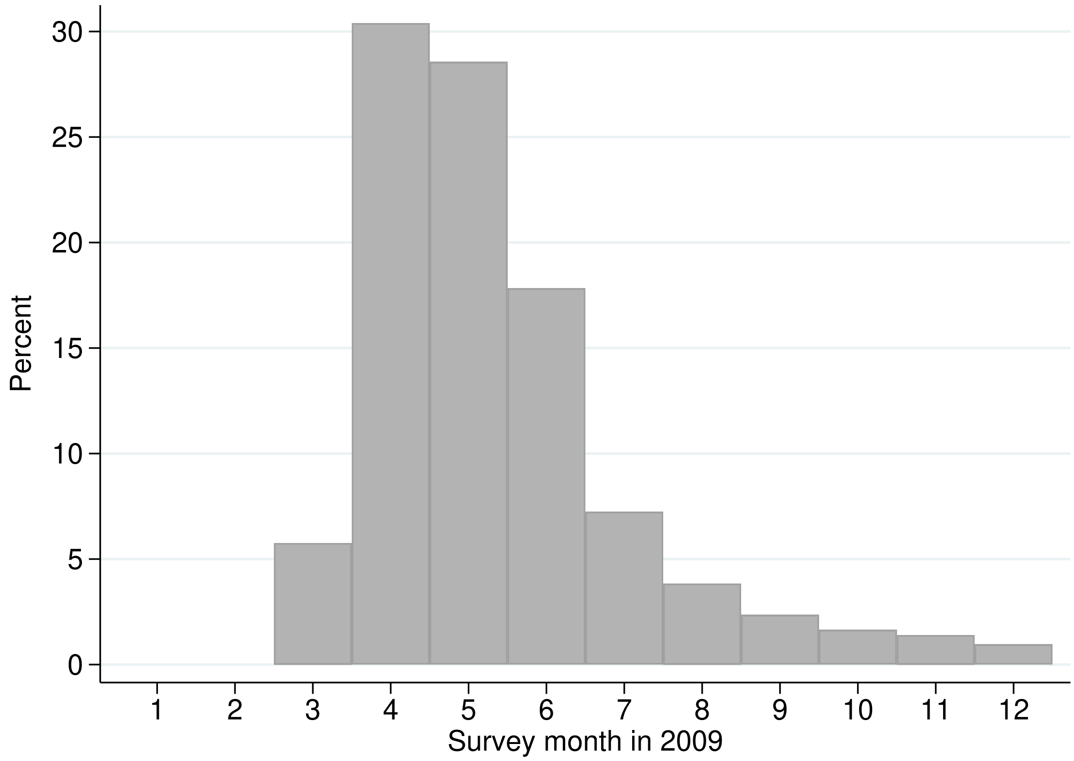
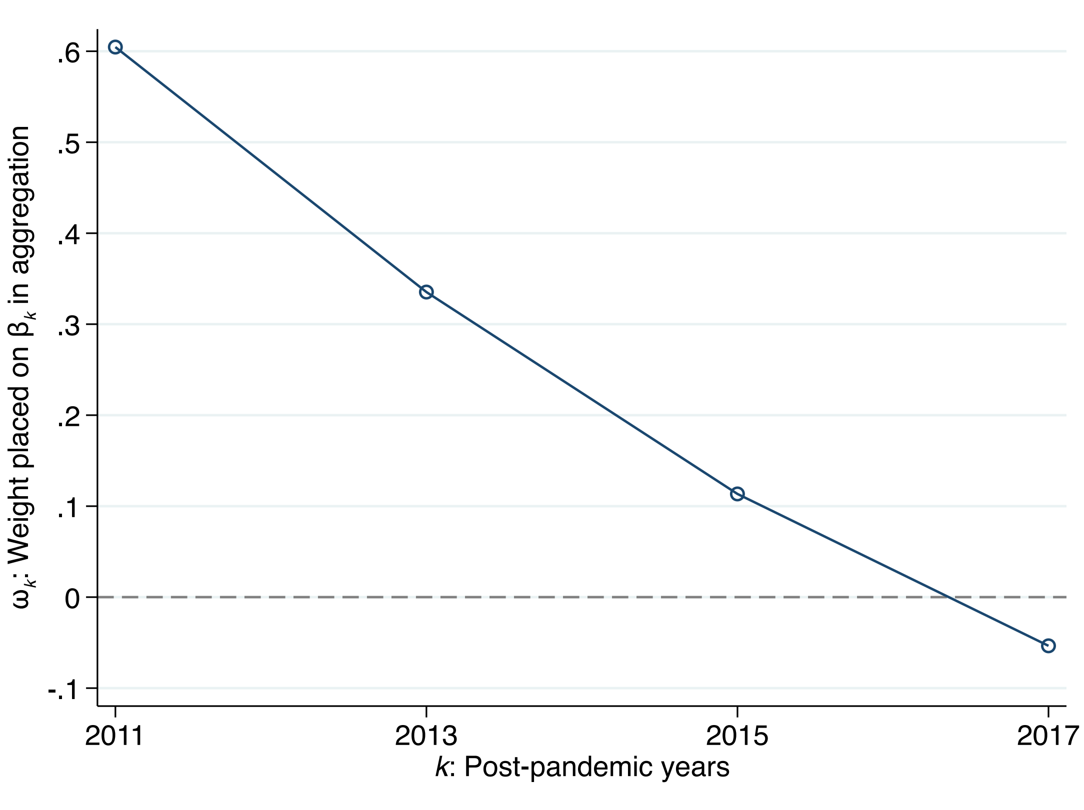


Figure A5. Consort Figure on Sample Size



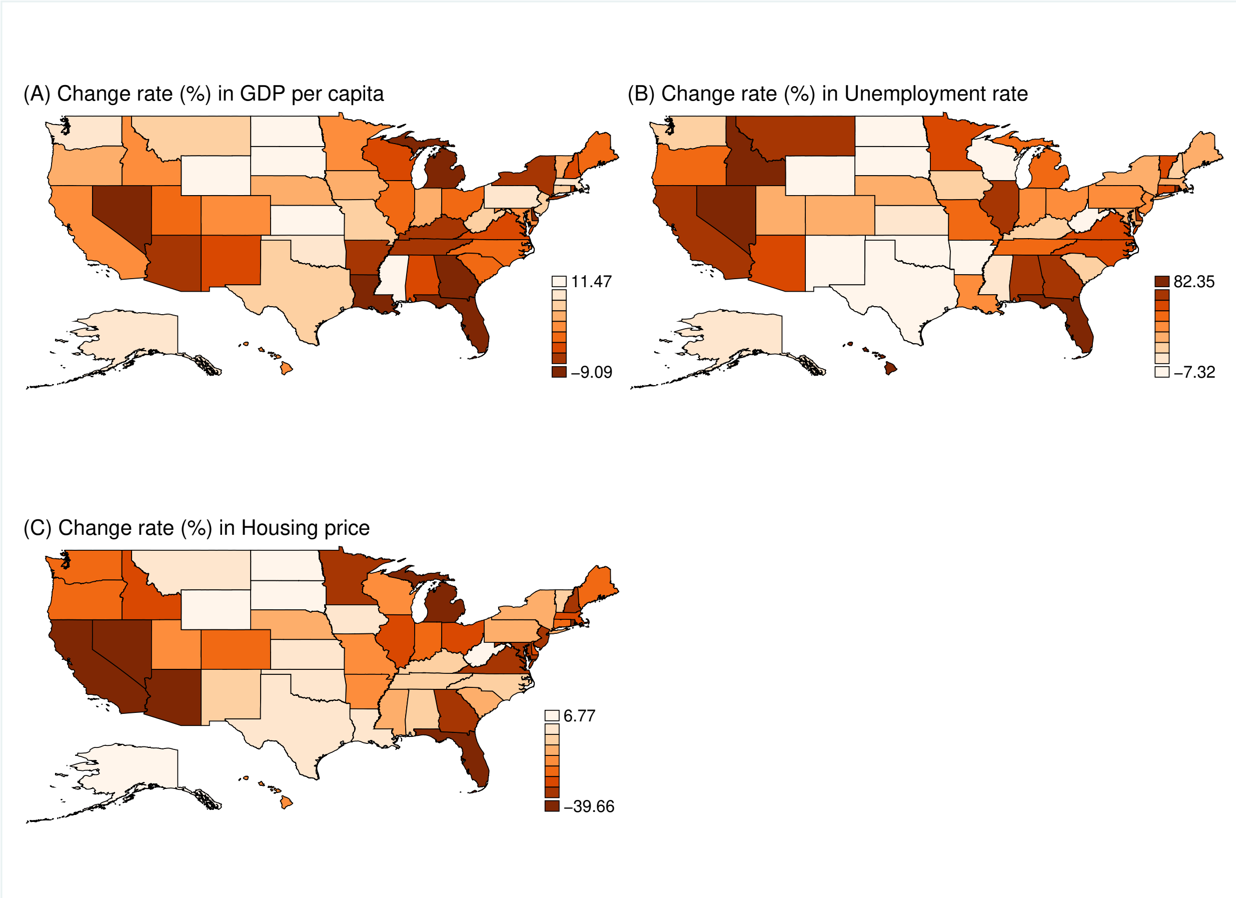
Data source: PSID wave 2009.

Figure A6. Distribution of Survey Month in 2009



Notes: This figure is plotted following Downey (2024)'s approach.

Figure A7. Weights Placed on Underlying Dynamic Treatment Effects in Aggregation



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 B4 for the data source of GDP per capita, unemployment rate, and housing price index.

Figure A8. Percentage Changes of GDP Per Capita, Unemployment Rate, and Housing Price, During the 2007-2008 Crisis

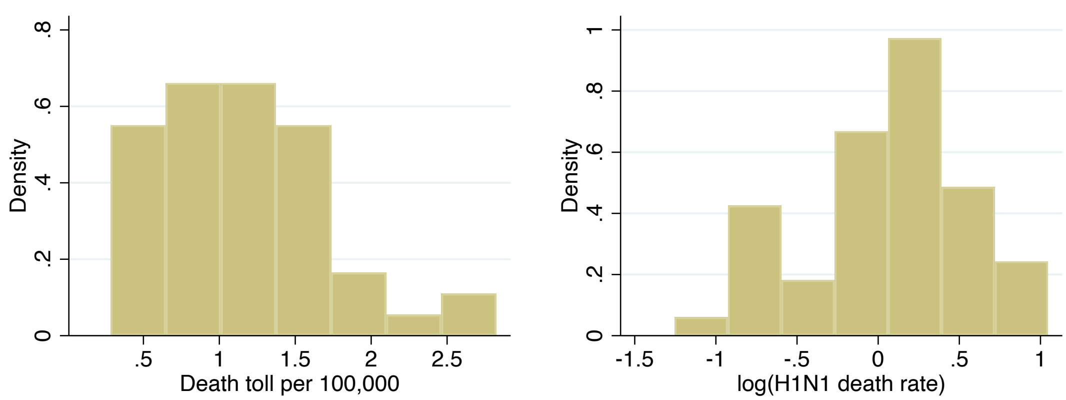


Figure A9. Distribution of H1N1 Death Rates

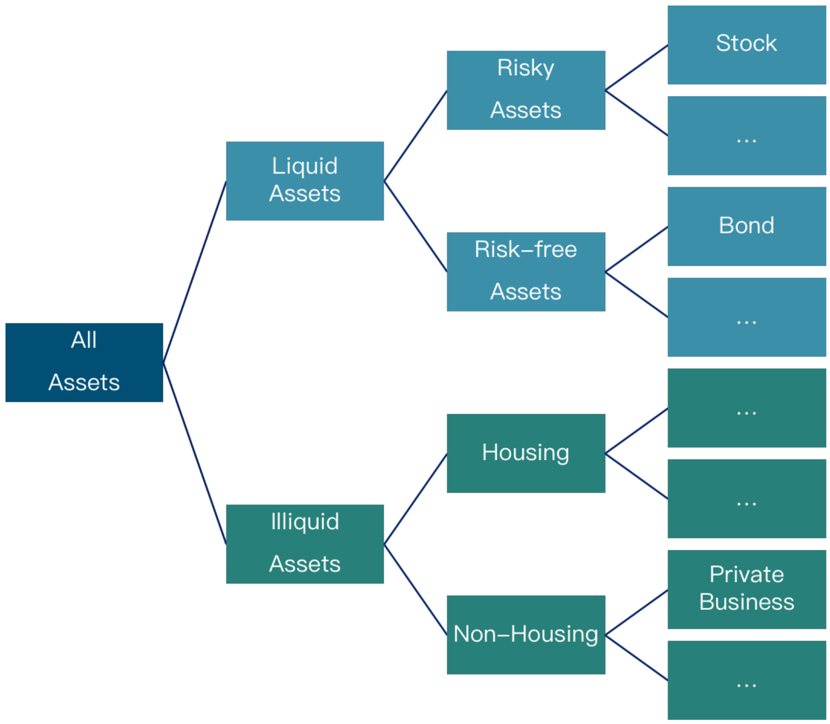
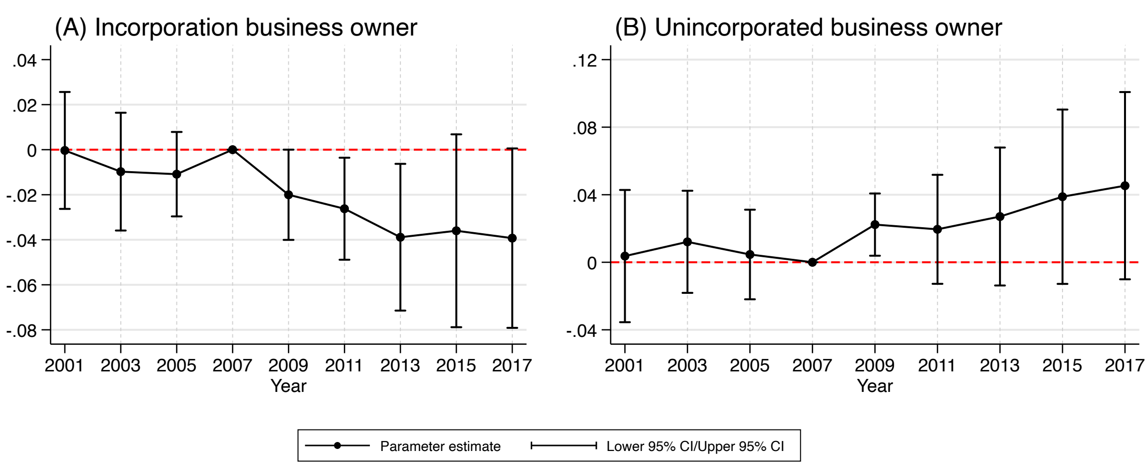
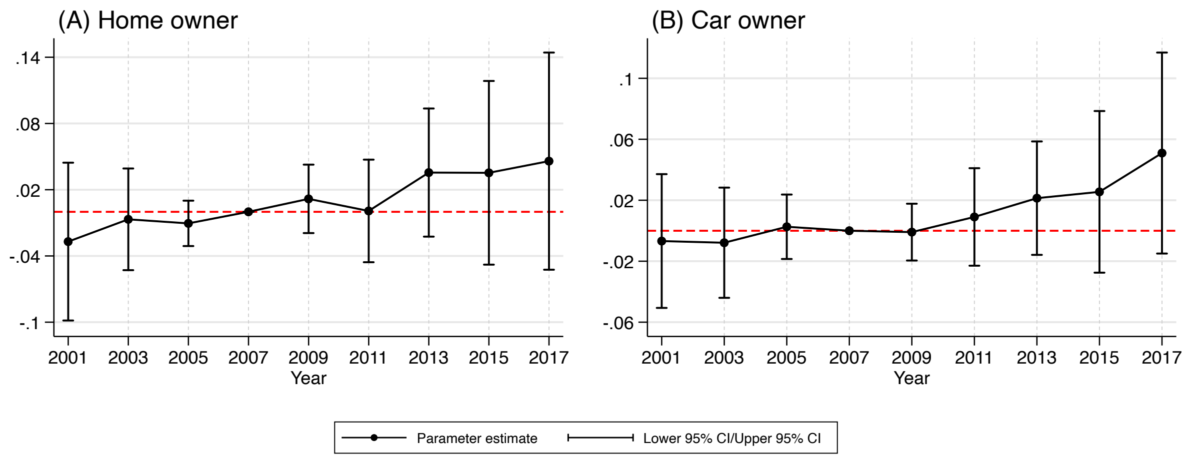


Figure A10. Portfolio Composition Chart



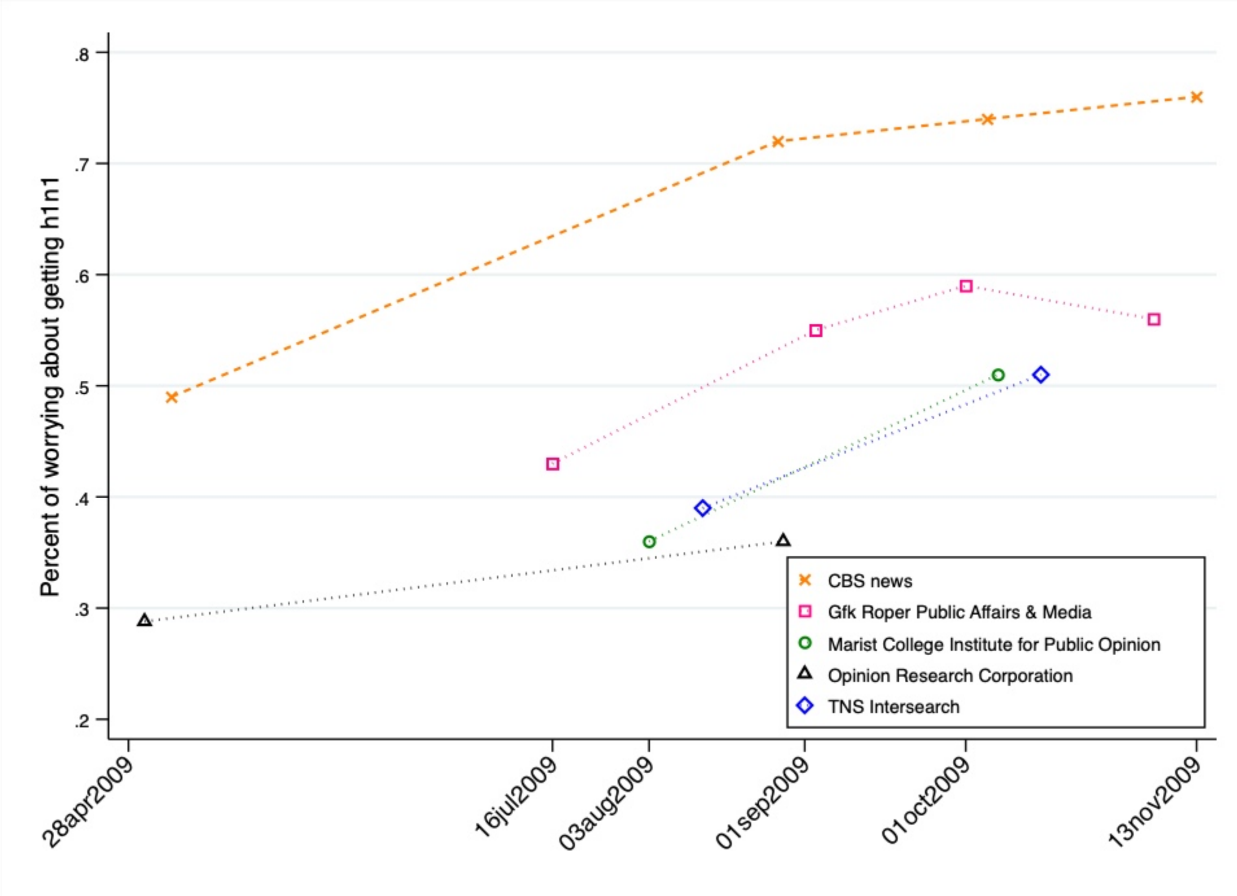
Notes: The figure plots the estimates of β_t in Eq. (3). The regression controls fixed-effects of family, state, year, and state-specific year trend, and household features, and the effect of the financial crisis. The effect of the financial crisis incorporated by interacting year dummies and the percentage change of a state-level economic indicator (i.e., GDP, unemployment rate, housing price index) during the financial crisis. The capped spikes indicate 95 percent confidence intervals, with robust standard errors clustered at the state level. (*Data sources: PSID, waves 2001–2017, in odd-numbered years.*)

Figure A11. Exposure Effect of the 2009 H1N1 Pandemic on Entrepreneurship



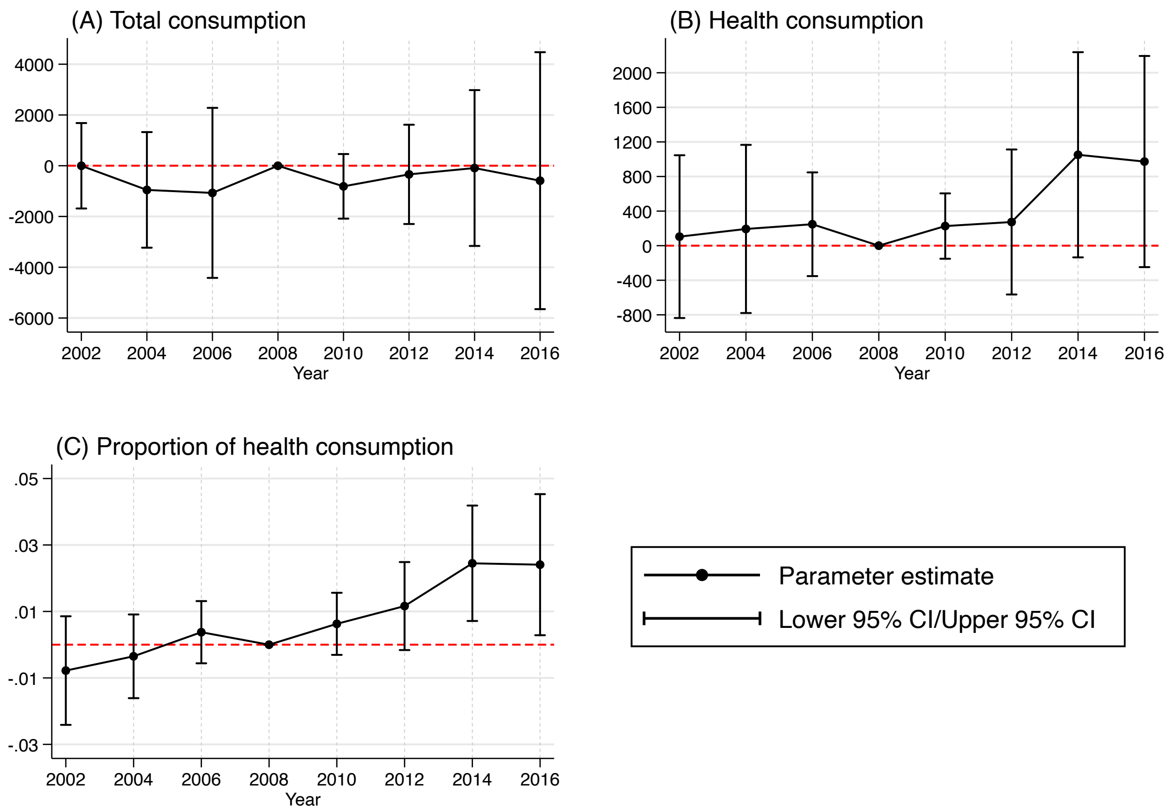
Notes: The figure plots the estimates of $\hat{\beta}_t$ in Eq. (3). The regression controls family fixed effects, state fixed effects, year fixed effects, state-specific year trend, household features, and the effect of the financial crisis. The effect of the financial crisis is captured by interacting year dummies and the percentage change of a state-level economic indicator (i.e., GDP, unemployment rate, housing price index) during the financial crisis. The capped spikes indicate 95 percent confidence intervals, with robust standard errors clustered at the state level. (*Data sources: PSID, waves 2001–2017, in odd-numbered years.*)

Figure A12. Exposure Effect of the 2009 H1N1 Pandemic on Home and Car Owners



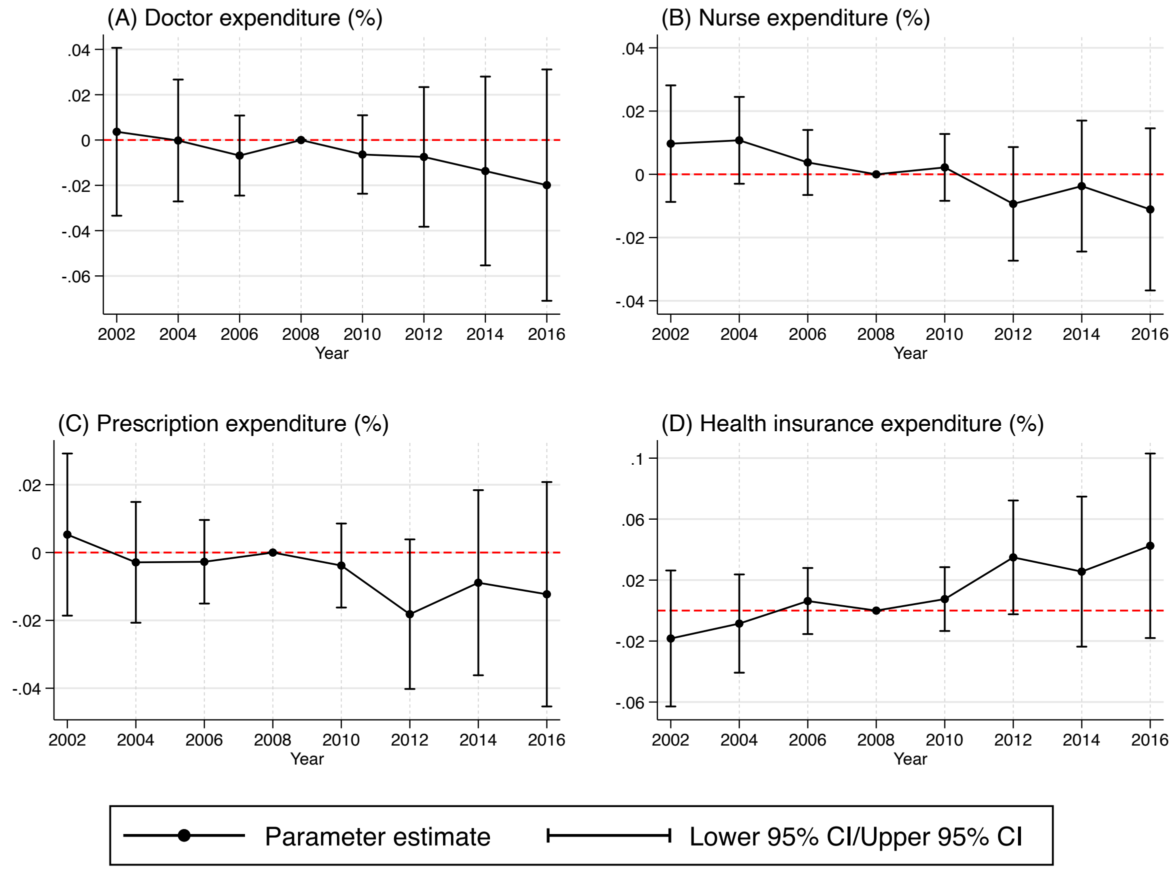
Notes: The figure plots the average percent of worrying about getting H1N1 in 2009 collected by different institutions and research centers, including CBS News, GfK Roper Public Affairs & Media, Marist College Institute for Public Opinion, Opinion Research Corporation, and TNS Intersearch. We collect the opinion data from Pew Research Center (www.pewresearch.org).

Figure A13. Public Concerns about H1N1 in 2009



Notes: The figure plots the estimates of $\hat{\beta}_t$ in Eq. (3). Total consumption is computed using Eq. (F.2). The details of the imputed total consumption are introduced in Appendix F. The proportion of health consumption refers to the share of total consumption allocated to health. All monetary variables are adjusted by the 2017 US dollar. The capped spikes indicate 95 percent confidence intervals, with robust standard errors clustered at the state level. (*Data sources: PSID, waves 2001–2017, in odd-numbered years.*)

Figure A14. Changes in Consumption in Response to the H1N1 Pandemic



Notes: The outcome variables of (A)–(D) are the share of health consumption allocated to doctors, hospitals/nursing home, prescriptions, and health insurance, respectively. The expenditure on doctors includes out-of-pocket payments for doctors, outpatient surgery, and dental bills. The expenditure on hospitals/nursing home refers to the out-of-pocket payment on hospital bills and nursing home. The expenditure on prescriptions includes out-of-pocket payments on prescriptions, in-home medical care, special facilities, and other services. The expenditure on health insurance refers to the total health insurance premiums, excluding those paid by someone outside the family. Standard errors are clustered at the state level and shown in parentheses. (*Data source: PSID, waves 2001–2017, in odd-numbered years.*)

Figure A15. Changes in Different Health Consumption in Response to the H1N1 Pandemic

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 in the US from April 2009 to August 2010. Death numbers for 50 states are collected from the website of `https://FluTrackers.com`.

Table B2. Results of Granger Causality Test

Dependent variable	Excluded variable	F statistics	p-value
	Panel A: Weekly S&P index price and Weekly H1N1 cases		
S&P index price (FD)	H1N1 cases (FD)	0.013	0.908
H1N1 cases (FD)	S&P index price (FD)	0.000	0.987
	Panel B: Weekly return of S&P index and Weekly H1N1 cases		
S&P index return (level)	H1N1 cases (FD)	0.320	0.572
H1N1 cases (FD)	S&P index return (level)	0.015	0.903
	Panel C: Within-week stock market volatility and Weekly H1N1 cases		
Within-week stock market volatility (level)	H1N1 cases (FD)	2.577	0.109
H1N1 cases (FD)	Within-week stock market volatility (level)	0.005	0.942

Notes: FD denotes "first-difference". The table reports the results of pairwise Granger causality tests for vector autoregressive (VAR) models using 2009-2017 weekly data with the *vargranger* command in Stata. The weekly H1N1 cases are collected from the CDC Fluview with the R command "*cdcfluview*". The weekly stock market price, return, and volatility are sourced from CRSP. The unit-root tests (Appendix Table B3) show that the first difference of S&P index price, the first difference 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, the selected lag order is 1. In Panels B and C, the selected lag order is 4. The null hypothesis is that the lagged values of the excluded variable do not Granger cause the dependent variable. The F statistics and p-values are used to test the null hypothesis, i.e., whether the coefficients of the lagged values are jointly equal to zero.

Table B3. 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 (level)	0.968	0.964
Weekly S&P index price (FD)	0.000	0.000
Weekly return for S&P index (level)	0.000	0.000
Within-week stock market volatility (level)	0.000	0.000
Weekly cases of H1N1 cases (level)	0.033	0.000
Weekly cases of H1N1 cases (FD)	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 B4. 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	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 B5. Balanced Checks for States

Variable	LDR states	HDR states	Diff
	(1)	(2)	(2)-(1)
A. Macroeconomic indicators			

Continued on next page

Table B5 – *Continued from previous page*

Variable	LDR states	HDR states	Diff
	(1)	(2)	(2)-(1)
GDP per capita (in chained 2012 million dollars)	0.05	0.05	-0.001
	(0.00)	(0.00)	(0.003)
Personal income per capita	45972.88	43318.59	-2654.288
	(1520.18)	(1042.61)	(1843.365)
Unemployment rate	5.40	5.14	-0.252
	(0.25)	(0.25)	(0.356)
Homeownership rate	0.70	0.70	0.006
	(0.01)	(0.01)	(0.013)
Housing price index	197.18	225.30	28.115***
	(4.13)	(8.45)	(9.407)
Bankruptcy cases per 100,000 people, filed by state	329.16	280.32	-48.838
	(28.98)	(21.42)	(36.036)
Assets per capita (in million dollars)	0.03	0.13	0.095*
	(0.01)	(0.05)	(0.053)
Deposits per capita (in million dollars)	0.02	0.04	0.014
	(0.00)	(0.01)	(0.010)
Population density	258.52	124.89	-133.632*
	(56.47)	(42.75)	(70.830)
B. Medical resources			
Hospital beds per 100,000 population	291.92	276.34	-15.575
	(15.40)	(17.61)	(23.392)
Active physicians per 100,000 population	2.85	2.45	-0.406**
	(0.13)	(0.08)	(0.153)
Physicians in patient care per 100,000 population	2.64	2.28	-0.354**
	(0.11)	(0.08)	(0.135)
Registered nurse per 100,000 population	911.63	838.98	-72.644*
	(25.33)	(34.34)	(42.674)
States	25	25	

Notes: This table reports the summary statistics by H1N1 death rates for state characteristics in 2008. States in which H1N1 death rates are below the median level of all states are low death-rate (LDR) states. States in which H1N1 death rates are above the median level of all states are HDR states. GDP per capita is in chained 2012 dollars. The 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 reflect 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 are 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 the 2017 dollars, adjusted by the CPI-U index. Standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data sources: see Appendix Table B4.*)

Table B6. Robustness Check for Balanced Checks for States: Discard the "Middle States"

Variable	LDR states	HDR states	Diff
	(1)	(2)	(2)-(1)
A. Macroeconomic indicators			
GDP per capita (in chained 2012 million dollars)	0.05	0.05	0.001
	(0.00)	(0.00)	(0.003)
Personal income per capita	46634.46	44184.16	-2450.306
	(1731.88)	(1394.87)	(2223.750)
Unemployment rate	5.39	5.09	-0.300
	(0.33)	(0.30)	(0.447)
Homeownership rate	0.70	0.70	-0.003
	(0.01)	(0.01)	(0.017)
Housing price index	197.89	237.40	39.513***
	(5.85)	(11.16)	(12.600)
Bankruptcy cases per 100,000 people, filed by state	341.08	263.94	-77.140*
	(30.32)	(26.27)	(40.115)
Assets per capita (in million dollars)	0.04	0.15	0.116
	(0.01)	(0.08)	(0.076)
Deposits per capita (in million dollars)	0.02	0.04	0.020
	(0.00)	(0.01)	(0.014)
Population density	288.31	70.95	-217.367**
	(75.04)	(27.09)	(79.777)
B. Medical resources			
Hospital beds per 100,000 population	296.30	258.71	-37.589
	(21.01)	(23.17)	(31.277)
Active physicians per 100,000 population	2.95	2.40	-0.544***
	(0.17)	(0.09)	(0.190)
Physicians in patient care per 100,000 population	2.71	2.25	-0.466***
	(0.14)	(0.08)	(0.165)
Registered nurse per 100,000 population	932.20	808.27	-123.930**
	(29.87)	(45.94)	(54.794)
States	17	17	

Notes: This table reports the summary statistics by H1N1 death rates for state characteristics in 2008. To categorize states based on their H1N1 death rates during the pandemic, we initially rank all 50 states in the US by their respective rates. After discarding the middle 16 states, we identify the 17 states with the lowest death rates as LDR states and the 17 states with the highest death rates as HDR states. Standard errors are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See Table B5 for details of the variables. (*Data sources: see Appendix Table B4.*)

Table B7. Robustness Check for Balanced Checks for States:
Discard the "Extreme States"

Variable	LDR states	HDR states	Diff
	(1)	(2)	(2)-(1)
A. Macroeconomic indicators			
GDP per capita (in chained 2012 million dollars)	0.05	0.05	-0.001
	(0.00)	(0.00)	(0.003)
Personal income per capita	46381.66	43507.09	-2874.565
	(1626.36)	(1110.48)	(1969.316)
Unemployment rate	5.32	5.28	-0.039
	(0.27)	(0.25)	(0.368)
Homeownership rate	0.70	0.70	0.007
	(0.01)	(0.01)	(0.014)
Housing price index	198.95	224.93	25.980**
	(4.15)	(9.19)	(10.088)
Bankruptcy cases per 100,000 people, filed by state	320.41	288.45	-31.960
	(30.75)	(22.50)	(38.102)
Assets per capita (in million dollars)	0.03	0.09	0.069*
	(0.00)	(0.04)	(0.039)
Deposits per capita (in million dollars)	0.02	0.04	0.012
	(0.00)	(0.01)	(0.010)
Population density	265.00	134.57	-130.427*
	(60.99)	(45.98)	(76.381)
B. Medical resources			
Hospital beds per 100,000 population	290.56	269.63	-20.926
	(16.71)	(15.54)	(22.823)
Active physicians per 100,000 population	2.86	2.46	-0.408**
	(0.14)	(0.09)	(0.166)
Physicians in patient care per 100,000 population	2.65	2.29	-0.360**
	(0.12)	(0.08)	(0.146)
Registered nurse per 100,000 population	903.68	831.80	-71.883*
	(26.92)	(30.95)	(41.020)
States	23	23	

Notes: This table reports the summary statistics by H1N1 death rates for state characteristics in 2008. To classify states according to their H1N1 mortality rates during the pandemic, we initially sort all 50 US states based on their respective rates. We exclude the two states with the lowest death rates and the two with the highest death rates. Of the remaining 46 states, those with H1N1 death rates below the median are termed as LDR states, while those above the median are termed as HDR states. Standard errors are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See Table B5 for details of the variables. (*Data sources: see Appendix Table B4.*)

Table B8. Summary Statistic of the NFCS Sample

Variable	N	Mean	Std.
Aged 18–24	90,276	0.10	0.30
Aged 25–34	90,276	0.18	0.38
Aged 35–44	90,276	0.17	0.38
Aged 45–54	90,276	0.19	0.39
Aged 55–64	90,276	0.18	0.38
Aged 65+	90,276	0.18	0.38
White	90,276	0.67	0.47
Female	90,276	0.51	0.50
Not complete high school	90,276	0.04	0.21
High school degree	90,276	0.30	0.46
Some college, college degree and above	90,276	0.65	0.48
Own risky assets	90,276	0.45	0.50
Risk score	90,276	4.77	2.73

Notes: The table reports summary statistics for the sample used in the mechanism analysis in Section 5. All summary statistics are weighted using the national-level weighting factor in the NFCS to ensure the representativeness of the U.S. population. (*Data source: NFCS, waves 2009, 2012, 2015, and 2018.*)

Table B9. Parallel Trends Test

	Stock market participation	log risky share
	(1)	(2)
β_{2001}	0.007	-0.034
	(0.028)	(0.109)
β_{2003}	0.005	-0.144
	(0.026)	(0.110)
β_{2005}	-0.011	0.040
	(0.024)	(0.055)
β_{2009}	-0.005	-0.056
	(0.016)	(0.061)
β_{2011}	-0.027	-0.158**
	(0.028)	(0.077)
β_{2013}	-0.019	-0.276***
	(0.033)	(0.072)
β_{2015}	-0.047	-0.270***
	(0.033)	(0.098)
β_{2017}	-0.066	-0.288**
	(0.043)	(0.120)
Average of the outcome variable	0.410	-0.886
Family FE, State FE, Year FE	✓	✓
State-specific time trends	✓	✓
Family controls	✓	✓
Observations	25,947	9,790
Adj.R^2	0.476	0.285

Notes: This table reports estimates of β_ts in Eq. (3). All regressions control for family fixed effects, year fixed effects, state fixed effects, state-specific time trends, and household features. Standard errors are clustered at the state level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: PSID, waves 2001–2017, in odd-numbered years.*)

Table B10. Exclude IRA and Private Annuities from Risky Assets

	Stock market participation	log risky share
	(1)	(2)
During × log(H1N1 death rate)	0.003	-0.001
	(0.015)	(0.081)
After × log(H1N1 death rate)	-0.036**	-0.134
	(0.018)	(0.099)
$\bar{\beta}_{post}$	-0.054**	-0.210*
	(0.021)	(0.123)
Average of the outcome variable	0.239	-0.957
Family FE, State FE, Year FE	✓	✓
State-specific time trends	✓	✓
Family controls	✓	✓
Observations	26,846	5,689
Adj. R^2	0.459	0.338

Notes: Stock market participation is equal to 1 if the household owns positive values of non-IRA stocks. Risky share is defined as the proportion of risky assets (excluding IRAs and private annuities that are invested in stocks) in liquid assets (excluding any amount of money invested in IRA or private annuities). All regressions control for family fixed effects, year fixed effects, state fixed effects, state-specific time trends, and household features. Standard errors are clustered at the state level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.(*Data source: PSID, waves 2001–2017, in odd-numbered years.*)

Table B11. Robustness Checks

Dependent variable	log risky share										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Add additional controls			Drop migrants	Drop two states	Drop 2009 sample	HHS-level case rate		Discretized death rate		“Pseudo”
During × log(H1N1 death rate)	-0.028	-0.028	-0.061	-0.016	-0.020						
	(0.051)	(0.051)	(0.052)	(0.061)	(0.051)						
After × log(H1N1 death rate)	-0.206***	-0.206***	-0.229***	-0.189**	-0.214***	-0.173***					
	(0.058)	(0.058)	(0.066)	(0.083)	(0.060)	(0.055)					
During × log(H1N1 case rate)							-0.063*				
							(0.031)				
After × log(H1N1 case rate)							-0.131				
							(0.099)				
During × log(Flu case rate)								-0.030			
								(0.040)			
After × log(Flu case rate)								-0.020			
								(0.101)			
During×Above-median state									-0.000		
									(0.058)		
After×Above-median state									-0.112*		
									(0.065)		
During×Middle-tercile state										-0.071	
										(0.071)	
During×Upper-tercile state										-0.020	
										(0.064)	
After×Middle-tercile state										-0.241***	
										(0.076)	
After×Upper-tercile state										-0.195**	
										(0.079)	
Year2007 × log(H1N1 death rate)											-0.002
											(0.086)
$\bar{\beta}_{post}$	-0.299***	-0.299***	-0.344***	-0.358**	-0.309***	-0.259***	-0.151	-0.070	-0.177*		
	(0.070)	(0.070)	(0.076)	(0.140)	(0.072)	(0.075)	(0.105)	(0.103)	(0.091)		
$\bar{\beta}_{post}^{middle-tercile}$										-0.325***	
										(0.095)	
$\bar{\beta}_{post}^{upper-tercile}$										-0.295**	
										(0.110)	
Average of the outcome variable	-0.886	-0.886	-0.886	-0.886	-0.884	-0.872	-0.886	-0.886	-0.886	-0.886	-0.900
Family FE, State FE, Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State-specific time trends	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Family controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Macroeconomic controls 2008× year dummies	✓	✓									
Medical controls 2008× year dummies		✓									
Financial-crisis impact× year dummies			✓								
Observations	9,790	9,790	9,790	9,123	9,713	8,397	9,790	9,790	9,790	9,790	4,349
Adj.R^2	0.285	0.285	0.284	0.280	0.284	0.289	0.284	0.284	0.284	0.285	0.298

Notes: Column (1) adds the interactions between the state-level macroeconomic indicators in 2008 and year dummies. Column (2) further adds the interactions between the state-level medical resources in 2008 and year dummies. Column (3) includes the interactions between percentage change of state-level economic indicators during the financial crisis and year dummies. Column (4) restricts the sample to family units that did not emigrate to other states during our study period. Column (5) 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 (6) drops the 2009 sample. Column (7) adopts the H1N1 case rate during the pandemic to measure H1N1 intensity. The H1N1 case rate is defined as the number of case counts per 100,000 people in an HHS region from April 2009 to August 2010. Column (8) conducts a placebo test using the case rate of regular seasonal flu during the pandemic, which is defined as the total cases of (A)H1, A(H3), B, and other subtypes of influenza A viruses per 100,000 people in an HHS region from April 2009 to August 2010. Columns (9) and (10) discretize the H1N1 death rates into dummy variables. Column (11) drops data from 2009 and onward, assuming 2007 is the post-pandemic year. Standard errors are clustered at the state level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: PSID, waves 2001–2017, in odd-numbered years.*)

Table B12. Correlation between Migration and H1N1 Death Rate

Outcome variable	Whether Live in Different States between 2007 and 2011	
	(1)	(2)
log(H1N1 death rate)	0.012	0.013
	(0.009)	(0.009)
Average of the outcome variable	0.063	0.063
Controls		✓
Observations	2,337	2,337
Adj.R^2	0.000	0.041

Notes: Column (1) only controls the log of H1N1 death rate during the pandemic. Column (2) adds characteristics of household heads, including gender, age, square of age, and schooling years. Robust standard errors are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: PSID, waves 2007 and 2011, in odd-numbered years.*)

Table B13. 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 B4 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 B14. Response Categories of Risk Tolerance

Response category	Downside risk of risky job		Percent of respondents
	Accept (1)	Reject (2)	(3)
1	None	1/10	20.8
2	1/10	1/5	18.0
3	1/5	1/3	17.7
4	1/3	1/2	17.8
5	1/2	3/4	17.9
6	3/4	None	7.7

Notes: Respondents are given choices between a job with a fixed income and a job with risky earnings. In the latter, the riskier option, they face equal chances of either doubling their income or having it decreased by a specific fraction reported in columns (1) and (2). Column (3) shows the percent of respondents in each category used in our regression analysis in Panel F of Figure 5. The details about the gambles in the 1996 PSID are introduced in Appendix E.

Table B15. 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. (4). All regressions control for family fixed effects, year fixed effects, state fixed effects, state-specific time trends, 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 state level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: PSID, waves 2001–2017, in odd-numbered years.*)

Table B16. Mediation Analysis (First Stage)

Outcome variable	Good health (dummy) (1)	Married (dummy) (2)	Have children (dummy) (3)	log of total income (4)	Unemployed (dummy) (5)
During × log(H1N1 death rate)	-0.023	-0.006	0.005	-0.002	0.017
	(0.023)	(0.010)	(0.016)	(0.039)	(0.012)
After × log(H1N1 death rate)	-0.044	0.000	0.055**	-0.062	0.034*
	(0.038)	(0.019)	(0.023)	(0.053)	(0.018)
$\bar{\beta}_{post}$	-0.031	0.007	0.072**	-0.062	0.041**
	(0.040)	(0.027)	(0.031)	(0.059)	(0.017)
Average of the outcome variable	0.291	0.793	0.453	11.677	0.046
Family, year, state FEs	✓	✓	✓	✓	✓
State-specific time trend	✓	✓	✓	✓	✓
Family controls	✓	✓	✓	✓	✓
Observations	9,790	9,790	9,790	9,789	9,790
Adj.R^2	0.501	0.834	0.673	0.571	0.120

Notes: "Good health" is a dummy variable equal to 1 if the household head reports his/her health status is excellent. "Have children" is a dummy variable equal to 1 if the household has children aged between 0 and 17. Income is defined in the 2017 dollar adjusted by the CPI-U index. All regression controls for fixed effects of family, state, and year, state-specific trends, and family controls. See the description in Section 4.1 for the list of family controls. $\bar{\beta}_{post}$ is the average of estimated dynamic treatment effects in 2011, 2013, 2015, and 2017 (i.e., β_{2011}, β_{2013}, β_{2015}, and β_{2017}). Standard errors are clustered at the state level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: PSID, waves 2001–2017, in odd-numbered years.*)

Table B17. Exposure Effect of H1N1 Pandemic on Risky Share

Outcome variable	log(Risky share)					
Additional controls	None (Baseline)	Health status	Family structure	Labor market outcomes		All
	(1)	(2)	(3)	(4)	(5)	(6)
During × log(H1N1 death rate)	-0.028	-0.029	-0.029	-0.028	-0.027	-0.028
	(0.051)	(0.051)	(0.050)	(0.050)	(0.051)	(0.050)
After × log(H1N1 death rate)	-0.206***	-0.208***	-0.207***	-0.209***	-0.204***	-0.208***
	(0.058)	(0.059)	(0.059)	(0.060)	(0.059)	(0.061)
Good health		-0.033				-0.029
		(0.027)				(0.027)
Have children 0–17			0.007			0.006
			(0.040)			(0.040)
Married			-0.108**			-0.088**
			(0.044)			(0.044)
Log total income				-0.043**		-0.041**
				(0.019)		(0.018)
Unemployed					-0.063	-0.072
					(0.058)	(0.057)
$\bar{\beta}_{post}$	-0.299***	-0.300***	-0.298***	-0.302***	-0.296***	-0.300***
	(0.070)	(0.071)	(0.071)	(0.072)	(0.070)	(0.072)
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	✓	✓	✓	✓	✓	✓
Observations	9,790	9,790	9,790	9,789	9,790	9,789
Adj.R^2	0.285	0.285	0.285	0.285	0.285	0.286

Notes: “Good health” is a dummy variable that is equal to 1 if the household head reports his/her health status is excellent. “Have children” is a dummy variable that is equal to 1 if the household has children aged between 0–17. Income is defined in the 2017 dollar adjusted by the CPI-U index. All regression controls for fixed effects of family, state, and year, state-specific trends, and family controls. See the description in Section 4.1 for the list of family controls. $\bar{\beta}_{post}$ is the average of estimated dynamic treatment effects in 2011, 2013, 2015, and 2017 (i.e., β_{2011}, β_{2013}, β_{2015}, and β_{2017}). Standard errors are clustered at the state level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: PSID, waves 2001–2017, in odd-numbered years.*)

Table B18. 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)	-0.592	-1.016	-0.028	-0.029
	(1.417)	(1.509)	(0.051)	(0.051)
After × log(H1N1 death rate)	-1.589	-2.138	-0.206***	-0.206***
	(1.632)	(1.802)	(0.059)	(0.059)
Family wealth (exc. home equity)			0.000	
			(0.001)	
Family wealth (inc. home equity)				-0.000
				(0.001)
$\bar{\beta}_{post}$	-2.131	-2.408	-0.299***	-0.299***
	(2.147)	(2.282)	(0.071)	(0.071)
Average of the outcome variable	5.466	7.292	-0.886	-0.886
Family, year, state FEs	✓	✓	✓	✓
State-specific time trend	✓	✓	✓	✓
Family controls	✓	✓	✓	✓
Observations	9,790	9,790	9,790	9,790
Adj.R^2	0.590	0.647	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 the 2017 dollar adjusted by the CPI-U index. All regression controls for fixed effects of family, state, and year, state-specific trends, and family controls. See the description in Section 4.1 for the list of family controls. $\bar{\beta}_{post}$ is the average of estimated dynamic treatment effects in 2011, 2013, 2015, and 2017 (i.e., β_{2011}, β_{2013}, β_{2015}, and β_{2017}). Standard errors are clustered at the state level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (*Data source: PSID, waves 2001–2017, in odd-numbered years.*)

C Additional Robustness Checks and Evidence

We first discuss additional robustness checks in Appendix Table B11. Then we present evidence on how exposure to H1N1 pandemic affects illiquid assets.

Drop migrants from the sample. — Migration decisions can be non-random. For example, individuals with lower risky asset shares might migrate from states with lower death rates to those with higher death rates. In such as case, we could observe a reduction in risky shares in the higher-death-rate states compared to lower-death-rate states, even without a causal effect of the pandemic on portfolio choices. However, as shown in Appendix B12, we find no significant association between the H1N1 death rate and the probability of moving to a different state in 2011 compared to 2007, suggesting that the H1N1 pandemic does not affect households' migration decisions. In column (4) of Appendix Table B11, we restrict the sample to households who always lived in the same state in our study period, dropping about 6.8% of the sample. The state fixed effects are thus absorbed. The coefficients on our two key interaction terms barely change.

Drop the outlier states. — Among 50 states of the US, South Dakota, and New Mexico can be treated as outliers because their H1N1 death rates are nearly three deaths per 100,000 people during the pandemic and much higher than in other states (see Appendix Table B1). As seen from column (5), the result remains the same after we exclude these two states.

Drop the 2009 sample. — In our main results, we do not find a significant decrease in the risky share during the pandemic in 2009. In column (6), we run a supplementary regression excluding the 2009 sample and focus on the coefficient of $After \times \log(H1N1\ \textit{death rate})$. The results remain consistent with those reported in Table 2.

Use a different measure for H1N1 intensity. — We use the HHS-level H1N1 case rate as an alternative measure for H1N1 intensity. Column (7) shows that the risky share remains negatively affected by the HHS-level H1N1 intensity after the pandemic. However, the estimated exposure effects become less precise, as the HHS-level measure may fail to capture accurate information within an HHS region.

Placebo tests. — Theoretical models in economic epidemiology predict that agents engage in protective behavior only when the contagious disease passes a threshold prevalence (Philipson 2000). Within our context, it may imply that a change in risky shares is triggered only by an unexpected and widespread public health crisis and not by routine seasonal influenza viruses. As introduced in Section 2.2.1, we construct the case rate of regular seasonal flu during the 2009 H1N1 pandemic (i.e., April 2009–August 2010), which is at the HHS region level and drawn from the *FluView*. We estimate a model similar to Eq. (1) except that the seasonal flu case rates now interact with $During_t$ and $After_t$ dummies. The results are presented in column (8).

Discretize the H1N1 death rate. — As discussed in Section 3, the validity of a DID specification with a continuous treatment relies on the strong parallel trends assumption, which is stricter than the traditional parallel trends assumption. To validate our results, we discretize the H1N1 death rates in two ways. First, we categorize the 50 states into two groups based on whether their death rates were above or below the median, thereby creating a binary treatment variable, *Above-median state*. Second, we divide the states into three groups according to the terciles of the death rate distribution, creating two treatment variables, *Middle-tercile state* and *Upper-tercile state*. As shown in columns (9) and (10), households in higher-death-rate states reduce their risky asset share more compared to those in lower-death-rate states, which is consistent with the results obtained using continuous treatment variables.[47]

Falsification test. — If, for some reason (e.g., policy change), families exposed to higher H1N1 death rates tended to reduce their risky share before the 2009 H1N1 pandemic, then the coefficients

47. The estimated coefficient for *Middle-tercile state*, $\bar{\beta}_{post}^{middle-tercile}$ is slightly larger than that for *Upper-tercile state*, $\bar{\beta}_{post}^{upper-tercile}$. This is likely attributable to the right-skewed distribution of the H1N1 death rate, as illustrated in Appendix Figure A9. While taking the logarithm of the H1N1 death rate reduces the skewness, the log-transformed values still exhibit slight right skewness.

of our key interaction terms would be misunderstood as the result of the pandemic. Therefore, we conduct a falsification test by assuming 2007 is in the *hypothetical post-pandemic period* and retain data from 2001 to 2007. Thus, 2001, 2003, and 2005 become the *hypothetical pre-treatment periods.* Column (11) shows that the coefficient of the interaction term between the post-treatment dummy ($Year2007$) and the H1N1 death rate is close to zero and statistically insignificant. This result, together with the event study, verifies the parallel trend assumption.

The exposure effect on illiquid assets. — Household assets can be categorized into liquid and illiquid types (Appendix Figure A10). Our preceding analysis concentrates on the exposure effect of the H1N1 pandemic on the liquid assets holding. We now explore whether illiquid assets also exhibit changes in response to the H1N1 pandemic.

To account for the potential impact of the 2008–2009 financial crisis, we add the interaction between year dummies and percentage changes in state-level economic indicators in Eq. (3), following the approach in Section 4.3. As shown in Figure A11, during and after the H1N1 pandemic, the probability of owning an incorporation business (IB) falls significantly. In contrast, the probability of owning an unincorporated business (UB) marginally increases with H1N1 intensity, significant at the 10 percent level in 2009 and 2015. Our findings suggest that a pandemic may mimic the effects of a recession: incorporated self-employment is "procyclical," while unincorporated self-employment is "countercyclical".[48]

In addition to business assets, we examine non-business assets, including housing and cars, as shown in Appendix Figure A12. The H1N1 pandemic has no significant effect on the ownership of these asset types, perhaps because they are considered essential. In our PSID sample, a substantial majority–over 70% for housing and more than 90% for cars–of households own these assets. Therefore, an exogenous shock like the H1N1 pandemic appears to have a minimal impact on households' possession of these assets.

48. Rubinstein and Levine (2020) show that entrepreneurship generally moves in tandem with the economic cycle, while other self-employment moves against it.

D Decomposition of the Changes in Risky Share

We compute passive and active changes in risky share following Calvet, Campbell, and Sodini (2009).

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

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

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:

$$\Delta\omega_{i,t}^{Passive} = \omega_{i,t}^{Passive} - \omega_{i,t-1}. \tag{D.2}$$

As suggested by Calvet, Campbell, and Sodini (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, active change results from 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:

$$\Delta\omega_{i,t}^{Active} = \omega_{i,t} - \omega_{i,t}^{Passive}. \tag{D.3}$$

Combined with Eqs. (D.2) and (D.3), we can write the total change in the risky share as the sum of the passive and the active change:

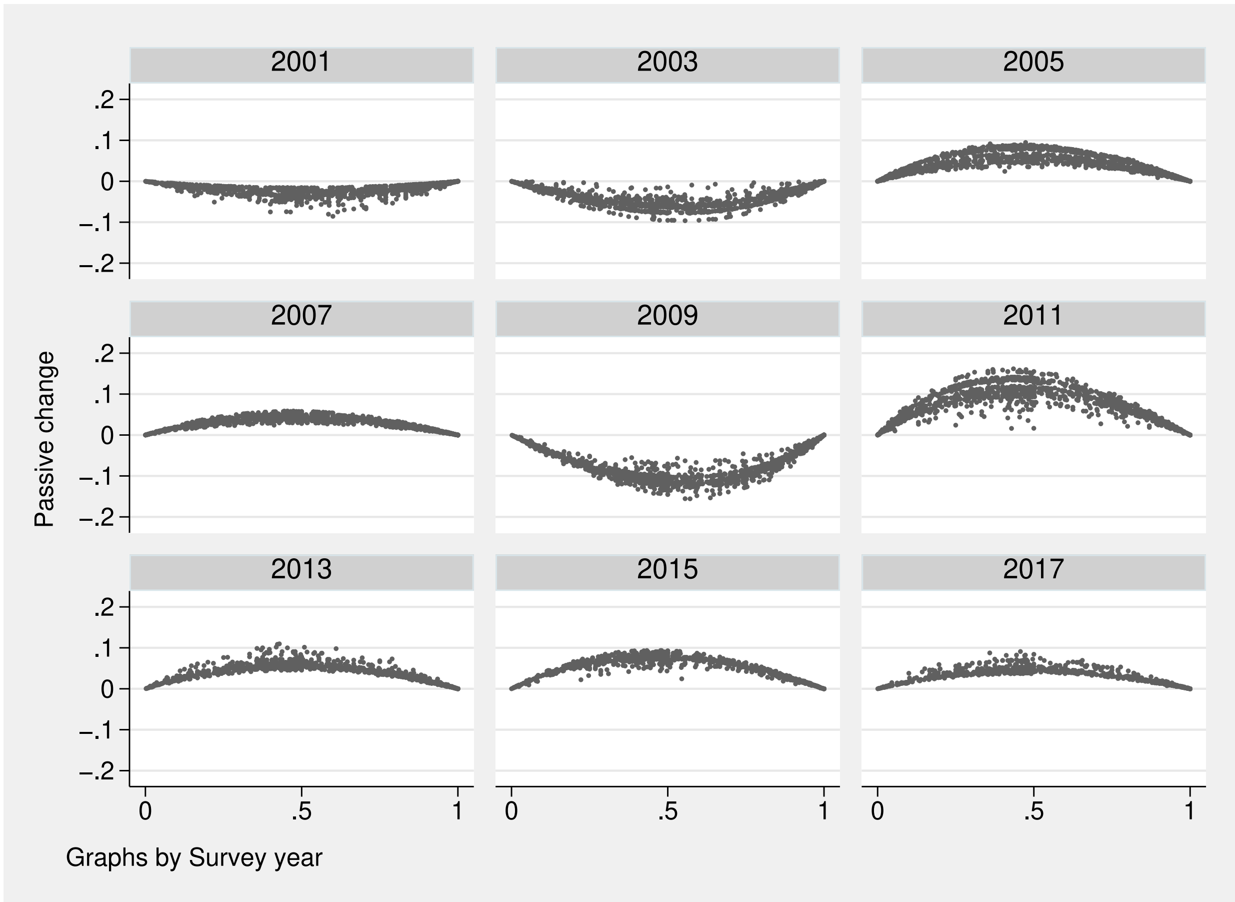
$$\omega_{i,t} - \omega_{i,t-1} = \Delta\omega_{i,t}^{Active} + \Delta\omega_{i,t}^{Passive}. \tag{D.4}$$

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.

We visualize the passive and active changes (calculated with *Vwretd*) in 2001–2017 in scatterplots.[49] As shown in Figure D1, 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 (i.e., $R_t > R_t^f$). The active changes plotted in Figure D2 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.

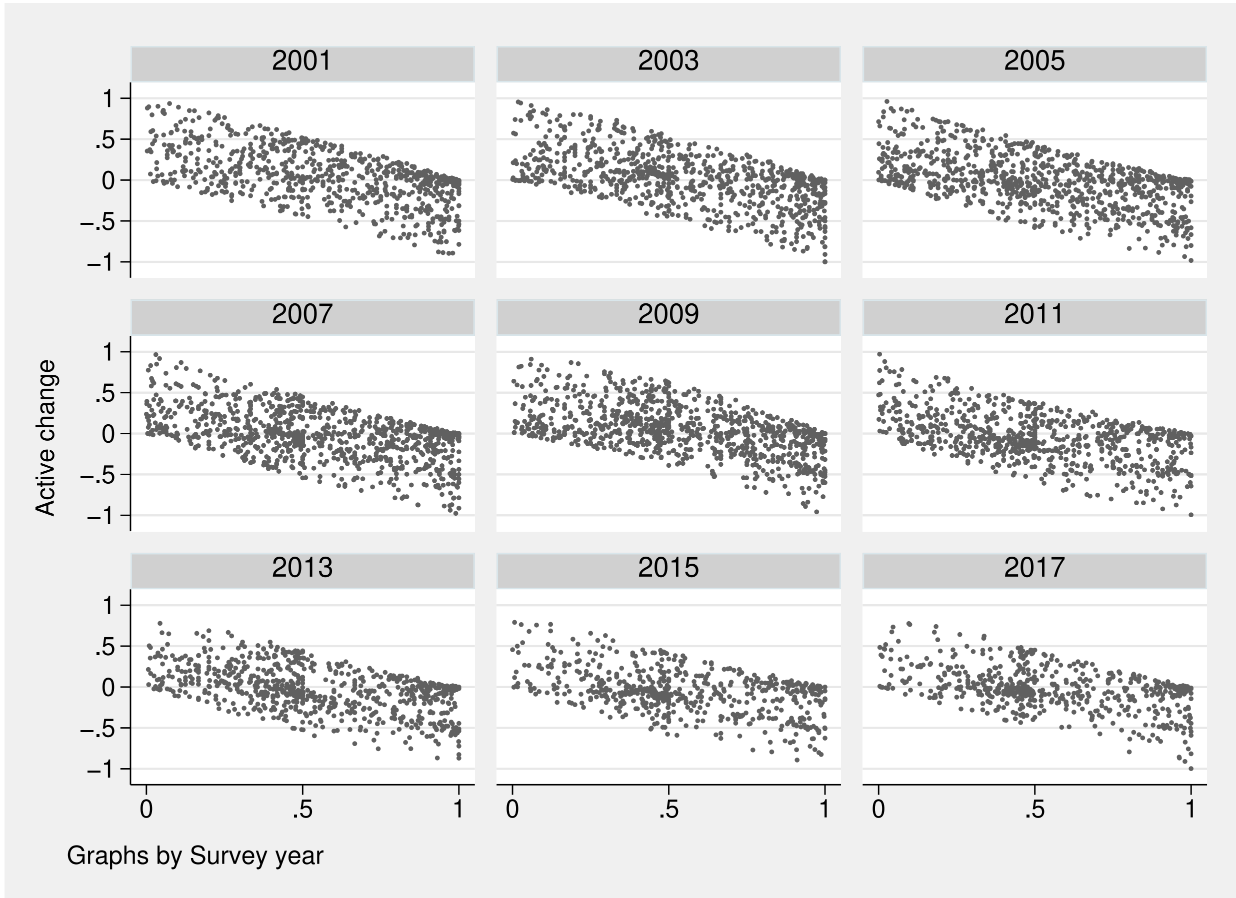
We further investigate whether active and passive changes in stock holdings change with the H1N1 pandemic, as presented in Table D2. To facilitate the coefficient interpretation, we present the passive and active changes in the percentage form. In the first five columns, the dependent variable is the passive change. Since passive changes depend solely on the realized return on risky assets, none of the five passive changes change significantly with the H1N1 death rate during or after the pandemic. The following five columns (6)–(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, active change has declined by about 0.07 percentage points if the H1N1 intensity increases by 1 percent.

49. The scatterplots of the passive and active changes computed with *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 Table D1.



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 D1. 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 D2. Scatterplots of Active Change versus the Initial Risky Share

To sum up, the reduction in risky share in response to the H1N1 pandemic, is primarily due to the net sales of stocks, since the value of liquid assets has remained constant. Our analysis on passive and active changes reinforces this observation. The decline in the risky share can be largely attributed to an active rebalancing strategy, as opposed to the change in realized asset returns.

Table D1. 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 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 D2. 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)	0.135	0.065	0.275	0.217	0.059	-3.933	-3.862	-4.073	-4.015	-3.856
	(0.365)	(0.373)	(0.433)	(0.441)	(0.380)	(2.733)	(2.736)	(2.708)	(2.710)	(2.733)
After × log(H1N1 death rate)	-0.129	-0.119	-0.335	-0.307	-0.123	-7.377	-7.387	-7.172	-7.200	-7.384
	(0.349)	(0.325)	(0.440)	(0.413)	(0.329)	(5.050)	(5.071)	(4.991)	(5.010)	(5.070)
$\bar{\beta}_{post}$	0.334	0.380	0.231	0.305	0.385	-9.090**	-9.135**	-8.987**	-9.061**	-9.141**
	(0.382)	(0.362)	(0.456)	(0.425)	(0.366)	(4.092)	(4.123)	(4.043)	(4.071)	(4.124)
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	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Family controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State-level controls 2008 × year dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
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 state level and shown in parentheses. (Data source: PSID, waves 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, and 2017.)

E Risk-tolerance Measurements in the 1996 PSID

The 1996 PSID contains income-related gambling questions that can be used to measure the risk tolerance of respondents. Respondents are asked to choose between a job with a guaranteed income and a job with an uncertain income. For the risky job, there is an equal probability of either doubling their earnings or reducing them by a specified fraction. The survey first poses the following scenario:

[M1] *Suppose you had a job that guaranteed you income for life equal to your current, total income. And that job was (your/your family's) only source of income. Then you are given the opportunity to take a new, and equally good, job with a 50–50 chance that it will double your income and spending power. But there is a 50–50 chance that it will cut your income and spending power by a third. Would you take the new job?*

Respondents who accept this risky job are then asked about a riskier offer:

[M2] *Now, suppose the chances were 50–50 that the new job would double your (family) income, and 50–50 that it would cut it in half. Would you still take the new job?*

Those rejecting the initial risky job (**M1**) are asked about a less risky job:

[M3] *Now, suppose the chances were 50–50 that the new job would double your (family) income, and 50–50 that it would cut it by 20 percent. Then, would you take the new job?*

Based on their first two choices, individuals are then asked to decide whether accept a risky a job with a 10 percent downside risk or one with a 75 percent downside risk.

Specifically, if the respondents rejects the job offer described in **M3**, they will consider the following job with a lower downside risk:

[M4] *Now, suppose that the chances were 50-50 that the new job would double [your/your family] income, and 50-50 that it would cut it by 10 percent. Then, would you take the new job?*

For those who would take the risky job described in **M2**, individuals are asked about a more risky job:

[M5] *Now, suppose that the chances were 50-50 that the new job would double [your/your family] income, and 50-50 that it would cut it by 75 percent. Would you still take the new job?*

Respondents are classified into six categories of risk tolerance according to their responses. Details of these response categories, along with the percentage representation of each, are presented in Appendix Table B14.

F Imputation of Total Consumption

Each PSID wave documents the consumption in the previous calendar year (e.g., wave 2017 documents the consumption in 2016). It is important to note that not all consumption domains are consistently collected throughout the study period (2001-2017). Table F1 provides an overview of the consumption domains collected in the PSID. Household expenditures on food, transportation, health care, housing, education, and child care are consistently collected between 2001 and 2017. However, the remaining domains were not available before 2005.

Table F1. Available Information on Consumption in PSID 2001–2017

Domains	Items	Waves available
Food	Food at home, food away from home, food stamps	
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	2001–2017
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	
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	2005–2017
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	

Following the method proposed by Attanasio and Pistaferri (2014), we calculate the overall consumption by utilizing other variables in PSID. Specifically, we estimate the following specification using data in the 2005–2017 waves (i.e., 2004–2016 calendar years):

$$\ln n_{it} = Z_{it}'\beta + p_t'\gamma + g(f_{it};\theta) + u_{it}. \tag{F.1}$$

n_{it} is the net consumption of household i in year t, i.e., the total consumption excluding food.[50] Z_{it} is a vector of socioeconomic household characteristics, including age, education, marital status, race, state, employment status, working hours of household head, home ownership, disability, number of family members, and number of children. p_t denotes a series of price indexes that include the overall CPI and the CPIs for food at home, food away from home, and rent. f_{it} is the total expenditure on food at home, food away from home, and food stamps. $g(\cdot)$ is a third-degree polynomial function. u_{it} is the residual term. Eq. (F.1) can be understood as a demand equation that links food consumption to total consumption (Attanasio and Pistaferri 2014). We report the estimated coefficients in Eq. (F.2) in Table F2.

Then the imputed overall consumption for 2001–2017, $\hat{c}_{it}$, is the sum of the food consumption and the estimated net consumption:

$$\hat{c}_{it} = f_{it} + exp\{Z'_{it}\hat{\beta} + p'_t\hat{\gamma} + g(f_{it}; \hat{\theta})\}. \tag{F.2}$$

We adjust the imputed total consumption ($\hat{c}_{it}$) with the overall CPI index to derive the real total consumption. Figure F1 presents comparative plots showing the trends in actual total consumption from 2005 to 2017 alongside the imputed real total consumption from 2001 to 2017. These plots include the mean, median, 25th percentile, and 75th percentile of the distribution. Notably, before 2007, there is a steady increase in household consumption, which then experiences a sharp decline between 2006 and 2008, followed by a steady recovery. The figure illustrates that the in-sample predictions, indicated by blue squares, closely align with the trends observed in the actual values, represented by red circles.[51]

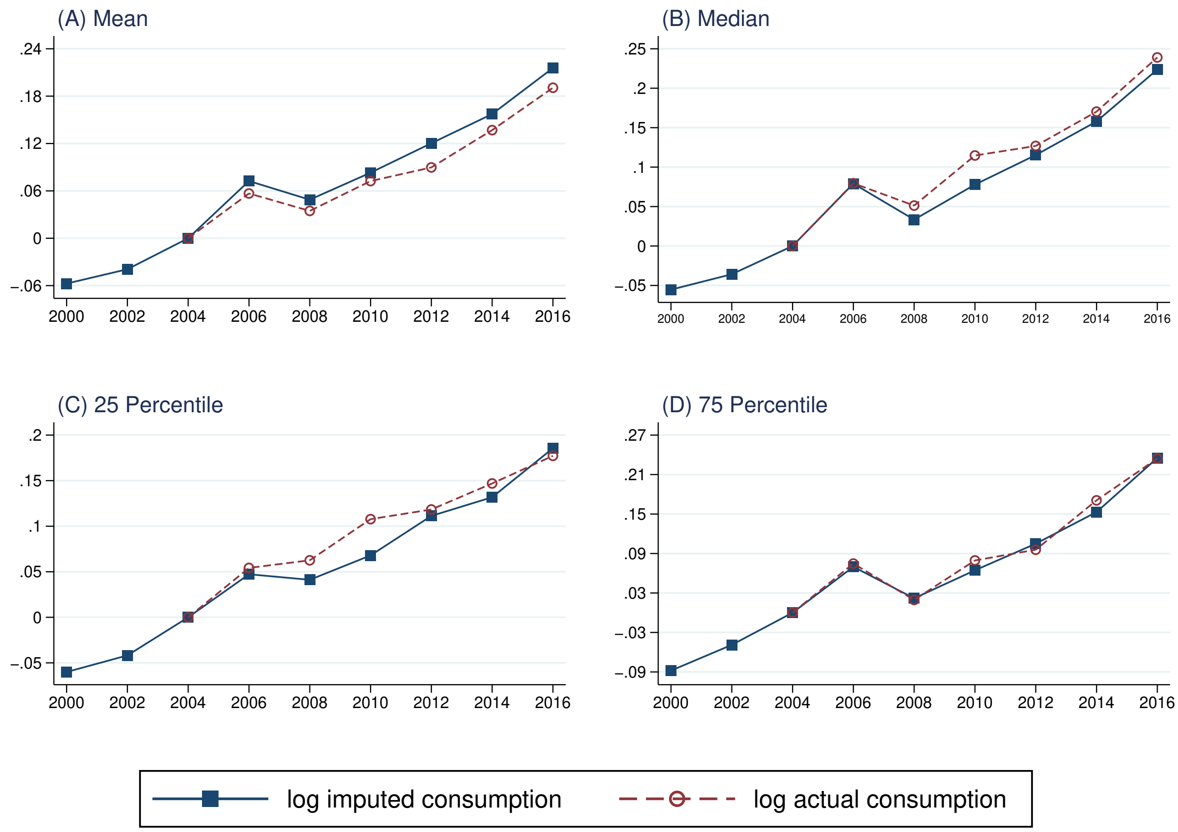
50. The net consumption n_{it} is the total spending on transportation, health care, housing, education, child care, home repairs and maintenance, household furnishings and equipment, clothing and apparel, trips and vacations, recreation and entertainment, and telephone and internet.

51. As an alternative approach, we calculate the real equivalized consumption by dividing the real total consumption by the OECD adult equivalence scale. This scale is formulated as $ES = 1 + 0.7 \times$ (number of adults $- 1) + 0.5 \times$ number of children. The imputed equivalized consumption closely mirrors the actual value.

Table F2. Estimate the Net Consumption

Outcome variable	log(net consumption)
$food/10^3$	0.091***
	(0.002)
$food^2/10^6$	-0.003***
	(0.000)
$food^3/10^12$	0.027***
	(0.002)
Number of family member	0.065***
	(0.004)
Black	-0.065***
	(0.006)
0-11 grades	-0.633***
	(0.011)
High school	-0.410***
	(0.006)
College dropout	-0.231***
	(0.006)
Home owner	0.333***
	(0.006)
Self-employed	0.058***
	(0.008)
Disabled	-0.072***
	(0.007)
Average of the outcome variable	10.1
CPI series	✓
Other dummy controls	✓
Observations	46,805
Adj.R^2	0.539

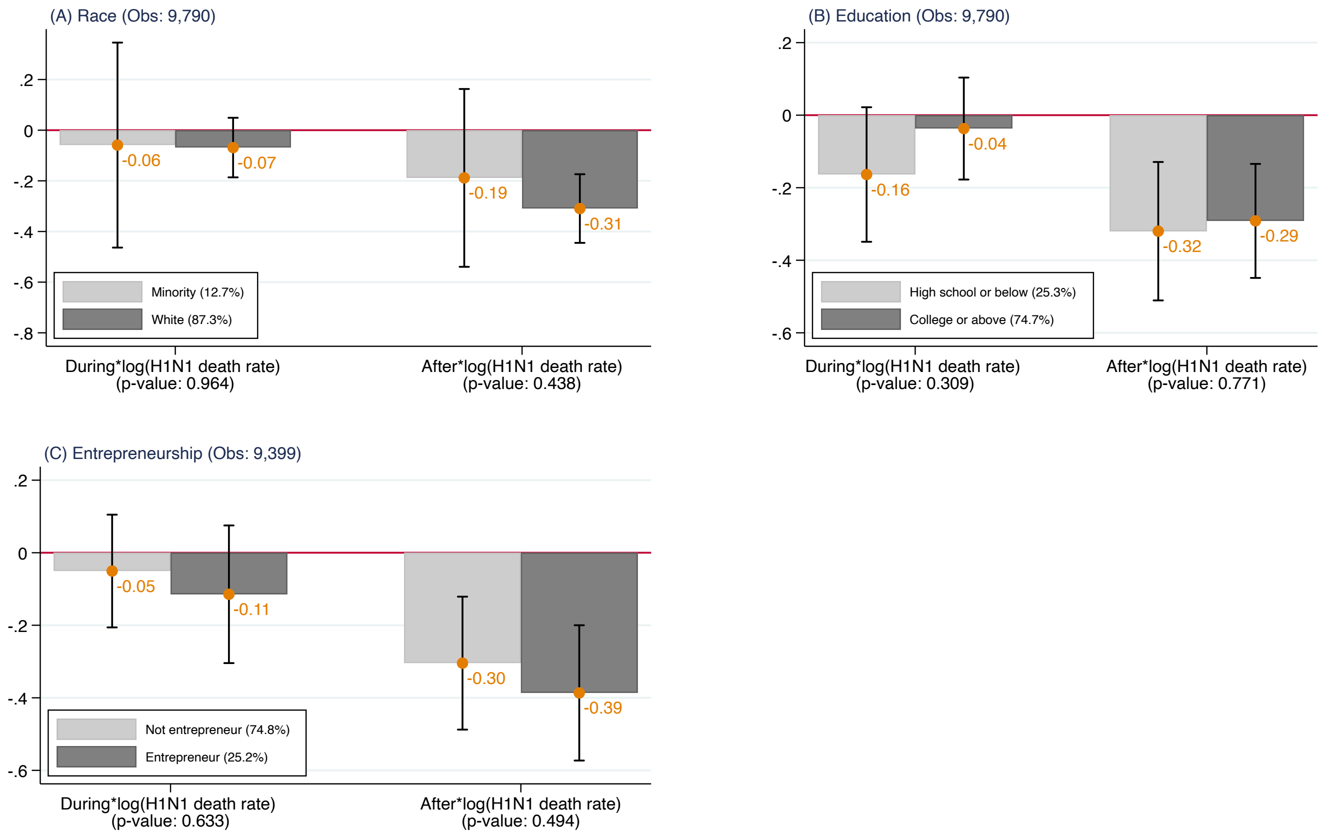
Notes: This table reports the estimated coefficients for Eq. (F.1). Dummy controls include dummies of state, age, employment status, marital status, and child number. Standard errors are clustered at the state level and shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *(Data source: PSID, waves 2001–2017, in odd-numbered years.)*



Notes: This figure plots the log of imputed total consumption estimated using Eq. (F.2) and the log of actual total consumption. All monetary variables are adjusted by the 2017 US dollar.

Figure F1. Imputed Consumption V.S. Actual Consumption

G Other Heterogeneity Analysis



Notes: This figure plots the estimates of β_{1g} and β_{2g} in Eq. (4). 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. (*Data source: PSID, waves 2001–2017, in odd-numbered years.*)

Figure G1. Additional Heterogeneous Effects of the 2009 H1N1 Pandemic

Race — For the ethnic minority and the white, when the H1N1 death rate increases by 1 percent, risky share decreases by 0.2% and 0.3%, respectively (Panel A of Figure G1). There is no significant difference between the ethnic minority and the whites (p-value = 0.65).

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

Entrepreneurship — Panel C examines whether heterogeneous responses between entrepreneurs and employees exist.[52] Given that the entrepreneurship status can be affected by the H1N1 pandemic, we use the entrepreneurship information in 2007, the year prior to the pandemic.[53] When the H1N1 death rate increases by 1 percent, entrepreneurs reduce their risky shares by 0.35%, while employees reduce risky shares by 0.26%. However, the difference between entrepreneurs and employees is statistically insignificant.

52. Entrepreneurs are defined as owning part or all of a farm or business, which account for 25% of our sample.

53. Likewise, due to the endogeneity concern, we use the information in 2007 to define working for the government and having a job covered by the union contract in our subsequent analysis.