Spouses in The Same Boat: Labor Income Risk and Intra-household Risk Sharing*

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Abstract

This paper proposes a novel channel for households' choices of risky asset allocation: more intra-household risk sharing reduces labor income risk for dual-earner couples, thus encouraging households' financial risk-taking. Capturing intra-household risk sharing by conditional income correlation between spouses' industries, I find that more income risk sharing within couples increases households' financial risk-taking. Using unexpected events of spousal death, I causally identify the impact of intra-household risk sharing on households' portfolio choices. My study implies an unintended consequence of positive assortative mating for wealth inequality by discouraging disadvantaged households' financial risk-taking.

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1 Introduction

The family economics literature, pioneered by Becker (1973, 1974), provides evidence that marriage serves as a fundamental tool for mitigating labor income risk. Dual-earner families, compared with single-earner households, not only benefit from additional income sources but also reduce overall income risk through diversification (Lundberg, 1985; Stephens, 2002). However, the role of income risk sharing between spouses has been understudied in finance, and we know little about its impact on households' financial risk-taking. This question is particularly important in light of the trend of marrying partners with similar education attainment and socioeconomic status.[1] While labor market outcomes have been more positively correlated between spouses since the 1980s (Hyslop, 2001; Hyatt, 2015), it remains an open question whether the economic resemblance within a couple affects households' financial behaviors. In this paper, I examine whether intra-household risk sharing matters for households' financial risk-taking in the context of labor income risk.

Consider a dual-income household where the husband and the wife work in different industries. A combination of uncorrelated occupations can essentially provide insurance for household income. For example, the risk of substantial loss in household income would be mitigated if the couple has uncorrelated income shocks (Shore, 2010; Blundell, Pistaferri, and Saporta-Eksten, 2016). In addition, when the couple does not share an occupation, this setting provides effective intra-household insurance against earnings losses due to unemployment if the timing of layoffs is independent (Shore and Sinai, 2010; Halla, Schmieder, and Weber, 2020). Hence, intra-household risk sharing can reduce households' exposure

[1] See Lam (1988), Kalmijn (1998), Greenwood, Guner, Kocharkov, and Santos (2014) and Shore (2015) among many others.

to labor income risk. Empirically, I have documented strong evidence supporting this intuitive relation between intra-household risk sharing and family income volatility. Then, building upon the established link between income risk and households' portfolio choices in the literature (Guiso, Jappelli, and Terlizzese, 1996; Angerer and Lam, 2009; Betermier, Jansson, Parlour, and Walden, 2012; Bonaparte, Korniotis, and Kumar, 2014), I propose the following mechanism: a higher degree of intra-household risk sharing, captured by low-income correlation between spouses, would reduce the overall labor income risk for the family, thereby encouraging a greater allocation of wealth to risky assets. I then find supporting evidence consistent with this intuition in later analysis. Furthermore, I establish causality between intra-household risk sharing and households' risk-taking behaviors through a novel identification strategy.

To begin with, I leverage microdata from two US household surveys. First, I draw on earnings data from the Current Population Survey (CPS) to measure the degree of intra-household risk sharing by examining the correlation of income growth between respective industries where spouses work. Given the limited time-series observations in the survey data, I capitalize on the extensive cross-section of job information across households by computing income correlations at the industry level. Compared with direct estimation at the household level, this approach provides a more comprehensive measure of the potential of risk-sharing between spouses who are employed in different industries. Second, I use detailed information on households' demographics, employment, and asset holdings from the Health and Retirement Study (HRS) to investigate the effect of intra-household risk sharing, proxied by industry correlation, on households' financial risk-taking behaviors. Controlling for education, occupation, wealth, and other key demographic characteristics, I find that households are significantly less likely to participate in stock markets (at the extensive margin) when couples experience higher industry correlations. Moreover, among participating households, those with higher industry correlations also allocate a smaller proportion of their total financial wealth to risky assets (at the intensive margin). These findings collectively suggest that intra-household risk sharing plays a significant role in shaping households' propensity to take financial risks.

However, industry correlations between spouses may have an endogenous effect on households' financial risk-taking behaviors. For example, unobserved time-varying factors at the industry level might affect both industry correlations and households' portfolio choices, even after including industry-time fixed effects. To address this concern, I employ a triple-differences empirical strategy that incorporates unique shocks at the household level: the unexpected death of spouses. I rely on a unique advantage of the HRS data which contains detailed information about health conditions and mortality of each respondent. This allows me to employ multiple criteria for ensuring the suddenness of death shocks which is crucial for my causal inference. Specifically, I adopt the remaining spouse's answer on whether the death was unexpected, a comprehensive assessment of pre-death health conditions for major illnesses, and a conservative medical definition of sudden death inspired by Andersen and Nielsen (2011). With these conditions, I exploit sudden death events as exogenous shocks on the risk-sharing between spouses to estimate the impact of intra-household risk sharing on households' portfolio choices.

One instant challenge for my empirical strategy is that unexpected death could fundamentally change the affected families in several ways, such as loss of spousal earnings and interruption of risk diversification within the household. To correctly identify the targeted effect of intra-household risk-sharing, I employ the following methods. First, I include a comprehensive set of controls and fixed effects to account for major individual and family characteristics that shape households' investment behaviors. I further include industry-year fixed effects to absorb the effect of time-varying industry-level factors for each spouse. Second, I construct a measure for the income share of the deceased spouse to control the effect of permanent income loss. By interacting this measure with the death indicator, I managed to capture the first-moment effect (changes in the level of labor income) of unexpected death. Consequently, this approach helps demonstrate the distinct second-moment effect (changes in intra-household risk-sharing), which is captured by the interaction of industry correlation with the shock indicator. Moreover, any unobserved death-induced changes in the family would not undermine the validity of my estimation as long as they are unconditional on income correlations.

Given the above advantages of this empirical strategy, I aim to test a straightforward intuition: households with a higher industry correlation engage in less intra-household risk sharing, which increases overall labor income risk and discourages financial risk-taking. Consequently, among households that experienced sudden spousal death, those with a lower pre-death level of intra-household risk sharing would have a smaller post-death reduction in financial risk exposure.

My finding supports this intuition. I find a substantial effect of intra-household risk sharing on households' financial risk-taking after the unexpected death of spouses: conditional on stock market participation, a one-standard-deviation increase in industry correlation leads to a significantly smaller reduction in shares of risky assets by 28% after the sudden loss of spouses. This finding is consistent with the hypothesis that couples with a high correlation between their industries are less likely to reduce financial risk exposure, underscoring the significance of intra-household risk sharing in shaping households' decisions regarding financial risk-taking.

An important implication of my findings relates to the unintended consequences of the recent trend towards people marrying partners with similar backgrounds and characteristics (*positive assortative mating*). The increase in economic resemblance of couples due to *homogamy* in marriage may limit their ability to share income risks, which has been identified as a crucial factor for households' financial risk-taking. I demonstrate that the channel of intra-household risk sharing is particularly important for households with lower levels of education and wealth, as well as households lacking health or life insurance coverage. Moreover, I show that the importance of internal risk diversification is more pronounced for households that are more sensitive to income risk. Furthermore, I find that households place a greater value on intra-household risk sharing during economic recessions, which is consistent with the counter-cyclical mechanism of intra-household risk-sharing (Shore, 2010). Given the growing economic resemblance between spouses and the fact that disadvantaged households rely more on intra-household risk sharing, positive assortative mating may reinforce wealth inequality by limiting effective wealth accumulation for these households, which are vulnerable to unemployment and other labor income shocks.

Existing literature in household finance mostly attributes discrepancies in households' financial decisions to individual biases or mistakes (Guiso and Sodini, 2013; Beshears, Choi, Laibson, and Madrian, 2018; Gomes, Haliassos, and Ramadorai, 2021). Yet this paper demonstrates that interactions among individuals *within* households also matter. Despite growing theoretical and empirical evidence emphasizing the importance of studying interactions within households, there is limited discussion about their relationship with households' financial behaviors. Hence, my work contributes to this emerging literature which examines intra-household interactions and their impact on households' financial decision-making (e.g., Love, 2010; Addoum, Kung, and Morales, 2016; Addoum, 2017; Olafsson and Thornquist, 2018; Ke, 2021). To the best of my knowledge, this is the first study that explores the role of intra-household income risk sharing in shaping households' portfolio choices.

My work connects to the household portfolio choice literature by offering new insights into labor income risk. Previous studies have established that labor income risk is negatively related to households' optimal portfolio choices (e.g., Eeckhoudt, Gollier, and Schlesinger, 1996; Heaton and Lucas, 2000; Campbell and Viceira, 2002; Calvet and Sodini, 2014; D'Astous and Shore, 2022; Catherine, Sodini, and Zhang, 2022). In this study, I go beyond this relation and investigate the role of intra-household risk sharing. I show that by working in less correlated industries, couples benefit from a smaller exposure to labor income risk and thus make larger investments in the stock market. Hence, this finding extends the linkage between labor income risk and households' portfolio choices by identifying the unique channel of intra-household risk sharing.

My work also relates to the literature on marriage and inequality. Research in economics and sociology suggests that stronger socio-economic resemblance within couples in the trend of positive assortative mating is connected to the increasing wealth inequality among households (e.g., Fernández and Rogerson, 2001; Schwartz, 2010; Greenwood, Guner, Kocharkov, and Santos, 2014; Larrimore, 2014; Greenwood, Guner, Kocharkov, and Santos, 2016; Eika, Mogstad, and Zafar, 2019). My findings in this paper indeed provide new evidence supporting this link. I show that intra-household risk sharing is particularly important for households that are disadvantaged in wealth accumulation. As a result, these disadvantaged households may suffer from ineffective wealth accumulation when their ability of intra-household risk sharing is unintentionally impaired by positive assortative mating.

Finally, this paper contributes to the general literature on household finance by demonstrating a unique empirical design. Empirical analysis of household behaviors rarely incorporates the death of family members because of its endogenous nature and confounding effects. One example is Andersen and Nielsen (2011) who use unexpected inheritance due to the sudden death of parents to examine households' stock market participation. In this paper, I also exploit the sudden death of family members and differentiate the major impacts of spousal death using a triple-difference model. To the best of my knowledge, this is the first study to investigate the effect of intra-household risk sharing by using exogenous variations of family composition from one of nature's own experiments.

The rest of the paper is organized as follows. Section 2 describes the data and variable construction. Section 3 introduces empirical strategies. Section 4 presents empirical results. Section 5 concludes.

2 Data

2.1 HRS Data

I employ data from the Health and Retirement Study (HRS) conducted by the University of Michigan to observe households' family structure and asset holdings for examining households' financial risk-taking behaviors. The HRS is a nationally representative panel survey of individuals aged over 50 and their spouses. It has been widely used to investigate household portfolio choice decisions (e.g., Hong, Kubik, and Stein, 2004; Rosen and Wu, 2004; Gormley, Liu, and Zhou, 2010; Love, 2010; Koijen, Van Nieuwerburgh, and Yogo, 2016; Ke, 2021). Despite its relatively smaller sample size compared to other well-known household surveys, the HRS offers three distinct advantages for my study.

First, it provides detailed information on household wealth which has been identified as a critical factor influencing household stock market participation (Mankiw and Zeldes (1991); Calvet, Campbell, and Sodini (2007)). Second, the HRS collects rich information on respondents' health conditions and mortality, enabling me to account for medical conditions and family members' judgments to ensure the suddenness of spousal death.[2] Third, apart from the usual household characteristics, the HRS also gathers information on the preferences and expectations of both spouses. This would be useful for examining how different attitudes towards income risk affect intra-household risk sharing.

My analysis leverages HRS data spanning the period 1992 to 2020, covering over 40,000 households in 15 waves. I apply three sample restrictions: (i) couple households aged 80 or below; (ii) no remarriage after divorce or spousal death; and (iii) no missing information on current employment (e.g., job industry and occupation) and other demographics for both spouses. Although Condition (iii) leads to a reduced sample size, it is crucial for studying risk sharing within dual-earner households. My final sample consists of 13,805 household-wave observations from 4,514 unique households.

[2]Restricted data of the Panel Study of Income Dynamics (PSID), another well-known household survey, also provides mortality information for matched records with the National Death Index (NDI). However, unlike the HRS, it does not contain the remaining partners' views on the suddenness of the death events or detailed health conditions of the deceased spouses. Therefore, the HRS data suits the best for my research purpose.

Following the literature (e.g., Hong, Kubik, and Stein, 2004; Agarwal, Aslan, Huang, and Ren, 2022; Elkamhi and Jo, 2022; Gao, Jo, and Lam, 2022), I construct two measures of households' financial risk-taking. The first measure is an indicator of stock market participation, defined as household ownership of stocks or mutual funds, without considering indirect stock investment through pension accounts or individual retirement accounts. The second measure is a continuous variable that measures the value of risky assets (stocks and mutual funds) as a fraction of the total financial assets, which include checking, savings, bonds, and risky assets. This is to capture households' wealth allocation to stock markets.

Table 1 presents descriptive statistics for the final sample. Panel A of Table 1 reports information about asset holdings and other household-level variables. All dollar values are deflated using the Consumer Price Index with 1990 as the base year. On average, 41% of households participate in stock markets by holding stocks or mutual funds. The average share of risky assets in financial wealth is 22%. These statistics indicate a relatively low stake in stock markets for US households.

[Insert Table 1 here]

Panel B and C of Table 1 present information on the basic demographics of respondents and their spouses, respectively. I define respondents as individuals who answer questions about finances or family matters for their households in the HRS survey. By this definition, I find that, on average, wives are more likely to take this role than husbands. Additionally, I observe that spouses are highly correlated in other characteristics like age, race, and education attainments, reflecting positive assortative mating. Given this finding, I control for these households' characteristics by interactive fixed effects on both spouses.

2.2 CPS Data

I use data from the Current Population Survey (CPS) by the U.S. Census Bureau and the Bureau of Labor Statistics to capture wage dynamics within and between industries in the U.S. economy. The CPS is one of the largest and most well-recognized micro-level datasets for labor studies of the U.S. population. To obtain weekly earnings and detailed industry codes, I rely on the NBER extracts of the Merged Outgoing Rotation Groups (MORG) files in the CPS. With more than 25,000 individuals surveyed per month, the CPS data has comprehensive coverage of workers across industries, making it ideal for my research purpose.

Compared to a direct estimation of income volatility from each spouse's income changes, using industry risks to proxy for spouses' income risks provides two advantages. First, the industry pairing of couples is more readily observable and easier to interpret in the household data. Employees can readily observe income dynamics within and across industries through their own work experiences, social networks, and access to news sources. Therefore, working couples can gain a better understanding of their income risk and achieve diversification by selecting industries with lower correlation and coordinating their work choices. Second, leveraging the extensive time series of wages available in the monthly CPS data offers a more comprehensive depiction of income volatility across industries than relying on short income streams from the HRS households. As a result, a more precise estimation of income correlation can reflect the potential scope for risk-sharing within couples employed in different industries.

To compute industry correlations, I exploit the employment information in the CPS data in the following steps. First, I group all 3-digit Census industries in the CPS data into 37 categories for easier calculation and interpretation of inter-industry correlations. I also apply this classification to the HRS industries for later matching. Table IA1 lists all industry groups in my classification. All wages are also deflated by the monthly CPI with 1983 January as its base. Then, I calculate the weighted mean of weekly earnings in each industry group for every month between 1982 and 2020. For each industry group, I compute the year-over-year growth rate of mean wage, which reflects its income dynamic. Finally, I calculate conditional correlations between every two industry groups in rolling windows of 36 months.

By exploiting more time variations, conditional correlations accurately capture industry dynamics and their interactions. Table IA2 shows examples of high- and low-correlation industry pairs in different years. For instance, the highly positive correlation between the finance and real estate sectors in 2005 coincides with the rapid growth of housing and mortgages in the United States housing bubble of the 2000s. Conditional industry correlations in terms of income growth are generally consistent with industry development at the time. Hence, this measure effectively reflects the degree of income risk-sharing between spouses working in different industries.

In addition, I use the extensive household sample in the monthly CPS data to compare industry groups in which husbands and wives from dual-earner families are employed. As illustrated in Figure 1, the ratio of households where both spouses work in the same industry group to total working couples exhibits a substantial increase from 1982 and 2020. Following a period of relative stability during the 1980s, the average ratio of same-industry couples began to rise persistently during the 1990s. Then, the upward trend started to accelerate in the late 1990s, resulting in an approximately 10% increment in the proportion of such households. This finding aligns with the previous literature (e.g., Hyslop, 2001; Greenwood, Guner, Kocharkov, and Santos, 2014; Hyatt, 2015; Shore, 2015), providing further evidence for the social phenomenon of homogamy in the U.S. from the perspective of occupation combinations.

[Insert Figure 1 here]

3 Empirical Strategy

3.1 Main Specification

Building on evidence from previous studies that households with high labor income risk are less likely to participate in the stock market (e.g., Eeckhoudt, Gollier, and Schlesinger, 1996; Campbell and Viceira, 2002), I investigate the impact of intra-household risk-sharing on households' portfolio choices. A higher degree of income risk-sharing between couples would reduce overall exposure to labor income risk for dual-earner households, making them more capable of taking financial risks. This could be reflected in a higher probability of stock market participation, and conditional on participation, a larger allocation of household wealth in the stock market.

To test these hypotheses, I use a multivariate regression framework and estimate the following model:

$$y_{h,t} = \alpha + \beta \cdot \text{Industry Correlation}_{h,i,j,t} + X'_{h,i,j,t}\mathit{\Gamma} + \epsilon_{h,t} \tag{1}$$

where $y_{h,t}$ is either an indicator of stock market participation (*Market Participation*) or the share of risky assets in total financial wealth (*Share of Risky Assets*) for a household h at time t. Following the literature, I condition on participation (intensive margin) when examining changes in the share of risky assets. The reason for this condition is that given factors like entry costs, changing the allocation to risky assets as a stockholder is a different decision compared with entering the stock market. *Industry Correlation*h, i, j, t is the conditional correlation of income growth between industry i and industry j in which the spouses of household h work, respectively, at time t. This measure is used as a proxy for intra-household risk sharing. Following Ke (2021), I include nonparametric controls as fixed effects through the vector Xh, i, j, t, which accounts for factors that are crucial for households' portfolio choices (**?**Guiso and Sodini, 2013). These controls include the gender, age, birth cohort, race, educational attainment, occupation, insurance ownership, and self-employment status of both spouses, as well as family income, the number of children, and home ownership. I further include industry-by-year fixed effects for both spouses and state-by-year fixed effects to control for changes within industries and local socio-economic environments over time. I also control for household wealth which is an important factor for stock market participation (Mankiw and Zeldes (1991); Calvet, Campbell, and Sodini (2007)). The coefficient of interest, β, captures the effect of industry correlation on households' exposure to financial risk, conditional on all the aforementioned controls. Due to the use of a large set of fixed effects, linear probability models are run with standard errors clustered by state.

The inclusion of the set of fixed effects described above provides several benefits to my research. First, as the focus is on intra-household interactions between family members, this study differs from previous research in household finance, which typically treats households as single agents. Therefore, instead of controlling solely for individual characteristics of one household member (e.g., the head), it is essential to consider the heterogeneity of personal characteristics among couples by taking both spouses into account. Second, by controlling for relative education within couples, I account for intra-household bargaining power, which may affect the willingness and patterns of interactions within the family. Third, the inclusion of the respondent's occupation by spouse's occupation fixed effects addresses the concern that different occupation combinations may matter even when both spouses are in the same industry. Similar to the approach of industry grouping, I reclassify HRS occupations into broad categories as in Acemoglu and Autor (2011). Finally, the use of industry-by-year fixed effects effectively controls for time-varying differences within both spouses' industries, which affect household financial risk-taking.

3.2 Identification Strategy

Despite the above efforts, the endogeneity issue of using industry correlation as the proxy for intra-household risk sharing may remain. This is because there could be time-varying omitted factors that concurrently affect both industry correlation and households' portfolio choices. For example, economic booms may occur in multiple industries at the same time. This would lead to an increase in industry correlation of income growth (less intra-household risk sharing) while households in these industries are also encouraged by income gains to take up more financial risks. Regarding this problem, using industry shocks for identification would not be the ideal strategy because these events could have confounding effects. For instance, it is difficult to accurately specify the scope of impact of industry shocks. Households in shocked industries may also be affected in unobserved ways other than the income risk channel.

To alleviate this concern about endogenous industry correlation, I examine the impact of intra-household risk sharing by adopting a triple-difference research design based on the unexpected death of spouses. The intuition of this design is straightforward. Given that households with higher industry correlation between spouses have a lower degree of intra-household risk sharing, they benefit less from internal diversification of income risk and are thus less capable of financial risk-taking. Intuitively, these high-correlation households would be less weakened in their abilities of risk-sharing after experiencing unexpected spousal death, compared to low-correlation households who also suffer from sudden loss of the spouse. Hence, through backward induction, I expect that high-correlation households are relatively less affected in terms of financial risk-taking after death shocks. This difference in the impacts of spousal death could be reflected by a smaller drop in the likelihood of stock market participation and, conditional on participation, a smaller reduction in the share of risky assets in total financial wealth.

To test this prediction, I estimate the following panel regression model.

$$\begin{aligned} y_{h,t} = \alpha &+ \beta_1 \cdot \text{Unexpected Death}_{h,t} + \beta_2 \cdot \text{Industry Correlation}_{h,i,j,t} \\ &+ \beta_3 \cdot \text{Unexpected Death}_{h,t} \times \text{Industry Correlation}_{h,i,j,t} \\ &+ \beta_4 \cdot \text{Unexpected Death}_{h,t} \times \text{Income Ratio}_{h,t} + X'_{h,i,j,t}\Gamma + \epsilon_{h,t} \end{aligned} \tag{2}$$

where $y_{h,t}$ is an indicator of stock market participation (*Market Participation*) or the share of risky assets in total financial wealth (*Share of Risky Assets*) for a household h at time t. *Unexpected Death*h, t is a dummy variable set to one after the unexpected death of the spouse in household h at time t. *Industry Correlation*h, i, j, t is the conditional correlation of income growth between industry i and industry j in which the spouses of household h work, respectively, at time t. *Income Ratio*h is constructed as the share of spousal income in family income in the last wave before sudden death in household h at time t. I interact this variable with the shock dummy to account for the first-moment effect (income loss) of death shocks. Therefore, $\beta 3$ is the parameter of interest that captures the difference in the second-moment effect (less risk-sharing) between high-correlation households and low-correlation households who are both hit by the sudden death of spouses. The vector $X_{h,i,j,t}$ contains the same set of fixed effects and controls in Equation 1 to consistently account for the major determinants of households' portfolio choices both before and after death shocks.[3] Standard errors are also clustered by state.

My identification strategy relies on the suddenness of spousal death shocks. If households have already expected the arrival of death events in the near future, they may reallocate wealth in advance to cope with income shocks. Moreover, anticipating the reduction of intra-household risk-sharing in case of spousal death, households may reduce their financial risk-taking beforehand. Together, these would lead to an overestimation of the impact of intra-household risk-sharing in the event of spousal death.

To address this concern, I exploit the unique information about health and mortality in the HRS data and apply an integrated definition of unexpected death. A death event would be defined as unexpected if it satisfies any one of the three conditions below.[4] First, thanks

[3]For this purpose, I have to extrapolate the information of deceased spouses by copying their time-invariant demographics to post-death periods. Since respondents do not frequently change their occupations and industries over time in the sample, I also assume that the employment of dead spouses remains unchanged from the last wave before death as if they were still alive. Meanwhile, their ages are mechanically adjusted by adding two for every wave since death.

[4]Table IA6 shows the composition of spousal death events documented in the final HRS sample. The contribution of each condition is also provided. The ratio of households hit by unexpected death shocks is 1.22%.

to a unique question in the HRS exit survey, I regard a spousal death event as unexpected if the remaining partner thinks the death was unexpected at the time it occurred. This subjective evaluation is essential for capturing the exogenous impacts of death shocks on households' investment behaviors which are now decided by the surviving spouse. Second, I apply a conservative medical definition of sudden death to complement the subjective evaluation of family members. Inspired by Andersen and Nielsen (2011), I treat a death event as unexpected if the length of time between the start of the final illness and death is less than a day. Compared with the strict medical definition adopted by the American Academy of Pediatrics (2002), the time requirement for unexpected death is slightly relaxed in this paper for concerns of unknown death cause and the limited sample size.[5] Third, thanks to the rich information about the health conditions of respondents in the HRS, I treat a death event as unexpected if the deceased spouse has never been diagnosed with any major health problems before death.[6] With these conditions, I eventually identified 55 unexpected spousal death events from 4,514 unique households in my final sample.[7] With consideration to multiple aspects of death events, this integrated definition of unexpected death can reasonably ensure the suddenness of spousal death, especially when I do not have

[5]According to the guidelines published by the American Academy of Pediatrics, sudden cardiac death is defined as a non-traumatic, nonviolent, unexpected event resulting from sudden cardiac arrest within six hours of a previously witnessed state of normal health.

[6]In each wave of HRS, respondents are asked to report if they have ever been diagnosed with any one of these eight conditions: 1) high blood pressure or hypertension; 2) diabetes or high blood sugar; 3) cancer or a malignant tumor of any kind except skin cancer; 4) chronic lung disease except asthma such as chronic bronchitis or emphysema; 5) heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems; 6) stroke or transient ischemic attack; 7) emotional, nervous, or psychiatric problems; and 8) arthritis or rheumatism. From Wave 13 forward, this list of conditions further includes sleep disorders.

[7]To ensure that my findings are not driven by the small number of treatment households, I relax the time gap condition for sudden death and thus identify 70 unexpected spousal death events in the final sample. As shown in Table IA10, the effects of intra-household risk sharing are still significant but only weaker in magnitudes. This finding also implies the importance of applying reasonably stricter definitions of sudden death.

the data about the causes of death.

Meanwhile, another concern about my empirical design is that spousal death may affect households' portfolio choices in multiple ways. For instance, an obvious channel of impact is through the reduction of family income. From this perspective, I measure the relative importance of the dead spouse by the share of her earnings in total household income before death. Then, I account for the impact of the income drop by interacting the income ratio with the difference-in-difference dummy of unexpected death shocks.

Moreover, any unobserved impacts of spousal death would not affect my estimation in the triple-difference setting, which essentially compares household financial behaviors within households struck by sudden death. To the extent that impacts of sudden spousal death through changes in unobserved household characteristics (e.g., risk aversion) are unlikely to vary by industry correlations, these impacts on low- and high-correlation households should be of similar directions and magnitudes. Therefore, this does not matter for my identification of the intra-household risk-sharing channel.

4 Empirical Results

4.1 Does intra-household risk sharing affect financial risk-taking?

I first examine whether intra-household risk sharing affects households' financial decision-making. Table 2 presents the baseline regression results. Columns (1) and (2) present the results for a binary decision to be a stockholder or non-stockholder (extensive margin). Columns (3) and (4) present the results for the share of risky assets in total financial wealth, conditional on market participation (intensive margin).

Controlling for age, education, income, and other relevant demographics, households with a high industry correlation of income growth are significantly less likely to invest in the stock market. This negative effect of high industry correlation increases further after controlling for household wealth, which is a major determinant of household stock market participation. A one-standard-deviation increase in income correlation, on average, is associated with a decrease in the likelihood of stock market participation by 0.86 percentage points. Given that 41% of households participate in the stock market, the difference of 0.86 percentage points represents a participation gap of 2.12%.

Furthermore, I find a smaller share of investment in the stock market for high-correlation households, conditional on participation. As shown in Column (4), this gap in the share of risky assets between high-correlation and low-correlation households is more significant after controlling for household wealth. A one-standard-deviation increase in industry correlation, on average, is associated with a decrease in the share of risky assets by 0.64 percentage points, or 2.11% evaluated at the mean.

The above findings suggest a negative relation between intra-household risk sharing and households' financial investment after controlling for major characteristics at the individual and household levels. Moreover, the respondent-spouse fixed effects of occupation help mitigate the concern that the baseline results could be driven by the careers of both spouses. It is also worth noting that the gap in financial risk-taking between high-correlation and low-correlation households is established conditionally on controlling for changes in each spouse's industry over time. Therefore, both the participation gap and the investment gap in the baseline analysis are robust, implying the crucial effect of intra-household risk sharing.

[Insert Table 2 here]

4.2 Does intra-household risk sharing reduce income risk?

Despite the intuitive nature of intra-household risk sharing as a fundamental tool for reducing income risk, it is important to first empirically examine the effect of internal risk diversification on the family income risk. Therefore, I investigate whether and how the volatility of total labor income varies with the conditional income correlation between spouses.

Since most households tend to remain in their job industries over time, I rely on the cross-sectional dispersion of family income across households with different levels of industry correlation. To measure income volatility, I compute mean-normalized standard deviations of labor income for each household group (high correlation versus low correlation) in each state and at each point in time. Furthermore, I analyze the effect of industry correlations on income volatility by exploiting both the HRS and the CPS household samples because of their respective advantages. While the former provides richer information about individual and family characteristics, the latter boasts a much larger sample size, offering an extensive depiction of labor income dynamics for households across different industries.

Table 3 presents compelling evidence for a negative relationship between income volatility and intra-household risk sharing. The cross-sectional dispersion of total labor income is significantly higher when households employ a lower degree of intra-household risk sharing, proxied by higher industry income correlations between spouses. This finding is robust when using the CPS household sample. Taken together, these results provide strong evidence for the risk diversification effect of intra-household risk sharing, consistent with previous studies in labor and family economics. Households with a higher degree of intra-household risk sharing indeed have lower overall income risk and are thus relatively more capable of taking financial risks.

[Insert Table 3 here]

4.3 Causal impact of intra-household risk sharing

Despite the above efforts, industry correlation may remain an endogenous measure of income correlation between spouses. To address this concern, I adopt a triple-differences research design based on the unexpected death of spouses. Before discussing the identification results, I first highlight the importance of exploiting the suddenness of spousal death. The intuition is straightforward. If the decease of the spouse is partially anticipated by the other partner, household investment decisions could be adjusted accordingly before the actual happening of death event. This would lead to an underestimation of the impacts on financial risk-taking for our purpose.

To illustrate this problem, I compare financial risk-taking behaviors before and after different types of spousal death shocks. Table 4 presents the results. As shown in Panel A, while there is no significant change in the likelihood of market participation for households after expected spousal death shocks, the reduction in mean likelihood is substantial and significant for households after unexpected spousal death shocks. Similar results are also documented in terms of the share of risky assets (unconditional on participation) in their financial wealth. Taken together, these results suggest the importance of using unexpected death for identification in order to avoid capturing households' pre-shock adjustments in financial risk-taking.

[Insert Table 4 here]

Then, I examine whether households with high industry correlation reduce their exposure to financial risk by a smaller magnitude than low-correlation households after the sudden death of spouses. Table 5 presents the triple-differences regression results. Column (1) shows that, compared with low-correlation households, households with higher industry correlations are less affected in their likelihood of market participation after experiencing spousal death. This result is consistent with a smaller impact of death shocks on the financial risk-taking of high-correlation households who were relatively inactive in financial investment due to a lower degree of intra-household risk sharing before shocks. Meanwhile, as shown in Column (2), the difference in the impact of death shocks between high-correlation and low-correlation households barely changes after controlling for the effect of income loss due to spousal death. This suggests that losing a working spouse indeed affects households' decisions of market participation through two distinct channels.

Moreover, I find strong evidence supporting the differential impacts of intra-household risk sharing on households' shares of risky investment after spousal death. Column (3) shows that conditional on participation, households in high-correlation industries indeed have a significantly smaller reduction in the share of risky assets after the unexpected loss of spouses. This gap in the impact of intra-household risk sharing, as shown in Column (4), is more pronounced after accounting for the impact of income ratio, implying the importance of the internal risk-sharing channel. The effect is now statistically significant at the 1% level. In terms of magnitude, a one-standard-deviation increase in industry correlation leads to a decrease in the reduction of the investment proportion by 8.5 percentage points. This difference in the impact on the share of risky assets would translate into an economically significant gap of 28.37% evaluated at the mean for high-correlation households relative to others after spousal death.

[Insert Table 5 here]

Compared with the results in the baseline analysis, the causal finding about the difference in impacts of intra-household risk sharing on household financial risk-taking is substantially larger in terms of magnitude. This may reflect the importance of incorporating unexpected spousal death in the triple-differences design to alleviate the problem of endogeneity. Unobserved individual characteristics (e.g., risk aversion) or industry-level factors (e.g., concurrent industry events) could affect both intra-household risk sharing (implied by industry correlation) and households' portfolio choices. Therefore, my identification can address this concern by looking at variations driven by the sudden death of key family members only.

Finally, the impacts of intra-household risk sharing are of different significance for distinct aspects of households' financial decision-making. Although the sign of the coefficient is consistent with the impact of intra-household risk sharing on the share of risky assets, and the coefficient is economically significant, the effect on participation is not statistically significant. This suggests that the disruption of intra-household risk sharing due to the loss of working spouses is pronounced for existing stockholders who would reduce their exposure to financial risk instead of exiting the stock market completely. Given this finding, I focus on the risky asset allocation choices of households conditional on participation (intensive margin) throughout my remaining analyses.

4.4 Dynamic effects

Figure 2 plots the dynamic effect of unexpected death shocks on the risk-taking behaviors of households with a high industry correlation of income growth. I display the coefficients on the triple-differences term of industry correlation.

For the share of risky assets, there are no significant differences between high-correlation and low-correlation households before the death shock, suggesting that the parallel pre-trend assumption is supported. Furthermore, high-correlation households are significantly less affected by the disruption of intra-household risk sharing, compared with low-correlation households who also lost working spouses. The differential impact on high-correlation households' allocation of risky assets instantly arises when the death event occurs and remains robust afterward for over 6 years (3 waves). This indicates the importance of intra-household risk sharing for households' financial risk-taking, as the impact of losing this diversification channel at the intensive margin could be long-lasting.

[Insert Figure 2 here]

4.5 Robustness

In this subsection, I provide robustness checks.

4.5.1 Alternative measures of industry correlation

Throughout my analysis, I use the correlation of income growth between industries where the respondent and the spouse work to reflect the degree of intra-household risk sharing [8]. I compute this measure in a rolling window of 36 months to capture the time-

[8] I also check the robustness of my findings using industry covariance as an alternative proxy for intra-household risk sharing. For brevity, I only show the results of using conditional industry covariance computed

varying connection between industries. This approach also implies a flexible assumption under which couples could learn from historical information about wages and dynamically coordinate their job choices. Hence, I test whether my key findings depend on the size of the wage information set, reflected by the size of the rolling window. I reconstruct the correlation measure with different rolling windows, ranging from 24, 48, 60 to 72 months.

Table 6 presents the regression results that demonstrate the differential effects of intra-household risk sharing, represented by industry correlations, on households' share of risky assets following a spousal death. The conditional industry correlation in Column (1) is calculated over a rolling window of 24 months. In comparison to households with low correlations, high-correlation households exhibit a significantly smaller decrease in the share of risky assets after the sudden loss of a spouse. Moreover, the coefficient of the triple-differences term for industry correlation is smaller than the one in Table 5 (0.346), suggesting a reduced impact of intra-household risk sharing for high-correlation households. This aligns with the notion that risk diversification among couples may rely on their comprehension of inter-industry relationships.

Evidence from other columns in Table 6 further supports this intuition. The investment gap between households in high-correlation and low-correlation industries remains robust across different measures of industry correlations. The magnitude of this gap increases when conditional correlations are computed in larger rolling windows, implying the importance of a comprehensive depiction of inter-industry dynamics. Overall, the results confirm the robustness of my findings on the impact of intra-household risk sharing with alternative

in a 36-month rolling window (Table IA4). The results of the identification test are presented in Table IA8, and my key findings in both tests hold.

measures of industry correlation.

[Insert Table 6 here]

4.5.2 Alternative definitions of unexpected death

My casual inference of the impact of intra-household risk sharing relies on the exogeneity of spousal death. Anticipation of the shock could lead to households' adjustment of financial risk exposure before the actual loss happens, resulting in an overestimation of the impact on households' financial risk-taking. To address this concern, I apply an integrated definition of sudden death which contains information about health and mortality. While my assessment of pre-death health conditions covers 8 common types of major illness (9 since Wave 13 in 2012), it is possible that I have mistreated death events as unexpected if they are caused by omitted health problems. Therefore, I exclude this criterion of no pre-death illness and rely solely on the remaining spouse's judgment as well as a medical definition that is based on the abruptness of the final illness. Then, I reexamine my key findings to check if there are any misestimations.

Table 7 presents the results. A stricter definition of sudden spousal death does not undermine my findings on the substantial impact of intra-household risk sharing. Conditional on participation, households with high industry correlations have a significantly smaller reduction in the share of risky assets, compared with low-correlation households after death shocks. This is robust for different conditional correlations computed in various rolling windows. Moreover, coefficients of the triple-differences term of industry correlation in each column are all larger than that in the original regression (0.346), implying a larger magnitude of the investment gap. Therefore, while my causal inference with the benchmark definition of sudden death is not spurious, adopting a stricter definition also helps identify a larger impact of intra-household risk sharing.

[Insert Table 7 here]

The above findings emphasize the importance of using stringent definitions of unexpected death. Nevertheless, it is crucial to acknowledge that this approach would inevitably reduce the number of households affected by these rare events. Therefore, to address this concern about the small treatment group, I introduce new definitions of unexpected death and re-test the impact of intra-household risk sharing. Specifically, I relax the requirement of the length of time between the start of final illness and death from less than one day to less than one year. With this adjustment, the treatment group expands by 27%, containing a total of 70 households who experienced unexpected spousal death during the sample period.

Table IA10 presents the results. The impact of intra-household risk sharing on households' financial risk-taking remains robust even when employing a more lenient criterion for unexpected spousal death. Conditional on participation, couples employed in industries with high income correlations are significantly less affected in their allocation of risky assets after spousal death, compared with those in industries with lower correlation. This finding substantiates the validity of previous conclusions regarding the impact of intra-household risk sharing since it is not driven by the small number of treatment households. More importantly, the gap of impact between households in high- and low-correlation industries narrows, as reflected by smaller coefficients of the key triple-differences term. This result underscores the importance of employing stringent definitions of sudden death to ensure the exogenous nature of death shocks, albeit at the cost of reducing the size of the treatment group.

4.6 Heterogeneous effects

In this subsection, I examine the heterogeneous effects of intra-household risk sharing on households' financial risk-taking choices. If intra-household risk sharing is indeed a crucial channel for couples to diversify labor income risk, I expect a weaker impact of losing this channel for high-education or high-wealth households after death shocks. This is because they have more ability to hedge against labor income risks than others and may rely less on the basic tool of internal diversification. To test this hypothesis, I interact the triple-differences term of industry correlation with high-education and high-wealth dummy variables.

Table 8 reports the heterogeneous effect results with high-education and high-wealth households, respectively. Conditional on participation, the reduction in the share of risky assets is significantly smaller for high-correlation households after death shocks if the remaining spouse has some college education or more. Meanwhile, the negative impact of the disruption of intra-household risk sharing on risky asset allocation is significantly smaller for high-correlation households if their wealth levels are higher than the sample mean. These findings show that the education level and the wealth level are two important factors in explaining the heterogeneous effects of intra-household risk sharing on households' financial risk-taking.

Similarly, the relative importance of intra-household risk sharing as a risk management tool would be smaller when households own any health or life insurance, which protects them against long-term risks, especially in unexpected events like death. As shown in Panel C of Table 8, the heterogeneous effect with the insurance owner corroborates this notion. Compared with other high-correlation households, the decrease in the share of risky assets after spousal death is significantly reduced when the remaining spouse owns any health or life insurance. Hence, this evidence further emphasizes the nature of intra-household risk sharing as a major tool of income risk management.

[Insert Table 8 here]

From another perspective, the relative importance of intra-household risk sharing does not just depend on households' ability to manage and hedge income risks, but also on their attitudes towards labor income risk. Following this intuition, I expect a stronger effect of unexpected spousal death on households' allocation of risky assets if they care more about their exposure to labor income risk. To test this hypothesis, I interact the triple-difference term of industry correlation with two indicators of households' risk attitudes.

Given the unique questions about beliefs and expectations in the HRS, I define two proxies for households' attitudes toward income risk. Firstly, a respondent would be regarded as having "high risk aversion" if they choose any option other than the least risky one in a hypothetical income gamble question. Secondly, a respondent would be regarded as having a "long horizon" if the length of time is a year or longer when asked about financial planning for family saving and spending. This is because a longer financial planning horizon implies a stronger incentive for income risk management to ensure consumption smoothing.

Panels A and B of Table 9 report the results of the heterogeneous effects with proxies of risk attitudes, respectively. I find that, conditional on participation, the reduction in the share of risky assets is significantly larger for high-correlation households after death shocks if the remaining spouse is more risk averse to income. Similarly, the negative impact of losing intra-household risk sharing is significantly stronger for high-correlation households if their financial planning is for a longer period.

[Insert Table 9 here]

Moreover, I examine the relative importance of intra-household risk sharing from the perspective of the business cycle. Inspired by Shore (2010), I focus on the heterogeneous effect on households' financial risk-taking choices during economic recessions. The intuition is that households value intra-household risk sharing more during bad times since they may face more income shocks in these periods. The result in Table 10 shows that intra-household risk sharing indeed matters more for households' portfolio choices during economic recessions. Since earnings are more volatile during these difficult periods, this result is also consistent with my previous finding about the relative importance of risk sharing for households who are more sensitive to income risks.

[Insert Table 10 here]

5 Conclusion

In this paper, I examine whether intra-household risk sharing can affect households' financial risk-taking through the labor income risk channel. To this end, I exploit the inter-industry measure for conditional correlation of income growth as well as micro-level household data for portfolio holdings and both spouses' job industries. I find that households with high industry correlation indeed face higher income volatility. These households are also less likely to participate in the stock market and conditional on participation, invest a smaller proportion of wealth in risky assets. I further identify the causal impact of intra-household risk sharing on households' portfolio choices by exploiting unexpected events of spousal death. The effect is robust to both various risk measures and alternative definitions of sudden death. Overall, I identify intra-household risk sharing as a novel determinant of households' financial risk-taking.

An important implication of my finding is that positive assortative mating may have unintended consequences for wealth inequality among households. The growing economic resemblance of spouses could increase the correlation within the couple regarding their employment and earnings. This may impair the fundamental function of marriages in risk sharing, which is particularly important for low-education, low-wealth, and income risk-sensitive households. Therefore, this trend of family composition could reinforce wealth inequality by discouraging investment for households that are already disadvantaged in wealth accumulation.

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Table 1. **Descriptive Statistics**

This table provides descriptive statistics for households in the final HRS sample. *Market participation* is an indicator equal to one if the household owns any direct investment in either stock or mutual fund, excluding investment through retirement accounts. *Share of risky assets* is the percentage of the value of stocks and mutual funds in the value of total financial wealth, where total financial wealth consists of savings, checking, bonds, stocks, and mutual funds. *Log household income* is the logged total income received by both spouses. *Log household wealth* is the logged net value of total household wealth which includes real estate, vehicles, businesses, retirement accounts, and financial assets. *Home ownership* is an indicator equal to one if the household owns any primary, secondary residence, or other real estate. *Number of children* is the number of children for each household. Individual characteristics are reported for both respondent and spouse. All dollar-valued variables are deflated by the CPI with 1990=100. p1, p50, and p99 denote the value of 1-, 50-, and 99-th percentile.

	N	Mean	SD	p1	p50	p99
Market participation	13,805	0.41	0.49	0	0	1
Share of risky assets	13,797	0.22	0.33	0	0	0.99
Log household income	13,805	10.94	0.88	8.95	10.95	12.85
Log household wealth	13,805	11.86	1.49	7.47	11.95	14.86
Home ownership	13,805	0.94	0.23	0	1	1
Number of children	13,805	3.20	1.84	0	3	10
Male respondent	13,805	0.23	0.42	0	0	1
Respondent age	13,805	55.90	6.69	39	56	73
Respondent race						
White	13,805	0.86	0.35	0	1	1
Black	13,805	0.10	0.30	0	0	1
Other	13,805	0.04	0.19	0	0	1
Respondent education						
Less than high school	13,805	0.11	0.31	0	0	1
High school graduate	13,805	0.37	0.48	0	0	1
Some college	13,805	0.26	0.44	0	0	1
College graduate	13,805	0.26	0.44	0	0	1
Respondent self-employed	13,805	0.20	0.40	0	0	1
Log respondent income	13,805	8.29	3.62	0	9.73	11.61
Male spouse	13,805	0.77	0.42	0	1	1
Spouse age	13,805	57.96	6.59	41	57	76
Spouse race						
White	13,805	0.86	0.35	0	1	1
Black	13,805	0.10	0.30	0	0	1
Other	13,805	0.04	0.21	0	0	1
Spouse education						
Less than high school	13,805	0.15	0.36	0	0	1
High school graduate	13,805	0.32	0.47	0	0	1
Some college	13,805	0.24	0.42	0	0	1
College graduate	13,805	0.29	0.45	0	0	1
Spouse self-employed	13,805	0.27	0.44	0	0	1
Log spouse income	13,805	8.17	3.99	0	9.95	11.88

Table 2. **Baseline Regressions**

This table reports the baseline regression results. The dependent variable is a dummy equal to one if the household owns any stock or mutual fund in Columns (1) and (2). The dependent variable is the ratio of the value of stocks and mutual funds to the value of total household financial wealth in Columns (3) and (4). *Industry correlation* is the conditional correlation between year-to-year growth rates of mean wage from the two industry groups in which the respondent and spouse are employed respectively. The correlation is computed in a rolling window of 36 months. Wages in each industry group are collected from the Merged Outgoing Rotation Group (MORG) Earnings Data in the NBER-extract of the Current Population Survey (CPS) Basic Monthly Data. All wages are also deflated by the monthly CPI with 1983 January as its base. The list of my reclassification of 37 industry groups is in Appendix IA1. Gender is a dummy equal to one if the person is male. Age is grouped into five-year intervals and birth cohorts are defined as 10-year birth intervals. Race is grouped into three categories. Education is grouped into four categories. Occupations are grouped into 10 broad categories following Acemoglu and Autor (2011). Insurance is a dummy equal to one if the person owns any health insurance, long-term care insurance, or life insurance. Self-employment is a dummy equal to one if the person is reported as self-employed. Industries are grouped into 37 broad categories listed in Appendix IA1. Household income is classified into 28 bins: (n-1) $\times$ \$5,000 $\leq$ household income $\leq$ n $\times$ \$5,000 (n=1,2,...,24), \$120,000+(n-1) $\times$ \$40,000 $\leq$ household income $\leq$ \$120,000+n $\times$ \$40,000 (n=1,2,3), and household income $\geq$ \$40,000. Home ownership is a dummy equal to one if the household owns any real estate. Number of children is grouped into five categories. Standard errors are clustered by state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var	Market participation		Share of risky assets	
Industry correlation	-0.033**	-0.035**	-0.022*	-0.026**
	(-2.34)	(-2.45)	(-1.98)	(-2.36)
Log household wealth		0.101***		0.084***
		(18.70)		(14.70)
Fixed Effects				
Respondent gender	Yes	Yes	Yes	Yes
Spouse gender	Yes	Yes	Yes	Yes
Respondent age group	Yes	Yes	Yes	Yes
Spouse age group	Yes	Yes	Yes	Yes
Respondent cohort of birth	Yes	Yes	Yes	Yes
Spouse cohort of birth	Yes	Yes	Yes	Yes
Respondent race $\times$ Spouse race	Yes	Yes	Yes	Yes
Respondent edu. $\times$ Spouse edu.	Yes	Yes	Yes	Yes
Respondent occ. $\times$ Spouse occ.	Yes	Yes	Yes	Yes
Respondent ins. $\times$ Spouse ins.	Yes	Yes	Yes	Yes
Respondent self-employed	Yes	Yes	Yes	Yes
Spouse self-employed	Yes	Yes	Yes	Yes
Respondent industry $\times$ Year	Yes	Yes	Yes	Yes
Spouse industry $\times$ Year	Yes	Yes	Yes	Yes
Household income	Yes	Yes	Yes	Yes
Number of children	Yes	Yes	Yes	Yes
Home ownership	Yes	Yes	Yes	Yes
State $\times$ Year	Yes	Yes	Yes	Yes
Observations	14,106	13,805	9,926	9,807
Adj. R^2	0.171	0.213	0.066	0.108

Table 3. **The Effect of Income Correlation on Distribution of Family Income**

This table shows the effect of intra-household risk sharing, proxied by income correlations, on the distribution of family income. Dependent variables in Columns (1) and (2) are the standard deviation of family income for each state, each wave, and the high-income correlation group versus the low-income correlation group (classified by the mean value of conditional correlation at each wave). Standard deviations are normalized by the group mean. Family income refers to the total income received by both spouses. *Industry correlation* is the conditional correlation between year-to-year growth rates of mean wage from the two industry groups in which the respondent and spouse are employed respectively. For the HRS sample in Column (1), log household wealth and all of the fixed effects in Table 2 are included as controls. In Column (2), the CPS sample is used for the test. Since there is only limited information about household and individual characteristics in the CPS survey, I am only able to account for parts of the previous set of controls. This includes fixed effects for gender, age group (five-year intervals), and self-employment at the individual level; interactive fixed effects for race, education, and job occupation of both spouses; industry-by-year-month fixed effects for both spouses; fixed effects for total income and number of children at the household level; and state-by-year-month fixed effects. For both tests, standard errors are clustered by state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Dep. Var	Std. Dev. of total labor income	
	HRS	CPS
Industry correlation	0.009***	0.007***
	(3.60)	(17.92)
Controls	Yes	Yes
Observations	13,834	989,532
Adj. R^2	0.579	0.563

Table 4. **Comparison of Risk-taking Behaviors: Death Shocks**

This table reports the results of a comparative analysis of financial risk-taking behaviors for households before and after experiencing spousal death shocks in the final HRS sample. For households who have experienced spousal death during the sample period, they are divided into two groups based on the suddenness of death shocks, which is defined by any one of these three conditions: (i) the remaining partner thinks the death was unexpected at the time it occurred; (ii) the length of time between the start of the final illness and death is less than a day; (iii) the deceased spouse has never been diagnosed with any major health problems before death. Then, I compare households' investment behaviors between the pre-shock and the post-shock period in two different aspects. In Panel A, I focus on market participation which is defined as any direct investment in either stock or mutual fund, excluding investment through retirement accounts. In Panel B, I focus on the share of investment in risky assets. This is captured by the percentage of the value of stocks and mutual funds in the value of total financial wealth, where total financial wealth consists of savings, checking, bonds, stocks, and mutual funds. Mean values of both measures are reported for each household group before and after the spousal death shock. The last column reports the result of mean-comparison T-tests, based on Heteroskedasticity-consistent (HC3) standard errors, of whether the two samples (households before death shock vs after death shock) have equal means where ***,**, and * indicate significance at 1%, 5%, and 10% from mean-comparison T-tests, respectively.

Panel A: Market Participation			
	Before death	After death	Difference (Before – After)
Total	0.404		/
Households with expected spousal death	0.368	0.366	0.002
Households with unexpected spousal death	0.538	0.277	0.260***
Panel B: Share of Risky Assets			
	Before death	After death	Difference (Before – After)
Total	0.214		/
Households with Expected Spousal Death	0.196	0.195	0.001
Households with Unexpected Spousal Death	0.262	0.131	0.131***

Table 5. **Causal Impacts of Industry Correlation on Risk-taking Behaviors**

This table reports the results of identification which exploits unexpected death of spouses. The dependent variable is a dummy equal to one if the household owns any stock or mutual fund in Columns (1) and (2). The dependent variable is the ratio of the value of stocks and mutual funds to the value of total financial wealth in Columns (3) and (4). *Unexpected death* is an indicator taking one for years after unexpected spousal death events. *Industry correlation* is the conditional correlation between year-to-year growth rates of mean wage from the two industry groups in which the respondent and spouse are employed respectively. To exploit the death shock, certain information about the deceased spouse is extrapolated for treatment households. Specifically, the industry group of the deceased spouse in the last wave before death is copied into later waves. Time-invariant characteristics of the deceased spouse are also copied except age, which is assumed to be growing normally. *Income ratio* is defined as the ratio of the deceased spouse's income to the total household income in the last wave before death. It is set as missing for households that have never experienced unexpected spousal death during the sample period. Log household wealth and all of the fixed effects in Table 2 are included as controls. Standard errors are clustered by state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var	Market participation		Share of risky assets	
Unexpected Death	0.022	0.031	-0.025	-0.069
	(0.37)	(0.35)	(-0.54)	(-0.82)
Industry correlation	-0.036**	-0.036**	-0.030**	-0.030**
	(-2.29)	(-2.30)	(-2.70)	(-2.68)
Unexpected Death × Industry correlation	0.056	0.054	0.326**	0.346***
	(0.40)	(0.38)	(2.69)	(2.81)
Unexpected Death × Income ratio		-0.022		0.101
		(-0.19)		(0.75)
Controls	Yes	Yes	Yes	Yes
Observations	14,450	14,435	10,229	10,226
Adj. R^2	0.210	0.210	0.108	0.108

Table 6. **Robustness Check with Industry Correlation**

This table shows the result of the robustness check of the effect of industry correlation on risk-taking behaviors by using alternative measures of industry correlations in the identification setting. Specifically, different lengths of rolling windows (24/48/60/72 months) are used to compute industry correlation. The dependent variable is the ratio of the value of stocks and mutual funds to the value of total financial wealth. *Unexpected death* is an indicator taking one for years after unexpected spousal death events. *Industry correlation* is the conditional correlation between year-to-year growth rates of mean wage from the two industry groups in which the respondent and spouse are employed respectively. *Income ratio* is defined as the ratio of the deceased spouse's income to the total household income in the last wave before death. It is set as missing for households that have never experienced unexpected spousal death during the sample period. Log household wealth and all of the fixed effects in Table 2 are included as controls. Standard errors are clustered by state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) Window: 24 months	(2) Window: 48 months	(3) Window: 60 months	(4) Window: 72 months
Dep. Var	Share of risky assets			
Unexpected Death	-0.070	-0.083	-0.078	-0.081
	(-0.81)	(-0.94)	(-0.89)	(-0.92)
Industry correlation	-0.028**	-0.029**	-0.031**	-0.030**
	(-2.68)	(-2.56)	(-2.54)	(-2.36)
Unexpected Death × Industry correlation	0.342***	0.378***	0.361***	0.370**
	(3.13)	(3.02)	(2.76)	(2.67)
Unexpected Death × Income ratio	0.115	0.110	0.094	0.091
	(0.84)	(0.80)	(0.68)	(0.67)
Controls	Yes	Yes	Yes	Yes
Observations	10,226	10,226	10,226	10,226
Adj. R^2	0.108	0.108	0.108	0.108

Table 7. **Robustness Check with Unexpected Death (Stricter Definitions)**

This table shows the result of a robustness check of the effect of industry correlation on risk-taking behaviors by using an alternative definition of unexpected spousal death in the identification setting. Specifically, I exclude the condition of no major illness before death. Unexpected death is now defined based on either households' subjective evaluation or the length of time from the start of final illness to death. The dependent variable is the ratio of the value of stocks and mutual funds to the value of total financial wealth. *Unexpected death* is an indicator taking one for years after unexpected spousal death events. *Industry correlation* is the conditional correlation between year-to-year growth rates of mean wage from the two industry groups in which the respondent and spouse are employed respectively. *Income ratio* is defined as the ratio of the deceased spouse's income to the total household income in the last wave before death. It is set as missing for households that have never experienced unexpected spousal death during the sample period. Log household wealth and all of the fixed effects in Table 2 are included as controls. Standard errors are clustered by state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) Window: 24 months	(2) Window: 36 months	(3) Window: 48 months	(4) Window: 60 months
Dep. Var	Share of risky assets			
Unexpected Death	-0.165	-0.150	-0.170	-0.148
	(-1.55)	(-1.24)	(-1.43)	(-1.22)
Industry correlation	-0.028**	-0.029**	-0.029**	-0.030**
	(-2.63)	(-2.62)	(-2.49)	(-2.46)
Unexpected Death × Industry correlation	0.461***	0.393**	0.412**	0.363**
	(3.48)	(2.30)	(2.46)	(2.04)
Unexpected Death × Income ratio	0.206	0.165	0.193	0.155
	(1.27)	(0.93)	(1.09)	(0.86)
Controls	Yes	Yes	Yes	Yes
Observations	10,226	10,226	10,226	10,226
Adj. R^2	0.108	0.108	0.108	0.108

Table 8. **Heterogeneous Effect of Industry Correlation on Risk-taking Behaviors: The Ability of Risk Diversification**

This table shows the heterogeneous effect of industry correlation on risk-taking behaviors, depending on the ability of risk diversification. Specifically, I interact the triple-difference term of industry correlation with different proxies of the ability of risk diversification. The dependent variable is the ratio of the value of stocks and mutual funds to the value of total financial wealth. In Panel A, *High education* is an indicator equal to one if the degree of education is some college education or above for the respondent. In Panel B, *High wealth* is an indicator equal to one if the total household wealth is larger than the full-sample mean. In Panel C, *Insurance owner* is an indicator equal to one if the respondent owns any health insurance, long-term care insurance, or life insurance. *Unexpected death* is an indicator taking one for years after unexpected spousal death events. *Industry correlation* is the conditional correlation between year-to-year growth rates of mean wage from the two industry groups in which the respondent and spouse are employed respectively. The effect of income ratio, log household wealth, and all of the fixed effects in Table 2 are included as controls except in Panel B where log household wealth is replaced with the wealth dummy. Standard errors are clustered by state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var	Share of risky assets
Panel A: Education	
Unexpected Death × Industry correlation	-0.197*
	(-1.76)
Unexpected Death × Industry correlation × High education	0.717***
	(3.80)
Controls	Yes
Observations	10,226
Adj. R^2	0.109
Panel B: Household Wealth	
Unexpected Death × Industry correlation	-0.459*
	(-1.89)
Unexpected Death × Industry correlation × High wealth	0.824***
	(2.80)
Controls	Yes
Observations	10,226
Adj. R^2	0.071
Panel C: Insurance Ownership	
Unexpected Death × Industry correlation	-0.763**
	(-2.11)
Unexpected Death × Industry correlation × Insurance owner	1.119***
	(2.87)
Controls	Yes
Observations	10,226
Adj. R^2	0.108

Table 9. **Heterogeneous Effect of Industry Correlation on Risk-taking Behaviors: The Attitude Towards Income Risks**

This table shows the heterogeneous effect of industry correlation on risk-taking behaviors, depending on the attitude towards income risks. Specifically, I interact the triple-difference term of industry correlation with different proxies of the attitude towards income risks. The dependent variable is the ratio of the value of stocks and mutual funds to the value of total financial wealth. In Panel A, I exploit a hypothetical income gamble question in HRS. Respondents are asked whether they would take a job (i) with an equal probability of doubling income or cutting it in half, (ii) with an equal probability of doubling income or cutting it by a third, (iii) with an equal probability of doubling income or cutting it by 20%, or (iv) none of the above. *High risk aversion* is an indicator equal to one if the respondent chooses any answer other than (i). In Panel B, I explore a question about financial planning in HRS. Respondents are asked which time period is most important to them in planning their family's saving and spending: (i) next few months, (ii) next year, (iii) next few years, (iv) next 5-10 years, or (v) longer than 10 years. *Long horizon* is an indicator equal to one if the respondent chooses any answer other than (i) and (ii). *Unexpected death* is an indicator taking one for years after unexpected spousal death events. *Industry correlation* is the conditional correlation between year-to-year growth rates of mean wage from the two industry groups in which the respondent and spouse are employed respectively. The effect of income ratio, log household wealth, and all of the fixed effects in Table 2 are included as controls. Standard errors are clustered by state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var	Share of risky assets
Panel A: Income Risk Aversion	
Unexpected Death × Industry correlation	3.041***
	(5.48)
Unexpected Death × Industry correlation × High risk aversion	-2.074*
	(-1.78)
Controls	Yes
Observations	3,523
Adj. R^2	0.108
Panel B: Financial Planning Horizon	
Unexpected Death × Industry correlation	1.520***
	(4.77)
Unexpected Death × Industry correlation × Long horizon	-1.290***
	(-3.83)
Controls	Yes
Observations	4,659
Adj. R^2	0.117

Table 10. **Heterogeneous Effect of Industry Correlation on Risk-taking Behaviors: Business Cycle**

This table shows the heterogeneous effect of industry correlation on risk-taking behaviors over the business cycle. Specifically, I focus on economic recessions and interact the triple-difference term of industry correlation with a recession indicator. The dependent variable is the ratio of the value of stocks and mutual funds to the value of total financial wealth. *Economic Recession* is a dummy equal to one for periods defined as recessions. I rely on the monthly NBER-based recession indicators which are based on a subjective assessment of a variety of measures for aggregate real economic activity in the United States. *Unexpected death* is an indicator taking one for years after unexpected spousal death events. *Industry correlation* is the conditional correlation between year-to-year growth rates of mean wage from the two industry groups in which the respondent and spouse are employed respectively. The effect of income ratio, log household wealth, and all of the fixed effects in Table 2 are included as controls. Standard errors are clustered by state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var	Share of risky assets
Unexpected Death $\times$ Industry correlation	0.373***
	(3.05)
Unexpected Death $\times$ Industry correlation $\times$ Economic Recession	-0.817**
	(-2.19)
Controls	Yes
Observations	10,226
Adj. R^2	0.108

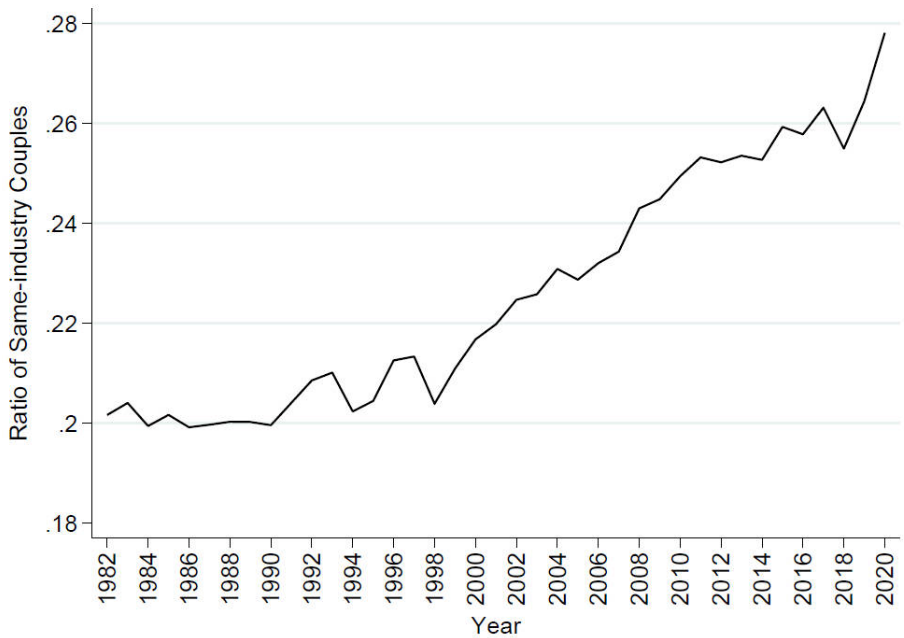

Figure 1. **Same-industry Combinations among Working Couples: 1982-2020**

This figure shows the trend of same-industry combinations among working couples in the U.S. between 1982 and 2020. I capture the trend with ratios of households in which both spouses work in the same industry group to total households of working couples. I use household data from the NBER extracts of the Merged Outgoing Rotation Groups (MORG) files of the Current Population Survey (CPS) published by the U.S. Census Bureau and the Bureau of Labor Statistics. For easier interpretation, I group all 3-digit Census industries into 37 industry groups. Table IA1 lists all industry groups. I then compute weighted ratios of same-industry couples for every month between 1982 and 2020. Lastly, I compute and plot annual averages of the monthly ratio during this period.

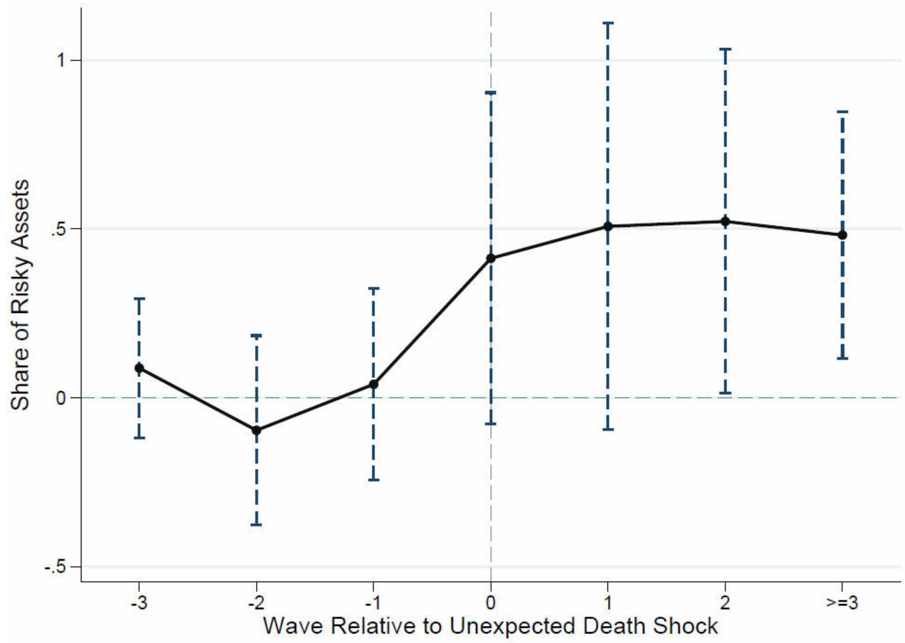

Figure 2. **Dynamic Effects of Unexpected Death Shock on Risk-taking Behaviors**

This figure shows the dynamic effect of unexpected death shock on risk-taking behaviors for households with high industry correlation relative to those with low industry correlation. I plot point estimates as well as a 95% confidence interval using standard errors clustered at the state levels. The specification is the same as that in Equation 2, except that the triple-differences term is replaced by time-indicators interacted with the industry correlation variable where time-indicators take one for 1, 2, or 3 waves before death shock as well as the wave of death shock or 1 and 2 waves after or longer than 2 waves after death shock. I focus on the share of risky assets in total financial wealth to capture dynamic effects on households' risk-taking behaviors in the intensive margin.

Internet Appendix to "Spouses in The Same Boat: Labor Income Risk and Intra-household Risk Sharing"

September 30, 2023

Table IA1. **Classification of Industry Groups**

This table shows the list of 37 industry groups I used in matching the CPS earning data and the HRS household sample. The classification is based on the Census Industry Codes.

1	Agriculture
2	Forestry and fisheries
3	Mining
4	Construction
	Manufacturing
	Durable goods
5	Wood products
6	Furniture and fixtures
7	Nonmetallic mineral products
8	Metal products
9	Machinery, except electrical
10	Computer and electronic products
11	Electrical equipment and appliance
12	Transportation equipment
	Non-durable goods
13	Food and kindred products
14	Tobacco
15	Textile, apparel, and leather
16	Paper and allied products
17	Petroleum and coal
18	Chemicals
19	Plastics and rubber
20	Miscellaneous and not specified
21	Wholesale trade
22	Retail trade
23	Transportation
24	Utilities and sanitary services
25	Printing and publishing
26	Communications
27	Internet service and other information services
28	Finance
29	Insurance
30	Real Estate
31	Business services
32	Repair services
33	Personal services (except private households)
34	Private households
35	Entertainment and recreation services
36	Professional and technical services
37	Public Administration

Table IA2. **Examples of industry pairs and correlations**

This table shows examples of industry pairs by sorting correlation. Specifically, I compute the mean correlation for each industry pair in 1995, 2005, and 2015. I then sort all industry pairs by the mean correlation and list out the Top 5 (Panel A) and Bottom 5 (Panel B) industry pairs in these three years respectively. Mfg stands for manufacturing. Svcs stands for services.

	Panel A: Top 5	
	1995	
1	Mfg: petroleum and coal	Real Estate
2	Mfg: nonmetallic mineral products	Private households
3	Mfg: tobacco	Entertainment and recreation svcs
4	Mfg: food and kindred products	Mfg: chemicals
5	Mfg: wood products	Mfg: electrical equipment and appliance
	2005	
1	Wholesale trade	Utilities and sanitary svcs
2	Forestry and fisheries	Utilities and sanitary svcs
3	Finance	Real Estate
4	Forestry and fisheries	Wholesale trade
5	Mfg: food and kindred products	Mfg: petroleum and coal
	2015	
1	Professional and technical svcs	Public Administration
2	Mfg: chemicals	Transportation
3	Construction	Repair svcs
4	Personal svcs	Private households
5	Retail trade	Internet svcs and other information svcs
	Panel B: Bottom 5	
	1995	
1	Mfg: wood products	Mfg: metal products
2	Construction	Professional and technical svcs
3	Mfg: electrical equipment and appliance	Mfg: petroleum and coal
4	Mfg: paper and allied products	Business services
5	Mfg: tobacco	Mfg: petroleum and coal
	2005	
1	Mfg: transportation equipment	Entertainment and recreation svcs
2	Wholesale trade	Professional and technical svcs
3	Real Estate	Public Administration
4	Mfg: wood products	Mfg: chemicals
5	Forestry and fisheries	Personal svcs
	2015	
1	Finance	Repair svcs
2	Forestry and fisheries	Mfg: nonmetallic mineral products
3	Wholesale trade	Professional and technical svcs
4	Finance	Professional and technical svcs
5	Agriculture	Insurance

Table IA3. **Baseline Regressions with Correlation (Robustness)**

This table shows the result of the robustness check of the baseline effect of intra-household risk sharing by using an alternative approach for computing industry correlation. The dependent variable is a dummy equal to one if the household owns any stock or mutual fund in Columns (1) and (2). The dependent variable is the ratio of the value of stocks and mutual funds to the value of total financial wealth in Columns (3) and (4). *Industry correlation* is the conditional correlation between year-to-year growth rates of median wage from the two industry groups in which the respondent and spouse are employed respectively. The correlation is computed in a rolling window of 36 months. Wages in each industry group are collected from the Merged Outgoing Rotation Group (MORG) Earnings Data in the NBER-extract of the Current Population Survey (CPS) Basic Monthly Data. The list of my reclassification of 37 industry groups is in Appendix IA1. All of the fixed effects in Table 2 are included as controls. Standard errors are clustered by state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var	Market participation		Share of risky assets	
Industry correlation	-0.029**	-0.031**	-0.016	-0.020*
	(-2.11)	(-2.15)	(-1.42)	(-1.76)
Log household wealth		0.101***		0.084***
		(18.66)		(14.66)
Controls	Yes	Yes	Yes	Yes
Observations	14,106	13,805	9,926	9,807
Adj. R^2	0.171	0.213	0.066	0.108

Table IA4. **Baseline Regressions with Covariance**

This table reports the baseline regression results with using industry covariance as the alternative measure of intra-household risk sharing. The dependent variable is a dummy equal to one if the household owns any stock or mutual fund in Columns (1) and (2). The dependent variable is the ratio of the value of stocks and mutual funds to the value of total financial wealth in Columns (3) and (4). *Industry covariance* is the conditional covariance between year-to-year growth rates of mean wage from the two industry groups in which the respondent and spouse are employed respectively. The covariance is computed in a rolling window of 36 months. Wages in each industry group are collected from the Merged Outgoing Rotation Group (MORG) Earnings Data in the NBER-extract of the Current Population Survey (CPS) Basic Monthly Data. The list of my reclassification of 37 industry groups is in Appendix IA1. All of the fixed effects in Table 2 are included as controls. Standard errors are clustered by state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var	Market participation		Share of risky assets	
Industry covariance	-3.990*	-5.943**	-3.766	-5.423*
	(-1.71)	(-2.42)	(-1.22)	(-1.78)
Log household wealth		0.102***		0.084***
		(18.49)		(14.77)
Controls	Yes	Yes	Yes	Yes
Observations	14,106	13,805	9,926	9,807
Adj. R^2	0.170	0.212	0.066	0.108

Table IA5. **Baseline Regressions with Covariance (Robustness)**

This table shows the result of the robustness check of the baseline effect of intra-household risk sharing by using an alternative approach for computing industry covariance. The dependent variable is a dummy equal to one if the household owns any stock or mutual fund in Columns (1) and (2). The dependent variable is the ratio of the value of stocks and mutual funds to the value of total financial wealth in Columns (3) and (4). *Industry covariance* is the conditional covariance between year-to-year growth rates of median wage from the two industry groups in which the respondent and spouse are employed respectively. The covariance is computed in a rolling window of 36 months. Wages in each industry group are collected from the Merged Outgoing Rotation Group (MORG) Earnings Data in the NBER-extract of the Current Population Survey (CPS) Basic Monthly Data. The list of my reclassification of 37 industry groups is in Appendix IA1. All of the fixed effects in Table 2 are included as controls. Standard errors are clustered by state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var	Market participation		Share of risky assets	
Industry covariance	-1.974	-2.939*	-1.204	-1.972
	(-1.42)	(-1.86)	(-0.74)	(-1.16)
Log household wealth		0.101***		0.084***
		(18.55)		(14.76)
Controls	Yes	Yes	Yes	Yes
Observations	14,106	13,805	9,926	9,807
Adj. R^2	0.170	0.212	0.066	0.108

Table IA6. **Composition of Unexpected Spousal Death**

This table reports the composition of spousal death events documented in the final HRS sample. For households who have experienced spousal death during the sample period, they are divided into two groups based on the suddenness of death shocks, which is defined by any one of the three conditions listed below: (i) the remaining partner thinks the death was unexpected at the time it occurred; (ii) the length of time between the start of the final illness and death is less than a day; (iii) the deceased spouse has never been diagnosed with any major health problems before death. For each category of death events, I provide the number of unique households and their proportion to the total household sample accordingly.

	# Unique households	Proportion to the total sample (%)
Total	4,514	100
Households with expected spousal death	176	3.90
Households with unexpected spousal death	55	1.22
Regarded as unexpected by the remaining spouse	28	0.62
Died within a day after the start of final illness	1	0.02
No major health problems before death	26	0.58

Table IA7. **Causal Impacts of Industry Correlation on Risk-taking Behaviors (Robustness)**

This table shows the result of the robustness check of the identification test by using an alternative approach for computing industry correlation. The dependent variable is a dummy equal to one if the household owns any stock or mutual fund in Columns (1) and (2). The dependent variable is the ratio of the value of stocks and mutual funds to the value of total financial wealth in Columns (3) and (4). *Unexpected death* is an indicator taking one for years after unexpected spousal death events. *Industry correlation* is the conditional correlation between year-to-year growth rates of median wage from the two industry groups in which the respondent and spouse are employed respectively. To exploit the death shock, certain information about the deceased spouse is extrapolated for treatment households. Specifically, the industry group of the deceased spouse in the last wave before death is copied into later waves. Time-invariant characteristics of the deceased spouse are also copied except age, which is assumed to be growing normally. *Income ratio* is defined as the ratio of the deceased spouse's income to the total household income in the last wave before death. It is set as missing for households that have never experienced unexpected spousal death during the sample period. Log household wealth and all of the fixed effects in Table 2 are included as controls. Standard errors are clustered by state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var	Market participation		Share of risky assets	
Unexpected Death	0.036	0.049	-0.012	-0.051
	(0.60)	(0.53)	(-0.25)	(-0.58)
Industry correlation	-0.031**	-0.031**	-0.025**	-0.025**
	(-2.10)	(-2.11)	(-2.11)	(-2.08)
Unexpected Death $\times$ Industry correlation	-0.020	-0.022	0.292**	0.306**
	(-0.16)	(-0.17)	(2.44)	(2.49)
Unexpected Death $\times$ Income ratio		-0.029		0.090
		(-0.26)		(0.64)
Controls	Yes	Yes	Yes	Yes
Observations	14,450	14,435	10,229	10,226
Adj. R^2	0.210	0.210	0.108	0.108

Table IA8. **Causal Impacts of Industry Covariance on Risk-taking Behaviors**

This table reports the results of identification which exploits unexpected death of spouses. The dependent variable is a dummy equal to one if the household owns any stock or mutual fund in Columns (1) and (2). The dependent variable is the ratio of the value of stocks and mutual funds to the value of total financial wealth in Columns (3) and (4). *Unexpected death* is an indicator taking one for years after unexpected spousal death events. *Industry covariance* is the conditional covariance between year-to-year growth rates of mean wage from the two industry groups in which the respondent and spouse are employed respectively. To exploit the death shock, certain information about the deceased spouse is extrapolated for treatment households. Specifically, the industry group of the deceased spouse in the last wave before death is copied into later waves. Time-invariant characteristics of the deceased spouse are also copied except age, which is assumed to be growing normally. *Income ratio* is defined as the ratio of the deceased spouse's income to the total household income in the last wave before death. It is set as missing for households that have never experienced unexpected spousal death during the sample period. Log household wealth and all of the fixed effects in Table 2 are included as controls. Standard errors are clustered by state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var	Market participation		Share of risky assets	
Unexpected Death	0.031	0.040	-0.007	-0.047
	(0.55)	(0.49)	(-0.16)	(-0.56)
Industry covariance	-5.448**	-5.472**	-5.165*	-5.146*
	(-2.21)	(-2.21)	(-1.76)	(-1.74)
Unexpected Death $\times$ Industry covariance	10.729	10.501	121.496***	125.758***
	(0.23)	(0.22)	(3.17)	(3.37)
Unexpected Death $\times$ Income ratio		-0.023		0.092
		(-0.20)		(0.69)
Controls	Yes	Yes	Yes	Yes
Observations	14,450	14,435	10,229	10,226
Adj. R^2	0.210	0.210	0.108	0.108

Table IA9. **Causal Impacts of Industry Covariance on Risk-taking Behaviors (Robustness)**

This table shows the result of the robustness check of the identification test by using an alternative approach for computing industry covariance. The dependent variable is a dummy equal to one if the household owns any stock or mutual fund in Columns (1) and (2). The dependent variable is the ratio of the value of stocks and mutual funds to the value of total financial wealth in Columns (3) and (4). *Unexpected death* is an indicator taking one for years after unexpected spousal death events. *Industry covariance* is the conditional covariance between year-to-year growth rates of median wage from the two industry groups in which the respondent and spouse are employed respectively. To exploit the death shock, certain information about the deceased spouse is extrapolated for treatment households. Specifically, the industry group of the deceased spouse in the last wave before death is copied into later waves. Time-invariant characteristics of the deceased spouse are also copied except age, which is assumed to be growing normally. *Income ratio* is defined as the ratio of the deceased spouse's income to the total household income in the last wave before death. It is set as missing for households that have never experienced unexpected spousal death during the sample period. Log household wealth and all of the fixed effects in Table 2 are included as controls. Standard errors are clustered by state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var	Market participation		Share of risky assets	
Unexpected Death	0.028	0.036	0.001	-0.037
	(0.50)	(0.44)	(0.03)	(-0.43)
Industry covariance	-2.773*	-2.759*	-2.008	-1.995
	(-1.84)	(-1.82)	(-1.21)	(-1.20)
Unexpected Death $\times$ Industry covariance	15.818	15.627	52.201**	54.371***
	(0.46)	(0.45)	(2.58)	(2.76)
Unexpected Death $\times$ Income ratio		-0.020		0.090
		(-0.18)		(0.65)
Controls	Yes	Yes	Yes	Yes
Observations	14,450	14,435	10,229	10,226
Adj. R^2	0.210	0.210	0.107	0.108

Table IA10. **Robustness Check with Unexpected Death (Relaxed Definitions)**

This table shows the result of a robustness check of the effect of industry correlation on risk-taking behaviors by using an alternative definition of unexpected spousal death in the identification setting. Specifically, I change the time condition from the start of the final illness to death and relax its requirement from less than a day to less than a year. Meanwhile, other conditions for suddenness of death remain unchanged. The dependent variable is the ratio of the value of stocks and mutual funds to the value of total financial wealth. *Unexpected death* is an indicator taking one for years after unexpected spousal death events. *Industry correlation* is the conditional correlation between year-to-year growth rates of mean wage from the two industry groups in which the respondent and spouse are employed respectively. *Income ratio* is defined as the ratio of the deceased spouse's income to the total household income in the last wave before death. It is set as missing for households that have never experienced unexpected spousal death during the sample period. Log household wealth and all of the fixed effects in Table 2 are included as controls. Standard errors are clustered by state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) Window: 24 months	(2) Window: 36 months	(3) Window: 48 months	(4) Window: 60 months
Dep. Var	Share of risky assets			
Unexpected Death	-0.086	-0.078	-0.089	-0.082
	(-1.07)	(-1.03)	(-1.15)	(-1.07)
Industry correlation	-0.029***	-0.030***	-0.030**	-0.031**
	(-2.76)	(-2.76)	(-2.64)	(-2.60)
Unexpected Death $\times$ Industry correlation	0.346***	0.330***	0.356***	0.334***
	(4.51)	(4.23)	(4.49)	(3.93)
Unexpected Death $\times$ Income ratio	0.137	0.116	0.121	0.104
	(1.09)	(0.96)	(1.00)	(0.86)
Controls	Yes	Yes	Yes	Yes
Observations	10,225	10,225	10,225	10,225
Adj. R^2	0.109	0.108	0.108	0.108

Table IA11. **Heterogeneous Effect of Industry Correlation on Risk-taking Behaviors: Business Cycle (Robustness)**

This table shows the result of the robustness check of the heterogeneous effect of industry correlation on risk-taking behaviors over the business cycle. Specifically, I focus on economic recessions and interact the triple-difference term of industry correlation with a different recession indicator. The dependent variable is the ratio of the value of stocks and mutual funds to the value of total financial wealth. I use an alternative recession indicator which is mechanically and solely based on the historical GDP data for the United States. *Economic Recession* is a dummy equal to one for periods defined as recession accordingly. *Unexpected death* is an indicator taking one for years after unexpected spousal death events. *Industry correlation* is the conditional correlation between year-to-year growth rates of mean wage from the two industry groups in which the respondent and spouse are employed respectively. The effect of income ratio, log household wealth, and all of the fixed effects in Table 2 are included as controls. Standard errors are clustered by state. Data on recession indicators is from the Federal Reserve Bank of St. Louis. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var	Share of risky assets
Unexpected Death × Industry correlation	0.373***
	(3.05)
Unexpected Death × Industry correlation × Economic Recession	-0.817**
	(-2.19)
Controls	Yes
Observations	10,226
Adj. R^2	0.108