Income Volatility and Portfolio Choices*

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Abstract

Based on administrative data from Statistics Norway, we find economically significant shifts in households' financial portfolios around individual structural breaks in labor-income volatility. According to our estimates, when income risk doubles, households reduce their risky share of financial assets by 5 percentage points, thus tempering their overall risk exposure. We show that our estimated risky share response is consistent with a standard portfolio choice model augmented with idiosyncratic, time-varying income volatility.

JEL Classification: E2, G1, J3.
Keywords: Income Volatility, Portfolio Choice, Risky Share

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1 Introduction

How do households respond to income risk? According to the standard theory (starting with Aiyagari, 1994), households save more, work more, or adjust their financial portfolios in response to uninsurable wage risk. This paper studies the last channel empirically and quantitatively: when faced with higher wage risk, households lower the share invested in risky assets, thus tempering their overall risk exposure (Merton, 1971; Kimball, 1993; Constantinides and Duffie, 1996; Heaton and Lucas, 1996, 2000).

The purpose of our analysis is twofold. First, based on administrative panel data from Statistics Norway, we confirm a significant negative relationship between wage risk and the risky share of financial assets by further elaborating on the method developed by Fagereng, Guiso, and Pistaferri (2017).[1] Second, we introduce idiosyncratic stochastic volatility (e.g., second moment) shocks to the wage process in an otherwise standard life-cycle model of portfolio choice (e.g., Cocco, Gomes, and Maenhout, 2005). We then ask whether the standard model can reproduce the portfolio response we estimated from the data. This is a new attempt, since existing quantitative models of portfolio choice do not reflect the idiosyncratic and time-varying component of income risk.

Households in Norway are obliged to report detailed information about their income and wealth to the tax authority every year. As a result, our data set includes a complete description of households' labor income and financial assets as well as their allocation to safe and risky financial accounts. We merge the households' income and financial data with other data regarding labor market status, demographic characteristics, and, more importantly for our analysis, employer information.

We employ two techniques to generate a large response of portfolio to income risk. First, we identify the "structural" breaks in income volatility, which are the periods when an individual worker experiences the largest change in the standard deviation of income growth. By looking at big events, we can potentially avoid noisy variations unrelated to true regime changes. Second, we use firm volatility as an instrumental variable to isolate exogenous (or unpredictable) events to households—an innovative method pioneered by Fagereng, Guiso, and Pistaferri (2017). Indeed, a recent literature suggests that a substantial portion of the residual variation in earnings is predictable and reflects individual choices rather than risk (e.g., Primiceri and van Rens, 2009; Guvenen and Smith, 2014). Misinterpreting the

[1] There has been increased use of the administrative data from Statistics Norway. For example, Fagereng, Gottlieb, and Guiso (2017) analyze the portfolio responses to volatility or portfolio allocation over the life cycle. Fagereng and Halvorsen (2015) study household debt and heterogeneity in the marginal propensity to consume. Eika, Mogstad, and Vestad (2017) analyze consumption expenditure using data on income and assets. Fagereng, Holm, Moll, and Natvik (2019) analyze the saving rate across the wealth distribution and highlight the importance of capital gains.

predictable (or endogenous) variations in income as risk is likely to bias the estimated response of the portfolio toward zero.

We estimate a clear and large negative response of risky share to income volatility. When income volatility (that is not anticipated by households) doubles, a typical (median) worker decreases her risky share by 5 percentage points (over a 4-year horizon), whereas the ordinary-least-squares (OLS) estimate predicts a mere 0.4 percentage point reduction in the risky share. Thus, isolating pure income risk from noisy or endogenous variations of income volatility increases (in absolute terms) the estimated response of the portfolio by an order of magnitude.

To test whether a standard model of portfolio choice is consistent with our estimated response, our benchmark model features: (i) a life-cycle economy with incomplete asset markets, (ii) a portfolio choice between risk-free bonds and risky equity (e.g., Cocco, Gomes, and Maenhout, 2005 and Gomes and Michaelides, 2005), (iii) an exogenous borrowing limit, (iv) labor earnings that consist of a mix of heterogeneous income profiles (Guvenen and Smith, 2014) and uninsurable stochastic shocks, and finally (iv) our highlighted new element, idiosyncratic shocks to income volatility (stochastic volatility). We show that our model—calibrated to various income and financial moments from the Norwegian panel—reproduces the portfolio response we see in the data fairly well. According to our structural model, the welfare cost of time-varying income risk is large: 4% in consumption-equivalent units. The welfare gain from being able to adjust financial portfolio (between risky and risk-free assets) in response to such risk is about 1%.

Our analysis contributes to the empirical literature by combining individual structural breaks in income volatility with a firm-side instrumental variable and yields a large and precisely estimated response of risky share. Most of the literature (based on cross-sectional data) reports an effect of background risk on risky share that is qualitatively consistent with economic theory but quantitatively small (e.g., Guiso, Jappelli, and Terlizzese, 1996; Palia, Qi, and Wu, 2014). An exception is Angerer and Lam (2009), who find large differences in portfolio composition with respect to permanent components of income volatility. Our analysis also complements the work by Fagereng, Guiso, and Pistaferri (2017), who first used the firm-side information as an instrument to isolate the orthogonal variations in households' income volatility. According to our analysis, using structural breaks further reduces the influence of frequent noisy events, generating a response 16% larger than what the instrument alone can generate.

We contribute to the literature on the quantitative analysis of portfolio choices (e.g., Heaton and Lucas, 2000; Haliassos and Michaelides, 2003; Cocco, Gomes, and Maenhout, 2005; Gomes and Michaelides, 2005; Benzoni, Collin-Dufresne, and Goldstein, 2011; Athreya, Ionescu, and Neelakantan, 2015; Huggett and Kaplan, 2016; Fagereng, Gottlieb, and Guiso, 2017; Chang, Hong, and Karabarbounis, 2018; Catherine, 2019) by introducing the idiosyncratic volatility shocks into the standard model.

Our paper is also related to the literature analyzing the dynamic process for idiosyncratic volatility. Meghir and Pistaferri (2004) model volatility dynamics using an ARCH specification based on data from the Panel Study of Income Dynamics. Guvenen, Karahan, Ozkan, and Song (2015) use tax-record data to document a series of stylized facts regarding higher-order moments of the earnings distribution. We consider a dynamic process for volatility and exploit higher-order moments of earnings (e.g., the kurtosis of earnings) to discipline the size of the volatility shocks.

The rest of the paper is structured as follows. Section 2 estimates households' portfolio response to income risk using the administrative data from Norway. Section 3 builds a structural model augmented with idiosyncratic, time-varying income volatility. In Section 4 we calibrate the model to match the key statistic from the Norwegian panel and perform a quantitative analysis. Section 5 conducts the welfare analysis. Section 6 explores a few alternative model specifications (with respect to adjustment costs in portfolio choice, the stochastic process of income volatility, and imperfect information). Section 7 concludes.

2 Empirical Analysis

We utilize a wealth of information regarding labor income, asset holdings, and portfolio composition from Statistics Norway and document two main facts:

1. A large fraction of workers experience sharp changes in the volatility of their labor income growth.

2. The risky share of financial assets significantly decreases (increases) in response to an increase (decrease) in labor income volatility.

2.1 Data

The Norwegian Registry is a set of comprehensive, relatively measurement-error-free data with detailed information on labor income and household financial assets. Households in Norway are subject to not only an income tax but also a wealth tax. Thus, they are obliged to report their complete income and wealth holdings to the tax authority every year. Employers, banks, brokers, insurance companies, and any other financial intermediaries are also obliged to send information on the value of personal assets to both the individual and the tax authority.[2]

The financial accounts in our data include bank deposits, financial securities, shares in mutual funds, shares in private companies, pension agreements, insurance policies, total debt (loans, credit purchases, mortgages), and others. We also have information on homeownership as well as house values.[3]

We merge our wealth data with other data sets such as: (1) the Income Registry Data, which have detailed information on earned income, including cash salary, taxable benefits and sickness and maternity benefits each year, capital investment income, entrepreneurial income, unemployment benefits, and pensions; (2) the Central Population Register, which contains yearly individual demographic information (e.g., gender, date of birth, marital status, number of children, to name a few); (3) the National Educational Database, which has the history and the latest education record for each resident, and finally, (4) the Employer-Employee Register, which provides annual information on workers' labor market status (full-/part-time employment, employer ID, beginning/ending time of job, total payments from each employer, industry, occupation, etc.). All data sets are merged using unique personal identifiers assigned to each individual and firm (similar to Social Security numbers and employment identification numbers in the U.S.). For more details on our data, see Appendix A.1.

The data are uniquely suitable to address many challenges arising in the empirical analysis of portfolio choices and income volatility. Traditional data sets, which are typically based on surveys, present at least four issues. First, respondents often misreport their labor income or wealth intentionally or unintentionally.[4] In our data, information is directly collected by third parties (employers or financial institutions) for tax purposes, which substantially reduces measurement errors. Second, household surveys are often top-coded. This is problematic when analyzing higher-order moments of earnings that may be driven by top earners (Guvenen, Karahan, Ozkan, and Song, 2015). Third, traditional data with detailed information on households' financial assets (such as the Survey of Consumer Finances) are repeated cross-sections. Thanks to the panel dimension of our data, we can eliminate bias stemming from

[2]Traded financial securities are reported at market value. The value of shares in private companies is reported by individuals as well as private companies to the tax authority. The tax authority will then combine the information from companies' reports with those from individual households and adjust if necessary.

[3]Reliable information on house value is available only for the period 2010-2014. For earlier years, the housing value for homeowners reported in the tax registry data may not be the true market values, typically under-reported, due to self-reporting errors and/or treatment policies of wealth tax. This is well-documented in the literature (see Eika, Mogstad, and Vestad (2017), Fagereng and Halvorsen (2017), among others). For our definition of the risky share, we focus on financial assets and exclude housing and mortgage debt. Nonetheless, in the empirical analysis, we include homeownership dummies in the list of control variables in the regression.

[4]For example, see the handbook chapter "Measurement Error in Survey Data," by Bound, Brown, and Mathiowetz (2001).

unobserved fixed heterogeneity (e.g., different risk preferences across individuals) in the estimation. Fourth, there is frequent attrition in traditional data, whereas attrition in our data occurs only due to migration or death.

For our sample we start with the whole population of Norwegian natives from 1994 to 2014, with no missing records on income and wealth tax registration and other important demographic variables. We first exclude individuals younger than 25 years old and older than 65 years old. We drop individuals working in the public sector. We also require workers to have positive labor earnings each year and to be associated with an identified firm ID in the data. This leaves us with 5,712,476 person-year observations. We further restrict the sample to individuals with at least 500 Norwegian kroner in financial assets (roughly the first percentile of the distribution) and with annual earnings growth smaller than 150% in absolute value. This gives us 5,399,332 person-year observations and 342,875 persons. Finally, we require that individuals have a positive amount in risky investments for at least 16 years (we define risky investment below) – this allows us to focus more clearly on portfolio choices conditional on participation; nevertheless, later on we conduct robustness analysis from various different perspectives and confirm that our main conclusions are not affected by these restrictions. In spite of our sample criteria, we are left with a large sample: 1,879,771 person-year observations and 125,874 individuals. For more details on our sample selection and construction, see Appendix A.2.

Risky Share Following the standard literature, we classify financial assets into two categories: safe and risky. Safe assets include deposits in Norwegian banks, the cash value of life insurance policies, and debt securities traded in the financial market (mainly government bonds). Risky assets include shares in mutual funds, shares in private companies, and financial securities (mainly stocks and equity certificates traded in financial markets).[5] Total financial assets are the sum of safe and risky assets at the household level. The risky share of financial assets is the value of risky assets over the value of total financial assets. In our benchmark definition, we do not consider debt and focus on gross savings. As mentioned, in our benchmark sample households should have positive risky shares for at least 16 years;[6] thus, we focus on households' portfolio choices conditional on participation in the stock market.[7]

Table 1 presents summary statistics for households' financial accounts (expressed relative

[5]Since we do not have detailed information on the riskiness of the individual's investment in mutual funds, we use aggregate statistics from Statistics Norway to split the assets in mutual funds into risky and risk-free components. Our results are quite robust to different splitting rules.

[6]Section 2.4 presents the result when this 16-year requirement is relaxed.

[7]We analyze the case where households make decisions on the stock market participation in Section 6.

Table 1: Summary Statistics for Financial Accounts

Variable	Mean	SD	Percentiles 10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
Share in Financial Assets							
Deposits	0.55	0.31	0.09	0.28	0.59	0.84	0.96
Life Insurance	0.05	0.12	0.00	0.00	0.00	0.02	0.16
Private Equity	0.16	0.30	0.00	0.00	0.00	0.20	0.74
Mutual Funds	0.16	0.21	0.00	0.00	0.07	0.23	0.46
Securities	0.08	0.17	0.00	0.00	0.00	0.06	0.27
Risky Assets	0.38	0.31	0.02	0.11	0.32	0.64	0.86

Notes: Cross-sectional statistics for financial accounts expressed as a fraction of total financial assets. The risky share of financial assets is defined as risky assets divided by total financial assets.

to total financial assets). The average Norwegian household in our benchmark sample has 55% of its money in bank deposits, 5% in life insurance, 16% in private equity, 16% in mutual funds, and 8% in financial securities. Conditional on a participation, the mean risky share is 38%, and the dispersion in risky shares is large, with a standard deviation of 31%. For more information on summary statistics, please see Table A1 in the appendix.

2.2 Individual Structural Break in Income Volatility

We measure changes in background risk based on individual structural breaks in workers' income volatility.[8] The main idea is to identify an episode of a "large" change in labor-income volatility. By looking at big events we can potentially avoid noisy variations unrelated to true regime changes and generate larger responses than those typically found in the literature. More specifically, we look for a year when an individual worker experiences the largest change in terms of the standard deviation in labor-income growth.[9] The algorithm to identify the structural volatility break is as follows:

1. Compute the residual (net of age and time effects) for log of annual labor earnings of individual i at time t: $y_{i,t}$.

[8] For an application of this approach in the context of neighborhood segregation, see Card, Mas, and Rothstein (2008), and for housing and labor markets, see Charles, Hurst, and Notowidigdo (2018).

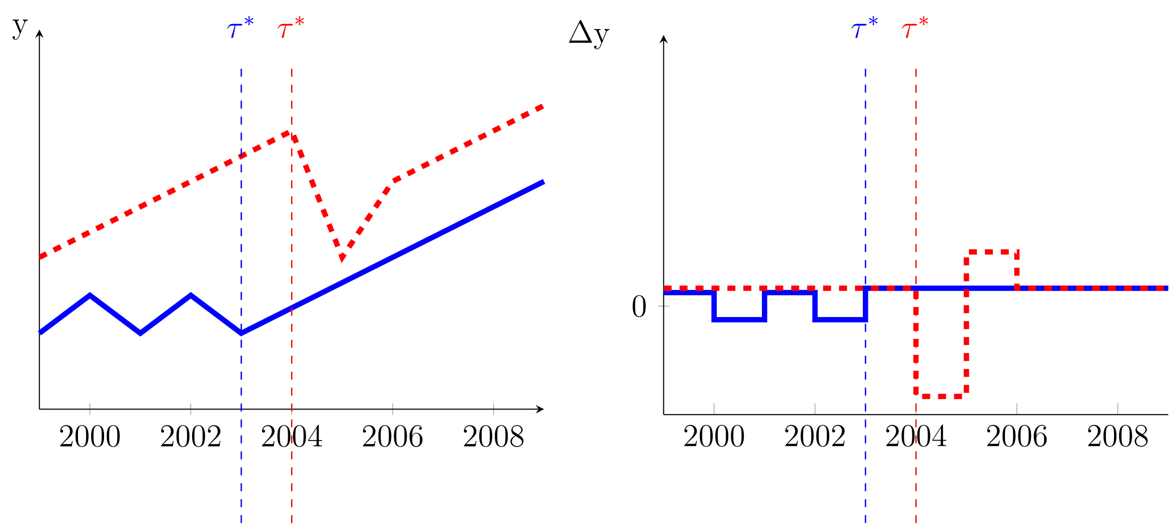
[9] It is well known that there is a significant amount of intra-household insurance and the portfolio decisions are often made at the household level. In Section 2.4 below, we repeat our analysis with the households' total disposable income. In fact, the estimated response of portfolio choice is stronger with respect to volatility changes in households' total disposable income.

2. Construct labor-income growth: $\Delta y_{it} \equiv y_{it} - y_{i,t-1}$. We focus on the changes in income *growth* rather than the *level* to eliminate potential income variations due to heterogeneity in income profiles (which is strongly supported by the data).[10]

3. We then construct the standard deviation before and after τ, $SD(\Delta y)_{i,t<\tau}$ and $SD(\Delta y)_{i,t\geq\tau}$, respectively, for all τ.[11] The change in income volatility for a worker i in year τ is $\Delta SD_{i,\tau} = SD(\Delta y)_{i,t\geq\tau} - SD(\Delta y)_{i,t<\tau}$.

4. Given the sequence of volatility changes for worker i: $\{\Delta SD_{i,\tau}\}$, we identify the structural break period τ^* such that $\tau^* = \text{argmax}_\tau \ \text{abs}(\Delta SD_{i,\tau})$. The corresponding volatility change in the structural-break year is denoted by $\Delta SD_{i,\tau^*}$.

Figure 1: Construction of Individual-Specific τ^*



Notes: The left (right) panel shows hypothetical income paths (growth rates) for two workers. For each worker we show the year identified as a structural break by our method.

Using this methodology we identify the structural break year τ^* for each worker. Each structural break is associated with a positive or a negative change in the standard deviation of labor-income growth. Since we identify the largest change in the worker's income history, each worker has a single structural break.

[10]According to the labor-income specification in Section 3, labor income for worker i at age j is $y_{ij} = a_i + \beta_i \times j + x_{ij}$. Labor-income growth equals $\Delta y_{ij} = y_{ij} - y_{i,j-1} = \beta_i + \Delta x_{ij}$. Therefore, variability over some periods $Var(\Delta y_{ij})$ will ignore the constant term β_i and only consider the variability in the time-varying component $Var(\Delta x_{ij})$.

[11]To compute standard deviations, we require at least 5 observations and thus consider τ between 1999 and 2009.

We demonstrate our methodology to identify the individual structural break in Figure 1. The left panel plots hypothetical labor-income paths, y, for two workers: worker A (solid line) and worker B (dotted line). The right panel shows the growth rate of income, Δy. Worker A's growth rate fluctuates before 2003, and stabilizes after 2003. The structural break τ^* occurs in 2003 and the volatility of income growth decreases after the structural break. Worker B's growth rate is constant up to 2004 and fluctuates thereafter. The structural break τ^* occurs in 2004, and the volatility of income growth increases after the structural break.

Table 2: Summary Statistics for $\Delta SD_{i,\tau^*}$

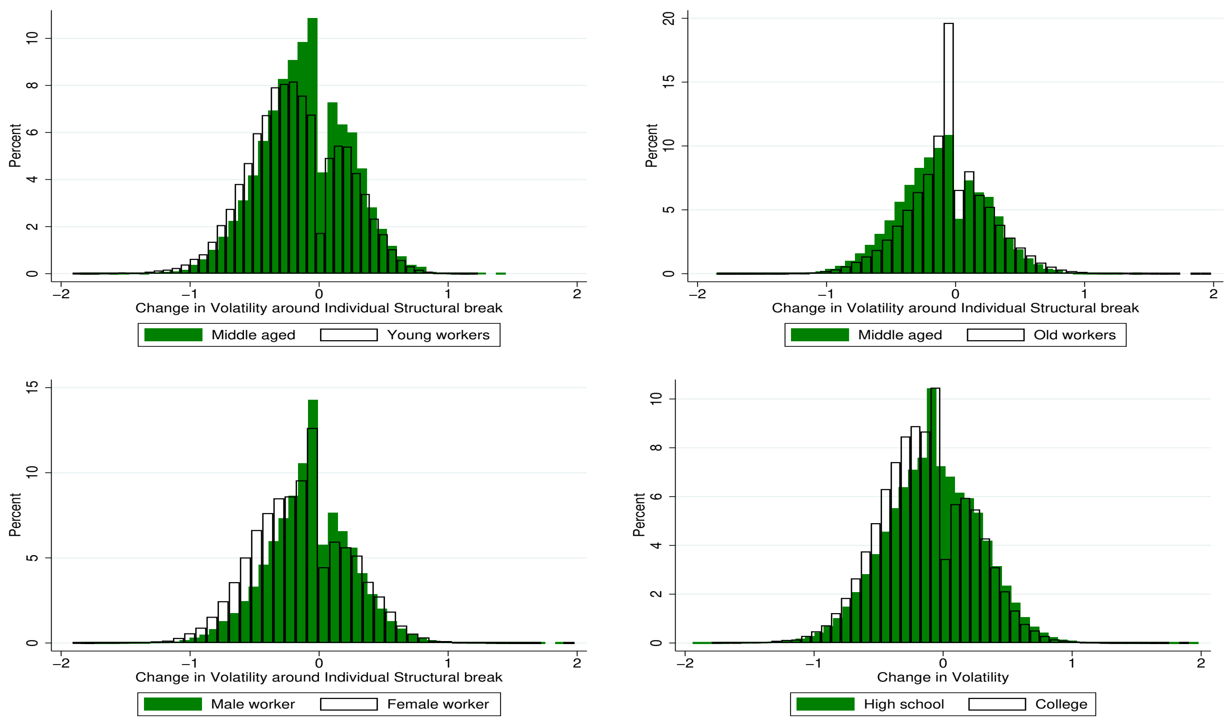
			Percentiles				
$\Delta SD_{i,\tau^*}$	Obs.	S.D.	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
All	125,874	0.34	-0.53	-0.31	-0.09	0.13	0.34
Education:							
High school	88,889	0.34	-0.52	-0.30	-0.08	0.13	0.34
College	36,985	0.35	-0.56	-0.35	-0.13	0.11	0.32
Age:							
Young	32,942	0.37	-0.63	-0.43	-0.20	0.11	0.31
Middle	23,591	0.34	-0.54	-0.33	-0.11	0.13	0.32
Old	66,854	0.32	-0.45	-0.24	-0.06	0.13	0.35
Wealth:							
1^{st} quartile	11,599	0.37	-0.68	-0.45	-0.23	-0.01	0.27
2^{nd}	24,488	0.34	-0.60	-0.39	-0.16	0.06	0.28
3^{rd}	37,662	0.33	-0.52	-0.31	-0.09	0.11	0.32
4^{th}	52,125	0.33	-0.45	-0.24	-0.05	0.17	0.38

Notes: The cross-sectional distribution of $\Delta SD_{i,\tau^*}$. Young is defined as individuals younger than 40, middle-aged between the ages of 40-45 and old as individuals older than 45. The wealth quartile refers to the cross-sectional distribution of households' real wealth.

Table 2 shows summary statistics for $\Delta SD_{i,\tau*}$. A large cross-sectional dispersion of 0.34 suggests a large dispersion in the distribution of changes in the biggest change in income process across workers. The size of individual structural breaks is not symmetric: there are more negative changes (decrease of volatility). In terms of the cross-sectional dispersion of the structural breaks, there is no distinctive difference across demographic groups.

Figure 2 shows the histogram $\Delta SD_{i,\tau^*}$ by age (upper two panels), gender (bottom-left), and education (bottom-right). The biggest change in income volatility is centered around -0.2 (volatility decrease) for young workers, whereas it is centered around zero for middle-aged or old workers. A larger fraction of female workers experience a volatility decrease on average (compared to male workers). The same is true with college graduates.[12]

Figure 2: Distributions for $\Delta SD_{i,\tau^*}$ by Age, Gender, and Education



Notes: The distribution of $\Delta SD_{i,\tau^*}$. The upper-left panel represents the young vs. middle aged and the upper-right the middle aged vs. old. The lower-left panel represents males vs. females and the lower-right high school vs. college graduates.

What's Behind Structural Breaks? We have identified structural breaks in workers' income volatility based on sharp changes in the standard deviation of labor-income growth. Understanding the exact reasons for drastic changes in income process is by itself an important question. Do the volatility breaks occur randomly across individuals or are they correlated with some typical life-cycle events? The events we consider are changes in employer, industry, occupation, location, and homeownership. Consider a simple probit model:

$$\text{Probit}(S_{i,t} = 1) = \sum_{j=1,5} \beta_j D^j_{i,t} + \alpha X_{i,t} + \epsilon_{i,t}, \tag{1}$$

where $S_{i,t}$ equals 1 if individual i's structural break occurs within a two-year window around t, e.g., $S_{i,t} = 1$ if $\tau^* \in [t-2, t+2]$. Dummy variables D^j_{it} $(j = 1, .., 5)$ denote the following 5

[12] According to our sample, the cross-sectional distributions of $\Delta SD_{i,\tau^*}$ in Norway do not significantly differ by year, sectors, and regions in Norway (available in Figures O1, O2 and O3 in the On-line Appendix).

events: changes in employer, 2-digit industry code, 2-digit occupation code, home ownership, and municipality. $D^j_{it} = 1$ if event j has occurred between $t-2$ and $t+2$.[13] The set of control variables $X_{i,t}$ includes age and age squared, dummies for marital status, education and sex, total number of children, number of children younger than 10, and number of children younger than 5. The year dummies are also included to control for business-cycle effects.

Based on the estimated probit, Table 3 displays the marginal effect of each event on the probability of an occurrence of a structural break. Holding all other variables constant at their means, a change of employer significantly increases the probability of having a structural break: an increase by 9.1 percentage points. Other events such as changes in industry, occupation, location, and homeownership have a statistically significant but moderate effect on the occurrence of a structural break (between 0.6 and 1.8 percentage points).

Table 3: Life-Cycle Events and Probability of Structural Break

Event	Probability of Structural Break (β_j)
Changes in	
Employer	9.13*** (0.08)
Industry	1.71*** (0.10)
Occupation	1.43*** (0.10)
Municipality	1.78*** (0.07)
Homeownership	0.60*** (0.13)

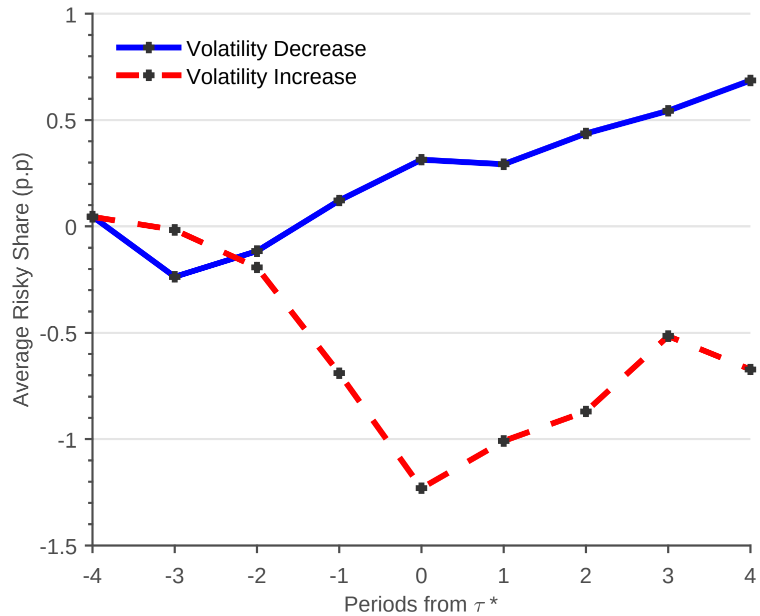
Notes: The estimated coefficients from the probit regression in (1). Three stars denote statistical significance at 1%.

2.3 Response of the Risky Share to Income Volatility

We have identified individual structural breaks (τ^*'s) based on the biggest change in individual income volatility during the sample period. Figure 3 plots the dynamics of risky share around the structural break for two groups of workers. The solid line represents the average risky share of workers with a large decrease in income volatility ($\Delta SD_{i,\tau^*} < -0.47$, the 15^{th} percentile of the cross-sectional distribution of ΔSD's). The dotted line represents the share with a large increase in income volatility ($\Delta SD_{i,\tau^*} > 0.28$, the 85^{th} percentile). The risky shares are relative to their individual mean and normalized to the starting year in the graph.

[13] We have also considered different windows ($t-k$ and $t+k$ where k equals 0, 1, or 3). The results are similar and available upon request.

Figure 3: Dynamics of Risky Share



Notes: The solid line represents the average risky share of workers with a large decrease in income volatility ($\Delta SD_{i,\tau^*} < -0.47$, the 15^{th} percentile). The dotted line represents the share with a large increase in income volatility ($\Delta SD_{i,\tau^*} > 0.28$, the 85^{th} percentile).

Consistent with our priors, workers who experience a large "volatility increase" (dotted line) reduce their risky share in financial assets and vice versa.[14]

Figure 4 shows a simple scatter-bin plot between the "largest" change in income volatility (ΔSD_{τ^*}) and the change in the risky share over a four-year window ($\Delta RS_{i,\tau^*}$, defined below). It shows a clear negative relationship between changes in labor-income volatility and changes in the risky share. The plot confirms that around periods of heightened income volatility, households reduce their exposure to risk in financial investments by decreasing the risky share.

Now, to estimate the response of risky share with respect to labor-income risk, consider the following regression:

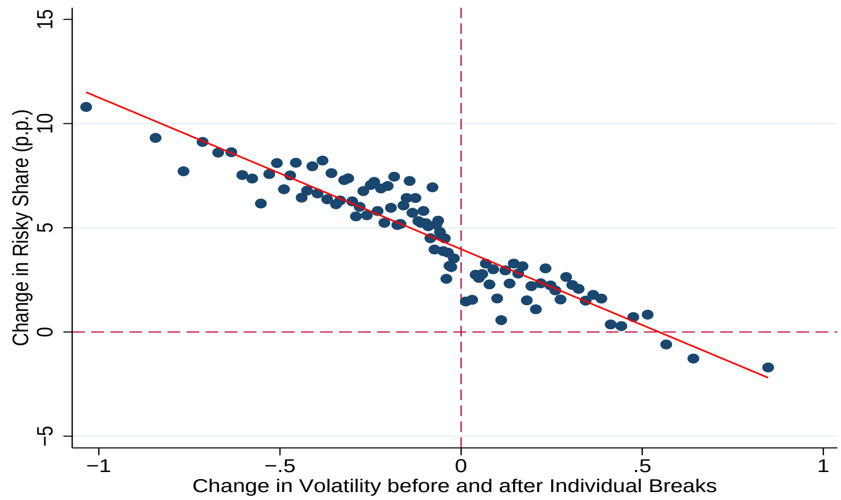
$$\Delta RS_{i,\tau^*} = \beta \Delta SD_{i,\tau^*} + \quad \alpha X_{i,\tau^*} + \epsilon_{i,\tau^*}. \tag{2}$$

where the dependent variable is an (average) change of risky share over a four-year window: $\Delta RS_{i,\tau^*} = \frac{1}{2}(RS_{i,\tau^*+1} + RS_{i,\tau^*+2}) - \frac{1}{2}(RS_{i,\tau^*-1} + RS_{i,\tau^*-2})$.[15] In addition to the set of control

[14]This pattern is robust with respect to alternative choices on the cut-off percentiles (such as 10^{th} and 90^{th}, or 25^{th} and 75^{th}). We also use a simple regression equation and examine the dynamics of risky shares around the structural breaks for the two groups. See our on-line appendix for details (Figures O5 and O6).

[15]Our results are robust with respect to different windows around τ^* (see Section 2.4).

Figure 4: Change in Risky Shares vs. Change in Volatility



variables X_{i,τ^*} used as in equation (1), we also include the *levels* of log household income and wealth and the *changes* (between $\tau^* - 2$ and $\tau^* + 2$) in log of the household's disposable income, log of the household's wealth.

Equation (2) uses the observations around the structural break only. On one hand, this helps us to focus on big events and avoid small noisy ones. On the other hand, we lose a lot of potentially useful information. Alternatively, we also employ a specification that uses all observations (e.g., using all t) as follows:

$$\Delta RS_{i,t} = \beta \Delta SD_{i,t} + \quad \alpha X_{i,t} + \epsilon_{i,t} \tag{3}$$

where $X_{i,t}$ refers to the same set of variables described above at time t.

Table 4 reports the various estimates of β. In column (A) we use all available observations of $\Delta RS_{i,t}$ and $\Delta SD_{i,t}$. The coefficient $\hat{\beta} = -1.59$ corresponds to a regression in Equation (3). Column (C) reports the estimates when we restrict the observations to those around the structural breaks τ^* (e.g., Equation (2)). We obtain slightly larger coefficients: $\hat{\beta} = -1.70$. In our benchmark sample the median of income volatility (the standard deviation of income growth, $SD_{i,t}$) is 0.25 (see Table A3 in Appendix B). According to these estimates, when the income volatility doubles, the median worker would reduce her risky share by $0.42 \sim 0.44$ percentage point ($\hat{\beta} \times 0.25$).

Looking at columns (A) and (C), our results indicate that structural breaks alone do not generate substantially larger coefficients than those in the literature. One possible reason may be that households already anticipate the changes in income volatility even if we restrict our attention to big events. In fact, a recent literature suggests that a substantial portion of

Table 4: Regression of Risky Share (ΔRS) on Income Volatility (ΔSD)

	(A)	(B)	(C)	(D)
	Using all t		Using τ^*	
	OLS	IV	OLS	IV
$\hat{\beta}$	-1.59***	-17.58***	-1.70***	-20.01***
	(0.09)	(1.48)	(0.21)	(5.10)
Obs.	1,214,798	583,512	125,874	46,084

Notes: Columns (A) and (B) use all observations, whereas columns (C) and (D) use the observations around the structural breaks (τ^*) only. The robust standard errors are in parentheses. Three stars denotes statistical significance at the 1 percent.

the residual variation in earnings is predictable and reflects individual choices rather than risk (e.g., Primiceri and van Rens, 2009; Guvenen and Smith, 2014). According to Cunha and Heckman (2007), the statistical decomposition of earnings cannot distinguish uncertainty from other sources of income variability. Misinterpretation of labor-income volatility as pure income risk is likely to bias the estimated response of portfolio choice toward zero.

Therefore, as the second part of our methodology, we use an instrumental variable based on the firm-side information, the method pioneered in the seminal work by Fagereng, Guiso, and Pistaferri (2017). Here, the identifying assumption is that an individual worker cannot influence the firm's overall performance. More specifically, the volatility of sales and/or value added (both scaled by the firm's assets) of firm f where a worker i is employed is used to identify the orthogonal component of the worker's income risk.[16] Using the exact same steps 1-3 described above, we compute the change in the volatility of sales, $\Delta SD^s_{f,t}$, and value added, $\Delta SD^v_{f,t}$, before and after period t. Henceforth, to simplify the notation, we bundle both instruments in vector $\Delta SD_{f,t}$. As a first-stage regression, we run the following:

$$\Delta SD_{i,t} = \gamma \Delta SD_{f,t} + \theta X_{i,t} + u_{i,t}, \tag{4}$$

where $X_{i,t}$ is the same set of worker characteristics described in Equation (2) at period t.[17] According to the standard test for over-identifying restrictions, both sales and value added are valid instruments (Hansen's J test has a p-value of about 0.6).[18] By projecting $\Delta SD_{i,t}$

[16]Firm sales refer to gross revenue minus operating costs, and value added is gross revenue net of operating costs and wage bills.

[17]To remove outliers from the estimation, we exclude the observations outside the 1st and 99th percentiles of $\Delta SD_{f,t}$'s in each cross-section.

[18]This suggests considerable insurance on behalf of the firms to the workers (see also Guiso, Pistaferri, and Schivardi (2005) and Fagereng, Guiso, and Pistaferri (2017)).

on $\Delta SD_{f,t}$, we obtain $\widehat{\Delta SD}_{i,t}$, an orthogonal component of a worker's earnings volatility.[19]

Table 5 compares the summary statistics of $\Delta SD_{i,\tau^*}$'s and $\widehat{\Delta SD}_{i,\tau^*}$'s. Clearly, the exogenous variation of income volatility shows a much smaller dispersion, as the standard deviation of the volatility change decreases from 0.23 to 0.03. This occurs because our raw measure of volatility $\Delta SD_{i,\tau^*}$ is a mix of predictable and unpredictable episodes and possibly noisy measurement errors, while $\widehat{\Delta SD}_{i,\tau^*}$ isolates episodes that are closer to how we think of background risk.

Table 5: $\Delta SD_{i,\tau^*}$ and $\widehat{\Delta SD}_{i,\tau^*}$

	Obs.	S.D.	Percentile	
			10^{th}	90^{th}
$\Delta SD_{i,\tau^*}$	125,874	0.23	-0.34	0.20
$\widehat{\Delta SD}_{i,\tau^*}$	46,084	0.03	-0.07	0.06

Columns (B) and (D) in Table 4 report the IV estimates for β, respectively, for using all t and τ^* only. The IV estimates are substantially larger than those of OLS, confirming that households respond much more sharply to income *risk*. Using the instrument alone increases the estimate by a factor of 10: $\hat{\beta} = -17.5$ (from -1.59) and the use of structural breaks in combination with the instrument further increases the estimate to $\hat{\beta} = -20$. As a result, when the income risk in the labor market doubles, a median worker reduces her risky share by a significant size of 5 percentage points (-20 $\times$ 0.25). In Section 3 below, we incorporate the stochastic volatility shock into the standard portfolio choice model (e.g., Cocco, Gomes, and Maenhout (2005) and Gomes and Michaelides (2005)) to assess whether the standard model can reproduce the estimated response of the portfolio with respect to income risk (e.g., $\hat{\beta}$) that we found from the Norwegian data.

2.4 Robustness and Heterogeneity

In this subsection, we examine whether our findings are robust with respect to different specifications of the regression, sample-selection criteria, and measurements. By and large, our baseline results are robust across the following variations: households' disposable income (as opposed to individual income), a different set of control variables (e.g., mortgage debt, capital income, and non-linear wealth effects), different windows (k), sample-selection criteria,

[19]We also inspect the correlation between the current change in risky share, $RS_{i,t+1} - RS_{i,t}$, and future shocks, $\widehat{\Delta SD}_{i,t+k}$, $k \geq 2$. We find that there is no statistically significant correlation, suggesting that households do not anticipate our identified orthogonal components of income risk.

firm size, employer changes, industry/occupation effects, and alternative definitions of risky share and income volatility. We also estimated the response by demographic groups. We only report the IV estimates ($\hat{\beta}_{IV}$) based on all observations here and more detailed results are available upon request.

Household Disposable Income In the benchmark specification, we constructed income volatility using the individual's earnings. However, it is well-known that there is a significant amount of intra-household insurance as well as public provision (tax/transfer). Furthermore, savings decisions are often made at the household level. Thus, we repeat our estimation using the household's disposable income. We follow exactly the same steps (i.e., identification of structural break, etc.). With the household's disposable income, the estimated response of the portfolio increases to $\hat{\beta} = -31.8$ (see Appendix Table A4 Column (11)).

Different Controls and Windows We considered different sets of control variables X_{it} in Equation 3 (see Appendix Table A4 Columns (2)-(5).) Without any control variable, the estimated response is $\hat{\beta} = -58.8$. As we add more controls, the estimated response becomes smaller. While CRRA preferences are popular in macroeconomic analysis, non-homothetic preferences are commonly used in finance. Thus, we included high-order polynomials in income and wealth to possibly control for non-linear wealth effects in portfolio choices. The estimated response is similar to our benchmark case (Column (6) in Table A4) The estimated response is also similar with respect to controlling mortgage debt and capital income in the regression (Table A4 Columns (7)-(8)). The benchmark specification uses the change in the risky share over a 4-year window ($k = 2$). The estimated response is similar $\hat{\beta} = -21.7$ with a 6-year window ($k = 3$) but becomes smaller $\hat{\beta} = -13.5$ with a narrow window ($k = 1$) (see Table A4 Columns (9)-(10)).

Job Stayers vs. Switchers Changing jobs is an endogenous choice, and it might be influenced by some unobserved factors that also affect portfolio decisions, undermining our estimation procedure. However, the regression based on a subsample of job stayers (roughly about 80% of the total sample) yields a similar estimate (Table A4 Column (12)).

Other Robustness Analysis One possible concern about our instruments might be (i) in small firms firm's performance may not be exogenous to workers and (ii) workers in managerial positions may directly influence firms' performance. We re-estimate the regression excluding (i) small firms (the bottom quartile in terms of employment size) and (ii) managerial workers from our sample. The estimated response is slightly smaller ($\hat{\beta} = -14.3$ in both cases). We have also conducted other various robustness analyses: earlier years (before 2007) only, with industry/occupation fixed effects, requiring only 14 years of non-zero risky shares (as opposed to 16 years in the benchmark) and also analyzing for all available risky shares.

By and large, the estimated responses of risky shares remain unchanged.[20]

Alternative Structural Break In our benchmark analysis, we identify the structural break based on the largest change in income volatility, $\Delta SD_{i,t}$'s. Alternatively, one might define the structural break based on the instrumented time series of $\widehat{\Delta SD}_{i,t}$'s. When we identify the structural break using the instrumented income volatility, denoted by $\hat{\tau}$, and run the regression (around structural breaks), the estimated responses are similar (see Table A5 in Appendix).[21]

Heterogeneity Across Groups Table A6 reports the estimated response of risky shares across different demographic groups—by education, age, gender, wealth, marital status, and homeownership. The differences across groups are not particular large except for the following. Young ($\hat{\beta} = -19.6$) or single (-20.4) workers show slightly stronger responses, whereas male (-10.9) or poor (-11.4) workers show weaker responses of portfolios to changes in income risk.[22]

3 Life-Cycle Model

We now incorporate stochastic volatility shocks into the standard portfolio choice model (e.g., Cocco, Gomes, and Maenhout (2005) and Gomes and Michaelides (2005)) to assess whether the standard model can reproduce the estimated response of portfolios with respect to the income risk we found from the Norwegian data.

3.1 Economic Environment

Demographics The economy is populated by a continuum of workers with total measure of one. A worker enters the labor market at age $j = 1$, retires at age j_R, and lives until age J. The decision to retire is exogenous. The age-dependent probability of surviving is s_j.

Preferences Each worker maximizes the time-separable discounted lifetime utility:

$$U = E\sum_{j=1}^{J} \delta^{j-1}(\mathbf{\Pi}_{t=1}^{j} s_t)\frac{{c_j}^{1-\gamma}}{1-\gamma}, \tag{5}$$

where δ is the discount factor, c_j is consumption in period j, and γ is the relative risk

[20]See our on-line appendix (Tables O1-O3) for the detailed summary statistics when we do not require participation in investment in risky assets.

[21]In our on-line appendix we also show the dynamics of risky shares around $\hat{\tau}$ for those with "large" volatility changes (Figures O5 and O6) .

[22]Here, "poor" workers are those in the bottom quartile of the wealth distribution.

aversion.[23] For simplicity, we abstract from the labor effort choice and assume that labor supply is exogenous.

Labor-Income Profile We assume that the log earnings of a worker i with age j, $\log Y_{ij}$, is:

$$\log Y_{ij} = z_j + y_{ij} \quad \text{with} \quad y_{ij} = a_i + \beta_i \times j + x_{ij}. \tag{6}$$

Log earnings consist of common (z_j) and individual-specific (y_{ij}) components. The common component, z_j, represents the average age-earnings profile, which is assumed to be the same across workers. The idiosyncratic component, y_{ij}, consists of an individual-specific profile, $a_i + \beta_i \times j$, which is constant along the life cycle, and stochastic shocks, x_{ij}, which follow an AR(1) process:

$$x_{ij} = \rho_x x_{i,j-1} + \nu_{ij}, \qquad \text{with} \quad \nu_{ij} \sim \text{ i.i.d. } N(0, \sigma^2_{ij}). \tag{7}$$

Note that the volatility of income shocks, σ^2_{ij}, is also idiosyncratic, time-varying, and its stochastic process is described below.

Variance of Labor Income The idiosyncratic labor-income volatility is assumed to follow an AR(1) process:

$$\log(\sigma^2_{ij}) = (1 - \rho_\sigma)\log(\sigma^2_\nu) + \rho_\sigma \log(\sigma^2_{i,j-1}) + \zeta_{ij}, \qquad \text{with} \quad \zeta_{ij} \sim \text{ i.i.d. } N(0, \sigma^2_\zeta). \tag{8}$$

We use a log specification to ensure that income volatility is positive. Three parameters govern its dynamics: (i) σ^2_ν, which is the average variance of x, (ii) σ^2_ζ, which is the variance of the volatility shocks, and (iii) ρ_σ, which governs their persistence. We approximate the autoregressive process for the volatility shock using a Markov chain. In particular, we assume that the labor-income volatility takes N possible values (regimes): $\sigma^2 = \{\sigma^2_1, ..., \sigma^2_N\}$. The Markov chain is defined as $\Gamma(\sigma^2_j|\sigma^2_{j-1})$. In our benchmark model, workers have perfect information about their individual labor-income volatility. In Section 6 we relax this assumption and analyze portfolio responses with imperfect information about the volatility regime.

Savings There are two types of assets for savings: a risk-free bond, b (paying a gross return of R in consumption units) and a stock, s (paying $R_s = R + \mu + \eta$), where μ (> 0)

[23] Alternative preferences have also been proposed in the literature analyzing portfolio choice. For example, Gomes and Michaelides (2005) use Epstein-Zin preferences with heterogeneity in both risk aversion and inter-temporal elasticity of substitution. Wachter and Yogo (2010) use non-homothetic preferences.

represents the risk premium and η is the stochastic rate of return.[24] We denote the probability distribution of the stock realization by $\chi(\eta)$. Workers save for insuring themselves against labor-income volatility (precautionary savings) as well as for retirement (life-cycle savings). We allow workers to borrow using the risk-free bond ($b' \geq \underline{b}$), where $\underline{b}$ is the credit limit.

Tax System and Social Security The government performs two functions in the model. First, it taxes individual earnings Y_{ij} using the tax function $T(Y_{ij})$. We specify a flexible tax function based on Heathcote, Storesletten, and Violante (2014) that allows for transfers (see Section 4.1). Second, it runs a social security system. When a worker retires from the labor market at age j_R, the worker receives a social security benefit. To avoid the computational complexity of tracking one more state variable (history of earnings), we make the social security benefit dependent on earnings received in the last working year before the exogenous retirement (Guvenen, 2007). The social security benefit of worker i is denoted by $ss(Y_{J_R-1})$, which is financed by the social security tax rate τ_{ss}.

Value Functions We collapse financial wealth into one variable, "total financial wealth," $W = bR + sR_s$. Then, the state variables include workers' wealth (W), productivity type (a, β), stochastic productivity (x_j), and the current volatility regime, σ_j^2. The value function of a worker at age j is:

$$
\begin{aligned}
V_j(W, a, \beta, x_j, \sigma_j^2) = \max_{c, s', b'} \; & \Bigg\{ \frac{c_j^{1-\gamma}}{1-\gamma} \\
& + \; \delta s_j \sum_{\sigma_{j+1}^2} \int_{\eta'} \int_{x_{j+1}} \Gamma(\sigma_{j+1}^2 \mid \sigma_j^2) V_{j+1}(W', a, \beta, x_{j+1}, \sigma_{j+1}^2) dF(x_{j+1}|x_j, \sigma_{j+1}^2) d\chi(\eta') \Bigg\}
\end{aligned}
$$

$$
\begin{aligned}
\text{s.t.} \quad & c + s' + b' = [(1-\tau_{ss})Y_j - T(Y_j)] \times \mathbf{1}\{j < j_R\} + ss(Y_{J_R-1}) \times \mathbf{1}\{j \geq j_R\} + W \\
& F(x_{j+1}|x_j, \sigma_{j+1}^2) \text{ is the prob. distribution for } x_{j+1} \text{ given } x_j, \sigma_{j+1}^2 \\
& b' \geq \underline{b} \text{ and } s' \geq 0,
\end{aligned}
$$

where $\mathbf{1}\{\cdot\}$ is an indicator function and total labor income is $Y_j = e^{z_j + y_j}$ with $y_{ij} = a_i + \beta_i \times j + x_{ij}$.

[24] For simplicity, we abstract from the general equilibrium aspect by assuming exogenous average rates of return to both stocks and bonds.

4 Quantitative Analysis

4.1 Calibration

There are several sets of parameters to pin down: (i) life-cycle parameters $\{j_R, J, s_j\}$, (ii) preferences $\{\gamma, \delta\}$, (iii) asset-market structure $\{R, \mu, \sigma^2_\eta, \underline{b}\}$, (iv) labor-income process $\{z_j, \sigma^2_a, \sigma^2_\beta, \rho_x, \rho_\sigma, \sigma^2_\nu, \sigma^2_\zeta\}$, and (v) tax and transfers $\{\tau_1, \tau_2, \bar{\tau}, \tau_{ss}, ss\}$. One set of parameters is calibrated directly from the data or the existing literature. The remaining parameters are set by targeting specific data moments.

Table 6 gives the list of calibrated parameters. The model period is a year. Workers are born and enter the labor market at $j = 1$ and live for 80 periods, $J = 80$. This life cycle corresponds to ages 21 to 100. Workers retire at $j_R = 45$ (age 65) when they start receiving the social security benefit. We estimate the survival probability $\{s_j\}$ at each age using the data on mortality rates from Statistics Norway.

Table 6: Calibrated Parameters

Parameter	Variable	Value	Target / Source
Life Cycle	J	80	–
Retirement Age	j_R	45	–
Risk-free Rate	$R-1$	1.43%	Klovland (2004)
Equity-Risk Premium	μ	3.14%	Dimson, Marsh, and Staunton (2008)
Stock-Return Volatility	σ_η	23.8%	Dimson, Marsh, and Staunton (2008)
Social Security Benefit	ss	–	Statistics Norway
Tax Function	τ_1	0.73	Statistics Norway
Tax Function	τ_2	0.16	Statistics Norway
Tax Function	$\bar{\tau}$	0.85	Statistics Norway
Tax Function	Y^*	1.7	Statistics Norway
Survival Probability	$\{s_j\}$	–	Statistics Norway
Common Age-Earnings Profile	$\{z_j\}$	–	OECD
Number of Volatility Regimes	N	7	–
Variance of Fixed Component	σ^2_a	0.017	Var-cov. matrix of $\log(y)$
Variance of Growth Component	$\sigma^2_\beta \times 100$	0.0081	Var-cov. matrix of $\log(y)$
Persistence of Level Shocks	ρ_x	0.747	Var-cov. matrix of $\log(y)$
Variance of Level Shocks	σ^2_ν	0.027	Var-cov. matrix of $\log(y)$
Persistence of Volatility Shocks	ρ_σ	0.905	Annual freq. of employer change = 10%
Variance of Volatility Shocks	σ^2_ζ	0.25	Kurtosis of earnings = 8.31
Discount Factor	δ	0.91	Assets/income =2.19
Risk Aversion	γ	4.5	Risky assets/total assets= 0.57
Credit Limit	$\underline{b}$	-0.10	Debt/income= 4.9%

According to Dimson, Marsh, and Staunton (2008), the annualized real returns to equity for Norway for 1900-2005 were 4.28%. We follow Fagereng, Gottlieb, and Guiso (2017) and adjust the returns to reflect the 80% bias of Norwegian investors toward domestic over foreign stocks. Since the world average returns were 5.75%, according to Dimson, Marsh, and Staunton (2008) for the same period, we set the rate of returns to equity at 4.57%. Using the estimates from Klovland (2004), we set the real risk-free rate to 1.43%, which makes the equity premium in our model μ 3.14%. The standard deviation of the innovations to the rate of return to stocks, σ_η, is 23.8%, also computed using a weighted average of the standard deviation of Norwegian stocks and of foreign stocks, which are 26% and 17%, respectively, based on Dimson, Marsh, and Staunton (2008). We assume that the stock returns are orthogonal to labor-income risks.[25]

For the government tax and transfers, we use the following specification:

$$T(Y) = Y - \tau_1 Y^{1-\tau_2} + \mathbf{1}_{\{Y^* > Y\}} \bar{\tau}(Y - Y^*)$$

which has been used to analyze tax/transfers in the U.S. (Heathcote, Storesletten, and Violante, 2017). In particular, parameter τ_1 captures the average tax rate in the economy and parameter τ_2 the degree of progressivity of the schedule. As seen in the left panel of Figure 5, the tax system in Norway becomes very progressive for income levels around twice the average labor income. To capture the high progressivity of the Norwegian tax system, we add the term $\mathbf{1}_{\{Y^* > Y\}} \bar{\tau}(Y - Y^*)$. With our detailed administrative data, we can calibrate all parameters using information on before- and after-tax labor earnings. The before-tax earnings are cash salary, while after-tax earnings are before-tax earnings net of taxes and transfers. Transfers include unemployment benefits, sickness benefits, money received in government activity programs, and disability benefits. The left panel of Figure 5 shows that our model matches well the relationship between before- and after-tax individual labor income.

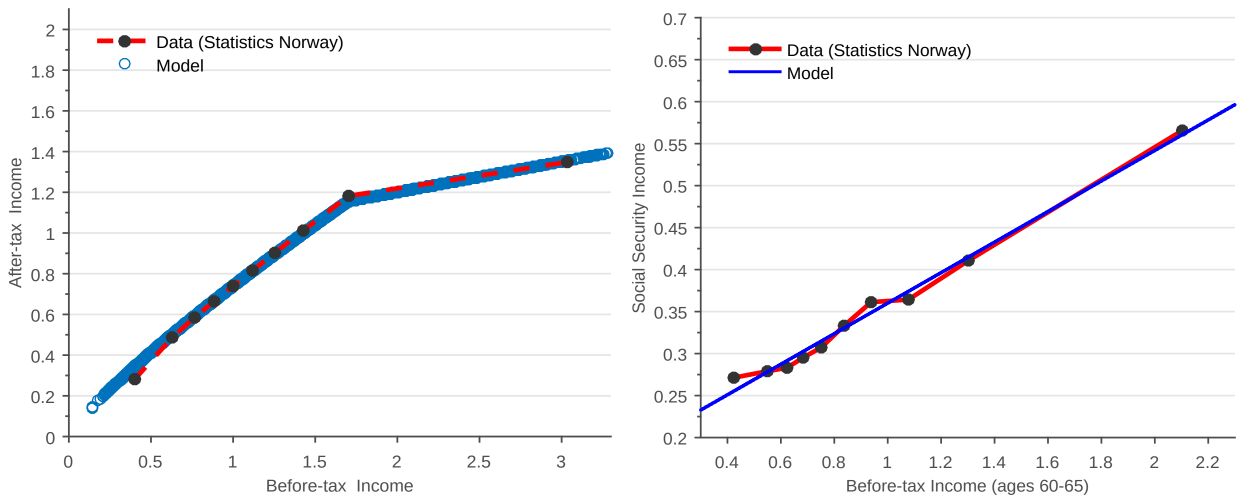
The social security benefit is calibrated to replicate the average benefit for each labor-income decile in the data (right panel of Figure 5). As mentioned, in the model we condition the social security benefit on the earnings received in the last working year before retirement. In the data a worker with the mean labor income during ages 60 to 65 receives a benefit equal to 36% of his/her pre-retirement labor income. A worker with twice the mean labor income during ages 60 to 65 receives around 55% of pre-retirement labor income.

We calibrate the common age profile of income (z_j) based on the age profile of real wages

[25]In our data, the correlation between stock market return and average real wage (using aggregate data from national accounts) is small and equal to -0.08 with a standard deviation of 0.16. These numbers are similar to the numbers reported in Heaton and Lucas (2000) for the U.S. In other studies that have used U.S. data, Davis and Willen (2000) find a small, positive correlation, while Campbell, Cocco, Gomes, and Maenhout (2001) find a positive correlation only for specific population groups.

in Norway from the OECD. The real wages for 30-, 40-, and 50-year-old workers are on average approximately 5, 15, and 20% higher, respectively, than those of 25-year-old workers. Finally, we assume that there are 7 regimes for income volatility: $N = 7$.

Figure 5: Tax and Social Security System: Model vs. Data



Notes: The left panel shows the relationship between before- and after-tax labor income for the model and the data. The right panel shows the relationship between before-tax labor income for ages 60 to 65 and the social security benefit in the model and in the data. We normalize labor-income data by the average earnings, 553,414 NOK. Data are from Statistics Norway and authors' calculations.

To set parameters $\{\sigma_a^2, \sigma_\beta^2, \rho_x, \sigma_\nu^2\}$, we follow the estimation technique described by Guvenen (2009). Specifically, we target the variance-covariance matrix of log labor earnings between ages 25-60.[26] We estimate the variance of the fixed effect component equal to $\sigma_a^2 = 0.057$, the variance of the slope $\sigma_\beta^2 = 0.0088\%$, and the average variance of the idiosyncratic shocks $\sigma_\nu^2 = 0.027$. The persistence of the idiosyncratic shocks is $\rho_x = 0.74$. Guvenen and Smith (2014) estimated these parameters using the U.S. data. Similarly to our results, they find a fairly large idiosyncratic growth component, implying a mildly persistent process for the shock to the income level. But in the Norwegian data, the variance of σ_ν^2 is half of what Guvenen and Smith (2014) estimate for the U.S. data, which reflects the sharper increase in the variance of log labor income over the life cycle, in the U.S. relative to Norway.

The process for income volatility depends on parameters σ_ζ^2 and ρ_σ. For σ_ζ^2, we exploit the fourth moment of earnings, the kurtosis, which is emphasized by Guvenen, Karahan, Ozkan, and Song (2015). Consider the case of high dispersion in volatility shocks. Every period, some workers draw from a narrower distribution (low volatility regime) and some

[26] To minimize the distance between the data and the model moments, we chose a weighting matrix that places larger weight on the cross-sectional variance of log-earnings.

draw from a wider distribution (high volatility regime). As a result, this mix of normals shows up as a leptokurtic cross-sectional distribution of earnings. In contrast, if volatility shocks have small dispersion, then the cross-sectional distribution of earnings approximates a normal distribution. We find $\sigma_\zeta^2 = 0.25$ targeting the kurtosis of earnings in our data equal to 8.3.

The persistence parameter ρ_σ is harder to pin down. Typical estimation techniques of the persistence of the stochastic volatility shocks rely on long panel data (for example, daily stock prices). But such techniques are not suitable for our data, which include for each worker at most 20 observations (annual frequency). Thus, we loosely infer the magnitude of ρ_σ using the average frequency of employer changes as a proxy for the regime change in stochastic volatility. We acknowledge that (i) not all employer changes necessarily qualify as volatility breaks and (ii) a worker may experience a volatility break even while working for the same firm. In the data, the annual probability of changing an employer is 10%, which implies that workers, on average, change employers 4.5 times in 45 years. In the model, we compute how many times workers experience big volatility events. A big event is defined as volatility lower than the 15^{th} percentile or higher than the 85^{th} percentile of the volatility distribution. This calibration procedure results in $\rho_\sigma = 0.905$.

We calibrate the discount factor δ to match the average financial assets to income ratio. In our data, the average financial assets for ages 25 to 60 are 1,212,000 NOK, and the average household income is 553,414 NOK. Therefore, we estimate the discount factor δ to match an asset-to-income ratio of 2.19. The risk aversion γ targets the risky assets to total assets ratio. Since the average financial assets in risky accounts (conditional on participation) are 690,830 NOK, we target an average risky share of 0.57.[27] According to data from the Bank of Norway, credit card debt accounts for 3% of total debt (which includes all types of borrowing and averages at 908,587 NOK). Therefore, the average credit card debt to income ratio is $3\% \times 908,587/553,414 = 4.9\%$. The debt-to-income ratio pins down the value of borrowing constraint $\underline{b}$.

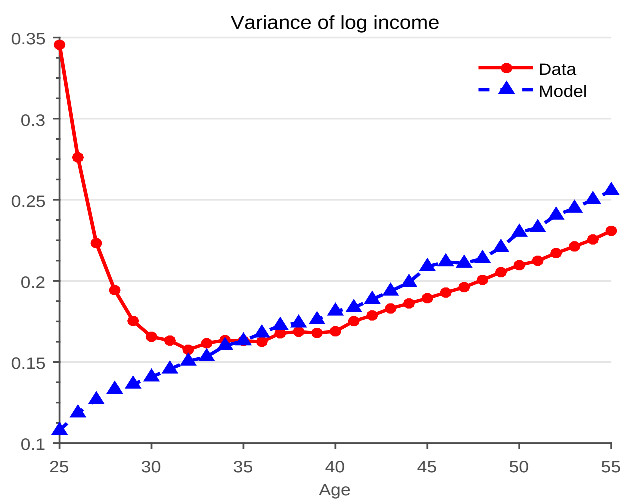
4.2 Response of Risky Share

The left panel of Figure 6 plots the cross-sectional variance of log earnings across ages net of cohort effects. In the data, there is a rapid decrease in the variance of income between ages 25 and 30, a pattern we cannot generate from the model. After age 30, we see a familiar

[27] The cross-sectional mean of the risky share in the Norwegian panel has a much lower value of 0.38. As is well-known, it is hard to match such low values of the risky share unless we resort to unrealistically high degrees of risk aversion or highly risky events such as a stock market crash or long-term unemployment spell. Instead, we base our calibration on a more feasible target, the average risky to average assets ratio.

increasing variance—also well documented in the U.S. data (see, for example, Storesletten, Telmer, and Yaron, 2004; Guvenen and Smith, 2014; Heathcote, Storesletten, and Violante, 2014). In Norway, it increases by about 10 log points over ages 30 to 55, while in the U.S. the increase is about 20-25 log points. The model captures this increasing profile fairly well after age 30. The right panel of Figure 6 plots the cross-sectional variance of log consumption across ages.[28] In the data, the variance of log consumption increases by about 4 log-points (from ages 25 to 50), which is matched fairly well by the model, although left untargeted. Table 7 shows that the model also matches targeted moments very well: the average assets-income ratio, the risky share, and the debt-income ratio.

Figure 6: Dispersion of Income and Consumption



Notes: The left panel shows the variance of log earnings over the life cycle. The right panel is the variance of log consumption.

Now we evaluate the ability of our model to reproduce the portfolio response (i.e., the marginal effect) to income risk in the data. The test statistic is the regression coefficient $\hat{\beta}$ based on our IV estimation. First we construct a panel data of 20,000 workers for 45 years using the model-generated data. Then we run the exact same regression as in Equation (2). Similar to the empirical analysis, the regression includes a set of individual controls such as age, levels of income and wealth, and changes in income and wealth. We also exclude outliers by keeping observations between the 1st and 99th percentiles of the distribution of the risky share as we did with the actual data. The benchmark model generates the response of the risky share to income risk, close to what we see in the data (-17.9 in the model versus -20 in

[28] We thank Martin Holm from the University of Oslo for providing statistics for this moment. In our data set, we could not have reliable estimates on individual consumption since we do not have access to those data required for constructing consumption (transaction data on housing prices; housing physical characteristics; detailed information on capital gains; and so on). See Eika, Mogstad, and Vestad (2017), among others.

Table 7: Model Fit: Selected Statistics

	Data	Model
Targeted Moments		
Financial Assets / Income	2.19	2.21
Risky Assets / Financial Assets	0.57	0.56
Credit Card Debt / Income	4.9%	4.9%
Kurtosis of earnings	8.31	8.27
Not Targeted		
Response of Risky Share: $\hat{\beta} = \frac{\partial \Delta RS}{\partial \Delta SD}$	-20.0	-17.9

the data).

Obviously, risk aversion is important not only for the average but also for the *marginal* effect of income risk on the risky share of financial assets. We examine how the marginal effect varies with respect to different values of $\gamma \in [2, 5]$ (keeping all other parameters unchanged except for the discount factor δ to match the same assets-income ratio as in our benchmark). Table 8 reports the marginal effect (the regression coefficient $\hat{\beta} = \frac{\partial \Delta RS}{\partial \Delta SD}$) as well as the average risky share from the model. Under a smaller value of risk aversion, the marginal response of the portfolio becomes smaller. This is mainly because the average risky share becomes larger, leaving less room for the portfolio choice. For example, with $\gamma = 2$, the average risky share is close to 1 (0.92) and the marginal effect becomes -1.1.

Table 8: Average and Marginal Effects of Income Risk

	Average Risky Share	Marginal Effect ($\hat{\beta} = \frac{\partial \Delta RS}{\partial \Delta SD}$)
Data	0.57	-20.0
$\gamma = 5$	0.50	-18.1
$\gamma = 4.5$	0.56	-17.9
$\gamma = 3$	0.80	-10.0
$\gamma = 2$	0.92	-1.1

Note: The marginal effect is the regression coefficient $\hat{\beta}$ in Equation (2).

5 Welfare Costs of Stochastic Volatility

One advantage of using a structural model is that we can assess the welfare of income risk. We ask two questions based on our model: (i) what is the welfare cost of stochastic volatility in the labor market? (ii) what is the welfare gain from having the ability to adjust the financial portfolio against income risk in the labor market?

In general, income risk undermines the household's welfare though two channels. One, households consume less on average due to precautionary savings and also due to re-balancing the financial portfolio toward safer, low-return assets. Two, households are unable to smooth their consumption because they cannot perfectly insure against income fluctuations (incomplete markets). We will call the former the *mean effect* and the latter the *volatility effect*.

To isolate each channel of welfare loss we adopt the decomposition proposed by Floden (2001). The ex-ante lifetime utility for a newborn worker is given by:

$$V = \sum_{j=1}^{J} \sum_{i} \delta^{j-1} (\mathbf{\Pi}_{t=1}^{j} s_t) \frac{{c_{ij}}^{1-\gamma}}{1-\gamma}$$

where c_{ij} is the consumption for worker i at age j computed from our simulated data. If workers had consumption equal to the average consumption of each age group, the ex-ante welfare would be:

$$V_M = \sum_{j=1}^{J} \delta^{j-1} (\mathbf{\Pi}_{t=1}^{j} s_t) \frac{\bar{c}_j^{1-\gamma}}{1-\gamma},$$

where $\bar{c}_j = \sum_i c_{ij}/N$ and N is the total number of workers in cohort j. The welfare gain/loss of being born in economy A relative to B is:

$$CEV = \left(\frac{V^A}{V^B} \right)^{\frac{1}{1-\gamma}} - 1.$$

The welfare gain/loss due to the difference in the mean consumption between economies A and B is:

$$CEV_M = \left(\frac{V_M^A}{V_M^B} \right)^{\frac{1}{1-\gamma}} - 1.$$

The welfare gain/loss due to the difference in the volatility of consumption (CEV_V) can be obtained by the difference in the above two consumption-equivalence variations: i.e., $CEV_V = CEV - CEV_M$.

We consider three model economies: (i) the benchmark economy with income risk and

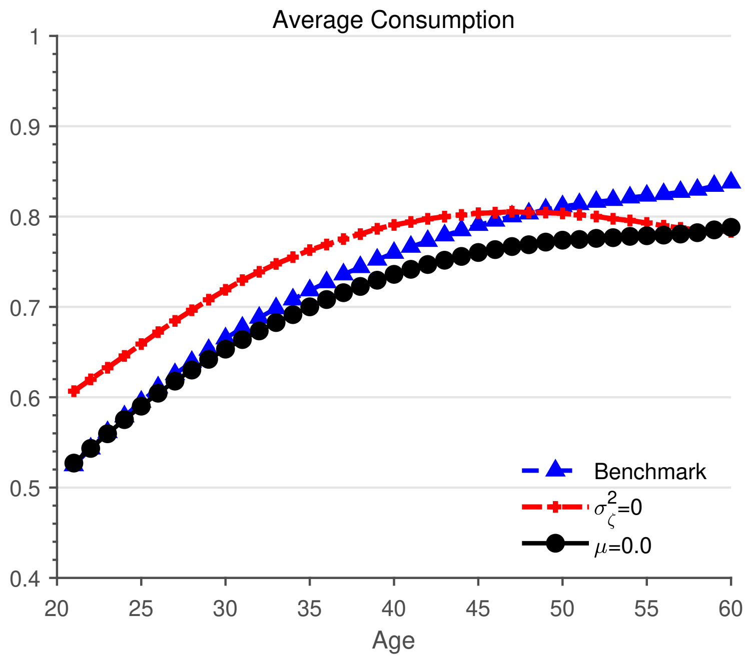
Table 9: Welfare Costs of Stochastic Volatility

Model	Benchmark ($\sigma_\zeta^2 = 0.2$, $\mu = 3.14\%$)	No Stochastic Volatility ($\sigma_\zeta^2 = 0$)	Bonds Only ($\mu = 0$)
Total Assets	2.16	1.25	1.90
Stocks	1.13	0.88	0.0
Bonds	1.03	0.37	1.90
Risky Share	0.52	0.70	0.0
Average Rate of Return	3.2%	3.4%	1.4%
Mean Consumption	0.73	0.75	0.70
S.D. of Log Consumption	0.29	0.36	0.28
CEV (Total)		4.0%	-0.9%
CEV_M (Mean Effect)		10.0%	-1.1%
CEV_V (Volatility Effect)		-6.0%	0.2%

Notes: The statistics (except for CEV's) reflect the averages over ages 21-65 (during which labor-income risk is operative). The welfare measures are based on lifetime values.

portfolio choice; (ii) no stochastic volatility shocks in the income process (with portfolio choice); and (iii) a bonds-only economy (with stochastic volatility shocks in income). Table 9 reports the average holdings of total assets; bonds and stocks; the average rate of return from savings; average consumption; and the standard deviation of log consumption (during the working period, ages 21 to 65) in each economy. First, consider the economy where there is no stochastic volatility shock ($\sigma_\zeta^2 = 0$). Without stochastic volatility in the income process, total asset holdings are less than half of that in the benchmark (1.25 vs. 2.16). At the same time, the average risky share is much higher (0.7 vs. 0.52). As a result, the average rate of return from the financial investment is higher than that in the benchmark (3.4% vs. 3.2%). Thanks to smaller precautionary savings and higher rates of return to investment, mean consumption is higher than that in the benchmark (0.75 vs. 0.73). While the households in this economy do not face additional stochastic volatility in their income, their consumption is actually more volatile than that in the benchmark (standard deviation equal to 0.36 vs. 0.29). This is because (i) average asset holdings are smaller, and thus, there is a smaller amount of assets to buffer income fluctuations and (ii) the risky share is higher, generating additional risk in total income. Figure 7 shows that average consumption without a volatility shock starts much higher than in the benchmark. Due to smaller savings, consumption eventually falls below that in the benchmark. Overall, removing the stochastic volatility shocks from the

Figure 7: Average Consumption by Age



Notes: The figure shows mean consumption for the benchmark model, the model with no idiosyncratic volatility shocks ($\sigma_\zeta^2 = 0$), and the model with no equity premium ($\mu = 0$). The benchmark economy features $\sigma_\zeta^2 = 0.2$ and $\mu = 3.14\%$.

benchmark yields a welfare gain of 4.0%, which reflects a 10% welfare gain from the higher average consumption (mean effect) and a 6% loss from the larger volatility (volatility effect).

Next, we consider the economy where there is only one asset: bonds. This is achieved by setting the equity premium to $\mu = 0$: stocks are dominated by bonds. Average asset holdings are slightly smaller than in the benchmark (1.9 vs. 2.16). Average consumption is 0.70. The volatility of consumption is slightly smaller than that in the benchmark (standard deviation equal to 0.28 vs. 0.29). Because of lower rates of return to savings, Figure 7 shows that consumption grows at a slower rate. As a result, the overall welfare cost of not being able to invest in stocks (portfolio choice) is a 0.9%, which reflects a 1.1% welfare loss from the lower average consumption (mean effect) and a 0.2% gain from the smaller consumption volatility.[29]

[29] We also considered an economy with half the equity premium $\mu = 1.57$. In that economy, the welfare loss is 0.7%, which reflects a 0.9% loss from the lower average consumption (mean effect) and a 0.2% gain from the less volatile consumption (relative to the benchmark).

6 Alternative Specifications

In this section we consider three alternative specifications that are commonly used in portfolio choice models: (i) adjustment costs in portfolio choice, (ii) ARCH for stochastic income volatility, and (iii) imperfect information about the volatility regime. The first alternative model is motivated by the substantial fraction (about half in our sample) of Norwegian households that have zero assets in risky accounts. Specifically, we assume an adjustment cost in making financial decisions that generates an extensive margin of risky investment (such stock market participation costs are common in the literature, e.g., Gomes and Michaelides (2005), Fagereng, Gottlieb, and Guiso (2017)). Second, we consider a model that features an ARCH for the income process (a popular specification for the empirical analysis of stochastic volatility, e.g., Engle (1982)). Finally, the benchmark assumes that workers know exactly about the changes in their income volatility. However, it is conceivable that workers may not have perfect information about the volatility regime. All model economies are re-calibrated to match the same target moments in Table 7.[30]

Adjustment Costs/Extensive Margin Suppose that a worker maximizes the time-separable discounted lifetime utility:

$$U = E\sum_{j=1}^{J}\delta^{j-1}(\mathbf{\Pi}_{t=1}^{j}s_t)\{\frac{{c_j}^{1-\gamma}}{1-\gamma} - \chi\frac{s_{j+1}^2}{2}\},$$

where s_{j+1} is the stock investment at age j and χ is a parameter governing the strength of the adjustment costs. We assume that χ depends on whether the worker is already participating in the stock market. Non-participants face a cost χ^0, while participants face a cost χ^1. We also assume that workers start their life out of the stock market and that participants never exit the market (transition between the two states occurs only once). As a result, our formulation also allows us to incorporate an extensive margin of risky investment. We calibrate $\chi^0 = 23.8$ to match an average participation rate of 50% and $\chi^1 = 0.08$ to match an average unconditional risky share of 20%. The value of risk aversion is set as in the benchmark model.

ARCH Suppose that the income process follows an ARCH (which is also used in Meghir

[30] All alternative models are calibrated to match the average risky share. In the model with adjustment costs (which also features a decision to participate in risky investment), the model calibrates the cost function to match (i) the participation rate and (ii) the unconditional risky share in the data.

and Pistaferri (2004)). The individual variance of labor-income growth is:

$$\sigma_{i,j+1}^2 = \sigma_\nu^2 + \phi(y_j - \mathbf{H}_j'\mathbf{M}_{j-1})^2.$$

Since the variance of income growth depends on the realization of current income ν_j $(= y_j - \mathbf{H}_j'\mathbf{M}_{j-1})$, the expected income volatility is linked to realized innovation in earnings. We calibrate the parameters similarly to our benchmark. The persistence of the volatility shocks is implicitly determined by the persistence of the level of idiosyncratic shocks (parameter ρ_x) and ϕ is chosen to match the average kurtosis of earnings.

Imperfect Information Suppose workers have imperfect information about their income volatility (imperfect information model, or IIM henceforth). In this case, workers enter age j with a prior probability $\boldsymbol{\pi}_{j|j-1} = \{\pi_{j|j-1}^g\}_{g=1}^N$ for each possible regime g with $\sum_g \pi_{j|j-1}^g = 1$ (in the benchmark, with perfect information, the prior is a just degenerate at the true regime). They form a posterior belief for each regime $\boldsymbol{\pi}_{j|j} = \{\pi_{j|j}^g\}_{g=1}^N$ based on Bayes' rule. In this case, we re-formulate the problem by defining the matrices $\mathbf{M}_{j-1}$ and $\mathbf{H}_j$:

$$\mathbf{M}_{j-1} = \begin{bmatrix} a \\ \beta \\ \rho_x x_{j-1} \end{bmatrix}, \quad \mathbf{H}_j = \begin{bmatrix} 1 \\ j \\ 1 \end{bmatrix}. \tag{9}$$

The following period's $\mathbf{M}_j$ is:

$$\mathbf{M}_j \quad = \quad \mathbf{R}\left[\mathbf{M}_{j-1} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} (y_j - \mathbf{H}_j'\mathbf{M}_{j-1})\right] \tag{10}$$

with $\mathbf{R}$ denoting a (3×3) matrix whose diagonal elements are $(1, 1, \rho_x)$. Note that $\mathbf{H}_j'\mathbf{M}_{j-1}$ is the conditional expectation of period j's labor income as of age $j-1$. Moreover, $y_j - \mathbf{H}_j'\mathbf{M}_{j-1} = x_j - \rho_x x_{j-1} = \nu_j$ is the innovation of the shock to x. When the worker enters period j, log labor earnings y_j are drawn from a normal distribution F with mean $\mathbf{H}_j'\mathbf{M}_{j-1}$ and variance σ_j^2 (denoted as $F(y_j \mid \mathbf{H}_j'\mathbf{M}_{j-1}, \sigma_j^2)$).

Therefore, workers compute the probability that a particular regime g is currently active given the available information $\{y, \mathbf{M}_{j-1}\}$. As a result, the posterior beliefs are given by:

$$\pi_{j|j}(\sigma_g^2 \mid y_j, \mathbf{H}_j'\mathbf{M}_{j-1}) = \frac{F(y_j \mid \mathbf{H}_j'\mathbf{M}_{j-1}, \sigma_g^2) \times \pi_{j|j-1}^g(\sigma_g^2)}{\sum_{h=1}^N F(y_j \mid \mathbf{H}_j'\mathbf{M}_{j-1}, \sigma_h^2) \times \pi_{j|j-1}^h(\sigma_h^2)}, \tag{11}$$

where $F(y_j \mid \mathbf{H}_j'\mathbf{M}_{j-1}, \sigma_g^2)$ is the probability that labor-income realization, y_j, is observed given that the last year's labor income is $\mathbf{H}_j'\mathbf{M}_{j-1}$ and that the current volatility regime is σ_g^2. If the absolute value of $y_j - \mathbf{H}_j'\mathbf{M}_{j-1}$ (the innovation ν_j) is small, the worker places a larger probability on the low-volatility regimes and vice versa. Given the posterior probabilities, the worker forms the next period's priors:

$$\pi_{j+1}(\sigma_g^2) = \sum_{h=1}^{N} \Gamma(\sigma_g^2 \mid \sigma_h^2) \times \pi_{j|j}(\sigma_h^2). \tag{12}$$

Note that in both perfect and imperfect information models, workers know the law of motion (transition probability) for the volatility regime, Γ. What is different in the two cases is the initial regime. Under perfect information, workers know the true regime, while under imperfect information, workers have a probability distribution over the possible regimes.

We write the value function for the individual agent for the case of imperfect information. The state variables include workers' wealth (W), current income (y_j), the expected income ($\mathbf{M}_{j-1}$), and the prior probability about the current volatility regime, $\boldsymbol{\pi}_{j|j-1}$. The value function of a worker at age j is:

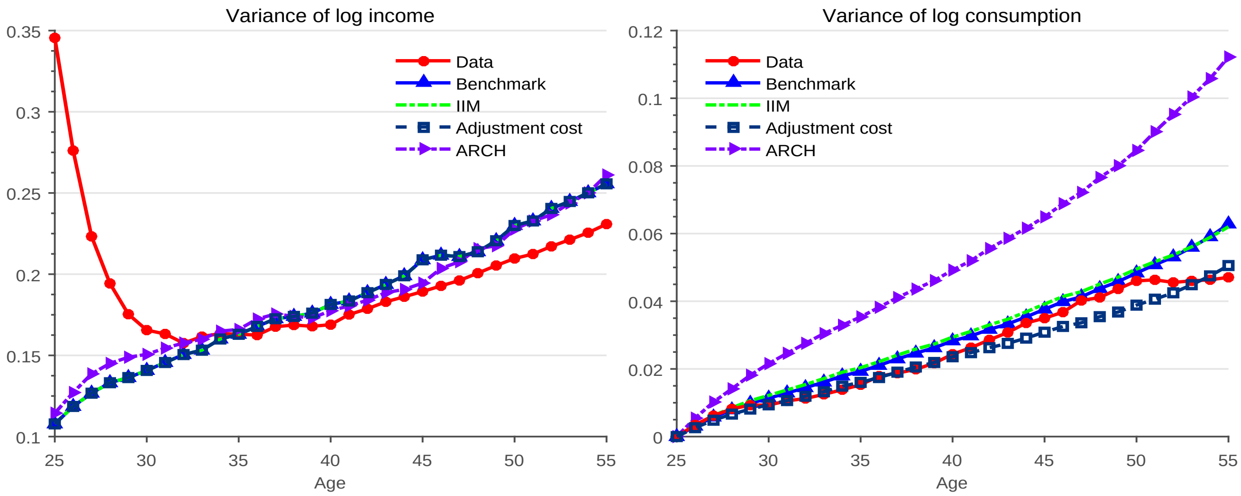
$$\begin{aligned} V_j(W, y_j, \mathbf{M}_{j-1}, \boldsymbol{\pi}_{j|j-1}) = \max_{c,s',b'} & \left\{ \frac{c_j^{1-\gamma}}{1-\gamma} \right. \\ & \left. + \ \delta s_j \sum_g \int_{\eta'} \int_{y_{j+1}} \pi_{j+1}(\sigma_g^2) V_{j+1}(W', y_{j+1}, \mathbf{M}_j, \boldsymbol{\pi}_{j+1|j}) dF(y_{j+1}|\mathbf{H}_{j+1}'\mathbf{M}_j, \sigma_g^2) d\chi(\eta') \right\} \end{aligned}$$

$$\begin{aligned} \text{s.t.} \quad & c + s' + b' = [(1-\tau_{ss})Y_j - T(Y_j)] \times \mathbf{1}\{j < j_R\} + ss(Y_{J_R-1}) \times \mathbf{1}\{j \geq j_R\} + W \\ & \pi_{j+1}(\sigma_g^2) \text{ is given by Equations (11) and (12)} \\ & \mathbf{M}_j \text{ is given by Equation (10)} \\ & F(y_{j+1}|\mathbf{H}_{j+1}'\mathbf{M}_j, \sigma_g^2) \text{ is the prob. distribution for the next period's income given } \mathbf{M}_j, \sigma_g^2 \\ & b' \geq \underline{b} \text{ and } s' \geq 0, \end{aligned}$$

where $\mathbf{1}\{\cdot\}$ is an indicator function and total labor income is $Y_j = e^{z_j + y_j}$.

Comparison of Models In all models, the parameters of the income process are recalibrated to match the age profile of income variance (left panel of Figure 8). The variances of consumption are *not* targeted (right panel of Figure 8). All models except for ARCH do pretty well in matching the age profile of consumption variance. This is because the

Figure 8: Cross-Sectional Variance of Income and Consumption



Notes: The left panel shows the variance of log labor income over the life cycle. The right panel is the variance of log consumption.

Table 10: Response of Risky Share to Income Risk

Model	$\hat{\beta}(= \frac{\partial \Delta RS}{\partial \Delta SD})$
Data	-20.0
Benchmark	-17.9
Adjustment Costs	-5.2
ARCH	-10.8
Imperfect Information	-11.5

ARCH process implies an increasing dispersion in wealth: a high income today increases the next period's expected variance of income, inducing high-income workers to save more for precautionary reasons. As a result, the ARCH model generates a large inequality in wealth and, thus, consumption.

Table 10 reports the marginal effect of income risk on the risky share from the models and the data. All three alternative models generate a smaller response of risky share than the benchmark ($\hat{\beta} = -18$). The adjustment cost substantially mitigates the response of the risky share (-5.2). The ARCH specification also generates a response that is 40% smaller (-10.8) because the ARCH implies less persistent volatility regimes than the benchmark specification. Finally, with imperfect information, the response (-11.5) is about two-thirds of the benchmark as workers gradually learn about the change in the volatility regime.

7 Conclusion

Households' portfolio decisions depend on the background risk in the labor market. Based on detailed administrative panel data from Statistics Norway, we find a statistically and economically significant shift in the risky share around the structural break in income volatility: if the standard deviation of labor-income growth doubles in size, the worker decreases her risky share by 5 percentage points on average. We find substantially larger estimates compared to many previous studies due to our identification strategy: individual-specific structural breaks of income volatility combined with a firm-side instrumental variable.

We then ask whether our estimated marginal effect is consistent with a standard model of portfolio choice with stochastic volatility shocks to the income process. When the model is calibrated to match various moments on income, consumption, and financial portfolio choices from the Norwegian panel, the model closely replicates the response of the risky share to the income risk we documented in the data. According to our structural model, the welfare cost of time-varying income risk is large: 4% in consumption-equivalent units. The welfare gain from being able to adjust financial portfolio (between risky and risk-free assets) in response to such risk is about 1%.

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Appendix

A Data

A.1 Data Sources

Based on Statistics Norway, we combined several data sets using unique personal identifiers. The details of the data are as follows.

Central Population Register: The data contain individual demographic information for all Norwegian residents from 1992 to 2014. This includes personal variables (country of birth, first stay date, immigration category, country background, gender, date of birth) as well as time-varying characteristics (marital status, spouse's ID if married). The family identifiers can be used to link spouses and cohabiting couples with common children. Family structure and family type variables are also available: total number of persons in the family, the age of youngest child, the age of youngest and oldest person in the family, the number of children under the ages of 18, 16, 11, and 6, family type, father ID and mother ID at the time of birth. Some of these variables are missing for several years (e.g., family type).

National Educational Database: All individual statistics on education have been gathered in the National Education Database (NUDB) since 1970. Educational attainment is reported by the educational establishment directly to Statistics Norway. By October 1 of each year, the completed education from the previous school/academic year is updated and the information about the highest attained level of education for the whole population is updated as well.

Administrative Tax and Income Records: All households in Norway are subject to an income tax and a wealth tax, and they are obliged to report their complete income and wealth holdings to the tax authority every year. Also, employers, banks, brokers, insurance companies and any other financial intermediaries are obliged to send the information on the value of the assets owned by the individual to the individual and to the tax authority as well. Traded financial securities are reported at market value; value of shares in private companies is reported by individuals as well as private companies to the tax authority. The tax authority will combine the information from companies' reports on net worth with individuals', and adjust if necessary. For more details, see annual reports from the tax authority (http://www.skatteetaten.no) as well as other literature (e.g., Fagereng and Halvorsen (2017))

Income Registry: From the income registry data, we gathered the following items:

- Earned income includes cash salary, taxable benefits and sickness and maternity benefits during the calendar year.
- Net entrepreneurial income includes the income from land and forestry, fishing and hunting, income from other business activities and sickness benefits in employment during the calendar year.
- Capital investment income includes interest income, dividends, realized gains and other investment income:
  - Interest income (from bank deposits and accounts receivable during the calendar year)
  - Dividends received during the calendar year
  - Realization gains: Taxable gains on the sale of real estate and financial securities during the calendar year.
  - Deductible losses on the sale of real estate and financial securities during the calendar year.

  - Other income: Net income from the rental of real property outside the industry, return on "spare part" of life insurance, income from abroad and other unspecified investment income during the calendar year.

- Unemployment benefits paid to wage earners and self-employed.

- Pensions:

  - Pensions from the scheme (ftryg): includes own pensions and national insurance, including a spouse's allowance and child benefit for children aged 16 or younger.
  - Own pensions: Occupational pensions include the payment to workers by different working conditions, including contractual pension (AFP). It also includes payments from individual pension agreements (IPA), annuities and maternity council benefits in agriculture and forestry.

- Transfers:

  - Tax-free transfers include child allowance, housing allowance, study grants, social assistance, basic and auxiliary disability compensations.
  - Taxable transfers include pensions from the National Insurance, pension, unemployment benefit and received contributions, as well as other taxable transfers.

- Miscellaneous items in the income tax record:

  - Alimony and annuities outside employment
  - Sum of income and wealth taxes and negative transfers
  - Sum of interest payments (interest on debt to Norwegian and foreign creditors) and residential income (imputed residential income and leisure property and shareholder's share of income from housing companies).

Wealth Registry Record: For persons who are older than 17 years, we can obtain the wealth data from the tax authority every year. Here are the descriptions quoted from the tax administration.[31]

- **Bank Deposits** *Deposits in Norwegian banks (entry 4.1.1 in the 2015 tax form)*

  "This item shows what deposits you and your children who are under 17 years of age at the end of the income year have in Norwegian banks as of 31 December. Deposits belonging to children under 17 will be split with half being assigned to each of the parents if they live together. The amount will normally be pre-filled with the amount that has been reported, so you should check that everything is correct."

- **Value of Shares in Mutual Funds** *(entry 4.1.4)*

  "The item is pre-filled with information concerning capital in Norwegian unit trusts and certain foreign unit trusts which the Tax Administration has received information about from the management companies concerned. You must enter any capital in the form of units in Norwegian and foreign unit trusts in 2015 that have not been pre-filled."

- **Value of Financial Securities** *(entry 4.1.7)*

  "This item shows the value of bonds and shares in the Norwegian Central Securities Depository (VPS) as of 31 December. The amount will normally be pre-filled with what has been reported, so you should check that everything is correct."

[31]For detailed information, see the corresponding 2015 tax form from the Norwegian Tax Administration: http://www.skatteetaten.no/en/person/Tax-Return/Find-item/#&del1=1&del2=1&del3=1&del4=1&del5=1.

- **Value of Shares in Private Companies** *(entry 4.1.8)*

  "This item shows the capital value of shares and other securities not registered with VPS."

- **Tax Value of Housing and Other Real Property** *(entry 4.3)*

  Capital such as dwellings, holiday homes, forest property, farms, agricultural property, plots and commercial property, etc.

- **Value of Home Owned** *(entry 4.3.2)*

  "If you own a home as of 31 December, the tax value must be entered under this item. The tax value is determined on the basis of factors such as location, size and year of construction. If the tax value exceeds 30 percent of the home's market value, you can change the value if you are able to document the market value. This concerns your primary home."

- **Premium Funds, Individual Pension Agreements** *(entry 4.5.1)*

  "This item shows your capital in the form of premium funds as of 31 December. The amount will normally be pre-completed with the amount that has been reported by the company you have entered into a pension agreement (IPA) with. You must check that everything is correct."

- **Value of Life Insurance Policies** *(entry 4.5.2)*

  "This item shows the surrender value of your annuities as of 31 December. The amount will normally be pre-filled with the amount that has been reported by the insurance company/companies or employer who has made deposits on your behalf. You must check that everything is correct."

- **Other Capital** *(entry 4.5.4)*

  "If you have other taxable capital as of 31 December, the value must be entered under this item. 'Other taxable capital' means for example assets in the form of capitalised ground rent, rights linked to forest/uncultivated land, share of company assessed as partnerships (RF-1221) and/or NOKUS (RF-1246)."

- **Total Debt** *(entry 4.8)*

  "The items under '4.8 Debt' concern negative capital such as loans, credit purchases, underpaid tax, private loans, debts in housing cooperatives/jointly owned properties, debts abroad and deductions for leasehold land, etc."

- **Total Net Worth** *(entry 4.9)*

  "Amounts specified under this item form the basis for the calculation of wealth tax payable to municipalities and the state. The basis for this is the sum of your wealth with a reduction for any debt."

Employer-Employee Register: Statistics Norway combines the required report from each firm that hires workers and the tax record from individuals. The data include detailed labor market information for every worker each year (worker ID, employers' ID, job starting date with each employer, job ending date with each employer, total payments to workers from each employer, industry, occupation, actual and expected working hours, total number of days worked, indicator for full-time/part-time employment, etc.).

Register of Social Assistance Received: For each person from 1992, the register records monthly the details of social assistance received. This includes any unemployment benefit, rehabilitation/medical rehabilitation, maternity, temporary disability insurance as well as the benefit for sickness.

A.2 Sample Selection

Data Merge Starting with the whole population of Norwegian natives (including all males and females) from 1994 to 2014, with no missing records on income tax registration, basic demographic variables (immigration category, country background, gender, date of birth, and family information) and no missing records on wealth tax registration. We first exclude any observations younger than 25 years old or older than 65. We then require workers to have positive labor earnings each year and to be associated with an identified firm ID in the data, since we focus on labor market activities and exclude other types of labor market status (unemployment, retired, or disabled, etc.). In the data, approximately 10% of workers have multiple jobs within a year. Some of them are associated with multiple employers (different establishment ID). Also, some workers with the same employer (establishment ID) have records of earnings with different starting and/or ending dates. The latter cases reflect, for most workers, changes in titles, job requirements, or new contracts with the same employer. Thus, we simply add up the earnings under the same establishment within a year. Following the literature, we only keep the main job among possibly different employers, as the one with the largest earnings within a year. In addition, we drop those with any public-sector employment spells (private sector employment are sectors of 710 or 717). Lastly, since we focus on labor market volatility, we need to compute standard deviations and changes in standard deviations for each individual; therefore, we select those workers with at least 16 years of working history in the private sector. After these basic selections, we have 5,712,476 person-year observations. Further, we restrict the sample to those with financial assets of at least 500 Norwegian kroner (in 2005 constant NOK; roughly the 1^{st} percentile of the 2005 cross-sectional distribution for financial assets in our sample) so that risky shares can be defined with less noise. We also require that the growth rates of workers' earnings over time cannot be too small or too large (between -150% and 150%) to exclude outliers (some of these extreme cases may reflect transitions in schools, part-time jobs or other reasons). This gives us 5,399,332 person-year observations and 342,875 persons.

Linking Household Information From the Central Population Register data, for each individual we obtain marital status and link to his/her spouse's ID. From the Central Population Register data, we obtain the person's father's ID and mother's ID at the time of his/her birth; we can also link to each of his children's IDs. This provides the information on family size, number of children, and number of young children with different ages. Based on person ID, spouse ID, father ID, mother ID, and children's IDs, we construct information on the spouse's income and wealth, father's income and wealth, and each child's income and wealth if older than 17. This yields household-level income and wealth. (The administration registry does not keep track of household-level income and wealth.)

B Additional Tables

Table A1: Summary Statistics

	Obs.	Mean	S.D.	Percentiles						
				5^{th}	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	95^{th}
Female	1,879,771	0.282	0.450	0	0	0	0	1	1	1
Age	1,879,771	44.919	8.126	31	34	39	45	51	56	58
College Dummy	1,879,771	0.293	0.455	0	0	0	0	1	1	1
Real Earnings (log)	1,879,771	12.819	0.550	11.883	12.188	12.548	12.838	13.143	13.443	13.638
Household Disposable Income (log)	1,879,771	13.192	0.523	12.369	12.557	12.906	13.180	13.455	13.765	14.018
Household Gross Wealth (log)	1,879,771	13.863	1.033	12.350	12.731	13.243	13.794	14.438	15.138	15.641
Household Financial Assets (log)	1,879,771	12.717	1.489	10.323	10.894	11.765	12.691	13.664	14.586	15.193
Risky Share	1,879,771	38.476	30.507	0.364	2.398	10.748	32.106	63.973	85.543	93.130
Financial Assets / Disposable Income	1,879,771	2.168	540.613	0.072	0.120	0.269	0.627	1.467	3.170	5.197
Deposits / Total assets	1,879,771	0.555	0.313	0.043	0.095	0.277	0.589	0.841	0.956	0.988
Private Equity / Assets	1,879,771	0.166	0.298	0.000	0.000	0.000	0.000	0.198	0.740	0.885
Financial Securities / Assets	1,879,771	0.077	0.166	0.000	0.000	0.000	0.000	0.063	0.266	0.457
Mutual Funds / Assets	1,879,771	0.156	0.205	0.000	0.000	0.004	0.069	0.227	0.460	0.622
Life Insurance / Assets	1,879,771	0.047	0.121	0.000	0.000	0.000	0.000	0.018	0.157	0.301
Years of Job tenure	1,879,771	8.707	7.229	1.000	1.333	3.000	6.667	12.750	19.417	23.417
Residual Earnings Growth	1,879,771	0.005	0.273	-0.417	-0.203	-0.062	0.001	0.073	0.225	0.430
Change Employer	968,727	0.099	0.298	0	0	0	0	0	0	1
Change Occupation	1,875,394	0.073	0.260	0	0	0	0	0	0	1
Change Industry	1,879,701	0.120	0.325	0	0	0	0	0	1	1
Change Community	1,879,771	0.123	0.328	0	0	0	0	0	1	1
Homeowner	1,879,771	0.949	0.221	0	1	1	1	1	1	1
Number of Large-Volatility Increase	1,879,771	0.355	0.585	0	0	0	0	1	1	1
Number of Large-Volatility Decrease	1,879,771	0.354	0.590	0	0	0	0	1	1	2

Note: All nominal variables are deflated by the CPI.

Table A2: Summary Statistics for $\Delta SD_{i,t}$

	Obs.	Mean	S.D.	Percentiles						
				5^{th}	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	95^{th}
All	1,214,798	-0.054	0.229	-0.458	-0.349	-0.175	-0.033	0.063	0.214	0.316
High School	861,253	-0.046	0.227	-0.448	-0.338	-0.161	-0.028	0.067	0.219	0.323
College	353,545	-0.073	0.233	-0.478	-0.373	-0.205	-0.049	0.053	0.200	0.300
Young	320,028	-0.097	0.249	-0.524	-0.420	-0.249	-0.075	0.053	0.201	0.298
Middle	240,076	-0.058	0.228	-0.457	-0.353	-0.185	-0.038	0.067	0.212	0.307
Old	639,781	-0.032	0.215	-0.408	-0.296	-0.129	-0.022	0.064	0.217	0.325
Wealth										
Q1	94,043	-0.075	0.261	-0.542	-0.418	-0.224	-0.040	0.080	0.227	0.326
Q2	227,361	-0.060	0.240	-0.491	-0.375	-0.188	-0.032	0.072	0.217	0.313
Q3	376,370	-0.054	0.226	-0.454	-0.347	-0.173	-0.032	0.061	0.209	0.310
Q4	517,024	-0.047	0.220	-0.428	-0.326	-0.162	-0.033	0.058	0.212	0.320

Note: "Young" refers to those younger than 40 in 2005, and "Old" refers to those older than 45 in 2005. "Wealth Q1" refers to those with real wealth in the 1^{st} quantile of the cross-sectional distribution.

Table A3: Summary Statistics for $\Delta SD_{i,t}$ and $\Delta SD_{i,\tau^*(i)}$

	Mean	S.D.	Percentiles						
			5^{th}	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	95^{th}
$SD_i[\Delta y_{it}]$	0.319	0.260	0.056	0.075	0.136	0.247	0.419	0.659	0.831
$\Delta SD_{i,t}[\Delta y_{it}]$	-0.054	0.229	-0.458	-0.349	-0.175	-0.033	0.063	0.214	0.316
$\Delta SD_{i,\tau^*}[\Delta y_{it}]$	-0.093	0.365	-0.689	-0.555	-0.334	-0.091	0.160	0.372	0.498

Table A4: Robustness: Response of Risky Share ($\hat{\beta}_{IV}$)

	(1)	(2)	(3)	(4)	(5)	(6)
	Benchmark	No Controls	Demographic Only	Levels	Income & Wealth Growth	Polynomial
	-17.58***	-53.83***	-29.55***	-36.67***	-18.73***	-19.49***
	(1.48)	(0.78)	(1.35)	(1.44)	(1.37)	(1.45)
Obs.	583,512	583,512	583,512	583,512	583,512	583,512
	(7)	(8)	(9)	(10)	(11)	(12)
	Mortgage Debt	Capital Income	$k = 3$	$k = 1$	Households' Disposable Income	Stayers
	-18.78***	-19.86***	-21.69***	-13.51***	-31.80***	-20.96***
	(1.45)	(1.47)	(1.44)	(1.64)	(4.77)	(1.75)
Obs.	583,512	557,892	582,344	583,563	697,966	456,130

Note: In Column (11), the household's disposable income is used for y_{it}, SD_{it} and so forth.

Table A5: Structural Breaks: τ^* versus $\hat{\tau}$

	(1)	(2)	(3)	(4)
	Using τ^*		Using $\widehat{\tau}$	
	OLS	IV	OLS	IV
$\hat{\beta}$	-1.70***	-20.01***	-2.24***	-17.73***
	(0.21)	(5.10)	(0.32)	(3.04)
Obs.	125,874	46,084	94,474	94,474

Note: $\hat{\tau}$ denotes the structural break based on the instrumented income volatilities.

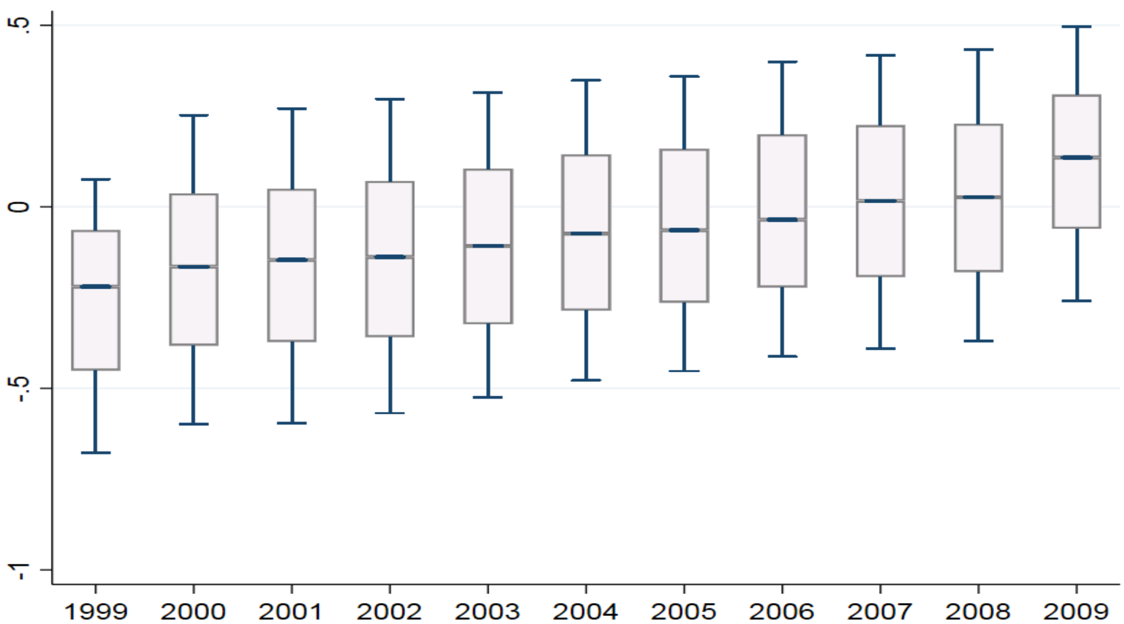
Table A6: Response of Risky Share by Group ($\hat{\beta}_{IV}$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	High school	College	Young	Middle	Old	Male
	-17.58***	-17.31***	-17.82***	-19.59***	-13.58***	-17.31***	-10.90***
	(1.48)	(1.76)	(2.73)	(3.01)	(3.42)	(1.97)	(2.80)
Obs.	583,512	435,052	148,460	148,976	113,206	316,029	162,012
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Female	Poor	Rich	Married	Singles	Homeowners	Renters
	-19.86***	-11.42***	-18.64***	-16.62***	-20.42***	-14.50***	-17.34***
	(1.74)	(3.10)	(1.67)	(1.63)	(3.43)	(6.10)	(1.52)
Obs.	421,500	130,189	453,323	467,450	116,062	37,681	545,831

On-Line Appendix
"Income Volatility and Portfolio Choices"

This on-line appendix collects additional statistics in our paper "Income Volatility and Portfolio Choices."

Figure O1: Distributions for $\Delta SD_{i,\tau^*}$ by Year

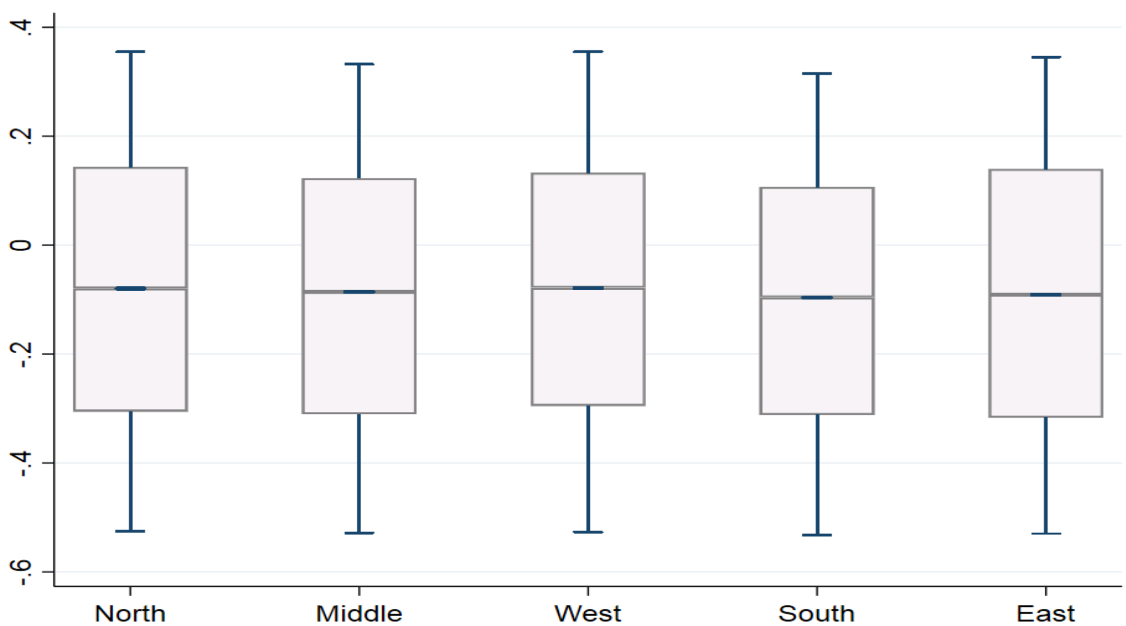


Note: Each plot represents $10^{th} - 90^{th}$, $25^{th} - 75^{th}$ percentiles and the median of the distribution.

Figure O2: Distributions for $\Delta SD_{i,\tau^*}$ by Sectors

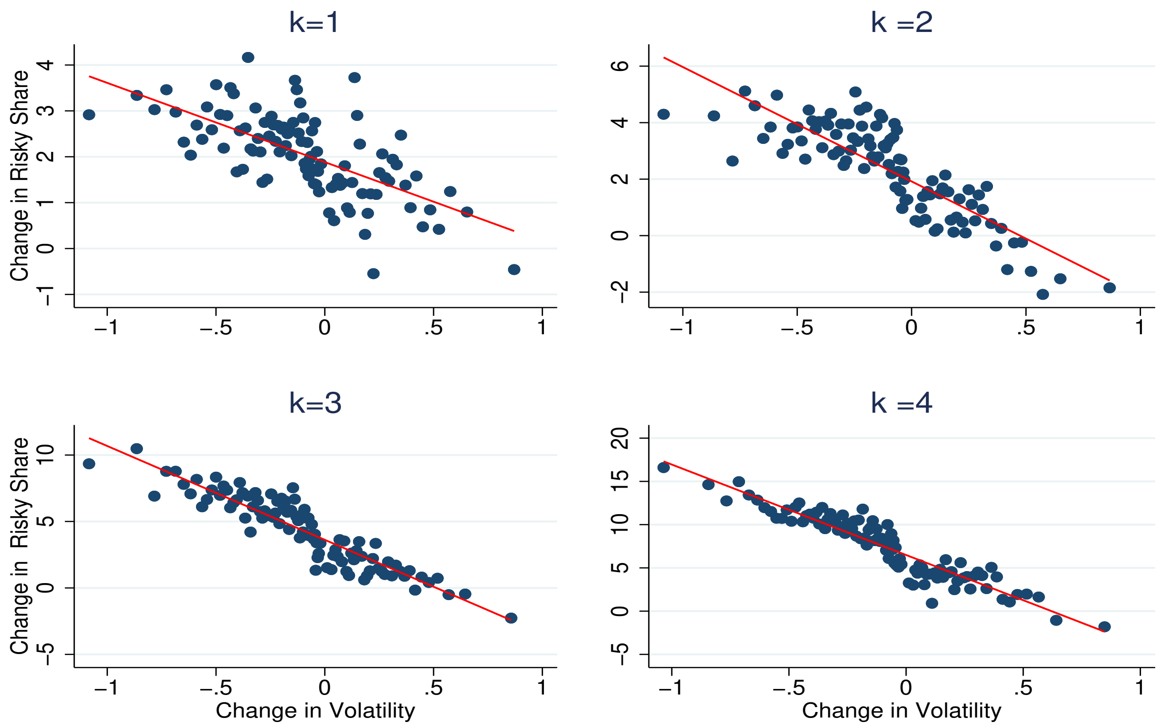
Note: Each plot represents $10^{th} - 90^{th}$, $25^{th} - 75^{th}$ percentiles and the median of the distribution.

Figure O3: Distributions for $\Delta SD_{i,\tau^*}$ by Regions



Note: Each plot represents the $10^{th} - 90^{th}$, $25^{th} - 75^{th}$ percentiles and the median of the distribution.

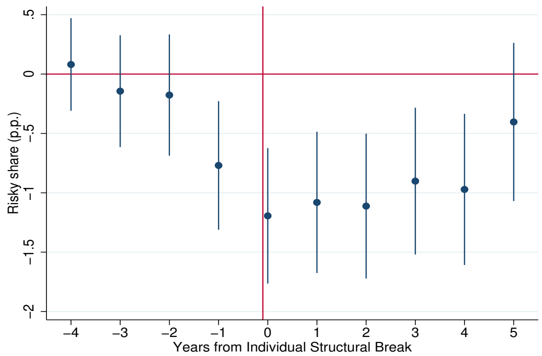
Figure O4: Change in Risky Shares vs. Change in Volatility at τ^*



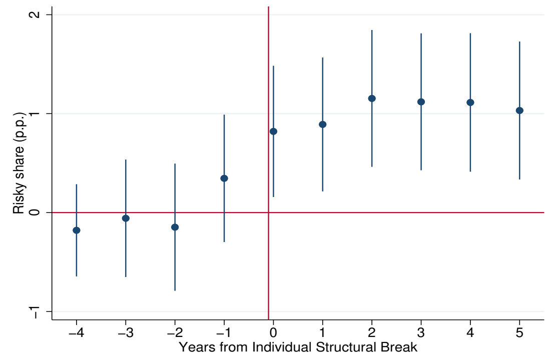
Note: These figures plot the change in income volatility (ΔSD_{τ^*}) and the average change in the risky share ($\Delta RS_{i,\tau^*}$) for various values of k. For example, for $k = 3$, $\Delta RS_{i,\tau^*} = \frac{1}{3}(RS_{i,\tau^*+1} + RS_{i,\tau^*+2} + RS_{i,\tau^*+3}) - \frac{1}{3}(RS_{i,\tau^*-1} + RS_{i,\tau^*-2} + RS_{i,\tau^*-3})$.

Figure O5: Dynamics of Risky Shares around τ^*

(a) Large Volatility Increase



(b) Large Volatility Decrease



Note: This figure reports the estimated coefficients from the regression (for the left panel):

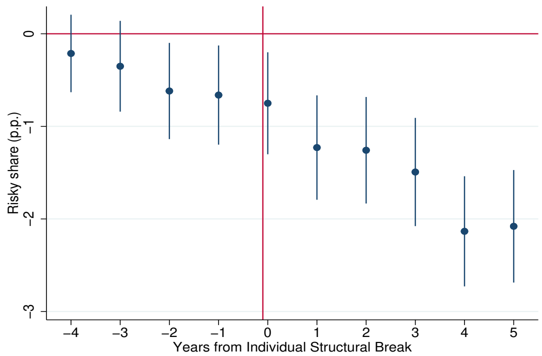
$$RS_{i,t} = \sum_{k=-5,5} \beta_k I_{t=\tau^*+k} D^I_{\tau^*} + \gamma I_{t=\tau^*+k} + \beta_I D^I_{\tau^*} + \delta X_{i,\tau^*} + D_t + \epsilon_{it},$$

where β_{-5} is normalized to 0 (not shown in the figure), and the dummy variable $D^I_{\tau^*}$ is 1 if a worker experienced a volatility increase larger than the 85^{th} percentile of the distribution ($\Delta SD_{i,\tau^*} > 0.28$). We use the same control variables as in the benchmark described in the text. The standard errors are clustered at the individual level. Similarly, the right panel with the dummy variable ($D^D_{\tau^*} = 1$), which takes a value of 1 if a worker experienced a volatility decrease larger (in absolute value) than the 15^{th} percentile of the distribution ($\Delta SD_{i,\tau^*} < -0.47$).

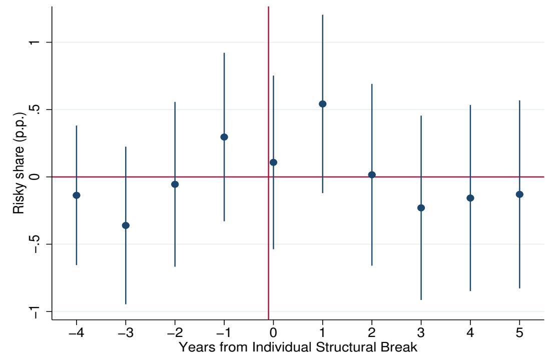
$$RS_{i,t} = \sum_{k=-5,5} \beta_k I_{t=\tau^*+k} D^D_{\tau^*} + \gamma I_{t=\tau^*+k} + \beta_I D^D_{\tau^*} + \delta X_{i,\tau^*} + D_t + \epsilon_{it}.$$

Figure O6: Dynamics of Risky Shares around $\widehat{\tau}$

(a) Large Volatility Increase



(b) Large Volatility Decrease



Note: The coefficients for the left panel are from the regression:

$$RS_{i,t} = \sum_{k=-5,5} \beta_k I_{t=\widehat{\tau}+k} D^I_{\widehat{\tau}} + \gamma I_{t=\widehat{\tau}+k} + \beta_I D^I_{\widehat{\tau}} + \delta X_{it} + D_t + \epsilon_{it},$$

where β_{-5} is normalized to 0 (not shown in the figure). The regression is similar to the one used in Figure O5. The dummy $D^I_{\widehat{\tau}}$ takes a value of 1 for the group of workers who experienced a volatility increase (in terms of instrumented values) larger than the 85^{th} percentile of the distribution. Similarly, the right panel uses the dummy variable for a worker experienced a volatility decrease (in terms of instrumented values) larger (in absolute value) than the 85^{th} percentile.

The following three tables (Tables O1-O3) report the summary statistics for the sample that does not require participation in investment in risky assets (as opposed to at least 16 years of positive risk shares in the benchmark case).

Table O1: Summary Statistics

	Obs.	Mean	S.D.	Percentiles						
				5^{th}	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	95^{th}
Female	5,399,332	0.273	0.446	0	0	0	0	1	1	1
Age	5,399,332	43.353	8.339	30	32	37	43	50	55	57
College Dummy	5,399,332	0.196	0.397	0	0	0	0	0	1	1
Real Earnings (log)	5,399,332	12.720	0.527	11.813	12.119	12.481	12.744	13.019	13.312	13.500
Household Disposable Income (log)	5,399,332	13.010	0.489	12.230	12.370	12.702	13.036	13.292	13.553	13.750
Household Gross Wealth (log)	5,399,332	13.238	1.200	11.181	11.974	12.714	13.299	13.891	14.529	14.993
Household Financial Assets (log)	5,399,332	11.635	1.740	8.672	9.404	10.521	11.689	12.780	13.786	14.406
Risky Share	5,399,332	20.755	29.038	0.000	0.000	0.000	3.316	35.235	72.191	86.084
Participation	5,399,332	0.564	0.496	0.000	0.000	0.000	1.000	1.000	1.000	1.000
Financial Assets / Disposable Income	5,399,332	1.044	319.486	0.017	0.034	0.093	0.269	0.727	1.738	2.903
Deposits/ Financial assets	5,399,332	0.737	0.317	0.084	0.191	0.518	0.892	1.000	1.000	1.000
Private Equity/ Assets	5,399,332	0.082	0.226	0.000	0.000	0.000	0.000	0.000	0.365	0.741
Securities / Assets	5,399,332	0.040	0.131	0.000	0.000	0.000	0.000	0.000	0.105	0.284
Mutual Funds / Assets	5,399,332	0.093	0.183	0.000	0.000	0.000	0.000	0.097	0.336	0.523
Life Insurance / Assets	5,399,332	0.048	0.143	0.000	0.000	0.000	0.000	0.000	0.152	0.345
Years of Job tenure	5,399,332	7.898	6.897	0.833	1.167	2.500	5.750	11.333	18.000	22.167
Residual Earnings Growth	5,399,332	0.003	0.291	-0.462	-0.229	-0.068	-0.001	0.073	0.244	0.472
Change Employer	5,399,332	0.111	0.315	0	0	0	0	0	1	1
Change Occupation	2,872,259	0.079	0.270	0	0	0	0	0	0	1
Change Industry	5,387,837	0.127	0.334	0	0	0	0	0	1	1
Change Community	5,399,129	0.124	0.330	0	0	0	0	0	1	1
Homeowner	5,399,332	0.899	0.301	0	0	1	1	1	1	1
Number of “Large” Volatility Increase	5,399,332	0.123	0.384	0	0	0	0	0	1	1
Number of “Large” Volatility Decrease	5,399,332	0.123	0.387	0	0	0	0	0	1	1

Table O2: Summary Statistics for $\Delta SD_{i,t}$

	Obs.	Mean	S.D.	Percentiles						
				5^{th}	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	95^{th}
All	3,432,940	-0.052	0.242	-0.474	-0.363	-0.184	-0.032	0.076	0.235	0.340
High school	2,760,289	-0.045	0.242	-0.468	-0.355	-0.173	-0.028	0.081	0.242	0.347
College	672,651	-0.080	0.243	-0.499	-0.393	-0.222	-0.055	0.054	0.207	0.308
Young	1,227,852	-0.083	0.260	-0.527	-0.418	-0.241	-0.061	0.074	0.231	0.332
Middle age	654,309	-0.052	0.237	-0.464	-0.357	-0.185	-0.033	0.079	0.232	0.332
Old	1,486,979	-0.028	0.223	-0.416	-0.303	-0.131	-0.020	0.072	0.234	0.344
Wealth Q1	779,249	-0.058	0.267	-0.528	-0.407	-0.211	-0.032	0.099	0.261	0.363
Wealth Q2	966,514	-0.051	0.243	-0.479	-0.366	-0.182	-0.029	0.081	0.235	0.337
Wealth Q3	942,046	-0.051	0.232	-0.454	-0.348	-0.177	-0.033	0.065	0.222	0.329
Wealth Q4	745,131	-0.048	0.225	-0.434	-0.333	-0.169	-0.035	0.059	0.220	0.331

Table O3: Summary Statistics for $\Delta SD_{i,\tau^*}$

	Obs.	Mean	S.D.	Percentiles						
				5^{th}	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	95^{th}
All	342,875	-0.097	0.364	-0.692	-0.557	-0.336	-0.093	0.157	0.366	0.491
High school	269,282	-0.086	0.363	-0.684	-0.548	-0.322	-0.081	0.164	0.375	0.500
College	73,593	-0.142	0.362	-0.719	-0.590	-0.383	-0.156	0.118	0.331	0.450
Young	103,011	-0.152	0.388	-0.762	-0.631	-0.419	-0.181	0.157	0.358	0.471
Middle age	67,596	-0.098	0.354	-0.678	-0.551	-0.335	-0.104	0.160	0.355	0.474
Old	160,323	-0.050	0.333	-0.604	-0.465	-0.243	-0.056	0.144	0.371	0.509
Wealth Q1	64,708	-0.162	0.389	-0.782	-0.645	-0.423	-0.177	0.123	0.354	0.475
Wealth Q2	104,687	-0.118	0.358	-0.703	-0.571	-0.353	-0.114	0.129	0.342	0.466
Wealth Q3	96,604	-0.064	0.347	-0.633	-0.504	-0.289	-0.066	0.171	0.373	0.502
Wealth Q4	76,876	-0.023	0.337	-0.578	-0.450	-0.236	-0.044	0.198	0.402	0.529