Hedging Labor Income Risk*

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May 2, 2011

Abstract

We investigate the relation between households' labor income risk and financial investment decisions. We find that the volatility of their wages affect their investment decisions, consistent with the idea that households hedge human capital risk in stock markets. In our study, we use a detailed Swedish panel data set on employment and portfolio holdings, and relate changes in wage volatility to changes in portfolio holdings for households that switched industries between 1999 and 2002. The results are statistically and economically significant. A household going from an industry with low wage volatility to one with high volatility will *ceteris paribus* decrease its portfolio share of risky assets by up to 35%, or USD 15,575.

*We have benefited from helpful comments by Jonathan Berk, Richard Stanton, and seminar participants at U.C. Berkeley and the LSE. Any errors are our own.

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1 Introduction

Labor income accounts for about two thirds of national income in the U.S. and, since the seminal work of Mayers (1973), it has been assumed to play an important role in theoretical asset pricing. In studies such as Bodie, Merton, and Samuelson (1992), Danthine and Donaldson (2002), Qin (2002), Santos and Veronesi (2006) and Parlour and Walden (2010), risky labor income—or more generally, human capital risk—affects investors' portfolio decisions, which in turn has general equilibrium asset pricing implications. Broadly, the theory suggests that the behavior of capital markets can only be understood together with labor markets. More specifically, the theory suggests that an important function of capital markets is to allow investors to hedge their labor income risk.

Are investors' portfolio decisions affected by their labor income risk? Studies that use aggregate labor income find mixed evidence. Fama and Schwert (1977) find that adding a labor factor does not improve the performance of the unconditional CAPM. By contrast, Jagannathan and Wang (1996) find that an aggregate labor factor significantly improves the performance of a conditional CAPM in explaining the cross section of expected returns (see also Palacios-Huerta, 2003). Given the highly aggregate data, noisy measurements, and incomplete real-world markets, it seems unlikely that an approach based on aggregate data can lead to a conclusive answer.

In this paper, we approach the question by using data at the individual household level. Specifically, we study panel data on employment and portfolio holdings of a large subset of the Swedish population between 1999 and 2003, and examine whether there is a relation between workers' wage structure (measured by wage level and volatility) and their portfolio holdings of risky assets.

We find that shocks to workers' wage volatility affect their portfolio holdings of risky assets. This is consistent with the idea that human capital risk affects portfolio decisions. For example, households adjust their portfolios in response to job changes. This hedging effect, which is highly statistically significant, is especially strong for job changes that lead to large changes in wage volatility: a household that experiences an increase in wage volatility by 20% decreases its portfolio share of risky assets by 20%. This means that a household going from the industry with the least variable wage in the sample (recycling metal waste) to the industry with the most variable wage (fund management) *ceteris paribus* decreases its share of risky assets by up to 35%, or 15,575 USD.

Although we establish a strong link between *changes* in human capital risk, and *changes* in portfolio holdings, the results are weaker when we examine *levels*. We take this as evidence of cross-sectional "taste" differences, e.g., in risk-preferences, familiarity bias, or heterogeneous information among households. If any of these "taste" factors vary with the business cycle, then our results are consistent with a world in which a human capital factor is of little help in an unconditional CAPM (as argued in Fama and Schwert, 1977), but significantly improves the performance of a conditional CAPM (as argued in Jagannathan and Wang, 1996). This may explain the weak evidence for the importance of labor risk in the aggregate.

Our study uses the Longitudinal Individual Data for Sweden (LINDA) database from 1999 to 2002, which provides detailed income and wealth information for a large representative sample of about 3% of the Swedish population at the end of each year. While we do not have information on agents' individual security holdings, we do know the share of the households' wealth invested in directly held stocks, mutual funds, and other financial assets such as derivative and capital insurance products. By definition, most firms bear a positive level of market risk. If we assume—in line with the theoretical literature—that the wages are on average positively correlated with the market, then workers can hedge their labor income risk by holding a lower share of risky assets and mutual funds.

Our results complement the previous literature, by using using better-quality data on portfolio holdings, and by controlling for "taste" differences in the form of household fixed effects. The previous literature has yielded mixed results when using individual portfolio holdings to test for hedging of labor income risk. Heaton and Lucas (2000) use the Panel of Individual Tax Returns, which provides information on income and assets for a large panel with annual frequency. They compute for each individual an estimate of wage volatility and then study the effect on their average portfolio share of risky assets. They find that, while levels of entrepreneurial risk have a significant influence on portfolio holdings,[1] the effects of wage income risk is not significant. Guiso, Jappelli, and Terlizzese (1996) use a cross-sectional dataset of Italian households in 1989 which asks them to attribute probability weights to intervals of nominal income increases one-year ahead. They find evidence that households that expect high future wage volatility hold relatively low shares of risky assets. Gakidis (1998) and Vissing-Jorgensen (2002) use panel data from the Panel Study of Income Dynamics and also find that high levels of future wage volatility have a negative effect on

[1] Calvet, Campbell, and Sodini (2007) find similar results using detailed stockholding data from Sweden.

both the probability of being a stockholder and the share invested in risky assets conditional on owning stocks. On the other hand, Massa and Simonov (2006) look at individual stock holdings using panel data from Sweden and find that households tend to hold stocks that are closely related to their labor income, which goes against the hypothesis of hedging of labor income risk. They argue this is because of a preference for familiar stocks due to heterogeneous information, which would fall within our definition of individual "taste" differences. Our main result—that we find a significant hedging demand for human capital risk when following individual households over time—is in fact consistent with Massa and Simonov's results, since they find that the familiarity bias is considerably smaller for households that switch professions or locations, or who experience an unemployment shock.

The rest of this paper is organized as follows. In Section 2, we introduce a stylized model to describe the predicted relation between wages and portfolio decisions. We describe the data in Section 3 and the methodology in Section 4. In Section 5, we provide the empirical results, and in Section 6 we offer some concluding remarks. Further information about the data sets is provided in the Appendix.

2 Theoretical background and empirical predictions

There is an extensive theoretical literature that studies the effects of human capital risk on portfolio choice and asset pricing. In the static framework of Mayers (1973), human capital risk introduces a hedging demand in capital markets. Investors exposed to human capital risk decrease their holdings of stocks that are positively correlated with this risk. The implication of human capital hedging is robust to generalizations, such as the dynamic framework of Bodie, Merton, and Samuelson (1992).

Recently, a literature has studied the general equilibrium asset pricing implications of human capital risk, see Dreze (1979), Danthine and Donaldson (2002), Qin (2002), Santos and Veronesi (2006), Lustig and Van Nieuwerbugh (2008), Parlour and Walden (2010), and Berk and Walden (2010). The main driver behind the results of these studies is the interplay between labor income risk and stock market risk in agents' portfolio problems. Therefore, documenting that agents treat labor income and capital market investments jointly, by hedging labor income risk, is necessary for the theoretical literature on human capital risk, portfolio choice and asset pricing to have any practical implications.

We introduce a stylized model to motivate the predicted relationships between wages and portfolio decisions. Our model is a simplified version of the model in Parlour and Walden (2010), although similar results also arise elsewhere in the literature. Parlour and Walden (2010) introduce a multi-sector model in which firms in different sectors have different labor productivity and where there is moral hazard between firms and workers, which leads to risky compensation. For our purposes, it is sufficient to introduce a two-sector model and we have no need to model the moral hazard between workers and firms.

Time is discrete, $t = 0, 1$. There are two units of agents with CARA utility, one unit of which have a risk aversion coefficient γ_L and the other unit γ_H, where $\gamma_L < \gamma_H$. Then the risk-aversion coefficient of the representative agent is $\overline{\gamma} = \frac{1}{\frac{1}{\gamma_H}+\frac{1}{\gamma_L}}$.

There are two firms ℓ and h, both generating total revenues of $R + \xi$ at $t = 1$ where $R > 1$ is a constant and $\xi \sim N(0, \sigma^2)$ is a normally distributed random variable. The volatility $\sigma > 0$ is constant as well. The total risk in the economy is therefore 2ξ, and in a full risk sharing equilibrium each agent should take on $\frac{\overline{\gamma}}{\gamma_i}\xi$, $i \in \{L, H\}$.

Each firm $j \in \{\ell, h\}$ employs one unit of workers and pays a risky wage of $s_j + w_j\xi$. Here we assume $s_j > 0$ and $0 \leq w_j < 1$. We also assume that $w_\ell < w_h$, so that the wages of firm h are riskier than those of firm ℓ. For a micro foundation for why firms differ in the riskiness of their wage contracts, see Parlour and Walden (2010). There is one share of each firm traded in the stock market. The remaining cash-flows, net wages, $D_j = R - s_j + (1 - w_j)\xi$, are paid out as a liquidating dividend at $t = 1$ to shareholders. There is also a risk-free asset in elastic supply, with returns normalized to zero.

It follows from a standard Walrasian equilibrium argument (similar to that made in Parlour and Walden (2010)) that the price of one unit of ξ risk in equilibrium is $-\overline{\gamma}\sigma^2$, that the market clearing price of firm $j \in \{\ell, h\}$ is $P_j = R - s_j - \overline{\gamma}\sigma^2(1 - w_j)$, and that the value of wages are $s_j - w_j\overline{\gamma}\sigma^2$. Now, given that labor markets are competitive and that the same human capital skills are needed for all jobs, it further follows that $s_j = W + w_j\overline{\gamma}\sigma^2$ for some constant W representing the market price of a worker's human capital (see Parlour and Walden (2010)).

Since there is only one risk-factor in the stock market, each agent can reach his optimal allocation by trading in the stock market portfolio, together with the risk-free asset. We therefore treat the total stock market payout of $\overline{D} = 2(R - W + \xi) - (w_\ell + w_h)(\xi + \overline{\gamma}\sigma^2)$ as that of a representative firm in the market with a supply of one share and a price of $\overline{P} = 2(R - W - \overline{\gamma}\sigma^2)$.

We now have all the ingredients to compare the portfolio holdings of the two types of agents. Let q^i_j denote the stock portfolio of agent $i \in \{L, H\}$, who works in firm $j \in \{\ell, h\}$. Using a standard hedging argument, we can show that

$$q^i_j = \kappa \frac{\overline{\gamma} - \gamma_i w_j}{\gamma_i}, \qquad \text{where } \kappa = \frac{1}{2 - w_\ell - w_h}, \tag{1}$$

and further that

$$q^i_\ell > q^i_h, \qquad i \in \{L, H\}. \tag{2}$$

Eq. (2) is the key relation that we would like to test. It relates wage risk (w_j) to the agents' portfolio decisions (q^i_j). Specifically, it says that any agent who works in the high wage risk firm h, i.e. who has a high wage volatility, will choose to have a lower share of his wealth invested in the stock market portfolio than if he works in the low wage risk firm. In other words, any agent who switches jobs from a high wage volatility firm to a low wage volatility firm (i.e. whether or not he has high or low risk aversion) will rebalance his stock market portfolio upward, and vice-versa.

Although our model is static, the extension to a dynamic version with a constant investment opportunity set, where some agents switch jobs in each period, is straightforward and leads to identical results at each point in time, which then allows for a dynamic interpretation of our results. We avoid this extension in the interest of notational simplicity. Also, it is clear that the rebalancing result is robust to several other extensions, e.g., the introduction of physical capital or idiosyncratic labor income risk, which we also avoid for the same reason. For example, in addition to the market component of labor income risk, there may be idiosyncratic components that may or may not be partially hedgeable in the market by trading in specific stocks. Now, as long as there is a positive relationship between aggregate human capital risk and stock market risk, the aggregate hedging results will still hold, i.e., agents who increase their labor volatility will on average decrease their stock market exposure. For further discussions on the positive relationship between aggregate human capital and asset pricing risk, see Lettau and Ludvigson (2001) and Berk and Walden (2010).

Now, given that a fraction $\alpha \in [0, 1]$ of L-agents work in the ℓ-firm, it follows that the average portfolio of agents working in ℓ-firms is

$$\bar{q}_\ell = \kappa \overline{\gamma} \left(\frac{\alpha}{\gamma_L} + \frac{1-\alpha}{\gamma_H} \right) - \kappa w_\ell, \tag{3}$$

and similarly the average portfolio of agents working in h-firms is

$$\bar{q}_h = \kappa \overline{\gamma} \left(\frac{\alpha}{\gamma_H} + \frac{1-\alpha}{\gamma_L} \right) - \kappa w_h. \tag{4}$$

It follows that

$$\bar{q}_l \geq \bar{q}_h \qquad \Leftrightarrow \qquad w_h - w_\ell \geq \left(\frac{\gamma_H - \gamma_L}{\gamma_H + \gamma_L}\right)(1 - 2\alpha). \tag{5}$$

Thus, as long as $\alpha \geq 1/2$, i.e., as long as at least half of the agents with low risk aversion work in the low labor-risk firm, the average investment portfolio of an agent in the low labor-risk firm will have higher market exposure than that of an agent working in the high labor-risk firm, i.e. $\bar{q}_l > \bar{q}_h$. When $\alpha < 1/2$, however, agents who work in high-risk firms may have *higher* risk exposure in the market than agents who work in low-risk firms. Therefore, in a statistical test of the relationship between wage risk and investment portfolios the outcome may be that of "anti-hedging." In other words, the endogeneity introduced by heterogeneous risk preferences makes such a test inconclusive, especially since one may expect that agents with high risk aversion naturally choose to work in low labor risk industries (i.e. the case where $\alpha < 1/2$). On the other hand, a test based on (2) where we study agents who switch jobs largely mitigates these issues of endogeneity. Our tests in this paper will therefore be based on (2).

We summarize the two hypotheses on the relationship between wage volatility and portfolio holdings, again emphasizing that the first hypothesis is vulnerable to heterogeneity in risk preferences:

H1: The higher a worker's wage volatility, the lower his/her exposure to the market through financial assets.

H2: A worker who switches to a sector with higher wage volatility decreases his/her exposure to the market through financial assets.

3 Description of the datasets

3.1 Overview

LINDA (Longitudinal INdividual DAta for Sweden) is an annual cross-sectional sample of around 300,000 individuals, or approximately 3% of the entire Swedish population.[2] Select individuals and their family members are tracked over the years, which allow us to examine household labor and investment decisions. The sampling procedure ensures that the panel is representative of the population as a whole, and each annual cohort is cross-sectionally

[2]The data set is a joint project between Uppsala University, The National Social Insurance Board ("Försäkringskassan") Statistics Sweden, and the Swedish Ministry of Finance.

representative. The values of all the variables in year t correspond to the values on December 31 of that year.

The data are primarily based on filed tax reports (available on an annual basis from 1968) and include various measures of income, government transfers and taxes in addition to individual characteristics such as gender, marital status, education, municipality of residence, and country of birth. From 1999 onwards, the market values of financial and real assets (e.g. stocks, bonds, mutual funds, and owner-occupied homes) are included in LINDA. The values for the financial assets are actual values and not estimates, because in Sweden banks and financial institutions are required by law to report the market values of individual holdings.[3] The values of real estate holdings are estimated from Statistics Sweden, which uses tax-assessed values and actual transaction prices in the surrounding areas.

To control for agent heterogeneity, we also use a Statistics Sweden demographic data set which provides information on the population density of the various Swedish regions. Since the region where individuals live is available in LINDA, we can merge these two datasets and use population density as a control in our regressions on portfolio holdings. This data set groups regions into six different categories, based on the population composition at the end of year 2002.

3.2 Excluded data

We have access to the LINDA dataset from 1993 to 2003. While we will use the entire data in a couple of instances, our primary period of focus is 1999-2002. There are three reasons for this. First, we need information on the portfolio holdings, which is only available from 1999. Second, the 2000-2002 period corresponds to the Bear market in Sweden. Since our measure of changes in portfolio holdings involves a three-year horizon and is sensitive to market returns, the 1999-2002 period provides a homogeneous environment for our tests. Finally, this period allows us to conduct robustness checks against Calvet, Campbell, and Sodini (2009), who have access to all individual stock holdings for the entire Swedish population during the same period. We have information on the market value of broad asset categories such as directly-held stocks and mutual funds and we show that our measure of changes in households' holdings of risky assets over time approximates the changes reported in Calvet,

[3]Note however that banks are not required to report bank accounts for which the interest rate earned is below 100 SEK a year.

Campbell, and Sodini (2009) quite well. Overall, there are 230,000 households that exist in the data for the entire 1999-2002 period and that do not undergo any major change in their civil status (see below).

We also run several additional filters to eliminate unusual data. First, there are many individuals who do not have a SNI code[4] but still generate positive disposable income.[5] This could occur if they receive welfare transfers from the government and are not employed. As we describe below, including these households can bias our measure of wage volatility. So we only retain the 137,000 households where individuals who report a positive disposable income and have a SNI code.

We also impose minimum financial requirements. Households whose financial wealth, net wealth or disposable income is extremely low or negative - less than SEK 3000, SEK 1000, and SEK 1000 respectively, as well as those with negative net holdings of risky assets, are eliminated.[6] This involves approximately 60,000 households.[7] We exclude households in which the largest income goes to someone younger than 18 years or older than 65 years, as well as observations in which information on the wage volatility is missing (about 14 SNI codes). Finally, we trim outliers.[8] We end up with a sample of 73,346 households. Unless specified otherwise, our tests are based on this sample.

4 Construction of variables

Portfolio decisions are typically made at the household level so we track households (h) over the years (t). Our approach requires that we keep track of the industries where household members work. We also need measures of portfolio holdings and wage volatility. While aggregating household financial holdings is straightforward, imputing wage volatility to a

[4]In LINDA, any working individual is assigned a five-digit SNI code for the industry in which he or she made most income during the year. These SNI-codes are equivalent to the NAICS/SIC codes in the USA.

[5]Disposable income is available at the individual-level because in Sweden individuals do not file their taxes jointly.

[6]Net wealth does not include the value of real assets such as yachts etc. unless the household is subject to wealth tax. It also does not include any retirement – tax-deductible – assets, human capital, and the values of private businesses and bank accounts for which less than SEK 100 is earned annually. All debt is included.

[7]For some of these households it has do do with the fact that in LINDA bank accounts for which the annual interest earned is under 100 SEK do not have to be reported. Since we impose a minimum financial wealth of 3000 SEK, we eliminate all the households who do not make the threshold because of their missing bank accounts. However, this concerns only a minority of these 60,000 households. The majority have a highly negative net worth.

[8]Specifically, we exclude households whose family income or house-to-wealth ratio ranges in the top 0.1% of the remaining sample in 1999 and 2002 and households for which the change in wage volatility between 1999 and 2002 is in the bottom or top 0.1% of the remaining sample.

household is less so.

4.1 Household characteristics and industries

In LINDA, two adult individuals belong to the same household in a given year if they are either married, legal partners, or if they live together and have children in common.[9] We study the households that existed for the entire 1999-2002 period and where the head couple (or the single head member) remained the same. To identify the head of the household, we select the two adults who generate the greatest levels of income in 2001. We sort these two individuals by income, and adopt the convention that Individual #1 (Ind1) generates the highest income and Individual #2 (Ind2) is the other adult.[10] We choose 2001 because it is the "switch" year for our sample of households that switched jobs (see below). In the case in which only one adult exists or generates income we treat Ind2 as missing.

We define a "switcher" as a household in which at least Ind1 changed industries at the three-digit SNI level between 2000 and 2001. In other words, our switcher worked in the old industry in 1999 and 2000, switched to a new industry in 2001, and stayed in the same new industry in 2002 (this also includes individuals who entered or quit the workforce in 2001). We choose 2000–2001 to take into account the fact that investors may not adjust their portfolios immediately before or after a job change.[11] We choose to work with SNI codes at the three-digit level because they provide sufficient granularity. In total, there are 223 3-digit codes. Finally, we refer to the households where individuals switch to industries with higher (lower) wage volatility as the "up-switchers" ("down-switchers"). For comparison, we also define a "non-switcher" as a household where neither Ind1 nor Ind2 changed industries between 1999 and 2002.

Summary statistics for the overall population as well as for the 3,815 switchers are displayed in Table 1 for 1999. The ex ante characteristics of switchers are broadly similar to the overall population. However, switchers are slightly more likely to live in one of Sweden's big three metropolitan areas, to have a college degree, and to have studied business.

[Table 1 about here.]

[9] Other cohabitants with no children in common are treated as separate households.

[10] If the two individuals have the same income, we adopt the convention that Individual #1 is the oldest individual.

[11] Calvet, Campbell, and Sodini (2009) find that households adjust their portfolios at different speeds depending on their characteristics.

4.2 Portfolios

4.2.1 The share of risky assets

For each household, we examine its non-retirement portfolio of directly-held stocks and risky mutual funds. We refer to this portfolio as the portfolio of risky assets. Unfortunately, retirement portfolios are not available in LINDA, but we note that in 1998, Sweden switched from a defined benefit plan ("Allmän Tjänste Pension," ATP) to a defined contribution plan (see Sunden, 2006). Since no changes were made retroactively, pension capital accumulated up to our time period was low-risk. Risky mutual funds include pure-equity funds as well as funds that invest only a positive fraction of their assets in stocks. Ideally we would like to separate these two types of mutual funds but unfortunately this information is not available after 1999. From the 1999 data, however, it seems that the vast majority of these funds are pure-equity (about 85%).

At the end of each year t, we define the "risky share," denoted $w_{h,t}$. This is the share of household h's holdings of risky assets over its financial wealth, which is the sum of cash (checking and savings accounts, money-market funds), bond-only mutual funds, stocks, and risky mutual funds, and capital insurance and other products.[12] So, $w_{12,03}$ refers to household #12's share of risky assets in its financial wealth at the end of the year 2003.

Summary statistics on portfolio shares of the overall population as well as those of switchers in 1999 appear in Panel A of Table 2. All the moments are equal-weighted by household. Although the switchers are broadly representative of the population, they are slightly more likely to invest in stocks than the other households.

[Table 2 about here.]

Compared to US investors, Swedes in our data hold more risky assets and are more likely to invest in mutual funds. To see this, consider statistics from the US 2001 Survey of Consumer Finances (SCF). In the first set of columns in Table 3 we report the (equal-weighted) moments of the 2001 portfolio shares for the overall Swedish population. In the

[12] Other products include lottery bonds, subscription rights, right offerings, and options. The highest share is invested in lottery bonds. Capital insurance products, which are another form of investment subjected to a special tax treatment, may also include risky assets. They exist in two forms: the traditional products which guarantee a minimum fixed return and are essentially risk-free, and the "unit link" savings, which are invested in mutual funds. Data on the exact composition of these products is very difficult to get but given the importance of the traditional products in the early 2000s and the special tax incentives for the elderly, it seems that these products were primarily risk-free during 1999-2002. For robustness, we created two additional measures: one where we exclude capital insurance and other products from financial wealth and another one where the share of risky assets includes half the value of capital insurance and other products. Our empirical results are robust to these two alternative specifications.

second set of columns (SCF I), we report the moments of the equivalent portfolio shares for the US population from the SCF. Note that to make the comparison relevant, these US statistics are not the ones that are usually reported from the SCF. In the standard definition of the risky share from the SCF, the amount of mixed mutual funds is halved and retirement assets are included. To see how these modifications affect our statistics from the SCF, we also report the standard statistics in the third set of columns (SCF II).

[Table 3 about here.]

Comparing the first two sets of columns of Table 3, it is evident that the participation rate in risky assets is much higher in Sweden than in the USA.[13] High Swedish stock-market participation rates have been documented elsewhere (Georgarakos and Pasini, 2009), and suggest that the selection bias in stock market participation is not as important as it is in the USA. Swedish households also tend to invest much more of their risky assets in mutual funds than American households. This may be due to the introduction in the late 1970's of highly accessible mutual funds (so-called "Allemansfonder"), which offered high tax-incentives. The tendency towards well–diversified investments is consistent with our empirical analysis because our measure of hedging is the share of financial assets invested in risky assets. As we cannot observe Swedish households' detailed portfolio of stock holdings, observing a high portfolio share in mutual funds indicates that these households are likely to be mostly invested in the overall stock market. As a result, if these households hedge their labor income risk, they are likely to do so by levering up or down their holdings of mutual funds.

4.2.2 Active portfolio rebalancing

In Panel B of Table 2, we also report statistics on portfolio shares in 2002. The equal-weighted average of the risky share dropped by about 9% (in levels) between 1999 and 2002. This drop is consistent with the significant decrease in the value of the Swedish stock market from 2000 to 2002. The total return on the Morningstar index for stock mutual funds[14] was .596 (i.e., the return rate was -41%). In comparison, the total return on the 12-month Swedish government bills (SSVX) during the same time period was 1.135.[15]

[13]If we relax the minimum financial wealth threshold, participation rates in stocks and mutual funds are still about 75% and 69% respectively, which is still considerably higher than in the USA.

[14]Available on www.morningstar.se. Morningstar mutual fund index for stock mutual funds are available, both for investments in Sweden and abroad.

[15]Source: Thomson Reuters.

To distinguish changes that simply come from changes in the returns on risky assets from changes that come from portfolio rebalancing decisions, we follow Calvet, Campbell, and Sodini (2009) and decompose the total change in the risky share $\Delta w_{h,02}$ of any household into a passive change, $\Delta^p w_{h,02}$, and an active change, $\Delta^a w_{h,02}$,

$$\Delta^p w_{h,02} = w_{h,99} \left(\frac{R_{02}}{w_{h,99} \cdot R_{02} + (1 - w_{h,99}) \cdot Rf_{02}} - 1 \right), \tag{6}$$

$$\Delta^a w_{h,02} = \Delta w_{h,02} - \Delta^p w_{h,02}, \tag{7}$$

where R_{02} and Rf_{02} correspond to the cumulative total returns on the risky and risk-free portfolios from 1999 to 2002. Since we do not observe the exact composition of these portfolios, we assume that $R_{02} = .596$ and $Rf_{02} = 1.135$ based on the indices described above. As we note below, our results approximate well those of Calvet, Campbell, and Sodini (2009) who have information on the households' exact portfolio holdings.

The passive change $\Delta^p w_{h,02}$ corresponds to the change in the risky share if household h did not trade any financial assets between 1999 and 2002. The active change $\Delta^a w_{h,02}$ is defined as the difference between the total change and the passive change. It represents portfolio rebalancing decisions. A positive (negative) active change means that household h bought (sold) risky assets between 1999 and 2002.

In Fig. 1, we show this decomposition of the total change into a passive change and an active change, as a function of initial share, $w_{h,99}$. To filter out noise and get a smooth approximation of total change as a function of $w_{h,99}$, household changes have been projected (regressed), using three cubic splines in the figure. Several insights follow from this decomposition. First, the average active change in the risky share across all households is close to zero, which is consistent with the general equilibrium restriction on portfolio rebalancing. Second, not all households experienced the same passive decrease in their risky share. The reason is purely mechanical. The passive change in the risky share is always negative because of the Bear market during these years and it follows a U-curve. By definition, if a household invested only in risk-free assets ($w_{h,99} = 0$) or in risky assets ($w_{h,99} = 1$) in 1999, changes in the value of the stock market do not affect the composition of the one-asset portfolio, so the passive change in the risky share is zero. For very unbalanced portfolios ($w_{h,99}$ close to 0 or 1), the passive change is small because, even with a highly negative stock return, the portfolio remains very unbalanced. For example, if a household owned \$99 of stocks and \$1 of bonds in 1999 ($w_{h,99} = .99$), a 40% decrease in the value of the stock market would decrease its risky share by only .6% (in levels). However, for balanced portfolios, the passive change in the risky share is much greater. If the same household owned \$50 of stocks and \$50 of bonds in 1999 ($w_{h,99} = .5$), then a 40% decrease in the value of the stock market would decrease its risky share by 12.5% (in levels). Finally, we note that our computation of active and passive changes based on the indices of risky and risk-free assets provide a close approximation to the results in Calvet, Campbell, and Sodini (2009). They have access to the exact stock holdings of the entire Swedish population and compute active and passive changes based on all individual stock returns between 1999 and 2002. The predicted values of the active and passive changes in Fig. 1 are very similar to those in Fig. III.A in Calvet, Campbell, and Sodini (2009).

[Figure 1 about here.]

4.3 Wage volatility

Computing a measure of annual wage volatility for switcher households is difficult because we only have data for at most two years after a 2001 switch. So we compute industry-averages of wage volatility (which we describe in detail below) and then attribute these values to all individuals based on the industry in which they worked that year, and aggregate by household each year.

Even though industry-averages of wage volatility are crude proxies for individual agents, if agents are unaware of how their particular careers will evolve, then industry averages may well reflect an agent's ex ante information about the true values. Therefore, these variables should be informative. Furthermore, for the switcher households, these measures should do a good job identifying the *change* in wage volatility or productivity that is associated with changing industries.

In the large LINDA sample from 1993 to 2003, we select all the individuals who work in the same industry for at least five consecutive years.[16,17] Then, we compute the volatility of the annual growth rate of each individual's real disposable income during these years,[18]

[16]Here, we restrict these individuals to have the same five-digit SNI code to make sure they do not switch jobs. We also exclude individuals who are receiving student aid and new job training (if they are unemployed), in order to exclude part-time jobs. Finally, we exclude individuals who are either self-employed or who are owners (or who are a close relative to an owner) of a closely held company, e.g. "3:12" firms, because these individuals are more likely to report their income in a non-conventional way. We choose a period of five consecutive years to maximize the sample size but results are robust to different specifications.

[17]Data on wages is also available from the Statistics Sweden output files, but we only have access to the aggregate wage per industry, which provides less information than the micro data from LINDA.

[18]We work with disposable income because it is more reliable than pre-taxed income. One weakness of

and average this volatility across all the households within the same three-digit sector. We only select industries for which we have more than 30 observations, and in doing so we calculate a wage volatility measure for 191 industries. This measure takes into account unemployment risk. If a worker is let go during a year, he will still be assigned his former SNI code as long as he was employed during part of the year.

Table 4 reports the top and bottom ten industries ranked by wage volatility. It is not surprising to find that industries such as "fund management," "legal representation activities," and "motion picture and video production" have high wage volatility whereas industries such as "recycling of metal waste and scrap" and "mining of iron and ores" have low wage volatility.

[Table 4 about here.]

Once we have computed these measures of the volatility and level of wages for each three-digit industry, we assign them to each individual-year given their SNI code. Finally, we aggregate these measures by household, weighting each individual by the amount of disposable income he or she earned during that year. In other words, if the household is composed of two working individuals, then the household labor income volatility measure is a weighted average of the individuals' volatility. In reality, the household labor volatility should also include the covariance between both individuals' labor income. However, given that we are working with industry-level estimates for their labor income, estimating this covariance precisely is difficult. In our regression we try to correct for this by creating a dummy to catch whether both individuals work in the same three-digit SNI code.

Another simple measure of wage volatility is whether an individual works in the public or the private sector. We have this information available in LINDA. It is well-known in Sweden that jobs in the public sector are less risky than in the private sector, in terms of unemployment risk and wage volatility. It is therefore not surprising to find in LINDA that the average wage volatility for employees in the public sector (12.9% per year) is lower than that in the private sector (14.9%). We use this measure as a robustness check. Note that while we keep the same sample of households, with this alternative measure we need to re-define which households are considered switchers and non-switchers. For this measure,

using disposable income is that we may be picking up tax effects that are not related to the individuals' labor income situation. On the other hand, it allows us to capture all the tax effects that are related to their labor income situation. Disposable income is available at the individual-level because in Sweden individuals do not file their taxes jointly.

the up-switchers (down-switchers) are households where at least Ind1 switches from the public sector (private) to the private one (public).[19] Non-switchers are households where both individuals don't switch between the public and the private sectors between 1999 and 2002.

4.4 Exogeneity of job switches

Our identification strategy focuses on the households where individuals changed industries between 1999 and 2002. For this strategy to work we need to make sure that these job changes are exogenous with respect to the households' investment decisions. There are two potential sources of endogeneity. First, it could be that switchers have different investment strategies than the rest of the households, because they have their own "type," and that they are therefore not representative. Second, a job switch may be part of a major life change, which also affects a household's attitudes toward savings, risk, and other determinants of its risky share.

While we do not observe the reason for job switches, we can compare the characteristics of the switchers and the other households before and after the change, as a first test to rule out endogeneity. The summary statistics from Tables 1 and 3 indicate that in 1999, the sample of switchers is fairly representative of the entire population. The equivalent summary statistics for 2002 are identical, which indicates that any major life change is likely to be idiosyncratic.[20]

In Table 5, we compare statistics on wage volatility for three categories of households: the up-switchers, the down-switchers, and the non-switchers. With the wage volatility measure, there are 1,739 down-switchers, 45,615 non-switchers, and 2,076 up-switchers. The average wage volatility in 1999 is highest for the down-switchers and lowest for the up-switchers. This result is to be expected given the finite number of industries. By definition, a worker who switches out of the safest industry must switch to a riskier industry and vice-versa. Finally, both up- and down- switchers are more likely than the non-switchers to be in the private sector in 1999. This is not surprising given the lower job turnover in the

[19] More specifically, to focus purely on the switch between the public and private sectors, we restrict the switcher individuals to work at all times between 1999 and 2002. In other words, they cannot enter or quit the workforce during that time period. Switchers also do not have to change three-digit SNI codes as long as they switch between the public and private sectors. Finally, because we have a smaller sample of switcher households, we do not restrict switchers to switch between the public and private sectors only between 2000 and 2001. They can switch anytime between 1999 and 2002 as long as they only switch once.

[20] Also, recall that to reduce the likelihood of these major life changes, we excluded households where the composition of the (Ind1, Ind2) couple changed between 1999 and 2002.

public sector. Thus, these systematic differences between switchers and non-switchers are most likely purely mechanical.

[Table 5 about here.]

In terms of industries, we study the distribution of industries in 1999 for the switchers and check whether they worked in different types of industries compared with non switchers. In Fig. 2 we plot histograms of the 3-digit SNI codes in 1999 for switchers and non switchers. The histograms are remarkably similar. The only main difference is the lower fraction of switchers households that have SNI code in the 850s, which correspond to industries in the public sector, such as healthcare or education. This result is consistent with the high share of switchers in the private sector from Table 5. Thus, Fig. 2 provides no evidence for systematic differences between switchers and non switchers.

[Figure 2 about here.]

We also examine whether individuals who have already switched jobs are more likely to switch jobs again in the future. Once again, we use the entire data from 1993 to 2003 at the individual-level and compare individuals who have already switched to all the other individuals. There are differences, but they are small. If we consider the individuals who have existed in LINDA during the entire sample (the vast majority of individuals), the switching frequency for our switchers is 24.5%, which is slightly higher than for the other households (22.6%). Again, this has to do with the fact that switchers are more likely to come from industries with higher turnover. If we exclude the individuals who worked in the public sector, there is less of a difference between the switching frequency of switchers (22.6%) and the other individuals (21.3%).[21]

Finally, we conduct two other types of robustness checks. First, we look at the transition matrix of SNI codes for switchers between 1999 and 2002 and exclude the cases in which an unusually high number of individuals switch from a particular SNI code in 2000 to another particular SNI code in 2001. The empirical results remain the same. Then, in the next section we compare the portfolio rebalancing decisions of the up-switchers to those of down-switchers and non-switchers. As we shall see, the active change in the risky share between 1999 and 2002 for the non-switchers is lower than for the down-switchers, but

[21]Both switching frequencies are lower in this case because we excluded switches between the public and the private sector.

higher than for the up-switchers. This result is consistent with switchers being of the same "type" and responding to shocks to their employment.

Altogether, we find little evidence of job switching being endogenous, with respect to individuals' investment decisions. In Section 5.3 we further discuss potential endogeneity issues in the light of our results.

5 Empirical tests and results

5.1 Cross-section analysis of H1

What is the relation between a household's wage volatility and its financial portfolio? We begin with a cross-sectional analysis and test hypothesis H1.

H1: The higher a worker's wage volatility, the lower his exposure to the market through financial assets.

If agents only differ in the industries in which they work, we would expect a cross-sectional comparison of agents' wage volatility and investments in risky assets to have a negative relation.

In our data, we do find some evidence of hedging but the results go the wrong way in some cases, in line with the results in Massa and Simonov (2006). Thus, our results are consistent with the mixed findings from the previous literature. It could be that investors do not hedge labor income risk, but it could also be that there are cross-sectional "taste" differences between agents that drive wage volatility and portfolio decisions jointly, so that individual agents hedge but it does not show cross-sectionally. Our tests that control for such fixed effects in the next section support the latter view.

As in Vissing-Jorgensen (2002) and Massa and Simonov (2006), we assume that the investment decision takes place in two steps: first, the investor decides whether to enter the stock market, and then he selects his portfolio holdings. To account for the first stage participation decision, we use a two-step estimation procedure following Heckman (1979). We model the decision to enter the stock market by estimating $\mathbf{1}\{w_{h,02} > 0\}$, the observed probability of participation in the portfolio of risky assets in 2002, with the probit regression,

$$\mathbf{1}\{w_{h,02} > 0\} = \alpha_1 + \beta_1 \cdot LABOR_{h,02} + {\gamma_1}' \cdot X_{h,02} + \epsilon_{1,h,02}, \tag{8}$$

where $X_{h,t}$ is a vector of explanatory variables for household h in year t, and $LABOR_{h,t}$ includes wage volatility along with an interaction variable for households where both individuals work in the same industry. We report results for year 2002 because it allows us to include 1999 values for some potentially endogenous regressors such as wealth and income. If we choose $t = 2000$ or $t = 2001$ the results are similar.

In this and the subsequent regressions, the choice of control variables in the vector $X_{h,02}$ is critical because of the potential endogeneity issues. We control for each household's composition, where it is located, the sources and composition of household wealth and financial sophistication.

To control for differences in household composition, we include the age of the head of the household, as well as age squared, dummies that indicate the civil status of the head (married or partnered, single parent, or single household), the number of children who are minors in the household, a dummy for whether at least one of the adults was born in a Nordic country, and dummies for the number of individuals who used to be part of the household but who have emigrated.

Location may affect portfolio decisions and so we use dummies for the population density of the area in which the household lives (high, medium, low). A high density region indicates one of the three metropolitan areas in Sweden: the Stockholm region, the Gothenbourg region, or the Malmo/Lund/Trelleborg regions. A medium density region is one in which the household lives in an other (less) urban area, which consists of municipalities with (i) more than 27,000 inhabitants, (ii) less than 90,000 inhabitants within 30 km (19 miles) of the municipality center, and (iii) more than 300,000 inhabitants within 100 km (62 miles) of the municipality center. Finally, a low density region represents all the other regions of Sweden.

Measures of labor income and employment include the logarithm of family disposable income, a dummy on whether at least one of the adults is receiving unemployment insurance, a dummy on whether at least one of the adults is receiving a retirement pension, and the ratio of debts to family income. In addition to our measures of labor income risk $LABOR_{h,t}$, we add two dummies on whether both adults work in the private sector or the public sector. Measures of real estate include a dummy on whether the household owns real estate and the ratio of house value to net worth.

Measures of education include dummy variables on whether at least one of the adults has a college degree and studied business after high school. We also add a dummy variable on whether at least one of the adults is receiving student aid. Finally, in terms of wealth, we include the logarithm of net worth. To avoid any endogeneity issues, both net worth and the ratio of house value to net worth are from year 1999. We avoid controlling for portfolio shares in previous years, because portfolio shares are extremely predictable over time, which means that including them would capture most of the information from the other variables, including $LABOR_{h,02}$.

Then, in the second stage, we regress the portfolio shares $w_{h,02}$ on $LABOR_{h,02}$, our proxy for wage volatility. Our main focus is on the portfolio share of risky assets (the risky share) but we also repeat the exercise for the portfolio shares of stocks and mutual funds. We also include the vector $X_{h,02}$ of control variables and Heckman's lambda variable ($\lambda_{h,02}$), which controls for possible selection at the first stage. The equation is as follows,

$$w_{h,02} = \alpha_2 + \beta_2 \cdot LABOR_{h,02} + {\gamma_2}' \cdot X_{h,02} + \theta_2 \cdot \lambda_{h,02} + \epsilon_{2,h,02}, \tag{9}$$

where h only includes the households that participate in the stock market in 2002. Households hedge their labor income risk if $\beta_2 < 0$.

The results of the second stage regressions are reported in Table 6. We run three specifications of Eq. (9). In the first column, we take a look at what the results look like if we do not control for selectivity. In the second column, we include $\lambda_{h,02}$ but only study the effect of wage volatility. In the third column, we include both $\lambda_{h,02}$ and the public-private sector dummies to see how much of the industry-wide differences in wage volatility comes from the differences between the private and the public sectors.

[Table 6 about here.]

Most of the control variables are strong predictors of the risky share. This is not surprising, and it is consistent with the literature. The coefficient on $\lambda_{h,02}$ also confirms the selectivity among market participants, despite the high overall participation rate in risky assets. We report the t-stats for the bootstrapped standard errors of the estimates and find that θ_2 is significantly different from zero. When we control for selectivity, the effect of wage volatility becomes more significant.

The results from Table 6 are consistent with H1. An increase in wage volatility does lead to a decrease in the risky share that is significant at the 1% level. This decrease is also fairly significant from an economic perspective. From the second column, a 5% increase in wage volatility (in levels) leads to a 1% decrease in share of risky assets (in levels). The magnitude of this effect is lower in the third column but that is because some of it is being picked up by the public-private sector dummies. A household where both individuals work in the public sector has a risky share almost 2% higher than a household where both individuals work in the private sector. These results are in line with those of Guiso, Jappelli, and Terlizzese (1996), Gakidis (1998), and Vissing-Jorgensen (2002).

However, once we decompose the risky share into the share of directly held stocks and the share of mutual funds, we get mixed results. In Table 7 we repeat the estimations of column 3 in Table 6 but this time with the shares of stocks and mutual funds as dependent variables.[22] The key result is the opposite effect that $LABOR_{h,02}$ has on the shares of stocks and mutual funds. An increase in wage volatility leads to a significant *increase* in the share of stocks and a significant *decrease* in the share of mutual funds.

[Table 7 about here.]

The positive effect of $LABOR_{h,02}$ on the shares of direct stock-holdings reinforces the idea that our cross-sectional analysis is prone to an omitted-variable bias. This is consistent with what is found in Massa and Simonov (2006), who look at the levels of individual stock holdings and find that households' investments in stocks also come from factors other than hedging, such as a preference toward stocks they are more familiar with, for information reasons. Indeed, they argue that less-informed agents choose to invest more in stocks closely related to their labor income because they are more familiar with these stocks, via either location or professional proximity.

5.2 Analysis of job switches, H2

The main weakness of the cross-sectional analysis above is that one can conjecture other sources of heterogeneity that are correlated with labor income and affect portfolio selection. For example, it may be that the less risk averse agents choose to work in riskier industries and invest more in the stock market. Or, as Massa and Simonov (2006) point out, workers may want to invest more in the industry they work in because they are more familiar with this industry. Since our cross-section analysis cannot control for these unobserved "taste" differences, we turn to our main estimation strategy and look instead at changes in the portfolio shares of households over time, with a particular focus on those households where individuals change industries. We test hypothesis H2.

[22] While a more formal analysis should involve estimating a system of simultaneous equations, we find that this heuristic analysis already provides interesting information.

H2: A worker who switches to a sector with higher wage volatility decreases his exposure to the market through financial assets.

Our focus on changes in portfolio holdings over time is similar to adding fixed effects to Eq. (9) in that it allows us to control for any unobserved heterogeneity that is constant over time and correlated with the independent variables. It is important to point out, however, that a standard panel estimation of Eq. (9) with fixed-effects is hardly applicable in our setting. As mentioned earlier, since our time-series is short and not all households adjust their financial portfolios frequently, it is difficult to measure changes in the levels of wage volatility of households over time as well as their effect on the households' risky share. Consequently, a standard panel estimation would have very little power. We overcome this issue by modifying the standard panel model in three major ways.

The first unique feature is that we focus specifically on the households that switched industries between 2000 and 2001 and their portfolio re-balancing decisions between 1999 and 2002. This feature allows us to identify changes in labor income risk that are exogenous with respect to household investment decisions. It also provides us with a pool of observations where the variation in our measures of changes in wage volatility over time is relatively high. Finally, the three-year horizon provides a relatively large window of time to capture portfolio re-balancing decisions.

The second unique feature has to do with the way we control for past portfolio choices. Instead of adding lagged values of the risky share to the right-hand side of Eq. (9), we study the variation in the active change in the risky share $\Delta^a w_{h,02}$ that is *orthogonal* to the initial level of the risky share $w_{h,99}$. This allows us to fully control for past portfolio choices and compare households that had the same initial risky share in 1999. Among these households, do the ones that switch to riskier industries between 1999 and 2002 reduce their risky share, relative to those that do not switch industries and to those that switch to safer industries?

Finally, the third unique feature is that even though our focus is on the switchers, we also use the group of non-switchers as a benchmark in the first stage where we back out the variation in $\Delta^a w_{h,02}$ that is orthogonal to $w_{h,99}$. Instead of running a first-stage regression of $\Delta^a w_{h,02}$ on $w_{h,99}$ over the pool of switchers and then using the residuals as our dependent variable for our second-stage regression on changes in wage volatility, we compare the switchers to the non-switchers in the first stage. That is, we begin with the pool of non-switchers and model their active change in the risky share, $\Delta^a w_{h,02}$, on their initial risky share, $w_{h,99}$. We keep the predicted values from this estimation. We then turn to the switchers and compute the difference between their active change in the risky share, $\Delta^a w_{h,02}$, and the *predicted value* of the active change for the non-switchers given the same level of $w_{h,99}$. This difference term becomes our dependent variable, which we can then regress on changes in wage volatility for the switchers between 1999 and 2002. Fig. 3 provides a visual representation of this construction, which allows us to test whether households that switch to sectors with the same level of wage volatility are equivalent (observationally) to the non-switchers.

[Figure 3 about here.]

This approach complements the one taken in Massa and Simonov (2006), who also use panel data from LINDA but focus more on the cross-sectional differences between households' labor income risk and their portfolio holdings. While their approach provides the opportunity to estimate any "taste" variable that does not vary much over time (if at all) and that can be measured like their indices of familiarity, it comes at the cost of not being able to include fixed effects and control for other sources of unobserved heterogeneity. In our approach, we only look at *changes* in household characteristics and portfolio holdings between 1999 and 2002. In doing so we are not able to estimate the effects of any of these "taste" variables, but we can fully control for all of them, whether they are observed or unobserved. This allows us to focus purely on the effects of the time variation in the wage volatility of households. We will see below that we find strong support for hedging along the time dimension. Their study and ours thus together suggest that both "tastes" (broadly defined) and hedging are present in the data.

From Fig. 1, it is clear that a household's active change in risky share depends on its initial risky share.[23] We control for this dependence on the initial risky share, using the same approach as in Fig. 1, i.e. by regressing the changes on three cubic splines. In the first stage we carry out this estimation for the population of non-switchers. The fitted values are depicted in the two left quadrants of Fig. 4. In the top left quadrant, we use the baseline sample of non-switchers that we defined in Section 4.1, which is tailored to the main wage volatility measure. In the bottom left quadrant, we use a slightly modified sample of non-switchers that is tailored to our second measure of wage volatility (whether

[23] Such a dependence even arises for purely mechanical reasons. For example, the active change can only be positive if the initial share is zero, whereas it can only be negative if the initial share is one.

individuals work in the public or the private sector, see Section 4.3). The results for both samples are very similar.

[Figure 4 about here.]

As a first test of whether switching jobs affects portfolio holdings, we also generate splines for the populations of households that switch to industries with higher wage volatility (the up-switchers) and those that switch to industries with lower wage volatility (the down-switchers) and we plot the *additional* $\Delta^a w_{h,02}$ (i.e. relative to the non-switchers) in the top right quadrant of Fig. 4.[24] In the bottom right quadrant, we generate the same splines for households that switch between the private and public sectors. The top line (red) in each quadrant is the locus of predicted values for the down-switchers, and the bottom line (blue) is the equivalent line for the up-switchers.

The results from Fig. 4 provide strong evidence in favor of hedging. The first key result is that the active change in the risky share $\Delta^a w_{h,02}$ is *always* greater for the down-switchers than for the up-switchers, which is consistent with the predictions. The difference between the two groups is economically important as well. From the top left quadrant, we see that switchers that experience an increase in wage volatility tend to decrease their risky share by 1.57% relative to those that experience a decrease in wage volatility. From the bottom left quadrant, we see that households that switch to the private sector tend to decrease their risky share by 2.6% relative to those that switch to the public sector.[25]

These results are very robust to the types of basis functions used. The advantage of using splines is that they are local functions and therefore capture local variations well. We also used a regression with (global) polynomials as basis functions and the results of the empirical analysis are again remarkably similar. In Table 10, we show the results with three other basis functions: a simple linear regression, a quadratic regression, and another cubic spline with 6 degrees of freedom this time. In Panel A., we report the average predicted difference in the active change of the risky share between down-switchers and up-switchers. The estimates for each method are almost identical to the ones we just reported above. In Panel B., we report the estimates of our quantitative analysis that we introduce next and we find once again that the results are not sensitive to the way we model the basis function.

[24] Regarding the top two quadrants, we only select for clarity the switchers whose wage volatility changes by more than 1% (in levels). This involves about two-thirds of the switchers.

[25] These averages are taken from the predicted values and are weighted equally by $w_{h,99}$.

The second result from Fig. 4 is that the average differences between the active changes of the risky share $\Delta^a w_{h,02}$ of switchers and non-switchers are *negative* for the up-switchers and *positive* for the down-switchers. In other words, the up-switchers tend to decrease their risky share relative to the non-switchers, and the down-switchers tend to increase their risky share relative to the non-switchers. This result, although not as strong as the previous result, is still quite significant. We verify the result statistically, using a simple but very robust non-parametric sign test. The results are reported in Table 8.[26] The hypotheses that the fitted curves for the up- and down-switchers are respectively above and below the fitted curve for the non-switchers are both strongly rejected at the 1% level. It is thus clear that changes in labor income risk affect the portfolio decisions of households, in line with our theoretical predictions.

[Table 8 about here.]

We next analyze the magnitude of these effects, to understand how big the hedging demand for labor income risk is. Let $\widehat{\Delta^a w_{s,02}}$ be the difference between the *observed* active change in the risky share $\Delta^a w_{s,02}$ of switcher household $h = s$ and the *predicted* active change in the risky share of non-switcher household $h = ns$ given the same initial share $w_{s,99}$. In Fig. 3, $\widehat{\Delta^a w_{s,02}}$ corresponds to the double-arrow vertical vector. We test the effect of a change in labor income risk on $\widehat{\Delta^a w_{s,02}}$ by estimating the following equation,

$$\widehat{\Delta^a w_{s,02}} = \alpha_3 + \beta_3 \cdot \Delta LABOR_{s,02} + \gamma_3 \cdot (\Delta Z_{s,02} - \overline{\Delta Z_{s,02}}) + \epsilon_{3,s,02}, \tag{10}$$

where s represents the switcher population, $\Delta LABOR_{s,02}$ represents the change in our measure of labor income risk between 1999 and 2002, and $(\Delta Z_{s,02} - \overline{\Delta Z_{s,02}})$ is a set of demeaned independent regressors. Note that we restrict the switchers to participate in the stock market in 1999. We do not include Heckman's lambda variable ($\lambda_{s,99}$), which controls for possible selection in 1999. Since our measure of $\widehat{\Delta^a w_{s,02}}$ is orthogonal to levels of the risky share in 1999, the selection bias is no longer an issue.[27]

We test the parameters α_3 and β_3. The first test is whether $\beta_3 < 0$. The theory predicts that switchers who experience an increase in labor income risk should decrease their risky share relative to the other switchers. The second test is whether $\alpha_3 = 0$. Since we demeaned

[26] To be consistent with Fig. 4, we only retain the switchers whose wage volatility changes by more than 1% (in levels). The results of the sign tests with the entire population of switchers are similar.

[27] We tried a version where we include $\lambda_{s,99}$. It comes up as insignificant and does not affect the other results.

the ΔZ variables, α_3 corresponds to the value of $\Delta^a \widehat{w_{s,02}}$ if $\Delta LABOR_{s,02} = 0$. The theory predicts that switchers who do not experience any change in their level of labor income risk should not invest differently than non-switchers. Their active change in the risky share should, on average, equal the predicted value of the active change of the non-switchers.

In addition to employment, other household characteristics may have changed during 1999-2002. $\Delta Z_{h,02}$ is defined as the vector of these changes. These variables include a dummy on whether the household moved from a low density area to a high density area, a dummy on whether at least one member of the household has emigrated, and a variable that captures the change in the number of children. We also look at the change in the logarithm of family disposable income, the change in the Debt-to-Income ratio and we include dummies on whether at least one of the individuals found a job, lost a job, or retired from the job market during the time period. In terms of real estate, we include two dummies on whether households started or stopped owning real estate as well as a variable that captures the change in the ratio of house value to net worth. In terms of education, we include a dummy on whether at least one of the individuals has graduated.[28] In terms of changes in wealth, one has to be careful because of the potential endogeneity issues. We try two specifications: one with the change in net wealth between 1999 and 2002, and one without it. In both cases, all the other coefficients are approximately the same, which confirms that we can include net worth.

The results of our estimation are reported in Table 9. We run six specifications of Eq. (10). In the first column, we include all the variables in the vector $\Delta Z_{h,02}$. Unlike our regressions on the levels, only a select few of the control variables predict our measure of change in the risky share. So, to improve the precision of the estimation, we only retain in the second column the variables whose coefficient was statistically significant in the first column. In the third column, we exclude the change in net worth, to check whether it affects the other coefficients. In the fourth column, we interact $\Delta LABOR_{s,02}$ with dummies on whether the switchers are up-switchers or down-switchers. This is to check whether the effect of $\Delta LABOR_{s,02}$ is symmetric across both types of switchers. In the fifth column, we test whether the effect of the absolute value of $\Delta LABOR_{s,02}$ is quadratic rather than linear. Finally, in the sixth column, we focus on our sample of switchers with respect to the public-private measure. $\Delta LABOR_{s,02}$ becomes a dummy variable, so we include dummies for the up- and down- switchers and test that these dummies are negative and positive

[28]We define graduation as a stop in the individual's student aid.

respectively.[29]

[Table 9 about here.]

The results provide further evidence in favor of hedging, i.e., they support hypothesis H2. For the linear model (columns 1 to 3), an increase in wage volatility by 3% (in levels) leads to an active decrease in the share of risky assets by 1% (in levels). This means that a household going from the industry with lowest wage volatility to the industry with highest wage volatility would decrease its risky share by almost 10%. The one-tailed test that $\beta_3 < 0$ is statistically significant at the 1% level. The magnitude of this hedging effect is even stronger in the quadratic model in column 5. Because of the quadratic nature of the model, the effect on portfolio shares is quite small for small changes in wage volatility. But for large changes in wage volatility, the effect on the risky share increases considerably. For example, an increase in wage volatility of 20% leads to a decrease in the share of risky assets of almost 20%. The same household going from the industry with lowest wage volatility to the industry with highest wage volatility would decrease its risky share by 35%. Finally, we can check in column 4 that this hedging effect is fairly symmetric across the up- and down-switchers. Neither β_3 coefficient is as statistically significant as in the first three columns, but both coefficients are about the same size economically (although slightly greater for the down-switchers).

As for the second test on the value of α_3, we focus on the first five columns of Table 9.[30] Across all the estimations, we cannot reject the null hypothesis that $\alpha_3 = 0$. This is again consistent with the theory, i.e., switchers who do not experience any change in their level of labor income risk should have the same active change in the risky share as non-switchers. While this test is not as statistically powerful as the test on β_3, we see that the estimated value of α_3 is minimal from an economic perspective. The difference between the active changes in the risky share of switchers with no change in wage volatility and non-switchers is about 0.5%.

In terms of the estimation with the public-private sector dummies in column 6, the effects of the dummies are strong as well and consistent with the theory. Households where the high-income individual switches to the private sector decrease their risky share by 1.6% relative to non-switcher households. Households where the high-income individual

[29] This regression has to be run without an intercept.

[30] Recall that the estimation with the public-private sector dummies in column 6 is run without an intercept.

switches to the public sector increase their risky share by .08% relative to the non-switcher households.[31] The one-tailed tests that the dummies for the up- and down-switchers are negative and positive respectively are statistically significant at the 1% and 10% level, respectively.

An alternative potential explanation for the fact that the coefficients of the changes in wage volatility are negative is if wage volatility is correlated with wealth. A change in wage volatility could be associated with a change in wealth, which could be the real driving force behind portfolio changes. As mentioned earlier, we control for this potential factor by looking at the change in net worth between 1999 and 2002. The addition of this variable acts not only as a control but it also indicates the effect of an increase in wealth on the risky share. If we compare columns 2 and 3, we find that the addition of net worth does not influence the effects of wage volatility and labor productivity. Moreover, we find that an increase in net worth leads to a significant decrease in the risky share.[32] This result suggests that this other potential explanation goes the other way, hence strengthening our results.

It could also be the case that this hedging effect comes from a change in the switchers' housing situation, if this change is correlated with their change in labor income risk. We control for these housing effects by including the change in the households' ratio of housing wealth to net worth between 1999 and 2002 as well as dummies on whether they bought or sold their home and moved from a high density region to a low density region. While most of these variables have a significant effect on the households' change in the risky share, they do not affect the negative coefficients of the changes in wage volatility. These coefficients remain the same if we exclude all the housing variables. We conclude that the labor income hedging effect we observe does not come from housing.

[Table 10 about here.]

As we noted earlier, we repeat our estimation of Eq. 10 with different basis functions for the predicted value of the active change in the risky share for the non-switchers. The

[31] Note that the difference of 2.4% between the risky shares of both types of switchers is equivalent to the difference between the two splines in the bottom right quadrant of Fig. 4.

[32] Note that we also control for changes in family income. Supposedly, households that switch to an industry where they obtain a wage increase have become wealthier. If we estimate Eq. (10) excluding labor income, we also find that the effects of wage volatility and labor productivity remain the same. And the coefficient on the labor income in all the columns is also negative.

results, which are reported in Panel B. of Table 10, are very similar to the ones in Table 9,[33] which suggest that our results are not biased by our first-stage estimation.

Finally, it is important to point out that once we decompose the risky share into the share of directly-held stocks and the share of mutual funds, we no longer obtain the mixed results on hedging that our cross-sectional analysis was subject to. In Table 11 we repeat the estimation of column 2 in Table 9 but this time with the stocks and the mutual funds as the dependent variables.[34] For example, for the stocks, our dependent variable becomes the difference in the observed active change of the share of directly-held stocks between switchers and predicted value of the active change for the comparable non-switchers.

[Table 11 about here.]

There are two main observations from Table 11. First, if we compare it to Table 7, we find that while the negative effect of $\Delta LABOR_{s,02}$ on the share of mutual funds remains, the positive effect of $\Delta LABOR_{s,02}$ on the share of stocks is no longer significant, both statistically and economically. In other words, the "anti-hedging" effect on directly-held stocks we found in the cross-section is no longer present in the time-series, which suggests that it really captures *time-invariant* differences in households' "taste" preferences. This result is consistent once again with the findings in Massa and Simonov (2006). The second observation from Table 11 is that the significantly negative effect of $\Delta LABOR_{s,02}$ on the shares of mutual funds is almost identical in size to the one on risky assets (from Table 9). This result confirms our intuition from Section 4.2.1 that households are most likely to hedge their labor income risk by levering up or down their holdings of mutual funds. Altogether, these two related observations provide additional support for hypothesis H2.

5.3 Controlling for endogeneity

In Section 4.4 we found little evidence of job switching being endogenous with respect to individuals' investment decisions. However, it could still be that the choice of switching jobs during the recession of the early 2000s is driven by the same risk preferences that govern the portfolio allocation decision. For example, individuals who switched from high volatility to low volatility industries during the bear market of 1999-2002 may have been more risk

[33] We only report the results for the estimation of column 2 in Table 9 but the results for different specifications of $\Delta LABOR_{s,02} = 0$ are similar.

[34] Once again, we only report the results for the estimation of column 2 in Table 9 but the results for different specifications of $\Delta LABOR_{s,02} = 0$ are similar.

averse than those who did not switch, and vice versa. This raises the question of whether our analysis of job switchers in Section 5.2 is prone to the same omitted variable bias as our cross-sectional analysis in Section 5.1.

As we noted in Sections 2 and 5.2, our tests are designed to avoid this bias. By focusing on the portfolio rebalancing decisions of switchers and by conditioning on their portfolio holdings before their switch, we control for any source of heterogeneity that is reflected in their initial portfolio holdings. Without further assumptions, any difference in risk aversion between switchers and non-switchers would also lead to *different* portfolio holdings before the switch.

Here is an example of an effect that is controlled for in our test. A reason for rebalancing could come from a change in investors' perceptions of their investment opportunities. The analysis of Merton (1969) suggests that investors should invest a fraction $\frac{\mu-r}{\gamma_i \sigma^2}$ of their wealth in the risky asset, where μ and σ^2 are the expected return and the variance of the asset respectively, and γ_i the relative risk aversion of CRRA agent i.[35] If households revise down their views on μ during the bear market years, they decrease the share of wealth invested in risky assets and the extent to which they do so depends on their level of risk aversion. If the highly risk averse agents are also the ones who switch into the lower risk jobs, this introduces a link between job switching and rebalancing. However, since there is a direct link between risk-aversion and the initial portfolio holdings in this case, this effect would be controlled for in our test.

We argue that most plausible sources of endogeneity are reflected in the agents' initial portfolio holdings. However, there may be other sources that lead to a link between job switching and portfolio rebalancing that is unrelated to hedging. For example, if households only rebalance infrequently (due to transaction costs), and there is a systematic relationship between job switching and risk-aversion so that, e.g., households with high risk-aversion tend to down-switch in down-turns, this introduces a source of endogeneity that is not controlled for in our tests.[36] Specifically, with infrequent rebalancing, two households may in 1999 have the same portfolio share in risky assets but have different levels of risk aversion: a household with low risk-aversion may have just rebalanced its risky share downward after the market run-up (along the lines of Merton (1969)), whereas a household with high risk-aversion may

[35] Given that there are no wealth effects in a CARA-normal framework, the analysis from our model in Section 2 is not as clean and the point is more easily with power utility and log-normal returns as in Merton (1969).

[36] We thank the referee for suggesting this example.

have a higher share in risky assets than what is optimal in the long-term because it has not yet rebalanced. In the market downturn between 1999-2002, the household with high risk-aversion becomes a down-switcher, and then both households rebalance their portfolios. Systematic differences in rebalancing may then occur, not because of hedging motives, but rather because of differences in risk-aversion, which leads to both heterogeneous rebalancing and switching decisions.[37] We stress that this effect is driven by a friction that leads to similar initial portfolio holdings for households with different levels of risk aversion, together with a correlation between job switching and risk aversion.

To further verify that our results are not driven by the type of effects discussed above, we first note that wage volatility has the same effect on portfolio holdings of risky assets in both the cross-section and the time-series (i.e. with and without the fixed effects). This provides some further evidence that hedging is indeed present. By definition, any source of endogeneity that is not reflected in the agents' initial portfolio holdings does not contaminate our first cross-sectional estimation. The results for the 1999 cross-section are nearly identical to the ones for 2002 that we reported in Table 6. Since we observe that wage volatility also has a significantly negative effect on the risky share in the initial cross-section, it is unlikely that an omitted variable would drive this effect of wage volatility both with and without the adjustment for the fixed effects.

Furthermore, we can verify that previous behavior of switchers and non-switchers in the years leading up to our test do not affect our results. We do not have information on the households' portfolio holdings prior to 1999 but we observe whether they also switched industries between 1996 and 1998, a period during which the market conditions were quite different from the recession of the early 2000s, notably with a large market run-up. Presumably, if the decision to switch to a riskier or safer industry during a recession depends on the type of an individual, then her type should also affect her decision to switch industries in a good economy. We can measure this effect by computing for each household the change in their wage volatility from 1996 to 1998 using the same method as for their 1999-2002 volatility change.

Our analysis is twofold. First, we study whether we can infer anything from the job switching behavior of our households in the years 1996-1998 (after having controlled for their portfolio holdings in 1999). Then, we test whether their change in wage volatility

[37] It is straightforward to show, using the results in Merton (1969), that the effects can go in both directions, depending on whether the initial risky share is high or low.

during these early years has any effect on their portfolio rebalancing decisions between 1999 and 2002. We find that while these 1996-98 changes in wage volatility do seem to pick up some additional unobserved heterogeneity in preferences, controlling for them does not affect our main results.

[Table 12 about here.]

When comparing the job switching behavior of our households between the 1996-98 and 1999-2002 periods, we do find some evidence that indeed there may be some unobserved heterogeneity behind the job switching decision that we are not fully capturing by conditioning on the households' portfolio holdings in 1999. In Table 12 we report the likelihood of "up" and "down" switches between 1996 and 1998 for our three types of households (i.e. our up-, down-, and non-switchers between 1999 and 2002), which we also split into three terciles to control for their portfolio share of risky assets held in 1999. Across all three terciles, the households that switched to safer industries between 1999 and 2002 (i.e. the down-switchers) were the most likely to switch to the riskier industries in the previous "boom" period. Likewise, the households that switched to the riskier industries between 1999 and 2002 were the most likely to switch to the safer industries in the previous period. This evidence suggests that if this switching behavior depends on the households' type, then observing the households' change in wage volatility between 1996 and 1998 will tell us something about their type that is unrelated to hedging during the 1999-2002 period.

[Table 13 about here.]

We can now test whether adding the change in the households' wage volatility between 1996 and 1998 as another control variable in Eq. 10 will affect our main results. In Table 13 we report the results of two additional regressions. In the first estimation, we simply add this new variable as another control in Eq. 10. In the second and more conservative estimation, we begin by regressing the same dependent variable $\Delta\widehat{^{a}w_{s,02}}$ on this variable in order to pick up anything that has to do with it. Then, we take the residuals from this regression and regress them on the change in wage volatility between 1999 and 2002 and all the other control variables.

In both estimations, the effect of the change in wage volatility between 1996 and 1998 is not statistically significant. Moreover, the effects of all the other variables including the change in wage volatility between 1999 and 2002 are nearly identical to those in Table 9. We conclude from these robustness checks that any potential endogeneity that is not reflected in the households' initial portfolio shares in 1999 is unlikely to bias our results. In other words, if risk preferences influence the households' decisions to switch jobs as well as to rebalance, beyond what is captured by conditioning on the initial risky share, then a household's change in wage volatility between 1996 and 1998 should affect future rebalancing decisions beyond what is captured by later job switches. Since we do not find this, we conclude that our documented rebalancing indeed seems to be driven by hedging motives.

6 Conclusion

The literature on labor income risk and the levels of portfolio holdings has led to mixed results. On the one hand, there is evidence that agents hedge human capital risk (Guiso, Jappelli, and Terlizzese, 1996; Vissing-Jorgensen, 2002). On the other hand, at the individual stock holdings level, households tend to own stocks that are closely related to their labor income (Massa and Simonov, 2006).

In this paper we take advantage of a unique Swedish panel dataset and provide a new approach to this issue by focusing on the households that switched industries between 1999 and 2002. We study the effect of their industry change — in particular the effect of changes in their wage volatility — on their portfolio holdings of risky assets. We find that households do hedge their labor income risk. This effect is economically significant. A household that moves from the lowest to the highest wage volatility industry decreases its exposure to risky assets by risky by 35%.

Our results are therefore in line with the findings of Guiso, Jappelli, and Terlizzese (1996) and Vissing-Jorgensen (2002). Our results are also, however, consistent with those of Massa and Simonov (2006), since we do not find consistent cross-sectional evidence of hedging. Our overall conclusion is therefore that individual agents hedge labor income risk, but that this hedging effect is more difficult to observe in the cross-section because of the presence of "taste" heterogeneity among agents (e.g., represented by a familiarity bias). This result also has asset pricing implications. If the strength of these two offsetting effects vary with the business cycle, then it is not surprising that the unconditional CAPM with human capital fails (as documented by Fama and Schwert, 1977) whereas the conditional CAPM with human capital is successful in explaining the cross section of stock returns (as documented by Jagannathan and Wang, 1996).

Data appendix

In this appendix we provide details on how we define variables from the LINDA dataset for the empirical analysis.

Table 1: Reported variables include the age of the household head (age), the number of children, household disposable income, in thousands of SEK, and household net wealth in thousands of SEK (which does not include the value of real assets such as yachts etc. unless the household is subject to wealth tax. Further, net wealth does not include any retirement – tax-deductible – assets, human capital, and the values of private businesses and bank accounts for which less than SEK 100 is earned annually. All debt is included). We also report the following dummy variables which are 1 if at least one adult satisfies the criterion: unemployed, Nordic, college education, business degree, married, single, student, lives in a high population density area (Stockholm, Gothenburg or Malmo/Lund/Trelleborg), medium population density (not a high density area but with more than 27,000 inhabitants and more than 300,000 within 100 km), low population density (not a high or medium density area), retired, homeowner.

Tables 6 and 7: In addition to the variables described in Table 1, "age^2" is the squared value of age (scaled by 1000), "house / networth" is the ratio of housing wealth over net worth (in 1999), and "debt-to-income" corresponds to the ratio of debts to household disposable income. Both family income and net worth (in 1999) are in log terms. "wage vol" is defined as the average volatility of annual returns to real disposable income across all individuals within a 3-digit SNI code who have stayed in the same 5-digit SNI code for at least 5 consecutive years between 1993 and 2003. "wage vol. same ind." is an interaction variable that is equal to wage volatility if the two adults in the household work in the same 1-digit SNI code. "public" ("private") is a dummy variable that is 1 if all the working individuals within the household work in the public (private) sector.

Tables 9: Explanatory variables are changes to family disposable income in logs (family income), changes to house-to-net wealth-ratio (house / networth), changes in the debt-to-income ratio (debt / income), changes to net worth in logs, and changes in wage volatility (Δ wage vol.). We also interact Δ wage vol. with dummies on whether the switchers are up- or down- switchers. "Δ sign(wage vol) $\cdot$ (wage vol)^2" is a variable whose absolute value is squared. "toPrivate" and "toPublic" are both dummy variables on whether the high-income generating individual switches to the private and public sectors respectively in 2002 (see Section 4.3 for details). Furthermore, we include dummy variables that equal 1 if at least one in the household satisfies the criteria: moved from a low population density to a high one (low to high), stopped receiving student aid between 1999 and 2002 (has graduated), retired between 1999 and 2002 (has retired), unemployed in 1999 but not in 2002 (found job), employed in 1999 but not in 2002 (lost job), owned no real estate in 1999 but owned real estate in 2002 (bought house), and owned real estate in 1999 but owned no real estate in 2002 (sold house).

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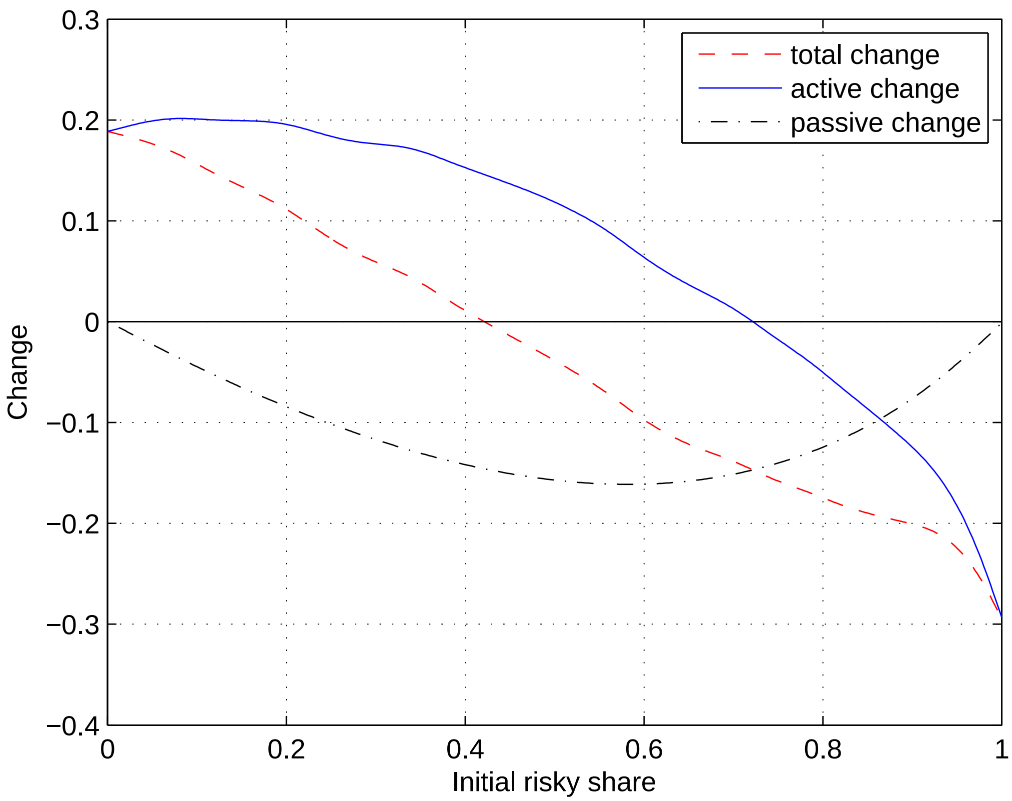
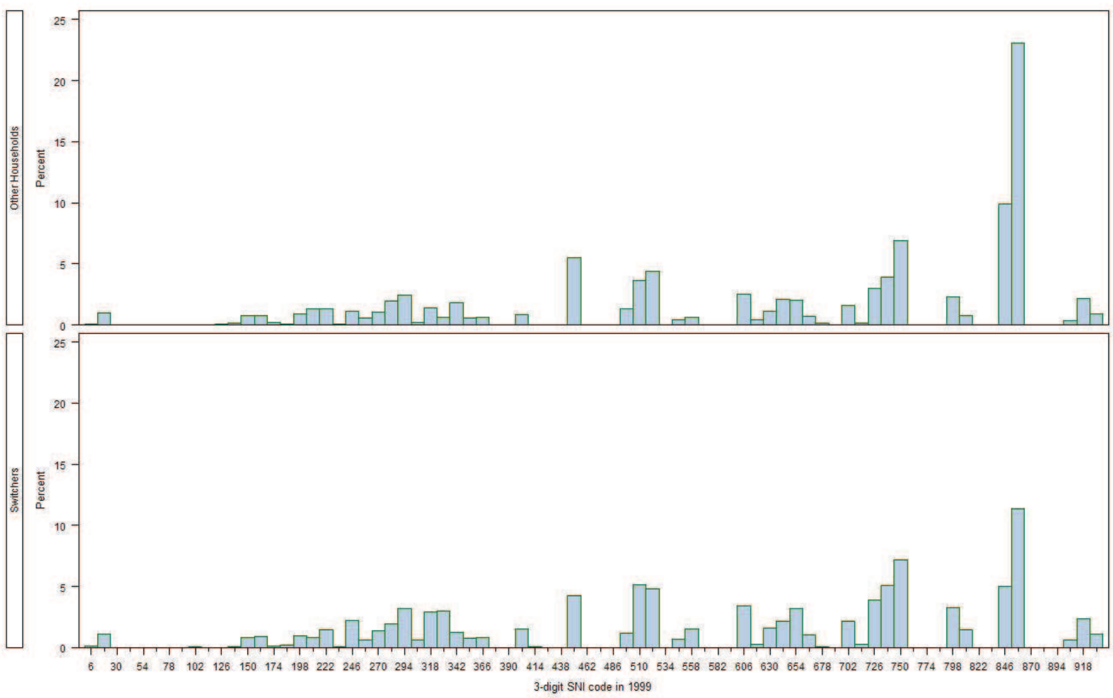
Figures

Figure 1: Total, active, and passive changes between 1999 and 2002



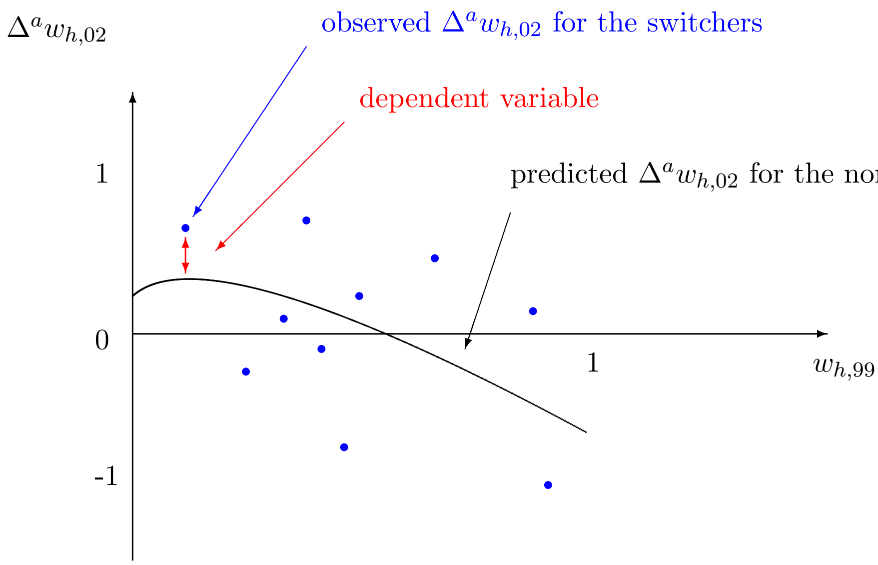
Decomposition of total changes in the risky share, $\Delta w_{h,02}$, as a function of initial risky share, $w_{h,99}$, into a passive change, $\Delta^p w_{h,02}$, and an active change $\Delta^a w_{h,02}$. The passive change is calculated using (6). To filter out noise and get a smooth approximation of total change as a function of $w_{h,99}$, household changes are projected (regressed), using three cubic splines. The active change is then defined as the difference between the projected total changes and the passive changes. The risky share is defined as the percentage of financial assets held in stocks and risky mutual funds. Financial asset are the sum of cash (checking and savings accounts, money-market funds), bond-only mutual funds, stocks, and risky mutual funds.

Figure 2: Histograms of industries for switchers and other households in 1999



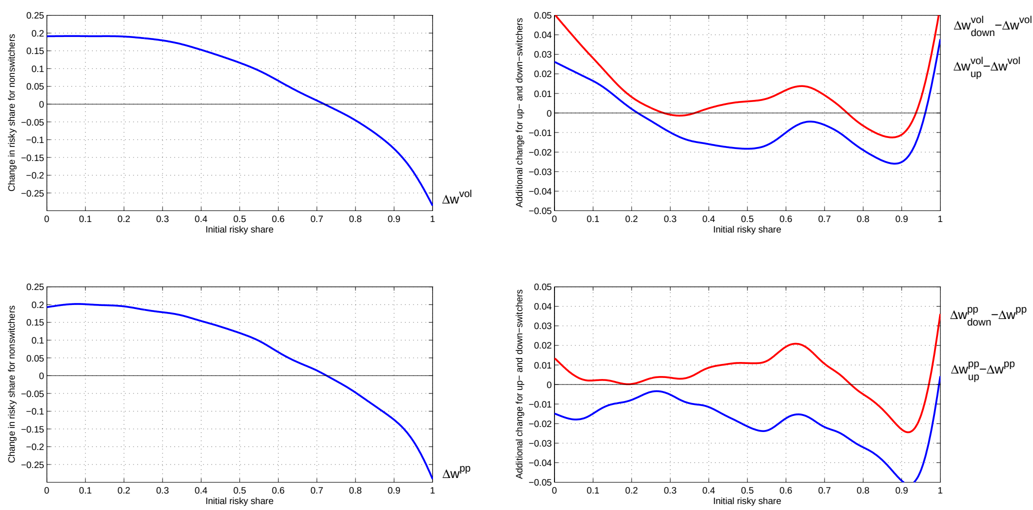
Industries are represented as 3-digit SNI codes. The bottom histogram represents switchers and the top histogram all the other households.

Figure 3: Construction of our dependent variable in the analysis of switchers



In this graph we explain how we derive our dependent variable for our analysis of switchers. The black line represents the predicted values of the active change in the risky share for non-switcher households. These values come from a cubic-spline estimation with three degrees of freedom. They are plotted against the initial risky share in 1999. The blue dots represent the observed active changes in the risky shares for the switcher households. Our dependent variable $\widehat{\Delta^a w_{s,02}}$ is defined as the double-arrow vertical vector (in red).

Figure 4: Fitted active changes for up-, down-, and non-switchers



In the two left quadrants we report the fitted active changes in the risky share between 1999 and 2002 for non-switcher households. In the top-left quadrant, non-switchers are defined as households where both individuals do not switch industries between 1999 and 2002. In the bottom left quadrant, non-switchers are defined as households where both individuals do not switch between the public and the private sectors. In the two right quadrants, we report the fitted values of the *additional* active changes in the risky share for up-switchers and down-switchers (that is, relative to the predicted change of the non-switchers given the same initial risky share). In the top right quadrant, up-switchers (down-switchers) are defined as switchers that experience an increase (decrease) in wage volatility. In the bottom right quadrant, up-switchers (down-switchers) are defined as switchers that switch from the public (private) to the private (public) sector. In each of the right quadrants, the top (red) line corresponds to the down-switchers, and the bottom (blue) line corresponds to the up-switchers.

Tables

Table 1: Household characteristics in 1999

	All Households				Switchers	
Variable	Mean	Std Dev	Min	Max	Mean	Std Dev
Demographics						
age	43.82	9.43	18	62	41.19	9.41
nordic	.98	.14	0	1	.98	.12
number of children	1.2	1.15	0	11	1.3	1.14
Civil Status						
married	.62	.48	0	1	.6	.49
single	.16	.37	0	1	.18	.38
Education						
student	.07	.26	0	1	.1	.29
college degree	.48	.5	0	1	.52	.5
business degree	.15	.36	0	1	.2	.4
Population Density						
high	.34	.47	0	1	.41	.49
medium	.55	.50	0	1	.51	.50
low	.11	.32	0	1	.09	.28
Labor income						
family income	326.73	170.58	1.8	3209.81	325.93	172.80
is unemployed	.16	.36	0	1	.17	.38
is retired	.08	.28	0	1	.07	.25
Housing and Wealth						
homeowner	.9	.33	0	1	.89	.31
net worth	1,098.42	2,037.08	1.02	157,096.07	1,018.90	1,482.36
fin wealth	445.01	1156.74	3	77,619.77	400.34	860.92

All monetary values are defined in thousands of Swedish kronor (SEK). The SEK/USD exchange rate on December 30th, 1999 was 8.52. The entire population consists of 73,456 households including 3,815 switchers. The reported variables are described in the Appendix.

Table 2: Participation rates and portfolio shares in 1999 and 2002

	All Households			Switchers		
Variable	Mean	Std Dev	Part.	Mean	Std Dev	Part.
Panel A: 1999						
risky assets	.62	.32	.90	.62	.32	.90
stocks	.28	.29	.48	.3	.29	.49
mutual funds	.52	.32	.81	.51	.33	.80
Panel B: 2002						
risky assets	.52	.31	.94	.52	.31	.95
stocks	.19	.23	.62	.2	.23	.63
mutual funds	.42	.29	.88	.42	.29	.87

Portfolio shares are conditional on participation. The category "stocks" consists of all non-retirement directly-held stocks. The category "mutual funds" consists of all mutual funds that are fully or partially invested in stocks. The category "risky assets" is the sum of stocks and mutual funds. The data set has 73,456 observations.

Table 3: Participation rates and portfolio shares in 2001: Sweden vs. USA

	LINDA			SCF I			SCF II		
Variable	Mean	Std Dev	Part.	Mean	Std Dev	Part.	Mean	Std Dev	Part.
risky assets	.57	.3	.94						
stocks	.22	.24	.59	.40	.31	.41	.29	.26	.41
mutual funds	.46	.29	.88	.30	.26	.30	.19	.19	.30

The first column (LINDA) refers to observations from the LINDA dataset in 2001. The data set has 73,456 observations. The other two columns refer to observations from the 2001 Survey of Consumer Finances (SCF). In the second column (SCF I), we adjust the SCF portfolios so that they are comparable to the ones computed in LINDA. In particular, we exclude retirement assets and we sum up the holdings of pure-equity and mixed mutual funds. The third column (SCF II) reflects more closely the true risky portfolio shares in the USA. The holdings of mixed mutual funds are halved to reflect the fact that they are not fully invested in stocks, and the retirement assets are included.

Table 4: Rankings of industries by their levels of wage volatility

SNI	Description	Est.
	Bottom 10	
371	Recycling of metal waste and scrap	.07
271	Manufacturing of iron and steel	.08
131	Mining of iron and ores	.08
173	Finishing of textile	.09
272	Manufacturing and casting of iron tubes	.09
172	Weaving of cotton	.09
365	Manufacturing of games and toys	.09
274	Production of precious metals, copper	.10
403	Steam and hot water supply	.10
175	Manufacturing of ribbons, curtains	.10
	Top 10	
21	Renting of household goods	.21
13	Mixed farming	.21
722	Publishing of software	.22
741	Legal representation activities	.23
672	Other finance activities	.24
744	Advertising	.24
924	Other Entertainment	.25
553	Restaurants	.26
921	Motion picture and video production	.26
671	Finance administration, fund management	.30

Wage volatility is defined as the average volatility of annual returns to real disposable income across all individuals within a 3-digit SNI code who have stayed in the same 5-digit SNI code for at least 5 consecutive years between 1993 and 2003. The rankings are based on 191 observations.

Table 5: Summary statistics of wage volatility for switchers

	Down switchers				Non-switchers				Up-switchers			
Variable	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max
Wage Volatility												
Vol 99	.16	.03	.1	.28	.14	.02	.08	.3	.13	.02	.08	.23
Private 99 (%)	.81	.39	0	1	.59	.49	0	1	.67	.47	0	1
Δ Vol 99-02	-.02	.02	-.12	0	0	0	0	0	.03	.02	0	.12
N	1,739				45,615				2,076			

Wage volatility is defined as the average volatility of annual returns to real disposable income across all individuals within a 3-digit SNI code who have stayed in the same 5-digit SNI code for at least 5 consecutive years between 1993 and 2003. It is assigned to each individual based on their 3-digit SNI code and then aggregated at the household level. "Private 99" is a dummy on whether the high-income individual worked in the private sector in 1999. Switchers are defined as households where the high-income individual switched to a new industry between 1999 and 2002 (see Section 4 for details). The up-switchers (down-switchers) are defined as switchers that experience an increase (decrease) in wage volatility. Non-switchers are defined as households neither individual switched industries between 1999 and 2002.

Table 6: Effects of wage volatility on the risky share in 2002.

	(1)		(2)		(3)	
Variable	Est.	t-stat	Est.	t-stat	Est.	t-stat
wage vol.	-.12	-2.51	-.22	-5.69	-.14	-2.86
wage vol. same ind.	.001	.02	.004	.16	-.004	-.15
public	.014	4.26			.011	2.69
private	-.004	-1.62			-.007	-2.12
Intercept	1.102	23.41	.707	8.70	.685	7.6
age	-.002	-1.95	-.005	-3.15	-.005	-3.14
$(\text{age})^2$	.015	1.05	.03	1.77	.031	1.89
nordic	.018	1.82	.047	4.79	.046	4.57
has emigrated	-.014	-.99	-.028	-1.56	-.029	-2.12
no. children	.024	17.2	.027	17.37	.027	16.79
single parent	.014	2.78	.028	4.69	.026	4.38
married	-.007	-2.31	-.006	-2.01	-.006	-1.76
student	.01	1.88	.017	2.81	.017	2.48
college degree	.012	4.37	.025	7.1	.021	5.99
business major	.012	3.53	.01	2.77	.012	3.68
high pop. density	.001	.03	-.017	-3.77	-.016	-3.02
medium pop. density	.033	8.77	.03	.003	.031	7.78
family income	-.04	-11.16	-.017	-3.17	-.015	-2.44
is unemployed	-.007	-.19	-.004	-1.16	-.003	-.087
is retired	-.017	-4.86	-.017	-4.5	-.017	-4.76
debt / income 99	.003	4.14	.003	3.82	.003	4.7
homeowner	.013	2.57	.018	3.27	.019	3.11
house / networth 99	-.016	-8.5	-.019	-9.18	-.019	-8.8
net worth 99	-.004	-3.34	.004	2.37	.004	2.41
lambda			.292	4.31	.292	5.49
No. Obs	69,097		69,097		69,097	
F	67***					
R-sq	.022					
Chi-sq			1,782		2,086	

We report second-stage estimates of the portfolio holdings of risky assets (stocks and risky mutual funds) as a percentage of financial assets (e.g. the "risky share") in 2002. Financial wealth is defined as the sum of cash (checking and savings accounts, money-market funds), bond-only mutual funds, stocks, and risky mutual funds. The sample is restricted to households with positive holdings. Four separate OLS regressions are run. In columns 2 to 4, lambda is the inverse mills ratio from the first stage estimation of Eq. (8). We report the bootstrapped t-stats. In column 1, where we do not control for lambda, we report the heteroskedasticity-consistent t-stats. All the goodness-of-fit F and Chi-sq tests are statistically significant at the 1% level. Other explanatory variables are described in the Appendix.

Table 7: Effects of wage volatility on the portfolio shares of stocks and mutual funds in 2002

	stocks		mutual funds	
Variable	Est.	t-stat	Est.	t-stat
wage vol.	.238	4.89	-.37	-8.08
wage vol. same ind.	-.002	-.001	-.07	.16
public	-.009	-2.73	.02	5.05
private	.012	4.41	-.019	-6
X variables	yes	yes	yes	yes
lambda	.607	11.59	-.315	-5.14
No. Obs	69,097		69,097	
Chi-sq	3,048		7,885	

We report second-stage estimates of portfolio holdings of directly-held stocks and mutual funds as a percentage of financial assets in 2002. The sample is restricted to households with positive holdings. Four separate OLS regressions are run. The dependent variables are the share of directly-held stocks over financial wealth and the share of risky mutual funds (equity and mixed) over financial wealth. Financial wealth is defined as the sum of cash (checking and savings accounts, money-market funds), bond-only mutual funds, stocks, and risky mutual funds. Lambda is the inverse mills ratio from the first stage estimation of Eq. (8). We report the t-statistics for the bootstrapped standard errors. All the goodness-of-fit Chi-sq tests are statistically significant at the 1% level. Other explanatory variables in the vector $X_{h,02}$ are included but we do not report the results.

Table 8: Sign tests on the active changes in the risky share between 1999 and 2002 for switchers

	wage vol.		public-private	
Variable	up	down	up	down
Sign	-	+	-	+
Est.	-8,770***	15,227***	-20,035***	17,077***

We test that the predicted values from the splines for the up- and down- switchers that are shown in Fig. 4 are different from the predicted values from the splines for the non-switchers. There are 59,025 observations for the wage volatility measure and 59,047 observations for the public-private measure. *** indicates statistical significance at the 1% level.

Table 9: Effect of changes in wage volatility for switchers on the active change in their risky share between 1999 and 2002

	(1)		(2)		(3)		(4)		(5)		(6)	
Variable	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Intercept	.005	1.09	.005	1.09	.005	1.08	.004	.6	.003	.47		
Δ wage vol	-.312	-2.25	-.323	-2.34	-.31	-2.24						
Δ wage vol - up							-.29	-1.23				
Δ wage vol - down							-.36	-1.4				
Δ sign(wage vol) $\cdot$ (wage vol)^2									-.482	-2.28		
to private											-.016	-2.84
to public											.008	1.39
has emigrated	-.058	-.87										
Δ no. children	-.022	-2.66	.023	2.48	.019	2.09	.023	2.24	.022	2.2	.022	2.74
has graduated	-.014	-.71										
low to high density	-.013	-1.21										
has retired	-.037	-1.92	-.035	-1.75	-.036	-1.91	-.035	-1.85	-.035	-1.83	-.036	-2.42
Δ family income	-.074	-4	-.074	-4.03	-.08	-4.35	-.074	-4.02	-.073	-3.99	-.045	-3.55
found a job	.024	1.33										
lost a job	-.016	.85										
Δ debt / income	-.007	-1.68	-.007	-1.83	-.01	-2.21	-.008	-1.83	-.007	-2	-.001	-1.33
bought house	.016	.47										
sold house	-.14	-3.49	-.147	-3.66	-.12	-3.01	-.147	-3.67	-.147	-3.67	-.16	-5.01
Δ house / networth	.021	2.08	.022	2.27	.038	4.54	.022	2.26	.022	2.3	.012	1.49
Δ net worth	-.022	-2.66	-.02	-3			-.02	-2.6	-.02	-2.58	-.032	-5.4
No. Obs	2,565		2,565		2,565		2,565		2,565		3,890	
F	4.67***		7.95***		7.78***		7.07***		7.94***		12.53***	
Adj R-sq	.021		.021		.018		.021		.021		.026	

We report estimates of the change in the portfolio share of risky assets between 1999 and 2002. The sample is restricted to households with positive holdings in 1999. Six separate OLS regressions are run. The dependent variable is the difference between the observed active change in the risky share for switchers and the predicted active change in the risky share for non-switchers (between 1999 and 2002) given the same initial risky share in 1999. See Fig. 3 for a visualization of the construction. We report the t-statistics for the heteroskedasticity-robust standard errors. Other explanatory variables are described in the Appendix.

Table 10: Robustness checks with different basis functions

	(cubic spline 3df)		(cubic spline 6df)		(linear reg)		(quad reg)	
A. Average predicted difference in the active change of the risky share between down- and up-switchers								
Variable	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
high → low wage vol.	1.57%		1.54%		1.17%		1.48%	
private → public	2.6%		2.6%		2.77%		2.56%	
B. Estimates of Eq. (11)								
Intercept	.005	1.09	.005	.1.09	.003	.62	.005	1
Δ wage vol	-.323	-2.34	-.323	-2.34	-.26	-1.83	-.325	-.236
Δ no. children	.023	2.48	.022	2.24	.021	2.06	.023	2.2
has retired	-.035	-1.75	-.035	-1.85	-.031	-1.61	-.034	-1.81
Δ family income	-.074	-4.03	-.073	-4.03	-.08	-4.26	-.076	-4.13
Δ debt / income	-.007	-1.83	-.007	-1.83	-.01	-2.24	-.008	-1.92
sold house	-.147	-3.66	-.147	-3.66	-.152	-4.03	-.145	-3.6
Δ house / networth	.022	2.27	.022	2.27	.022	2.31	.023	2.39
Δ net worth	-.02	-3	-.02	-2.6	-.024	-3.07	-.021	-3.16
No. Obs	2,565		2,565		2,565		2,565	
F	7.95***		7.95***		8.63***		8.35***	
Adj R-sq	.021		.021		.023		.022	

In Panel A, we report the average *predicted difference* in the 99-02 active change of the risky share between down-switchers and up-switchers. For each population (switcher, non-switcher...), the average is taken from the predicted values of their active changes of the risky share between 99-02 given their initial risky shares in 1999. We report the results using four different interpolation methods: our main one ("cubic spline 3df"), another cubic spline with 6 degrees of freedom ("cubic spline 6df"), a linear regression ("linear reg"), and a quadratic regression ("quad reg"). Values in the first row are computed from our main definition of switchers (w.r.t. wage vol.) and values in the second row are computed from our second definition (w.r.t. public or private sector).

In Panel B, we report estimates of changes in portfolio holdings as a percentage of financial assets between 1999 and 2002. The dependent variable is the difference between the observed active change in the risky share for switchers and the predicted active change in the risky share for non-switchers (between 1999 and 2002) given the same initial risky share in 1999. See Fig. 3 for a visualization of the construction. We repeat the estimations from Table 9 given the four different interpolation methods for the predicted active change in the risky share for the non-switchers. Column 1 is equivalent to column 2 of Table 9. The sample is restricted to households with positive holdings in 1999. We report the t-statistics for the heteroskedasticity-robust standard errors. Other explanatory variables are described in the Appendix.

Table 11: Effects of changes in wage volatility on changes in the the portfolio shares of stocks and mutual funds between 1999 and 2002

	stocks		mutual funds	
Variable	Est.	t-stat	Est.	t-stat
Intercept	.004	.82	0.000	-.12
Δ wage vol.	.007	.05	-.297	-2.12
Δ no. children	.001	.13	.015	1.54
has retired	.007	.39	.030	-1.68
Δ family income	-.009	-.57	-.082	-4.3
Δ debt / income	-.002	-.8	-.009	-2.35
sold house	-.097	-2.22	-.130	-3.25
Δ house / networth	.013	1.2	.021	2.07
Δ net worth	-.006	-.82	-.019	-2.81
No. Obs	1,346		2,294	
F	1.24		7.1***	
Adj R-sq	.001		.021	

We report estimates of the change in the portfolio shares of directly-held stocks and mutual funds between 1999 and 2002. The sample is restricted to households with positive holdings in 1999. Two separate OLS regressions are run. In column 1 (2), the dependent variable is the difference between the observed active change in the share of directly-held stocks (risky mutual funds) for switchers and the predicted active change in the share of directly held stocks (risky mutual funds) for non-switchers (between 1999 and 2002) given the same initial share of directly held stocks (risky mutual funds) in 1999. See Fig. 3 for a visualization of the construction. We report the t-statistics for the heteroskedasticity-robust standard errors. Other explanatory variables are described in the Appendix.

Table 12: Probability of up- and down-switches between 1996-98 for the various types of households.

	$w_{h,99}$ low tercile			$w_{h,99}$ medium tercile			$w_{h,99}$ high tercile		
	up	non	down	up	non	down	up	non	down
prob up switch 96-98	.051	.064	.255	.038	.061	.0222	.058	.06	.277
prob down switch 96-98	.15	.061	.064	.147	.057	.033	.165	.0579	.0477

We report estimates of the probability of up- and down- switches between 1996 and 1998 for various groups of households. First, we split all households into three terciles based on their risky share in 1999 ($w_{h,99}$). Then, within each tercile, we classify households as up-, non-, or down-switchers based on their decision to switch between 1999 and 2002 (see Section 4.1 for the definitions). The probability of an up switch in 1996-98 is computed as the fraction of households within each group that had at least one up-switch between 1996 and 1998 and more up-switches than down-switches in the event of multiple job switches.

Table 13: Effects of changes in wage volatility between 96-98 and 99-02 on changes in the portfolio shares of risky assets between 1999 and 2002

	Regular		Two-stage	
Variable	Est.	t-stat	Est.	t-stat
Intercept	.003	.69	0.000	-.12
Δ wage vol.	-.32	-2.23	-.3	-2.11
Δ no. children	.02	1.91	.02	1.9
has retired	-.032	-1.72	-.03	-1.71
Δ family income	-.07	-3.66	-.068	-3.63
Δ debt / income	-.006	-1.52	-.006	-1.51
sold house	-.15	-3.46	-.15	-3.44
Δ house / networth	.02	2.12	.021	2.12
Δ net worth	-.021	-2.92	-.02	-2.51
			first-stage	
Δ wage vol. 96-98	.23	.79	.44	1.48
No. Obs	2,456		2,456	
F	6.57***		7.02***	
Adj R-sq	.02		.019	

We report estimates of the change in the portfolio share of risky assets between 1999 and 2002. The sample is restricted to households with positive holdings in 1999. Two separate OLS regressions are run. In column 1, we conduct the same regression as in column 2 of Table 9 but adding an additional control variable: the households' change in wage volatility between 1996 and 1998 (which is computed the same way as the one between 1999 and 2002). The dependent variable is the difference between the observed active change in the risky share for switchers and the predicted active change in the risky share for non-switchers (between 1999 and 2002) given the same initial risky share in 1999. In column 2, we perform a two-stage analysis, where in the first stage we regress the same dependent variable on the change in volatility between 1996 and 1997. Then, in the second stage, we regress the residuals from the first-stage regression on the same variables as in Table 9. We report the t-statistics for the heteroskedasticity-robust standard errors. Other explanatory variables are described in the Appendix.