Hedging Labor Income Risk*

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Abstract

We investigate the relationship between workers' labor income and capital market investment. Using a detailed Swedish data set on employment and portfolio holdings we estimate wage volatility, and labor productivity for Swedish industries and, motivated by theory, demonstrate that highly labor productive industries are more likely to pay workers variable wages. We also find that both levels and changes in wage volatility are significant in explaining changes in household investment portfolios. 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 25%, i.e., 7,750 USD. Similarly, a household that switches from a low labor productivity industry to one with high labor productivity decreases its risky asset share by 20%. Our results suggest that human capital risk is an important determinant of household portfolio holdings.

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1 Introduction

Labor income accounts for about two thirds of national income and, since the seminal work of Mayers (1973), it has been shown to play an important role in theoretical asset pricing. In studies such as Bodie, Merton and Samuelson (1993), Danthine and Donaldson (2002), Qin (2003), Santos and Veronesi (2006) and Parlour and Walden (2008) risky labor income affects the portfolio decisions made by investors, which in turn has general equilibrium asset pricing implications. However, the empirical evidence is mixed as to whether an aggregate labor factor can explain stock returns. 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 (2005)).

Given a potentially incomplete market and noisy measurements, using aggregate labor income data to show the importance of human capital risk in investors' investment decisions, is a daunting task. So, we take a different approach: Since the effects of risky human capital on asset prices are driven by investors' portfolio decisions, we directly study their portfolio holdings. If there is no discernable relationship between agents' labor income and their investment decisions, then it is difficult to posit a plausible link between a labor factor and asset prices. We use panel data on employment and portfolio holdings of a large subset of the Swedish population; and we examine if there is a relationship between employees' labor productivity, wage structure (measured by wage level and volatility) and portfolio holdings.

We find that although there is only a weak link between the the *levels* of employee labor productivity, wage structure and portfolio holdings, there is a strong link between *changes* in these variables. For example, households adjust their portfolios in response to job changes. In particular, for households where both adults switch industries in the same year, an increase in wage volatility by 1% will lead to a decrease in the share of risky assets by 1.07%. This effect is statistically significant at the 5% level. This means that a household going from the industry with the least variable wage (recycling metal waste) to the industry with the most variable wage (fund management) will *ceteris paribus* decrease its share of risky assets by more than 25%, or 7,750 USD. Similarly, a household that switches from a low labor productivity industry to one with high labor productivity decreases its risky asset share by 20%. We also provide evidence on the link between wage volatility and the labor productivity of industries. We find that industries that require high levels of labor productivity also have wages that are (i) volatile and (ii) high on average.

Our results are consistent with a world in which households take human capital into account when making investment decisions, but in which other, offsetting, factors are also important, e.g., heterogeneity in risk-preferences, a familiarity bias, or heterogeneous information. If any of these other factors varies 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)).

Our tests are based on the predictions in Parlour and Walden (2008). Briefly, the paper develops a general equilibrium model with multiple industry sectors in which workers accept employment contracts offered by firms and their effort is used as an input into production. Firms face a moral hazard problem in that they cannot observe the effort level of employees, so optimal wage contracts include risky compensation. The theory explicitly links the level of labor productivity in a sector to (i) both the level and the volatility of wages offered to employees, and (ii) the portfolios that these employees hold in equilibrium. Firms that require high labor productivity choose a highly variable wage structure that is linked to performance in order to induce effort from their employees. As a result, employees of the high-productivity firms choose to reduce their exposure to risky assets in their investment portfolio.

We use the LINDA database, which provides detailed income and wealth information for a large representative sample of about 3% of the Swedish population from 1999 to 2003. While we do not have information on their 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. This information provides us with a measure of hedging of systematic risk. By definition, most firms bear a positive level of market risk. If we assume that the wages are on average positively correlated with the market then employees can hedge their labor income risk by holding a lower share of risky assets and mutual funds.

In addition to investigating the relationship between agents' portfolio composition and labor income, we also investigate individuals who change industries over the years. For these individuals, we look at their portfolio holdings one year before and one year after their industry switch, and we ask the following question: given their initial portfolio holdings, how does the industry switch affect the change in their portfolio holdings? In particular, do individuals who switch to sectors that are more productive and offer riskier income streams decrease their share of risky assets? Our measure of industry risk and volatility is estimated across all agents who work in the industry and therefore captures the ex ante uncertainty in an agent's human capital.

Our paper is related to a series of other empirical papers that use micro data to investigate the relationship between non-financial income risk and portfolio decisions. Malloy, Moskowitz and Vissing-Jorgensen (2005) find evidence that labor income risk, through a firing decision, can explain the value effect. Their focus is different from ours, however, since we are interested in the relationship between a firm's productivity, the wages it pays, its expected stock returns, and the portfolio holdings of investors.

Massa and Simonov (2006) also present a detailed study of the Swedish population. They look at individual stock holdings and find that households tend to hold stocks that are closely related to their labor income, which goes against the hypothesis of hedging. They argue this is because of a preference for familiar stocks, due to heterogeneous information. This is in line with our finding that the hedging motive does not appear in the levels of stock holding, but rather in the changes after a shock to human capital. In fact, this is consistent with one of Massa and Simonov's findings that investors' hedging demand is greater (or not as negative) for households who switch professions or locations or who experience an unemployment shock. They interpret this as familiarity shocks which prevent the investor from biasing his portfolio away from hedging. Our analysis thus differs from theirs in that we explicitly consider changes in employment but are agnostic about the determinants of portfolio composition.

Our paper is also related to another series of papers that look at the relationship between wage volatility and labor productivity. Our results indicate that industries with high coefficients of labor elasticity also provide more volatile wages, which is consistent with our theory as well as with the results of other studies. Abowd, Kramarz and Margolis (1999) use a French longitudinal sample and find that firms with higher (total) wages are more productive. Furthermore, the proportion of executive compensation from high productivity firms is found to be higher than in low productivity firms. (See, for example Gaver and Gaver (1993,1995), Bizjak, Brickley and Coles (1993), Smith and Watts (1992)). In the LINDA database, however, our workers are not necessarily executives.

The rest of the paper is organized as follows. In the next section we provide a brief review of the model in Parlour and Walden (2008) and describe the predictions on the relationship between firm productivity, wages, and portfolio decisions. In Section 3 we describe the data and the methodology, and in Section 4 we provide the empirical results. In Section 5 we offer some concluding remarks.

2 Theoretical Framework and Empirical Strategy

Our discussion in this section is aimed at providing an overview of, and intuition for, the predictions in Parlour and Walden (2008). For details, the reader is referred to the paper. The model is static and uses a CARA-normal framework. The economy is composed of N sectors, which for expositional purposes we will take to be two; each of which has a different level of labor productivity: sector 1 has high labor productivity and sector 2 has low labor productivity. Within each sector there are many firms and within each firm there are many workers. Workers need to exert effort to be productive, and since their effort level is not observable, firms face a moral hazard problem. As a result, firms choose to offer incentive contracts, which optimally consist of a fixed part and a variable part. The variable part depends on the performance of the firm, e.g., its profits. For simplicity, firms are assumed to have unlimited liability.

The central intuition of the paper is that an agent's stock portfolio does not accurately reflect his total exposure to systematic risk. Alternatively, in general equilibrium, a firm's equity also does not reflect all the systematic risk that it generates: firms payout risk through wages. Firms with high labor productivity find it optimal to pay most of their wage compensation as incentive wages, since it is relatively important for them to provide incentives to their workers. Thus, the compensation in the high productivity sector 1, $\tilde{w}_1$, is risky. Low productivity firms, in sector 2, pay most of their wage compensation through the fixed part, so their compensation, w_2, is essentially risk-free.

The model also provides implications for the cross-section of expected returns. For example, it is natural to obtain a size effect (and, under other additional assumptions, a value effect). In equilibrium, even though the total size of the high productivity sector is larger than that of the low productivity sector, high productivity firms are on average *smaller* than low productivity firms, because of the higher level of competition. Furthermore, since the high-productivity firms pay a *greater* fraction of their asset risk through wage compensation, their true risk is underestimated if one uses the stock market portfolio as a proxy for the true market portfolio. In other words, econometricians who use the stock market portfolio in their CAPM regressions should find that firms in sector 1 earn positive abnormal returns, $\tilde{\mu}_1$ in the stock market, whereas firms in sector 2 earn negative abnormal returns, $\tilde{\mu}_2$. The model is summarized in Figure 1.

While this framework generates several predictions about the relationship between the type of compensation (fixed versus variable) offered, the expected returns, and the type of firm that accords with existing empirical literature,[1] we focus on the novel implications that relate the productivity of the firm, the riskiness of the wage contract and the portfolio holdings of the workers. In particular, two sorts of predictions arise. First, there are predictions on levels:

H1: The higher the labor productivity of the industry, the higher the wage volatility.

H2: Workers with more variable wages have lower exposure to the market through financial assets.

H3: Workers in higher labor productivity industries have lower exposure to the market through financial assets.

Second, there are predictions on changes. While there might be agent specific heterogeneity outside the model that affects portfolio holdings, if an employee moves to an industry that offers a different wage contract then he should rebalance his portfolio. For example, consider a worker who changes jobs from a low productivity sector to a high productivity

[1] See for example, Abowd, Kramarz and Margolis (1999), Gaver and Gaver (1993,1995), Bizjak, Brickley and Coles (1993), Smith and Watts (1992), Kruse (1992), Mehran (1995), Frye (2004) and Kedia and Mozundar (2002).

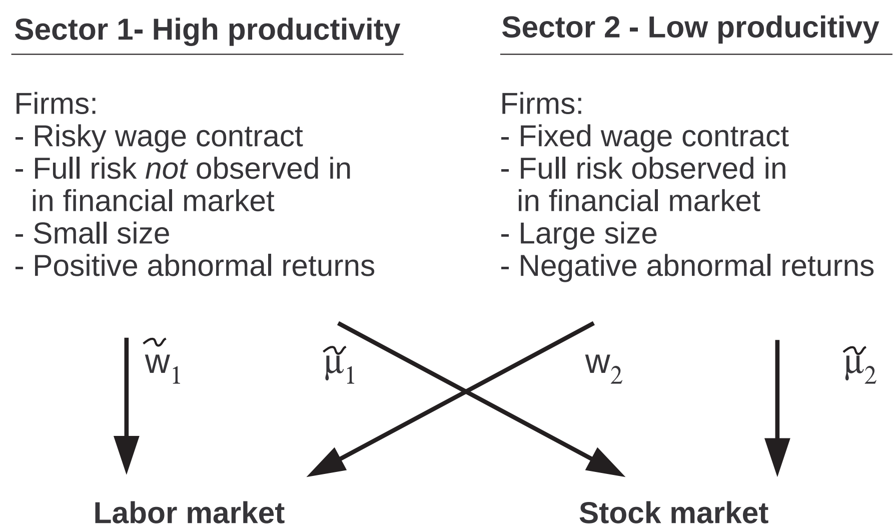

Figure 1: Summary of model — Two sector example.

sector. Through the labor market he has effectively increased his exposure to the market and therefore should decrease his exposure to risky assets in his investment portfolio.

H4: Workers who switch to a sector with higher wage volatility decrease their exposure to the market through financial assets.

H5: Workers who switch to higher labor-productive sectors decrease their exposure to the market through financial assets.

2.1 Data

To construct measures of portfolio holdings, we use a unique Swedish annual panel database called LINDA (standing for Longitudinal INdividual DAta for Sweden), a joint project between Uppsala University, The National Social Insurance Board,[2] Statistics Sweden, and the Swedish Ministry of Finance. LINDA contains an annual cross-sectional sample of around 300,000 individuals, which is approximately 3% of the entire Swedish population. These individuals are tracked over the years. Family members of sampled individuals are

[2]The National Social Insurance Board, "Förskringskassan," manages the Swedish social security system, see, http://www.fk.se/sprak/eng.

also included; this allows us to examine household labor and investment decisions. The sampling procedure ensures that the panel is representative for the population as a whole, and each annual cohort is cross-sectionally representative.

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 sex, 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 estimated by Statistics Sweden and included in LINDA.

To investigate labor income and working conditions, we rely on Statistics Sweden to obtain two more data sets. The first provides information on industry characteristics, and we use it to compute a measure of labor productivity for each industry. Every year, Statistics Sweden collects firm data such as total sales, the number of employees, and value added. Data from the 558 largest companies is collected through complete surveys. Information about the remaining number of companies is provided by the Swedish Tax Authorities. The coverage rate in 2006 was around 85%. However, the percentage of missing companies as shares of the total number of employees or net income was only around 3%. The data are reported by industry, which are classified according to 5-digit SNI codes. These are equivalent to the NAICS/SIC codes in the USA. We have access to industries at the 3-digit SNI level from 1997 to 2005.

In LINDA, any working individual is assigned a 5-digit SNI code each year, depending on the industry he or she works in.[3] Using the SNI codes, we can therefore merge the industry-level data with the household-level data from LINDA. We do this at the three digit SNI code level, which provides sufficient granularity. In total, there are 223 3-digit codes, however we only use a subset of these because the classification changed in 2002, and the mapping between the old codes (1992 classification) and the new codes (2002 classification) is not one-to-one. This classification change matters for our study because it occurs in the time period we are studying. To avoid any potential bias, we only use the subset of SNI codes that remain the same. In addition to other filters, we still end up with 104 SNI codes.

[3] In the event the individual has had two jobs during a year, the reported SNI code corresponds to the sector in which she generated most of her income during that year.

Finally, to control for agent heterogeneity, we use a Statistics Sweden demographic data set. Since LINDA provides information on the region where individuals live, we can also merge this one with the LINDA database and use population density as a control in our regressions on portfolio holdings. This data set groups regions into 6 different categories, based on the population composition at the end of year 2002.

We exclude observations in which information on the wage volatility or the level of labor productivity is missing, and households (defined below) whose financial wealth, net wealth or family income are extreme: less than 3000 SEK, 1000 SEK, and 1000 SEK respectively, and those with negative net holdings of risky assets. As we are interested in labor market participation, we also exclude households in which the largest income goes to someone younger than 18 years or older than 65 years, and households whose family income in 2000 ranges in the top 0.1% of the remaining sample.

2.2 Constructing Variables

Our tests require a measure of portfolio holdings in addition to agents' employment (the source of their returns to human capital). To understand the relationship between returns to human capital and portfolio returns, we also require a measure of wage volatility. Finally, to relate wage characteristics to industry characteristics, we need to estimate an aggregate industry production function.

2.2.1 Portfolios

Since portfolio decisions are typically made at the household level, we use these as our units of observation. However, we also keep track of the individuals within each household as each may work in a different industry. While aggregating household financial holdings is straightforward, imputing wage volatility or labor productivity to a household is less so. Our sample includes information on wealth from 1999 to 2003, we take 2001 as the base year in order to maximize the sample size. In 2001, we select the two adults within each household who generate the greatest levels of income. We then sort these two individuals by income, and adopt the convention that Individual #1 (Ind1) generates the highest income in 2001 and Individual #2 (Ind2) is the other adult.[4] We then retain and keep track of

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

these two individuals over the years.

We define a "switcher" as a household where at least one of the two adults changed sectors between 1999 and 2002. More precisely, in order to take into account the fact that investors may not adjust their portfolios immediately before or after a job change, we only look at the adults who switched industries between 2000 and 2001.[5] A change in industries is recorded as a 3-digit SNI code change. We eliminate switcher households that undergo a major change in their civil status, such as marriage or divorce and those that have increased or decreased their portfolio holdings of either risky assets, mutual funds, or stocks, by more than 100% between 1999 and 2002.[6] Summary statistics for the overall population as well as for the switchers are displayed in Table 1 for the reference year 2001. A first glance at the Table indicates that the sample of switchers is fairly representative of the overall population, however switchers tend to be slightly wealthier. In addition, a greater fraction of them are homeowners, and they are more likely to be married and to have a college degree.

For each household (h), we look at its non-retirement portfolio[7] of risky assets (ra), which contains directly-held stocks and risky mutual funds. We do not consider other risky financial assets, such as capital insurance products, as we do not have any information on the composition of their investments. Calvet, Campbell, and Sodini (2007) find that including capital insurance products do not change their results on the level of diversification of household's portfolios. 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 in LINDA. From the 1999 data, however, it seems that the vast majority of these funds is pure-equity. We also decompose the portfolio of risky assets and study in detail the portfolios of directly-held stocks (s) and risky mutual funds (mf). At the end of each year t, we define $w^i_{h,t}$ as the the share of household h's holdings of portfolio i over its financial

[5]In other words, adults households did not switch industries between 1999 and 2000 and between 2001 and 2002.

[6]These are absolute values.

[7]Retirement portfolios are not available in LINDA. Until 1998, Sweden had a low-risk defined benefit system, "Allmn Tjnste Pension," ATP, which was then replaced by a defined contribution system (see Sunden (2006)). Since no changes were made retroactively, a large part of the Swedish pension capital was therefore low-risk in our studied time period.

wealth, which is the sum of cash (checking and savings accounts, money-market funds), bond-only mutual funds, stocks, and risky mutual funds. So, $w^s_{12,2003}$ refers to household #12's share of directly held stocks in its financial wealth at the end of the year 2003.

We report summary statistics on portfolio shares of the overall population as well as those of switchers in 2001 in Panel A of Table 6. Again, the switchers are fairly representative of the population, even though they are slightly more likely to invest in the stock market. To benchmark, we compare the Swedish participation rates in risky assets and their portfolio shares with those from the USA, which we glean from the 2001 Survey of Consumer Finances (SCF). Since the information on household wealth is more precise in SCF, we present two Tables. In Panel 6B, 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. Panel 6C reflects more closely the true risky portfolio shares in the USA. The holdings of mixed mutual funds are halved in order to reflect the fact that they are not fully invested in stocks, and the retirement assets are included.

Comparing panels A and B of Table 6, it is evident that the participation rate in risky assets is much higher in Sweden than in the USA. Part of this is mechanical: 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 wealth of 3000 SEK, we eliminate all the households who do not make the threshold because of their missing bank accounts and who do not participate in the stock market. The SCF, which is a survey and not a report from a tax authority, does not exclude such observations. However, these missing bank accounts do not completely explain the difference in participation rates. Indeed, 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. This result indicates that the selection bias in stock market participation in Sweden is not as important as in the USA. The widespread stock market participation among the Swedish population is well known, and has, e.g., been explained with a high degree of trust and sociability in the Swedish society (see Georgarakos and Pasini (2009)). Second, Swedish households 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; since our measure of hedging is the share of financial assets invested in risky assets. As we do not know how Swedish households compose their portfolio of direct 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.

2.2.2 Wage volatility and Labor productivity

Given that our focus is on households who have switched jobs, computing a measure of annual wage volatility that comes directly from their total household income is difficult, because we only have data for two years after their switch in 2001. We proceed as follows. We begin by computing industry-averages of wage volatility, given the large LINDA sample from 1993 to 2003, and then we attribute these values to all individuals given the industry they work in each year.[8] Finally, we aggregate by household each year.

We proceed similarly for our measure of labor productivity, using the industry characteristics data from Statistics Sweden. While using industry-averages may not necessarily reflect an agent's exact wage volatility or labor productivity, it is not unreasonable to view them as ex ante measures of both productivity and wage volatility, given that agents are unaware of how their particular careers will evolve.

In the large LINDA sample from 1993 to 2003, we select all the individuals who work in the same industry for at least 5 consecutive years.[9] (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.) We calculate the wage growth volatility of each individual, which we then aggregate by industry sector.

[8] In some cases individuals have worked in two or more industries during the same year. We unfortunately do not have access to this information, but the SNI code that is reported is the one for which the individual earned most of his annual combined salary.

[9] We restrict these individuals to have the same 5-digit SNI code in order 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 5 consecutive years in order to maximize the sample size but results are robust to different specifications.

Then, we compute the volatility of the annual growth rate of their real disposable income during these years,[10] and average this volatility across all the households within the same 3-digit sector. We only select industries for which we have more than 30 observations, and in doing so we have a measure of wage volatility 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 2 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.

In Parlour and Walden (2008), the agents from the highly productive industries who receive volatile wages also receive higher wages on average, in order to be compensated for the high level of labor income risk. It is easy to test this relationship using data from LINDA. We select the same individuals as those from our measure of wage volatility and compute the average annual level of real disposable income for each 3-digit SNI code.

Once we have computed these measures on the volatility and level of wages for each 3-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 precisely this covariance is difficult. In our regression we try to correct for this by creating a dummy to catch whether both individuals work in the same 3-digit SNI code.

According to Parlour and Walden (2008), the volatility of wages should reflect the level of labor productivity for each industry sector. As a robustness check, we construct a

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

measure of labor productivity from the Statistics Sweden Output tables that does not come directly from wages. This specification allows us to test hypotheses (1), (3) and (5). We look at the elasticity of labor under the assumption that the industry's production function is Cobb-Douglas,

$$log(Y_{j,t}) = log(A_j) + a_j * log(L_{j,t}) + b_j * log(K_{j,t}) + \epsilon_{j,t}, \tag{1}$$

where indices j and t refer to the 3-digit SNI code j and year t, and where Y is the aggregate value added in real terms, L is the number of employees, and K is the real value of the industry's assets. We filter out a few SNI codes where data was missing or that had very few firms.[11]

We estimate the elasticity of labor, a_j via a random coefficients panel regression, where a_j, b_j, and $log(A_j)$ are treated as random effects. We also add year fixed effects, and we impose an AR(1) structure on the errors within each industry j to allow for potential serial correlation over time. The results conform with standard intuition. Summary statistics of a include a mean of .21, a standard deviation of .09, a minimum of .02, and a maximum of .35. In Table 2 we also report the top and bottom ten industries ranked by their level of labor productivity. Industries such as" manufacturing of construction products" and "recycling of metal waste and scrap" have low labor productivity, whereas industries such as "legal representation activities," "architecture," and "publishing of software" have high labor productivity. We have data on labor elasticity for 104 industries. As with our measures of labor income risk, once we have computed a measure of productivity for each industry, we assign it to each individual-year and aggregate these values by household.

3 Empirical Tests and Results

We are now in a position to test hypotheses H1-H5 in Section 2. For convenience, we repeat the hypotheses below.

H1: The higher the labor productivity of the industry, the higher the wage volatility.

One of the first conclusions of the optimal contracting approach is that in industries in which labor productivity is high, employers have a stronger incentive to elicit high effort

[11]Details are available upon request.

and so expose workers to more risk in order to motivate them. Furthermore, if agents are risk averse then in order to induce them to accept more volatile wages, they must be paid a higher wage. Therefore, there should be a positive correlation between wage levels and wage volatility. We report the correlations between the average level and the volatility of wages and the elasticity of labor in Table 3. The data suggest that the higher the labor elasticity (or productivity), the higher the mean level of wages. This is consistent with a payment that compensates a risk averse agent for wage volatility. In addition, there is a positive correlation between elasticity and wage growth volatility which is consistent with an optimal contracting framework.

Having established the positive correlation between labor productivity and wage volatility, we address the effect of both on portfolio levels and then, on portfolio changes. Here are the hypotheses on the levels.

- H2: Workers with more variable wages have lower exposure to the market through financial assets.

- H3: Workers in higher labor productivity industries have lower exposure to the market through financial assets.

First, consider H2. If human capital is an asset that generates a cash flow stream, then those working in high-productivity sectors, which *ceteris paribus* have riskier income streams, should have a lower share of risky assets and mutual funds. Of course, both employment and human capital are potentially endogenous variables.

As in Vissing-Jorgensen (2004) 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. In order 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 $p^{ra}_{h,t}$, the observed probability of participation in the portfolio of risky assets, with the probit regression,

$$p^{ra}_{h,t} = \alpha^{ra}_{1,t} + \beta^{ra\prime}_{1,t} \cdot \Phi_{h,t} + \gamma^{ra\prime}_{1,t} \cdot X_{h,t} + \epsilon^{ra}_{1,h,t}, \tag{2}$$

where $X_{h,t}$ is a vector of explanatory variables for household h in year t, and $\Phi_{h,t}$ includes either wage volatility or labor productivity along with interaction variables for households where both individuals work in the same industry.

In this and the subsequent regressions, the choice of control variables in the vector $X_{h,t}$ 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, partnered but not married, 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 are deceased or 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/Trellebord 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. 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. We avoid controlling for portfolio shares in previous years, because as we will see in the next section, portfolio shares are extremely predictable over time, which means that including them would capture most of the information from the other variables, including $\Phi_{h,t}$. We also avoid net wealth and financial wealth for the same reasons.

Then, in the second stage, we regress the portfolio shares $w^i_{h,t}$ on $\Phi_{h,t}$, our vector of proxies for either wage volatility (for H2) or labor productivity (for H3). Our main focus is on the portfolio share of risky assets ($i = ra$), but we also repeat the exercise for the portfolio shares of stocks and mutual funds. We also include the same vector $X_{h,t}$ of control variables and Heckman's lambda variable ($\lambda_{h,t}$), which controls for possible selection at the first stage. The equation is as follows,

$$w^i_{h,t} = \alpha^i_{2,t} + {\beta^i_{2,t}}' \cdot \Phi_{h,t} + {\gamma^i_{2,t}}' \cdot X_{h,t} + \theta^i_{2,t} \cdot \lambda_{2,h,t} + \epsilon^i_{2,h,t}, \tag{3}$$

where i refers to the asset class (risky assets, stocks, and mutual funds). Households hedge their labor income risk if $\beta^i_{2,t} < 0$.

The results of the second stage regressions are reported in Table 4 for wage volatility and Table 5 for labor productivity. We only report the results for the year 2002, but the results are almost identical across the years. The coefficients of the control variables are similar across Table 4 and Table 5. The table with wage volatility has 102,049 observations. The table with labor productivity only has 38,403 observations, the reason being that there are fewer industries for which we were able to compute a measure of labor productivity. In these cross-sectional regressions, both switcher and non-switcher households are included.

Multiple variables are strong predictors of portfolio shares. This is not surprising, and it is consistent with the results in Vissing-Jorgensen (2004), Massa and Simonov (2006), and Calvet, Campbell, and Sodini (2007). The richer and more educated households tend to tilt their portfolio toward stocks. This is especially the case for the households for which at least one adult has a business degree.

In terms of real estate and location, we find that conditional on owning real estate, a high ratio of house value to net worth does crowd out participation in the stock market, in line with Cocco (2006). Furthermore, while living in a small urban area does lead to an increase in the share of risky assets and mutual funds, relative to living in a rural area, living in one of Sweden's three metropolitan areas leads to a decrease in the share of risky assets. This may be due to the crowding out effect of the higher home prices in these areas.

In terms of other household characteristics, households who come from Scandinavian countries tend to invest more in mutual funds, which suggests a cultural effect that is consistent with the summary statistics presented earlier. Married, partnered, and single parent households tend to be more invested in risky assets than single households, but less invested in stocks. The coefficient on the number of children is similar, which suggests a potential risk aversion story.

The coefficient on λ_t confirms the selectivity among market participants, despite the high overall participation rate in risky assets. We report the bootstrapped standard errors of the estimates, and for both the shares of risky assets and mutual funds, θ_t is significantly different from 0.

Clearly, from Table 4, controlling for selection bias, the effect of the wage volatility variable is weakly consistent with H2. An increase in wage volatility does lead to a decrease in the portfolio shares of risky assets that is significant at the 5% level. However, it is not necessarily significant from an economic perspective. A 1% increase in wage volatility only leads to a .08% decrease in share of risky assets. Furthermore, from Table 5, the effect of an increase in the labor productivity variable actually leads to an increase, though not significant, in the share of risky assets.

The decomposition of risky assets into directly-held stocks and mutual funds provides some extra insight. For one, there is a clear substitution effect between stocks and risky mutual funds. While an increase in wage volatility leads to a significant increase in the share of stocks, it also leads to a similar decrease in the share of mutual funds. This result is consistent with 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.

One can conjecture other sources of heterogeneity correlated with labor income that affect portfolio selection. For example, households in high productivity industries could be more financially-educated and choose to invest more in individual stocks and less in mutual funds. They might also be of a different type and have separate investment policies. For example, it may be that the less risk averse agents choose to work in riskier industries and invest more in the stock market. Since our cross-section analysis cannot control for these issues, we turn to our main estimation strategy and look instead at changes in the portfolio shares of the switchers, conditional on their initial portfolio shares. This analysis allows us to abstract from the potential heterogeneity in the levels of portfolio shares, and to test H4 and H5 and consider how household investment behavior changes with employment changes.

H4: Workers who switch to a sector with higher wage volatility decrease their exposure to the market through financial assets.

H5: Workers who switch to higher labor-productive sectors decrease their exposure to the market through financial assets.

As with the levels analysis, we implement a two-stage analysis where we begin by controlling for the possibility of a selection bias among market participants, with 1999 as the base year. Equation (4) is similar to equation (2), except that t now refers to year 1999. Then, in the second-stage, we retain the switchers who participated in the stock market in 1999 and study the effect of a change in $\Phi_{h,t}$ between 1999 and 2002 on their portfolio holdings (recall that $\Phi_{h,t}$ contains either wage volatility or labor productivity along with interaction variables for households where both individuals work in the same industry). The equations take the form

$$p^{ra}_{h,t} = \alpha^{ra}_{3,t} + \beta^{ra\prime}_{4,t} \cdot \Phi_{h,t} + \gamma^{ra\prime}_{3,t} \cdot X_{h,t} + \epsilon^{ra}_{3,h,t}, \tag{4}$$

$$\Delta w^{i}_{h,t} = \alpha^{i}_{4,t} + {\beta^{i}_{4,t}}' \cdot \Delta\Phi_{h,t} + {\gamma^{i}_{4,t}}' \cdot X_{h,t} + \varphi^{i\prime}_{t} \cdot Y_{h,t} + \kappa^{i\prime}_{t} \cdot Z_{h,t} + \theta^{i}_{4,t} \cdot \lambda_{4,h,t} + \epsilon^{i}_{4,h,t}. \tag{5}$$

where t refers to year 1999, h indexes switchers, $X_{h,t}$, $Y_{h,t}$, and $Z_{h,t}$ are vectors of control variables, and $\Delta X_{h,t}$ refers to a change in X_h from year t (1999) to year $t+3$ (2002). As in the previous section, we expect households to hedge their labor income risk if $\beta^{ra}_{4,t} < 0$.

To control for different possible explanations, we decompose switchers into three groups: first, a group in which individual #1 switches industries, a second group in which individual #2 switches industries, and a third in which both individuals switch industries. For each group of households we also add an interaction variable that captures change in either their wage volatility or their labor productivity. These groups are not mutually exclusive. For example, the first group includes individuals #2 who are also switching. The idea behind this decomposition is to see whether (i) the hedging effect is strongest for the third group where both individuals switch during the same year, and also whether (ii) the hedging effect is stronger when (the rich) individual #1 switches than when (the less rich) individual #2 switches. We also add two interaction variables for the households who switch in such a way that they end up in the same industry in 2002 and for those who switch in such a way they are no longer in the same industry in 2002.

In the second stage, we include the vector of controls $X_{h,t}$ (described for the previous hypotheses) as well as two other sets of control variables, which we denote as $Y_{h,t}$ and $Z_{h,t}$. These include key variables such as the initial level of net worth and the initial portfolio shares of stocks and risky mutual funds, which captures all the information on the individuals' types under the assumption that types do not vary over time. $Y_{h,t}$ is defined as the vector of these extra controls.

In addition to employment, other household characteristics may have changed during 1999-2002. $Z_{h,t}$ is defined as the vector of these changes. These variables include a dummy on whether the household moved from a rural area to a metropolitan area, a dummy on whether at least one member of the household has died or emigrated, and a variable that computes the change in the number of children. We also look at the change in family disposable income, the change in the Debt-to-Income ratio and create dummies on whether at least one of the adults 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 households has graduated.[12] We avoid controlling for changes in wealth during the time period since some of it comes from the proceeds of the household's portfolio holdings.

The results of equation 5 are reported in Table 7 for wage volatility and Table 8 for labor productivity. For parsimony we do not report the coefficients of the $X_{h,t}$ control variables in 1999. The tables with wage volatility and labor productivity have 6,428 and 1,580 switchers respectively. As expected, the effects of the 1999 levels of portfolio shares are extremely significant, which confirms the high degree of predictability in portfolio shares.

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

Here we find strong evidence that switchers are hedging their labor income risk. Beginning with Table 7, the effect of a change in the level of wage volatility is significant for the switchers, both economically and statistically. In particular, for the double-switchers, an increase in wage volatility by 1% will lead on average to a decrease in the share of risky assets by 1.07%, in absolute terms. This effect is statistically significant at the 5% level.[13] We stress that this percentage is of financial wealth, which in 2002 was around 310,000 SEK (approximately 31,000 USD). This means that a household going from the industry with the least variable wage (recycling metal waste) to the industry with the most variable wage (fund management) will *ceteris paribus* decrease its share of risky assets by almost 25%, or 7,750 USD. The decomposition of risky assets into stocks and mutual funds indicates that the decrease in risky assets is fairly balanced among the two asset classes.

The hedging effect is not as strong but still there for the households where individuals #1 switched. For example, an increase in wage volatility by 1% leads the individual #1 switcher to reduce its share of risky assets by almost .12%.

Table 8 presents similar results with labor productivity. An increase in the coefficient of labor elasticity by 1% leads switchers to decrease their share of risky assets by .32% to .61%. Again, from an economic perspective, it means that households going from the least productive industry to the most productive industry would re-balance their share of risky assets by up to almost 20%. These effects are statistically significant at the 10% and 5% levels, respectively (one-tailed t-tests). We note, however, that the change in labor productivity has little effect on the portfolios of double-switchers. This is not surprising, since the sample size is much smaller with labor productivity. There are only 45 double-switchers, instead of 208 in Table 7. There is also little effect for the households where the individuals switch either to or from the same industry in both tables.

One alternative potential explanation for the fact that the coefficients of the changes in wage volatility and labor productivity are negative is if wage volatility is correlated with wealth. If so, a change in wage volatility could be associated with a change in wealth, which could be the real reason for portfolio changes. We control for this potential factor by looking at the change in household income between 1999 and 2002. Supposedly, households

[13] Although the reported p-value for this coefficient in Table 7 is about 6%, our test of hedging is a one-tail test, and so the relevant p-value is about 3%.

who switch to an industry where they obtain a wage increase have become wealthier. The addition of this variable acts not only as a control but it also indicates the effect of an increase in wealth on the portfolio share of risky assets. In both Tables 7 and 8, we find that an increase in household income leads to a significant decrease in the share of risky assets. This result suggests that this other potential explanation goes the other way, hence strengthening our results.

4 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 (2004)). 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 who switched industries between 1999 and 2002. We study the effect of their industry change – in particular the effect of changes in their wage volatility and labor productivity – on their portfolio holdings of risky assets. Focusing on changes in portfolio holdings for households who switch industries, we find that households do hedge their labor income risk, although the effects do now show in the cross section of levels of portfolio holdings. The effect is economically significant — A household that moves from the lowest to the highest productivity industry decreases its exposure to risky assets by risky by about 25%.

Our results are therefore in line with the findings of Guiso, Jappelli, and Terlizzese (1996) and Vissing-Jorgensen (2004), as well as with those of Massa and Simonov (2006), and suggest that both hedging and other, offsetting, effects are important in households' portfolio decisions. If the strength of these two offsetting effects vary with the business cycle, it is not suprising that the unconditional CAPM with human capital fails (as documented by Fama and Schwert (1977)) but the conditional CAPM with human capital is successful in explaining the cross section of stock returns (as documented by Jagannathan and Wang (1996)).

	All Households				Switchers	
Variable	Mean	Std Dev	Min	Max	Mean	Std Dev
Demograhics						
age	44.9	10.14	18	65	44.62	9.11
nordic	.97	.17	0	1	.98	.13
number of children	1.1	1.14	0	13	1.35	1.16
Civil Status						
married	.57	.49	0	1	.69	.46
partnered	.15	.36	0	1	.16	.37
single	.19	.4	0	1	.11	.31
Education						
student	.06	.23	0	1	.06	.23
college degree	.47	.5	0	1	.53	.50
business degree	.15	.35	0	1	.21	.40
Population Density						
high	.35	.48	0	1	.40	.49
medium	.54	.50	0	1	.51	.50
low	.11	.32	0	1	.09	.29
Labor income						
family income	366.07	161.32	1.07	1243.31	409.13	157.70
is unemployed	.13	.34	0	1	.17	.37
is retired	.13	.34	0	1	.13	.34
Housing and Wealth						
homeowner	.88	.33	0	1	.93	.25
net worth	1.09	1.81	0	154.18	1.3	1.71

Table 1: **Summary statistics from the 2001 wave of the LINDA data set. All monetary values are defined in Swedish kronor (SEK). The average SEK/USD exchange rate on December 28th, 2001 was 10.67.**

There are 102,049 observations and 6,428 switchers. Reported are the age of the household head (age), the number of children, the debt-to-income ratio, the house value-to-net worth ratio, household disposable income, in thousands of SEK, industry averages of wage growth volatility, the average level of wages, and unemployment rate, and household net wealth in millions 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, partnered, single parent, single, deceased, emigrated , student, lives in a high population density area (Stockholm, Gothenburg or Malmo/Lund/Trelleborg), medium population density (more than 27,000 inhabitants and more than 300,000 within 100 km), low population density, retired , homeowner.

Wave Volatility Rankings			Labor Productivity Rankings		
SNI Code	Description	Wage Volatility	SNI Code	Description	Labor Productivity
Bottom 10			**Bottom 10**		
371	Recycling of metal waste and scrap	.07	552	Youth hostels, camping sites	.02
271	Manufacturing of iron and steel	.08	519	Other wholesale	.02
131	Mining of iron and ores	.08	504	Sales and maintenance of motorcycles	.03
173	Finishing of textile	.09	371	Recycling of metal waste and scrap	.04
272	Manufacturing and casting of iron tubes	.09	202	Manufacturing of fibreboard, plywood, etc...	.04
172	Weaving of cotton	.09	364	Manufacturing of sports goods	.05
365	Manufacturing of games and toys	.09	911	Activities of business organizations	.05
274	Production of precious metals, copper	.10	263	Manufacturing of construction products	.06
403	Steam and hot water supply	.10	205	Manufacturing of other products of wood	.06
175	Manufacturing of ribbons, curtains	.10	245	Manufacturing of perfumes and toilet preparations	.06
Top 10			**Top 10**		
21	Renting of household goods	.21	453	Installation wiring, insulation, plumbing	.32
13	Mixed farming	.21	741	Legal representation activities	.32
722	Publishing of software	.22	742	Architecture activities	.32
741	Legal representation activities	.23	211	Manufacturing of pulp and newsprint	.32
672	Other finance activities	.24	601	Urban transport via railways	.33
744	Advertising	.24	341	Manufacturing of motor vehicles	.33
924	Other Entertainment	.25	452	General construction	.33
553	Restaurants	.26	244	Pharmaceutical operations	.34
921	Motion picture and video production	.26	722	Post activities	.35
671	Finance administration, fund management	.30	401	Publishing of software	.35

Table 2: **Rankings of industries by their levels of wage volatility and labor productivity.**

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 level of labor of productivity is defined as the elasticity of output with respect to labor. It is estimated via a random coefficients panel regression on the Output tables from Statistics Sweden. Rankings of the wage volatility and labor productivity measures are based on 191 and 104 observations, respectively.

Variable	Labor Elasticity	Wage Level Mean	Wage Growth Vol
Labor Elasticity	1		
Wage Level Mean	.26***	1	
Wage Growth Vol	.20**	.189*	1

Table 3: **The Pearson correlations between labor elasticity and wage measures.**

There are 104 observations. Labor Elasticity is computed from the Statistics Sweden Output tables. Wage Level Mean is the average level of log real wages per industry, and Wage Growth Vol is the average volatility of annual growth rate of real wages per industry. Both measures are computed from the LINDA data set for individuals who worked in a given sector for at least 5 consecutive years. Test statistics indicate the probability of observing the empirical correlation under the null hypothesis that the correlation is zero. Statistical significance is represented by *** for 1%, ** for 5%, and * for 10%.

Variable	Risky Assets	Stocks	Mutual Funds
Intercept	.912**	-.614***	1.53***
	(8.98)	(.157)	(.232)
wage volatility	-.081**	.536***	-.616***
	(.041)	(.034)	(.048)
wage volatility same industry	.046*	.083***	-.036
	(.026)	(.022)	(.027)
age	-.007***	-.003***	-.004**
	(.001)	(.001)	(.002)
age^2	.06***	.034***	.03*
	(.01)	(.001)	(.001)
nordic	.077***	-.009	.086***
	(.014)	(.019)	(.028)
has deceased	-.14***	-.003	-.137***
	(.041)	(.031)	(.035)
has emigrated	-.037***	.001	-.037***
	(.014)	(.019)	(.014)
number of children	.032***	-.006***	.038***
	(.001)	(.001)	(.002)
single parent	.039***	-.032***	.071***
	(.006)	(.006)	(.013)
partnered	.008	-.027***	.035**
	(.007)	(.008)	(.016)
married	-.002	-.038***	.036***
	(.006)	(.006)	(.011)
student	.024***	.016***	.009
	(.006)	(.005)	(.008)
college degree	.023**	.029***	-.007
	(.004)	(.004)	(.008)
business major	.01***	.025***	-.014***
	(.003)	(.003)	(.004)
high pop. density	-.031***	.025***	-.056***
	(.005)	(.006)	(.007)
medium pop. density	.023***	.005*	.019***
	(.004)	(.005)	(.003)
family income	-.029***	.054***	-.082***
	(.007)	(.053)	(.016)
is unemployed	-.003	-.003	-.001
	(.004)	(.003)	(.004)
is retired	-.002	.004	-.007*
	(.003)	(.003)	(.004)
homeowner	.033***	.046***	-.013
	(.006)	(.006)	(.09)
house value / net worth	.022***	-.017***	.038***
	(.003)	(.006)	(.008)
debt / income	-.001	.001	-.001
	(.001)	(.003)	(.004)
lambda	.269***	.206**	.063
	(.056)	(.086)	(.136)
No. Obs	102,049	102,049	102,049
F	3,209***	4,495***	17,291***

Table 4: **Second-stage estimates of portfolio shares in risky assets (ra), stocks (s), and mutual funds (mf) in 2002 on wage volatility.**

We report second-stage estimates of portfolio holdings as a percentage of financial assets in 2002. The sample is restricted to households with positive holdings only. Three separate OLS regressions are run. The dependent variables are the shares of risky assets (stocks and mutual funds) over financial wealth (columns 1-2), the share of directly-held stocks over financial wealth (columns 3-4), and the share of risky mutual funds (equity and mixed) over financial wealth (columns 5-6). 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. λ is the inverse mills ratio from the first stage estimation of equation (2). We report the bootstrapped standard errors. The superscripts ***, **, and * refer to coefficients statistically distinct from 0 at the 1, 5, and 10% level respectively. F refers to the Wald goodness-of-fit test. In addition to the explanatory variables of Table 1, "age^2" is the squared value of age (scaled by 1000), "house value / net worth" is the ratio of housing wealth over net worth, and "debt-to-income" corresponds to the ratio of debts to household disposable income. Both family income and net worth are in log terms. 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. "Wage Volatility Same Industry" 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.

Variable	Risky Assets	Stocks	Mutual Funds
Intercept	1.325***	-.555***	1.88***
	(.138)	(.203)	(.318)
labor productivity	.064	.111***	-.048
	(.047)	(.034)	(.042)
labor productivity same industry	.038**	.07***	-.032
	(.017)	(.017)	(.021)
age	-.004***	-.001	-.002
	(.018)	(.001)	(.002)
age^2	.03*	.01	.02
	(.02)	(.01)	(.02)
nordic	.04*	-.007	.046
	(.021)	(.026)	(.555)
has deceased	-.094*	-.036	-.057
	(.056)	(.048)	(.068)
has emigrated	-.02	-.003	-.017
	(.023)	(.014)	(.022)
number of children	.031***	-.011*	.042***
	(.003)	(.003)	(.003)
single parent	.033***	-.018*	.051***
	(.01)	(.003)	(.016)
partnered	-.007	-.018	.011
	(.012)	(.013)	(.02)
married	-.004	-.03***	.026*
	(.009)	(.009)	(.013)
student	.02**	.018**	.001
	(.008)	(.007)	(.01)
college degree	.012**	.037***	-.024**
	(.006)	(.007)	(.012)
business major	.001	.027***	-.026***
	(.009)	(.004)	(.007)
high pop. density	-.007	.039***	-.046***
	(.006)	(.005)	(.009)
medium pop. density	.035***	.012***	.023***
	(.004)	(.004)	(.007)
family income	-.063***	.048***	-.111***
	(.009)	(.013)	(.02)
is unemployed	-.003	-.004	-.001
	(.005)	(.004)	(.006)
is retired	-.005	.006	-.012*
	(.005)	(.004)	(.006)
homeowner	.14	.044***	-.03**
	(.009)	(.008)	(.014)
house value / net worth	.033**	-.017***	.05***
	(.005)	(.007)	(.01)
debt / income	-.001	.002	-.003
	(.001)	(.002)	(.003)
lambda	.111	.256**	-.145
	(.08)	(.111)	(.173)
No. Obs	38,403	38,403	38,403
F	2,059***	1,571***	3,485***

Table 5: **Second-stage estimates of portfolio shares in risky assets (ra), stocks (s), and mutual funds (mf) in 2002 on the level of labor productivity.**

We report second-stage estimates of portfolio holdings as a percentage of financial assets in 2002. The sample is restricted to households with positive holdings only. Three separate OLS regressions are run. The dependent variables are the shares of risky assets (stocks and mutual funds) over financial wealth (columns 1-2), the share of directly-held stocks over financial wealth (columns 3-4), and the share of risky mutual funds (equity and mixed) over financial wealth (columns 5-6). Financial wealth is defined as the sum of cash (checking and savings accounts, money-market fund), bond-only mutual funds, stocks, and risky mutual funds. λ is the inverse mills ratio from the first stage estimation of equation (2). We report the bootstrapped standard errors. The superscripts ***, **, and * refer to coefficients statistically distinct from 0 at the 1, 5, and 10% level respectively. F refers to the Wald goodness-of-fit test. In addition to the explanatory variables of Table 1, "age^2" is the squared value of age (scaled by 1000), "house value / net worth" is the ratio of housing wealth over net worth, and "debt-to-income" corresponds to the ratio of debts to household disposable income. Both family income and net worth are in log terms. 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. "Wage Volatility Same Industry" 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.

Variable	All Households Mean	Std Dev	Participation	Switchers Mean	Std Dev	Participation
Panel A: LINDA						
risky assets	.58	.33	.91	.57	.31	.95
stocks	.22	.26	.56	.22	.24	.63
mutual funds	.48	.32	.84	.46	.3	.88
Panel B: SCF I						
stocks	.40	.31	.41			
mutual funds	.30	.26	.30			
Panel C: SCF II						
stocks	.29	.26	.41			
mutual funds	.19	.19	.30			

Table 6: **Participation rates and portfolio shares for participants in 2001.**

Panel A refers to observations from the LINDA dataset. The data set has 102,049 observations overall and 6,429 observations for the switchers. Panels B and C refer to observations from the Survey of Consumer Finances (SCF). In Panel B, 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. Panel C reflects more closely the true risky portfolio shares in the USA. The holdings of mixed mutual funds are halved in order to reflect the fact that they are not fully invested in stocks, and the retirement assets are included.

Variable	Δ Risky Assets	Δ Stocks	Δ Mutual Funds
Intercept	-.44	-.97***	.527**
	(.39)	(.221)	(.29)
ind #1 switchers	-.126	-.01	-.115
	(.157)	(.094)	(.149)
ind#2 switchers	.346	.305	.041
	(.292)	(.194)	(.249)
double-switchers	-.1.073*	-.322	-.751*
	(.569)	(.38)	(.409)
to the same industry	.218	-.177	.395
	(.536)	(.297)	(.495)
from the same industry	-.09	.021	-.111
	(.497)	(.257)	(.409)
Δ household size	.022***	-.006	.028***
	(.008)	(.004)	(.007)
has graduated	-.017	-.009	-.008
	(.023)	(.014)	(.02)
low to high pop. density	-.029	.015	-.044*
	(.031)	(.021)	(.023)
Δ family income	-.154***	-.013	-.141***
	(.018)	(.01)	(.013)
found a job	-.028*	-.01	-.018
	(.016)	(.009)	(.015)
lost a job	.012	-.001	.012
	(.014)	(.007)	(.012)
has retired	.008	.0158	-.007
	(.016)	(.01)	(.012)
Δ debt / income	-.017***	-.001	-.016***
	(.003)	(.002)	(.003)
bought a house	.019	.014	.005
	(.035)	(.016)	(.023)
sold a house	-.086**	-.01	-.075**
	(.038)	(.02)	(.031)
Δ house value / net worth	.054***	-.001	.054***
	(.007)	(.005)	(.007)
net worth	.006*	.006**	.001
	(.004)	(.003)	(.003)
stocks	-.51***	-.464***	-.042***
	(.017)	(.014)	(.013)
mutual funds	-.512***	-.01***	-.502***
	(.012)	(.007)	(.013)
lambda	.634***	.37***	.257**
	(.164)	(.101)	(.153)
No. Obs	6,428	6,428	6,428
F	8,907***	2,813***	5,096***

Table 7: **Regression of changes in the shares of portfolio holdings between 1999 and 2002 on changes in wage volatility for switcher households.**

Second-stage estimates of changes in the shares of portfolio holdings between 1999 and 2002. Three separate OLS regressions are run. The sample is restricted to households with positive holdings of risky assets in 1999. The dependent variables are the change in the share of risky assets (stocks and mutual funds) over financial wealth (columns 1-2), the change in the share of directly owned stocks over financial wealth (columns 3-4), and the change in the share of mutual funds (equity and mixed) over financial wealth (columns 5-6). 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. λ is the inverse mills ratio from the first stage estimation of equation (4). We report the bootstrapped standard errors. The superscripts ***, **, and * refer to coefficients statistically distinct from 0 at the 1, 5, and 10% level respectively. F refers to the Wald goodness-of-fit test. Explanatory variables are changes to family disposable income in logs (family income), changes to house-to-net wealth-ratio (house value / net worth), changes in the debt-to-income ratio (debt / income), and changes in wage volatility (Δ wage volatility) for various groups: "individual#1 (2)" switcher consists of households where individual #1 (2) has switched industries between 2000 and 2001 and stayed in the same industry between 2001 and 2002, "double-switchers" consists of households where both individual #1 and individual #2 switched industries. We include interaction variables, "to (from) the same industry" consists of households where individuals switched industries in a way that they are both (no longer) in the same 1-digit SNI code in 2002. 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 a job), employed in 1999 but not in 2002 (lost a job), no real estate in 1999 but owns real estate in 2002 (bought a house), and if the household owns real estate in 1999 but owns no real estate in 2002 (sold a house). We also control for 1999 levels of net worth (logs) and shares of stocks and mutual funds.

Variable	Δ Risky Assets	Δ Stocks	Δ Mutual Funds
Intercept	.001	-.88**	.889*
	(.845)	(.414)	(.507)
ind #1 switchers	-.32	-.227**	-.092
	(.205)	(.105)	(.192)
ind#2 switchers	-.616**	-.221	-.395
	(.278)	(.165)	(.284)
double-switchers	-.037	-.159	.121
	(.559)	(.43)	(.548)
to the same industry	.661	.306	.355
	(.488)	(.291)	(.624)
from the same industry	.35	-.019	.369
	(.532)	(.326)	(.402)
Δ household size	.053***	.003	.05***
	(.015)	(.009)	(.017)
has graduated	-.018	.038	-.056
	(.061)	(.034)	(.056)
low to high pop. density	-.05	.037	-.087*
	(.061)	(.04)	(.052)
Δ family income	-.193***	.017	-.209***
	(.038)	(.02)	(.02)
found a job	-.006	.025	-.032
	(.031)	(.017)	(.027)
lost a job	.05*	.025*	.026
	(.026)	(.014)	(.031)
has retired	.006	.01	-.004
	(.03)	(.018)	(.022)
Δ debt / income	-.018***	.001	-.018***
	(.005)	(.003)	(.004)
bought a house	-.004	.01	-.014
	(.061)	(.023)	(.049)
sold a house	.0126	.032	-.0196
	(.078)	(.037)	(.075)
Δ house value / net worth	.05***	-.013	.063***
	(.015)	(.011)	(.013)
net worth	.007	.001	.006
	(.009)	(.005)	(.009)
stocks	-.513***	-.44**	-.073***
	(.034)	(.029)	(.028)
mutual funds	-.52***	-.002	-.518***
	(.023)	(.012)	(.024)
lambda	.51	.178	.33
	(.42)	(.228)	(.251)
No. Obs	1,580	1,580	1,580
F	2,280***	1,345***	1,357***

Table 8: **Regression of changes in the shares of portfolio holdings between 1999 and 2002 on changes in the level of labor productivity for switcher households.**

Second-stage estimates of changes in the shares of portfolio holdings between 1999 and 2002. Three separate OLS regressions are run. The sample is restricted to households with positive holdings of risky assets in 1999. The dependent variables are the change in the share of risky assets (stocks and mutual funds) over financial wealth (columns 1-2), the change in the share of directly owned stocks over financial wealth (columns 3-4), and the change in the share of mutual funds (equity and mixed) over financial wealth (columns 5-6). 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. λ is the inverse mills ratio from the first stage estimation of equation (4). We report the bootstrapped standard errors. The superscripts ***, **, and * refer to coefficients statistically distinct from 0 at the 1, 5, and 10% level respectively. F refers to the Wald goodness-of-fit test. Explanatory variables are changes to family disposable income in logs (family income), changes to house-to-net wealth-ratio (house value / net worth), changes in the debt-to-income ratio (debt / income), and changes in wage volatility (Δ wage volatility) for various groups: "individual#1 (2)" switcher consists of households where individual #1 (2) has switched industries between 2000 and 2001 and stayed in the same industry between 2001 and 2002, "double-switchers" consists of households where both individual

#1 and individual #2 switched industries. We include interaction variables, "to (from) the same industry" consists of households where individuals switched industries in a way that they are both (no longer) in the same 1-digit SNI code in 2002. 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 a job), employed in 1999 but not in 2002 (lost a job), no real estate in 1999 but owns real estate in 2002 (bought a house), and if the household owns real estate in 1999 but owns no real estate in 2002 (sold a house). We also control for 1999 levels of net worth (logs) and shares of stocks and mutual funds.

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