Benefits of Contribution: Individual Asset Allocation, Diversification and Welfare in a Defined Contribution Pension System

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Abstract

We analyse the new Swedish pension system, which constitutes a partial defined contribution plan where individuals can choose from hundreds of mutual funds to invest part of their pension savings, making them bearing part of the investment risks themselves. We perform a factor analysis in order to explore the actual asset classes that are driving the returns of the mutual funds available to individuals. The large amount of mutual funds can be represented with only a few orthogonal factors or distinct asset classes. Moreover, we investigate individuals' asset allocation choices and relate individuals' factor exposures to a number of demographic and socio-economic variables in order to find out who holds what, and whether asset allocation and diversification differ with respect to individual characteristics. We find that sophisticated individuals are more likely be active participants in the pension system and tend to load less on a general index factor and bond factors than less sophisticated individuals. Moreover, we find significant differences in individuals' portfolio performance, the most eye-catching result being that men show better performance than women. We argue that systematic differences in asset allocation and performance might give rise to unwarranted distribution effects in the new pension system.

Key words: Defined contribution pension plans; Individual investors; Asset allocation; Performance

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1. Introduction

Currently, there is a trend for countries to move away from defined benefit pension systems towards partially defined contribution plans. There are several reasons for this trend, the perhaps most important being the worldwide phenomenon of aging populations. The key issue in moving to a defined contribution plan is to make individuals not only more conscious of their own pension schemes, but also to let them bear investment risks previously borne by governments or employers (Bodie and Crane, 1998). We analyse the new Swedish pension system, a partial defined contribution plan, with hundreds of mutual funds available to individuals for investing part of their pension savings. Our focus is on the available actual asset classes, individuals' asset allocation and their performance within the defined benefit part of the pension plan.

Our analysis is carried out in three steps. In the first step, we perform a factor analysis in order to explore the latent factors, or actual asset classes, that are driving the returns of the mutual funds. We find that although there appears to be a wide range of choices available to individuals, the large amount of mutual funds can be represented with only a few orthogonal factors or distinct asset classes. By using the ten most important factors, we are able to account for more than 90 percent of the total variance of returns for the original set of 465 mutual funds. In other words, allowing for roughly ten percent noise, about ten orthogonal asset classes are available for investors to choose among in the initial round of investment in the defined contribution part of the Swedish pension system.

We identify the factors in terms of real world asset classes or indices. The by far most important factor is easily identified as an overall, world market index. Moreover, among the others we find factors covering equity from Japan, the Far East, and different types of fixed income securities. We argue that there are clearly a lot of redundant mutual funds present in the initial choice set. Also, a choice among say ten orthogonal factors, or distinctly different indices, would facilitate an easier and more efficient individual asset allocation than the actual choice between 465 different, or sometimes not so different, mutual funds.

In the second step of our analysis, we investigate individuals' asset allocation choices within the Swedish defined pension contribution system. Using a sample of individuals taking part in the defined contribution pension portfolio formation in the year 2000, we analyse the individuals' loadings and communalities with respect to the different factors. We also relate the individuals' factor exposures to a number of demographic and socio-economic variables, using the two-step procedure according to Heckman (1976), in order to find out who holds what, and whether asset allocation and diversification differ with respect to individual characteristics. Hence, we first use a probit model to estimate an individual's likelihood of making an active choice, rather than ending up in the default alternative, and second, use a seemingly unrelated regression system to model individuals' factor communalities, taking the likelihood of activity into account. The results show that sophisticated individuals are less inclined to load on the general index factor and bond factors than less sophisticated individuals. More sophisticated individuals have a higher probability of making an active choice, and the result of this activity is to reduce the loading on the overall market factor and domestic Swedish bond factors.

In the third part of the study, we investigate the performance of the individuals' portfolios over the first four years since the introduction of the new Swedish pension system. We use Jensen's alpha from a regression of an individual's monthly excess return on excess returns on a set of market indices as our measure of performance.

The contributions to previous research of this study are several. First, there are very few studies on the investment opportunities available for individuals in defined contribution plans (see Blake, et al., 2004). Our analysis of the investment opportunities of the Swedish defined contribution plan identifies 13 core assets classes among the available 464 mutual funds. Second, when using our extensive database of individuals' actual choices within the partial defined contribution pension system we can investigate diversities in asset allocation with respect to individuals' characteristics. The factor analysis of the offered set of mutual funds facilitates an analysis of individuals' choices of orthogonal asset classes, which highlights different individuals' tendencies to diversification, rather than the "naïve" diversification of simply investing in several, possibly highly correlated, mutual funds.[2] Third, we evaluate the performance of the individuals' portfolios within the pension plan. Here we extend the analysis of Blake et al. (2005) to an individual level. Again, we analyse individual performance in detail, highlighting differences with respect to individual demographic and socio-economic characteristics. Therefore, we can identify groups of superior performance relative other groups, who benefit from the shift from the old defined benefit to the new defined contribution pension system. Hence, our results have several policy implications, both on an individual investor level, e.g. for individual pensioners in terms of asset allocation and

[2] See Benartzi and Thaler (2001).

performance, and on a larger economy-wide scale, for policy makers dealing with the construction of pension schemes.

The rest of the study is organised into five sections. The following section briefly presents the Swedish pension system, with emphasis on individual choice in the defined contribution part. Section 3 outlines the factor analysis framework for extracting latent factors from the mutual funds available to the individuals. In section 4, we relate the factor analysis to the individuals' asset allocation and their factor loadings, whereas in section 5 we evaluate the performance of the individuals' portfolios. The study ends in section 6 with some concluding remarks.

2. The Swedish pensions system: a mixture of defined benefit and contribution

The new pension system was introduced in Sweden in the autumn of 2000 and consists of three parts. The first and largest part is the income pension, which is based on 16 percent of the annual income and is used to finance those who are retired today. The amount paid in also serves as a base in calculating future pension payments. The second part, the premium pension, is based on 2.5 percent of the annual income. In the first round in 2000, 2.5 percent of the previous four years of income was invested. This amount was allocated at each individual's discretion.

Each individual was presented with an investment opportunity set of 464 funds[3] and invited to choose between one and five funds.[4] If no choice was made, the allotted money was invested in the Seventh Swedish Pension Fund run by the government. This default alternative is an equity fund and cannot be chosen once the investor has made an active choice. The resulting investment portfolio can be altered as often as the individual investor wishes. The accrued amount will be paid out on a monthly basis to the individual at the time of her or his retirement. The third part of the system is a guaranteed pension level designed to ensure that no retiree will be completely without pension payments at the time of her or his retirement, regardless of her or his previous income. In total, 18.5 percent of the annual income for each individual is invested to finance this system, and all annual income from the age of 16 is included. However, an individual earning more than 7.5

[3] 464 funds were available in the 2000 brochure. The 2003 brochure contains more than 600 funds.
[4] The Swedish pension system is described in further detail at www.ppm.nu and www.pension.nu. See also Engström and Westerberg (2003), Karlsson (2005) and Säve-Söderbergh (2003).

income base amounts[5] per year will only be accredited an upper limit of 7.5 income base amounts, although he/she will still pay 18.5 percent of his/her income to finance the pension system.

During autumn 2000 all participants in the Swedish pension system were provided with a brochure containing 464 mutual funds with accompanying information on risk, historical returns, fees, and a few words briefly describing each fund. Table 1 provides an extract from the brochure, with information on one randomly chosen fund available for the investors as an example. Apart from the information exemplified in Table 1, the funds are also categorised at three different levels in the brochure (see Table 3).

3. Asset classes in the current Swedish pension system

In order to evaluate individuals' asset allocation and performance, we first investigate the investment opportunities available to the individuals at the time of the initiation of the partial defined contribution system in Sweden. In the year 2000, individuals could choose among 465 different mutual funds, including the default alternative, with different asset allocation approaches and fund managers. Our analysis aims at exploring the latent factors, or actual asset classes, driving the returns, and thus the investment performance, of the mutual funds. We extract a set of latent factors from the correlation matrix of mutual fund returns, and then try to identify the factors by comparing the factor loadings for the different underlying mutual funds.

3.1 Factor analysis: how many factors are covered by the current system?

In order to perform the factor analysis we need to estimate a correlation matrix of the mutual fund returns. We collect monthly data on mutual fund price quotes and dividends during the period from December 2000 through December 2004. Then we calculate monthly log returns, including dividends, for each mutual fund over the sample period, leaving us with 465 return series, each containing 44 monthly observations. During the four-year sample period a number of mutual funds have ceased to exist for different reasons. Our main purpose with the factor analysis is to evaluate the number of different asset classes available to the individual investors in 2000, when the defined contribution part of the pension system was initiated, and the initial choices of mutual funds were made. Hence, in order to retain an investor perspective, and to avoid a selection bias in the factor analysis, we keep track of all changes in the initial set of mutual funds over the sample

[5] For the year 2000, one income base amount equals SEK 38,800.

period. Over the four-year period, 58 mutual funds were terminated, and the invested money was transferred into another fund managed by the same company. In this case, we start to calculate monthly log returns from December 2000 using the initial mutual fund, and then simply roll over to the new mutual fund during the termination month, and continue to calculate log returns. Another 186 funds were terminated, where it was up to each individual investor involved to redistribute the invested money. Here, the investors could choose to invest the money from the terminated fund into any fund available at the termination date, including new funds not available in 2000. If no choice was made, the money was transferred to the default fund, which is a government run equity fund. For simplicity, we let the return series of terminated funds equal the default fund return from the termination date. Finally, four funds are excluded from the analysis due to lack of data. As a result, we have 449 mutual fund returns as input into the factor analysis, including the default fund.

We perform a principal component factor analysis on the 449 times 449 correlation matrix of fund returns, where the purpose is to identify the common factors that are responsible for the correlations among the mutual fund returns. We use the following basic factor model for the mutual fund returns:

(1) $$R_{i,t} = \alpha_{i,1}F_{1,t} + \alpha_{i,2}F_{2,t} + \ldots + \alpha_{i,m}F_{m,t} + \varepsilon_{i,t}$$

where $R_{i,t}$ denotes the standardised return on mutual fund *i* in period *t*, $F_{j,t}$ is the common factor *j* return, where *j* = 1, …, *m*, $\alpha_{i,j}$ is the loading of return *i* on factor *j*, and $\varepsilon_{i,t}$ is a factor return, unique to mutual fund *i*, with mean zero and variance equal to σ_i^2. Since we carry out the factor analysis using a correlation matrix, it is convenient to express the factor model according to equation (1) in terms of standardised returns.

Factor analysis rests on the assumption that the total variance of mutual fund returns can be decomposed into two components; the variance that is common with each factor, the commonality of the fund return with each factor, and the unique fund return variance. From equation (1), we can obtain the variance of the return on mutual fund *i* as:

(2) $$Var(R_{i,t}) = \alpha_{i,1}^2 Var(F_{1,t}) + \alpha_{i,2}^2 Var(F_{2,t}) + \ldots + \alpha_{i,m}^2 Var(F_{m,t}) + Var(\varepsilon_{i,t}) =$$

$$\alpha_{i,1}^2 + \alpha_{i,2}^2 + \ldots + \alpha_{i,m}^2 + \sigma_i^2$$

where the second equality follows from the standardisation that the variance of each factor *j* equals one. Using equation (2), the square of each loading is referred to as the shared variance between the fund and each factor returns, whereas σ_i^2 corresponds to the unique, idiosyncratic fund return variance. That is, the shared variance between a fund and a factor returns is the fund's communality with the factor. We use the communality as a measure of the degree to which the fund is a good and reliable measure of the factor. The sum of the squared loadings equals the total communality, i.e. the part of the fund return variance that is shared with all *m* factors.

Initially, the principal component factor analysis produces an equal number of latent orthogonal factors, as there are mutual fund return series. However, the aim with the analysis is to reduce the amount of relevant factors, and to keep the *m* most important ones, namely the factors that can explain a large part of the variation among the returns. Moreover, the rest of the factors are treated as noise, or according to equation (1) as unique factors, not common to all mutual fund returns. Table 2 presents the initial factor solution. Here, we retain $m = 23$ factors, together responsible for more than 97 percent of the variation among the returns. Each of the 23 factors is associated with an eigenvalue larger than one, i.e. sum of squared factor loadings, which is the most common rule of thumb used as an aid in selecting the appropriate number of factors.

The initial results of the factor analysis are very powerful. With only 23 orthogonal factors we are able to explain more than 97 percent of the variation in the original 449 mutual fund returns. Hence, we can deduce that with more than 97 percent accuracy, it is possible to represent the mutual funds with only 23 factors. As a result, the apparent wide range of choices available to an investor in the defined contribution part of the Swedish pension system can be reduced to a much more narrow choice among only 23 uncorrelated factors or asset classes.

3.2 Identifying the factors: which asset classes are covered?

The results from the factor analysis are useful only if we can identify the factors in terms of the asset classes each factor represents. First, we are interested in the real economic meanings of the factors. Indeed, if we can interpret the factors in terms of actual economic and/or financial variables it lends credibility to the factor analysis, and increases our confidence that we extract economic influences rather than random noise. Second, we must identify the factors properly to be able to use them in the subsequent analysis, where we first investigate individual factor loadings in terms of asset allocation, and then evaluate the performance of the individuals' portfolios.

To interpret the factors we perform an orthogonal factor rotation using the varimax rotation method. The varimax method is an orthogonal rotation procedure of the initial solution to the factor analysis from Table 2 that minimizes the number of fund returns with high loadings on each factor.[6] Table 2 presents the rotated factor solution. Note that the rotated factor solution consists of the same amount of 23 factors, explaining the same fraction, 97 percent, of the return variation among the mutual funds. However, each individual factor is left with a different fraction of the total explanatory power.

Turning to the actual interpretation of the rotated factor solution, in Table 3 we present average total communalities and factor loadings for the mutual funds, divided into the fund categories presented to the individual investors. All average total communalities are very high, with an overall average equal to 97.59 percent. This means that the 23 retained factors can explain more than 97 percent of the return variance for an average mutual fund. The first rotated factor has a reasonably straightforward interpretation as an overall (global) equity market portfolio. All general equity funds, domestic as well as foreign, have high loadings on this first factor, whereas the speciality equity funds and fixed income funds on average show lower corresponding loadings. We interpret the second factor as a Japan related equity factor, due to the high loadings for the Japan country equity funds, whereas we label the third an Asian or Far East equity factor, since the Asia and Far East regional equity funds show high loadings.

Mutual funds in the categories Europe and Euroland, and others, fixed income together with foreign equity and fixed income have high loadings on the fourth factor. Therefore, we interpret factor four as a European fixed income factor. Factors five and six are associated with high negative loadings for Swedish fixed income funds with long and short maturity respectively. We can label these factors as short in long- and short-term bonds or alternatively, long in corresponding bond yields.

The six most important rotated factors together account for 85 percent of the variance in the mutual fund returns (see Table 2). These factors are also relatively easy to interpret given the

[6] For details, see Sharma (1996).

average factor loadings in Table 3. From factor seven and onwards, the interpretation becomes somewhat more awkward. As an additional aid in the interpretation we present information of the fund with the highest absolute loading on each factor in Table 4. Here we also display a summary of our final identification of each of the 13 most important factors.

From Table 3 we see that European and UK equity funds load high on factor seven. Moreover, from Table 4 we can deduce that the highest loading on factor seven belongs to a European property fund. Given this information, we interpret this factor as a European real estate factor. Factor eight is relatively straightforwardly interpreted as a US bond factor. Factor nine appears to affect only two mutual funds in our sample, namely the two fixed income funds from the Norwegian company Industrifinans. Given the fact that each of the two loadings is quite high, almost 0.80, we associate this factor with a Norwegian fixed income dimension. Finally, based on loadings information from Tables 3 and 4, factors ten through 13 are associated with information technology stocks, high yield bonds, eastern European equity, and biotech stocks respectively.

To summarise the results from the factor analysis we see that by using e.g. the ten most important rotated factors, we are able to account for more than 90 percent of the total variance of returns for the set of 465 mutual funds. In other words, allowing for roughly ten percent noise, there are about ten orthogonal asset classes available for investors to choose among in the initial round of investment for the defined contribution part of the Swedish pension system. In practise it is of course not possible to invest in our latent orthogonal factors. Nevertheless, we argue that a similar set of choices can be obtained by replacing the rotated factors with real world indices according to the interpretations above. In any case, there are clearly a lot of redundant mutual funds present in the initial choice set. Remember that each individual could choose to invest in a maximum of five different mutual funds. We argue that a choice among say ten orthogonal factors, or distinctly different indices, would facilitate an easier and more efficient individual asset allocation than the actual choice between 465 different, or sometimes not so different, mutual funds.

4. Individual asset allocation: who holds what?

After identifying the factors driving the mutual fund returns, we now turn to the actual asset allocation choices made by individuals in the first round of the new Swedish pension system. Using a sample of individuals taking part in the 2000 defined contribution pension portfolio formation we analyse the individuals' loadings and communalities with respect to the different factors. We relate individuals' factor exposures to a number of demographic and socio-economic variables using regression analysis, in order to find out who holds what, and whether asset allocation and diversification differ with respect to individual characteristics.

4.1 Data on individual choices and characteristics

Our data comes from the first round of investment choices made in the new Swedish pension system, coupled with a number of surveys on demographic and economic variables. The data constitutes a sample from a cross section of individuals in the Swedish work force. The first pension investments in the new pension system, in autumn 2000, involved 4.4 million individuals. Their investment choices are linked with individual demographic data collected by Statistics Sweden for the year 2000.[7] Statistics Sweden surveys 15,000 households that represent a cross section of the whole population in Sweden. This compiled data set makes it possible to study investment behaviour in great detail. For each individual there is information on the amount invested, which funds and how many funds the individual has invested in. Also, the age, gender, education, occupation, disposable income and net wealth for the same individual are included in the data set. From the 15,651 individuals with complete individual information in the data set, 10,375 individuals (66.4%) made an active investment decision. The remaining 5,276 individuals (33.7%) did not make an active investment decision. Instead, they are assigned to the default alternative: the Seventh Swedish Pension Fund, which is an equity fund run by the government. Based on the information regarding the individuals' choices, we treat the default alternative as an entirely passive choice. Even if an individual considered the default fund to be the optimal choice, and acted accordingly, he/she shows up as making a passive choice in the data set.

4.2 Individual factor loadings and asset allocation

The initial portfolio for each individual in our sample can contain positions in a maximum of five mutual funds, where each mutual fund loads on the common factors according to equation (1). Hence, for each individual k, we characterise the individual portfolio return in period t as:

$$(3) \qquad r_{k,t} = \sum_{p=1}^{h} w_{k,p} R_{p,t} = \sum_{p=1}^{h} w_{k,p} (\alpha_{p,1} F_{1,t} + \ldots + \alpha_{p,m} F_{m,t} + \varepsilon_{p,t})$$

[7] Data sources from Statistics Sweden are, HEK 2000; a report on household economy, IoF 2000; income report and SUN 2000; educational status. These three reports are for the total population in Sweden. They are linked to a survey on 15,000 households reporting in-depth wealth statistics.

where h = 1, …, 5 denotes the number of mutual funds chosen by individual k, and the weight $w_{k,p}$ is defined as the relative amount of money spent on fund p by individual k. The variance of the individual return can be written as:

$$(4) \qquad Var(r_{k,t}) = \sum_{p=1}^{h} w_{k,p}^2 Var(R_{p,t}) + \sum_{\substack{p=1 \\ p \neq q}}^{h} \sum_{q=1}^{h} w_{k,p} w_{k,q} Cov(R_{p,t} R_{q,t}) =$$

$$\sum_{p=1}^{h} w_{k,p}^2 (\alpha_{p,1}^2 + \ldots + \alpha_{p,m}^2 + \sigma_p^2) + \sum_{\substack{p=1 \\ p \neq q}}^{h} \sum_{q=1}^{h} w_{k,p} w_{k,q} (\alpha_{p,1}\alpha_{q,1} + \ldots + \alpha_{p,m}\alpha_{q,m} + \sigma_{p,q})$$

where σ_p^2 denotes the unique return variance of fund p, and $\sigma_{p,q}$ is the covariance between fund p and q returns, that cannot be accounted for by the m most important factors. For each individual k, ignoring the unique variance and covariance terms in equation (4), we define the total communality as follows:

$$(5) \qquad \overline{\alpha}_k = \sum_{p=1}^{h} w_{k,i}^2 (\alpha_{i,1}^2 + \alpha_{i,2}^2 + \ldots + \alpha_{i,m}^2) + \sum_{\substack{p=1 \\ p \neq q}}^{h} \sum_{q=1}^{h} w_{k,p} w_{k,q} (\alpha_{p,1}\alpha_{q,1} + \ldots + \alpha_{p,m}\alpha_{q,m})$$

and the communality for each individual on a certain factor j as:

$$(6) \qquad \overline{\alpha}_{k,j} = \sum_{p=1}^{h} w_{k,p}^2 \alpha_{p,j}^2 + \sum_{\substack{p=1 \\ p \neq q}}^{h} \sum_{q=1}^{h} w_{k,p} w_{k,q} \alpha_{p,j} \alpha_{q,j}$$

In equation (5) $\overline{\alpha}_k$ is a measure of the exposure for all m factors for individual k, whereas in equation (6) $\overline{\alpha}_{k,j}$ is a corresponding measure of the individual's exposure to factor j only, where $j < m$. Both measures are calculated for individuals making an active choice, as well as for individuals with the passive choice of the default fund alternative. Note that all individuals with the default choice have the same exposure to the factors according to equation (5) and (6).

We want to analyse differences among individuals with respect to the factor communalities, and thus asset allocation. However, first we need to take into account the sample selection issue that we have “passive” individuals in our sample, the ones not making an active choice or with preference for the default alternative. To simply ignore the “passive” individuals would induce a selection bias if their characteristics prove to be different from those of the “active” individuals. Hence, it is necessary to jointly model the factor communalities and the likelihood of making an active choice. This is accomplished within a nested type of model. In essence, the model presumes that each individual jointly considers two investment choices. The first is the choice of whether to be active or passive, and the second, given that the individual decides to make an active choice, is to choose the desired loading on each factor. We estimate the model using the two-step procedure according to Heckman (1976), where we first use a probit model to estimate the likelihood of making an active choice, and second, use a regression analysis to model individuals’ factor communalities, taking the likelihood of activity into account.

First, consider the choice of activity for an individual. Let z be a nominal variable with two outcomes: $z = 1$ if the individual chooses to make an active investment decision and $z = 0$ if he or she chooses to be passive. Define $\Pr(z=1)$ and $\Pr(z=0)$ as the individuals’ probability of making an active or passive choice respectively. For each individual k we model the choice of activity according to:

$$z_k = \boldsymbol{\gamma}'\mathbf{w}_k + \xi_k \tag{7}$$

where $\mathbf{w}_k$ is a vector of explanatory variables for the activity choice of individual k, $\boldsymbol{\gamma}$ is a vector of coefficients measuring the effect of each explanatory variable on the activity choice, and ξ_k is a residual term. We estimate the coefficients in equation (7) by using the maximum likelihood probit estimation technique. Accordingly, $\Pr(z_k=1)=\Phi(\boldsymbol{\gamma}'\mathbf{w}_k)$ and $\Pr(z_k=0)=1-\Phi(\boldsymbol{\gamma}'\mathbf{w}_k)$, where $\Phi(.)$ denotes the standard normal cumulative distribution function.

Second, we relate the individual communality on each factor $\overline{\alpha}_{k,j}$ from equation (6) to a set of explanatory variables using regression analysis. In the regression analysis we analyse individuals with an active choice only. Hence, to take the activity choice into account, we need to perform a conditional regression analysis with the dependent variable $\overline{\alpha}_{k,j}\big|z_k=1$. Conditioning on the variables that are thought to help explaining individuals’ communalities, and using the second step in Heckman’s (1976) estimation procedure, the regressions are formulated as:

(8) $\overline{\alpha}_{k,j} = \boldsymbol{\beta}'_j \mathbf{x}_k + \beta_{\lambda,j} \lambda_k (\hat{\boldsymbol{\gamma}}'\mathbf{w}) + \eta_{k,j}$

Equation (8) forms a system of *m* regression equations, where $\mathbf{x}_k$ is a vector of explanatory variables, $\boldsymbol{\beta}_j$ is a vector of regression coefficients in equation *j*, including a constant term $\beta_{0,j}$ and slope terms $\beta_{q,j}$, relating the factor-specific communality *j* to explanatory variable *q*, and $\eta_{k,j}$ is a corresponding error term. The function $\lambda_k(\hat{\boldsymbol{\gamma}}'\mathbf{w}) = \phi(\hat{\boldsymbol{\gamma}}'\mathbf{w}) / \Phi(\hat{\boldsymbol{\gamma}}'\mathbf{w})$ is known as the inverse Mills ratio, or the hazard function, for the normal distribution from the probit estimation of equation (7). Heckman (1976) motivates the inclusion of $\lambda_k(\hat{\boldsymbol{\gamma}}'\mathbf{w})$ as an explanatory variable in equation (8). Given that we use only individuals who have made an active choice ($z_k = 1$) in the regressions according to equation (8), the regression coefficients in $\boldsymbol{\beta}_j$ now can be consistently estimated without incurring a selection bias.

In equation (8), for each individual *k*, we expect the asset allocation choices between the *m* different factors, and the individual factor communalities, to be interrelated, and thus the error terms to be correlated across equations. To take this cross-equation correlation into account, we estimate the *m* regression equations simultaneously using Zellner's (1962) SUR technique.

In the probit estimation of equation (7), we use a set of individual characteristics in the vector for explanatory variables $\mathbf{w}_k$. The inclusion of explanatory variables in the first pass analysis of individual activity is based on the results of Engström and Westerberg (2003), and Karlsson and Nordén (2004). We let the vector of explanatory variables $\mathbf{x}_k$ in equation (8) include all variables in $\mathbf{w}_k$, plus an additional set suitable for the SUR model, but not for the probit model.

Both individual activity and asset allocation are related to the level of investor sophistication (Grinblatt and Keloharju, 2001, Karlsson and Nordén, 2004). We represent investor sophistication by four sets of variables in both the probit and the SUR regression analysis: i) level of education, less than high school, high school or more than high school education, where we include dummy variables for less and more than high school education, EDU_1 and EDU_2 respectively; ii) the (natural log of the) amount of money invested in the pension system (MONEY), where we argue that a large amount of money should cause the investor to pay closer attention to his or her investment choice; iii) the natural log of disposable income (INCOME); and iv) the natural log of net wealth (WEALTH). We presume that these variables are positively correlated with investor sophistication and, following previous evidence, that more sophisticated individuals ought to invest in more diversified portfolios with respect to the different factors.

Related to the investor sophistication issue are individuals' total portfolios of financial holdings, apart from the investment in the defined contribution pension fund system. Accordingly, we include dummy variables RISKY = 1 if an individual owns risky assets (stocks or other mutual funds) prior to the pension investment, and zero otherwise, and NONRISKY = 1 if an individual has prior holdings of risk-free assets (bonds or other fixed income securities), and zero otherwise, in the SUR regression analysis. To some extent, an individual can be regarded as more sophisticated with respect to asset allocation if he or she has prior experience with assets like stocks, mutual funds or bonds. Hence, we incorporate the two dummy variables in the probit regression model as well.

Individuals' occupation also influences their asset allocation decisions, in particular when the decisions are related to pension investments. Karlsson and Nordén (2004) find it more likely for an individual to be home biased if she has a high level of job security. Such an individual is more likely to stay employed, and still earn an income, even if domestic markets go down. Also, the return on investments will increase if the domestic market goes up, thus hedging the individual's purchasing power. In Sweden, an individual working in the public sector usually has a high level of job security and the risk of unemployment is relatively small.[8] We expect a different asset allocation behaviour for government employees than for individuals who are privately or self-employed. Hence, we include dummy variables for private employment (OCC_2), self-employment (OCC_3), and unemployment (OCC_4), to separate from the base case individuals who are government employees. We include the occupation dummy variables in both the probit and the SUR model.

We include a gender dummy variable MEN = 1 if the individual is a man, and zero if she is a woman, a dummy variable MARRIED = 1 if the individual is married, and zero if he or she is unmarried, and an interaction term MEN_MAR = 1 if the individual is a married man, and zero otherwise. Barber and Odean (2001) find evidence suggesting that men are more overconfident than women, and also relatively more likely to take risks. Moreover, Barber and Odean (2001)

[8] According to statistics from Statistics Sweden and The National Board of Labor Markets, in the year 2000, the percentage of employees loosing their jobs was 1 percent in the private sector and 0.1 percent in the public sector.

argue that marriage might weaken the gender effect. Given these results, we expect to find differences in asset allocation and factor communalities with respect to marital status and gender, in particular individuals' choices between risky and not so risky factors according to the SUR model in equation (8). Given the results from Engström and Westerberg (2003), that gender and marital status seem to be important explanatory sources for the activity choice, we include the three dummy variables related to gender and marital status in the probit analysis as well. Finally, individual age is included in both the probit and the SUR model estimation. Age is directly related to the investment horizon, which is known to affect asset allocation decisions (Karlsson, 2005).

As additional explanatory variables in the SUR model, we use four dummy variables representing the number of chosen mutual funds for each individual within the pension system (each investor can choose one to five funds). We let $D_2 = 1$ if two funds are chosen and zero otherwise, $D_3 = 1$ if three funds are chosen and zero otherwise, etc., leaving us with the base case of choosing one fund in the regression model. Benartzi and Thaler (2001) indicate that the complicated reality of portfolio diversification may cause inexperienced investors to diversify in a naïve manner, believing that many assets diversify better than fewer assets. This is not always true in the Swedish pension system, where the investment opportunity set contains a lot of mutual funds but only a few asset classes, or orthogonal factors. Nevertheless, it is reasonable to assume that it is more likely for an individual to load on several factors the larger amount of funds he or she chooses.

We also control for the percentage transactions cost paid by each individual for the contribution pension fund investment (FEE) and a proxy for the risk associated with each individual investment. We use two measures of portfolio risk. The first measure (STDEV) directly uses the numerical value of the annualised standard deviation of three-year monthly historical portfolio returns for the three years 1997 through 1999. The portfolio standard deviation is calculated by taking each portfolio's weighted average returns for the past 36 months and then calculating the standard deviation of this average return series, thus capturing covariance in returns. The second measure (RISKCAT) is simply each individual's weighted average category of risk, according to the classification based on standard deviation (see Table 1).[9] Finally, the variable RETURN is calculated based on the fund information as exemplified in Table 1. We use the compounded

[9] In the empirical analysis we concentrate on the RISKCAT measure of risk, because the model fit is better using this measure rather than STDEV. However, the regression results are virtually the same irrespective of which measure of risk we use as explanatory variable.

annual return for the three years 1997 through 1999. For each individual, the return is calculated as the weighted average for all funds in the portfolio. One motivation for including historical returns in the regression analysis is to control for possible momentum effects (Chan et al., 1996), that individuals choose mutual funds, and thus factors, with positive historical returns, hoping for future positive returns as well.

We present the estimation results from both the first pass probit regression and the second pass SUR regression in Table 5. The first column of Table 5 contains the estimated coefficients and *p*-values in the probit model according to equation (7), where all 15,651 observations are used in the estimation. Evidently, most of the coefficients associated with the explanatory variables related to investor sophistication are significant, and consistent with the same story, namely that more sophisticated investors have a higher likelihood of making an active choice. Individuals with less than high school education (variable EDU_1) show a significantly lower likelihood of being active than the benchmark individuals with high school education. Moreover, more wealthy individuals, as measured with the variables MONEY and WEALTH, but not with INCOME, have a higher likelihood of making an active choice. Individuals with previous experience with risky assets are more likely to make an active choice, whereas previous holdings of non-risky assets like bonds are not important for the activity choice. Occupation matters to some extent as self-employed and unemployed individuals show a significantly lower likelihood of making an active choice. However, there is no significant difference between privately employed individuals and individuals employed by the government. Finally, gender, marital status and age matters for the choice, where it seems like young, married women are more likely to choose actively than older, unmarried men. The gender result is rather surprising, and runs counter the expectations based on Barber and Odean (1998).

The rest of Table 5 contains the estimated coefficients and *p*-values from the SUR model according to equation (8).[10] The model consists of $m = 13$ equations, where we retain the 13 most important factors. The explanatory variables are the same as in the probit equation, plus a set of control variables for the number of actively chosen funds, the funds' transactions costs, risk level, historical returns, and the inverse Mills ratio from the probit regression. We focus the analysis on the SUR results for the coefficients representing individual characteristics, and note that most of the control variables are associated with significant coefficients, and thus are important.

[10] Note that each reported regression coefficient in Table 5 equals 100 times the corresponding estimated coefficient.

When we analyse the coefficients for the variables that are proxies for investor sophistication, we see that individuals with a low education level (EDU_1) have a significant tendency for loading relatively higher on the first, overall market factor (the regression equation for the dependent variable $\overline{\alpha}_{k,1}$, in the second column of Table 5). Moreover, individuals with high income, high wealth, and with previous holdings of risky assets, have significantly smaller loadings on the first factor. This result is consistent with the significantly negative coefficient for the inverse Mills ratio (λ_k) in the regression equation for the first factor. This coefficient represents an indirect effect on the loading on the first factor from the explanatory variables in the probit model. Hence, more sophisticated individuals have a higher probability of making an active choice, and the result of this activity is to reduce the loading on the overall market portfolio.

The low education dummy variable (EDU_1) is associated with significantly negative coefficients in the regression equations for communalities for factor five and six (equations for $\overline{\alpha}_{k,5}$ and $\overline{\alpha}_{k,6}$). In the same equations, individual wealth (WEALTH) and previous experience of risky assets (RISKY) are associated with significantly positive coefficients. These results are consistent with the idea that more sophisticated individuals have relatively lower loadings on Swedish bonds than less sophisticated individuals.[11] Moreover, the coefficients for the Mills ratio are significantly positive in the equations for $\overline{\alpha}_{k,5}$ and $\overline{\alpha}_{k,6}$. Hence, the more active sophisticated individuals are using the activity not only to reduce the allocation to the market portfolio, but also to reduce the allocation to Swedish long- and short-term bonds.

Given the results that sophisticated investors tend to have relatively less of their holdings allocated to the market portfolio or to bonds than less sophisticated investors, we turn to analyze in which asset classes they have relatively larger holdings. In Table 5, in the regression equation $\overline{\alpha}_{k,11}$, i.e. the equation for individual communalities on the high yield bond factor, we can observe significantly negative coefficients for the EDU_1 variable, and significantly positive coefficients for the WEALTH and RISKY variables. In addition, these three equations have significantly positive coefficients for the λ_k variable. Hence, the sophisticated investors appear to first,

[11] According to the results in Table 3 and 4, Swedish bond funds have significantly negative loadings on factors five and six. Therefore, if an investor has a negative loading on either factor five or six it should be interpreted as a positive loading on actual bonds.

according to the probit analysis, be more likely to actively choose, and second, to use the active choice to add some high yield bonds to their portfolios.

For the gender and marital status variables we observe a significant higher tendency for men to load higher on the US bond factor (eight), and lower on the yield factor (eleven) and the biotech factor (13) than women. Interestingly, men's loadings on factors eight and eleven are more different than women's for single rather than married men. The interaction term between the male and marriage dummy variables have a significantly negative coefficient in the $\overline{\alpha}_{k,8}$ equation and a significantly positive coefficient in the $\overline{\alpha}_{k,11}$ equation. Hence, a asset allocation effect seems to be to make men to choose asset classes more in line with women's wishes. It might not be an overconfidence related issue, but the marital effect is similar to the argument in Barber and Odean (2001) that marriage might weaken a gender effect, in this case with respect to asset allocation.

Finally, at the five percent significance level, older individuals tend to load significantly higher on domestic long- and short-term bonds (lower loadings on factors five and six), lower on Far-East equities (factor three) and high yield bonds, which are consistent with a lower risk-taking at an older age, or the time diversification idea (see e.g. Karlsson, 2005). However, older individuals also load significantly higher on the IT and Eastern Europe factors (ten and eleven). These results contest the time diversification idea.

5. Individual performance

How well do the individual portfolios perform, and can we see any systematic differences among individuals' performance in the Swedish pension plan? To answer these questions, we compute Jensen's alpha for each individual portfolio over the four-year period, from the initiation of the new pension plan in 2000, through 2004, and compare alphas across individuals taking their demographic and socio-economic characteristics into account.[12] We estimate Jensen's alpha for each individual from the following regression:

$$(9) \qquad r_{k,t} - r_{f,t} = a_k + \sum_{s=1}^{S} b_{k,s}(I_{s,t} - r_{f,t}) + e_{k,t}$$

[12] Note that we evaluate the performance of each individual's portfolio, given the initial composition in 2000. Thus, we do not take into account the possibility of individuals dynamically changing their portfolios over the sample period.

where $r_{k,t}$ is the portfolio return for individual *k* in period *t*, $r_{f,t}$ is the risk-free rate of return in period *t*, a_k is Jensen's alpha for individual *k*, $I_{s,t}$ is the return on index *s* in period *t*, $b_{k,s}$ is the sensitivity of individual *k* to index *s*, and $e_{k,t}$ is the residual for individual *k* in period *t*.

Jensen's alpha, a_k in equation (9), is a measure of the return the individual earns in excess of what he/she would have earned if he/she held a portfolio with broad market indices with the same risk.[13] Having identified the factors generating the mutual fund returns over the sample period, we use the factor identification from Table 4 to specify appropriate indices in equation (9). Hence, for all individuals alike, we use a six-index model with the MSCI World index (to represent Factor 1 in Table 4), the MSCI Japan index (Factor 2), the MSCI Far East, excluding Japan (Factor 3), the Serfiex DEMI Euro Zone T-bill index (Factor 4), Handelsbanken Swedish 5-10 Years Government Bond index (Factor 5), and the Merrill Lynch Euro High Yield index (Factor 11). For the risk-free interest rate, we use monthly returns on the Swedish one-month Treasury bill rate (Factor 6).

Figure 1 displays a frequency diagram for Jensen's alpha for all individuals, including the people with the passive default choice. All passive individuals have a monthly alpha equal to -0.0017, whereas the average alpha for the active individuals equals -0.0043, with a standard deviation equal to 0.0040. Hence, on average the active individuals have a significantly worse performance than people in the default fund.[14]

To investigate individual differences with respect to performance, it is important to take the passive individuals properly into account. The results from the probit choice model according to equation (7) indicate significant differences between active and passive individuals. Therefore, we consider the passive individuals as a group with a common performance (alpha = -0.0071), and divide the active individuals into the following groups based on performance, $a_k \leq -0.002$, $-0.002 < a_k \leq 0.002$, and $a_k > 0.002$. Let y_k be a nominal variable with *J* = 4 categories defined as $y_k = 1$ if $-0.002 < a_k \leq 0.002$, $y_k = 2$ if $a_k \leq -0.002$, $y_k = 3$ if $a_k > 0.002$, and $y_k = 4$ to

[13] The overwhelming evidence is that alpha on average is negative for mutual funds; see e.g. Blake et al. (1993), Grinblatt and Titman (1996), Jensen (1968), Sharpe (1966), and Wermers (2000). Hence, a negative individual alpha on average is not inconsistent with individuals picking better performing funds; see Blake et al. (2005). Note also that we analyze the relative performance for different types of individuals, not individual performance per se.

[14] A *t*-test of the hypothesis that the average alpha for the active individuals is not different from alpha for the default fund results in a *t*-statistic equal to -64.3, and thus a rejection of the hypothesis at any reasonable significance level.

represent the default. Moreover, let $\Pr(y_k = m \mid \mathbf{w}_k)$, m = 1, …, 4, be the conditional probability for individual k of observing the outcome m given the explanatory variables $\mathbf{w}_k$. Following Theil (1969), we use the multinomial logit model to estimate the probabilities for individual k as:

(10)
$$\Pr(y_k = m \mid \mathbf{w}_k) = \frac{1}{1+\sum_{j=2}^{J}\exp(\mathbf{w}_k \boldsymbol{\beta}_j)} \qquad \text{for } m = 1$$

$$\Pr(y_k = m \mid \mathbf{w}_k) = \frac{\exp(\mathbf{w}_k \boldsymbol{\beta}_m)}{1+\sum_{j=2}^{J}\exp(\mathbf{w}_k \boldsymbol{\beta}_j)} \qquad \text{for } m > 1$$

The constraint $\boldsymbol{\beta}_1 = 0$ for m = 1 is made to ensure that the probabilities are identifiable. Note that we choose alpha close to zero ($-0.002 < a_k \leq 0.002$) as the base category in the multinomial logit model. The reasons are twofold; first, this formulation allows an evaluation of the probability of having better or worse performance than the middle, close to zero-alpha base case. Second, the alpha for the passive individuals is entailed in the base category, which to some extent isolates the probability of being passive from the performance issue.

Table 6 presents the results from the multinomial logit estimation. For each explanatory variable, we report a Wald test statistic, which is χ^2-distributed under the null hypothesis that the coefficients in the probability equations for y = 2 and y = 3 are jointly equal to zero. Thus, the test does not include the corresponding coefficient in the default probability equation. Each test statistic should be interpreted as a test for an effect of each explanatory variable on the probability of performing either better or worse than the group of individuals with an alpha close to zero. As in the Heckman analysis above, we use the default probability equation for control purposes only. Most of the results for the probability equation $\Pr(y_k = 4)$ are consistent with the results from the first pass probit regression in Table 5. However, note the opposite signs of the coefficients, as $\Pr(y_k = 4)$ refers to the probability of passive choice, whereas in the probit model in equation (7) is for the probability of an active choice.

From the probability equations of main interest, corresponding to worse or better performance than the base category, we see from Table 6 that well educated individuals have a significantly higher probability of a worse performance. Moreover, at the ten percent significance level, we see evidence on a lower probability for individuals with less than high school education to perform worse than the base category. Among the other proxies for investor sophistication we note that individuals with a lot of money invested in the premium pension have a significantly higher probability of performing worse (only at the ten percent level), and a lower probability of performing better than the base category. Likewise, previous experience with risky (non-risky) assets increase (decrease) the probability of having a worse (better) than a close-to-zero performance. These results are consistent with the idea that more sophisticated individuals perform significantly worse than less sophisticated people. As for the remaining two proxies for sophistication, income is not a significant determinant of alpha, whereas wealth is associated with significantly positive coefficients in both the worse- and better-performance categories. Hence, more wealthy individuals have a higher probability of performing worse and better than less wealthy individuals, who in turn are more likely to have an alpha close to zero.

Privately employed (and unemployed) individuals, represented by the dummy variable OCC_2 (OCC_4) in Table 6, show a significantly higher likelihood than government employees of performing better than the close-to-zero alpha category, at the five percent significance level. Moreover, self-employed individuals are significantly more likely to perform both worse and better than government employees.

Men have a significantly higher (lower) probability to be in the category with better (worse) performance than the zero-alpha category, at the one (ten) percent significance level. Hence, we observe a significantly higher likelihood for men to perform better than women. Interestingly, the gender effect that men perform better than women appears to be higher for single men than married men. The coefficient for the interaction term between the male and marriage dummy variables is significantly positive, at the five percent level, in the probability equation for the category with worse performance than the close-to-zero category. Although we observe no significant difference between married and unmarried men regarding the likelihood of being in the performance category with highest alpha, the gender/marriage results are rather straightforward. Men have better-performing portfolios than women in general, but single men perform even better than married men. One perhaps controversial way of interpreting these results is that married men are under “bad influence” from their spouses, where this influence tends to remove some of the “male performance edge”.

Finally, we note a significant age effect in Table 6. Older individuals have a significantly higher (lower) probability of having a higher (lower) alpha than younger individuals, at the ten percent (any) significance level.

6. Concluding remarks

Due to changes in the age structure in many industrialized countries, we are currently experiencing a trend where countries tend to shift pension systems from a defined benefit system to a defined contribution plan. These shifts may have far-reaching consequences for retirees. The key issue in moving from a defined benefit type of pension system to a defined contribution plan is to make individuals more responsible for their own pension investments, and to a larger extent than before, let them bear the actual investment risk. In this study, we analyse the consequences for different types of individuals in the recent redesign of the Swedish pension system. Since the redesign in 2000, the Swedish pension system is a partially defined contribution plan, in which individuals set aside 2.5 percent of their annual income at their own discretion, and another 16 percent into a traditional defined benefit type of account. Our basic intent is to analyse individuals' asset allocation and performance in the defined contribution part of the pension system.

We perform our analysis in three steps. First, we study the investment alternatives available to the investors when the partial defined contribution pension system was launched in 2000. We break down all available investment alternatives (465 mutual funds) into orthogonal factors using a factor analysis. The results from the factor analysis indicate that 23 latent factors account for more than 90 percent of the total variation among the 465 fund returns. We identify the most important latent factors in terms of real-world actual asset classes. The most important factor represents the world market portfolio, as approximated with e.g. the MSCI world index. Other important factors represented in the menu of mutual funds include various bond factors and industry-, country-, or sector-based equity factors.

In the second part of the analysis, we investigate the individual investment choices in terms of the latent factors or inherent asset classes from the factor analysis. In doing so, we identify which factors are most common in the portfolios of different demographic groups of individuals. Since approximately one third of the population have chosen to invest in a "passive" default alternative, rather than making an active choice of mutual funds, or asset classes, we face a potential selection bias. We use the procedure according to Heckman (1979) to take this selection bias into account.

Thus, we first model the individual choice of activity with a probit model, and then model the asset allocation choice within a seemingly unrelated regression (SUR) framework, taking the probability of making an active choice into consideration. Our results show that a more sophisticated individual has a higher probability of making an active investment choice. The default alternative consists of a fund, which is almost perfectly correlated with the world market portfolio. For the active individuals, our results show that more sophisticated individuals have significantly lower loadings on the market portfolio and Swedish long- and short- term bonds, and significantly higher loadings on high yield bonds. One interpretation of these results is that more sophisticated individuals have higher risk in their pension plan portfolios than less sophisticated individuals.

In the third and final part of the study, we study the performance of the individuals' pension plan portfolios. We measure performance with Jensen's alpha for each individual, which is obtained from a time series regression of individual monthly returns on a set of market indices representing the most important factors from the factor and asset allocation analysis in the first two parts of the study.

References

Barber, B. and T. Odean, 2001, Boys will be boys: gender, overconfidence, and common stock investment, Quarterly Journal of Economics 141, 261-292.

Benartzi, S. and R. Thaler, 2001, Naïve diversification strategies in defined contribution pension plans, American Economic Review 91, 79-98.

Blake, C., Elton E. and M. Gruber, 1993, The performance of bond mutual funds, Journal of Business.

Blake, C., Elton E. and M. Gruber, 2004, The adequacy of investment choices offered by 401(k) plans, Paper presented at the 2004 meeting of the European Finance Association.

Blake, C., Elton E. and M. Gruber, 2005, Participant reaction and the performance of funds offered by 401(k) plans, Working Paper, New York University.

Chan, L., Jegadeesh N. and J. Lakonishok, 1996, Momentum strategies, Journal of Finance 51, 1681-1783.

Choi, J., Labison, D., Madrian, B. and A. Metrick, 2002, Defined contribution pensions: plan rules, participant decisions, and the path of least resistance, in Poterba, J., Ed.: Tax policy and the economy, MIT Press.

Engström S. and A. Westerberg, 2003, Which individuals make active investment decisions in the new Swedish pension system? Journal of Pension Economics and Finance 2, 1-21.

Greene, W., 2000, Econometric analysis, Prentice Hall.

Grinblatt, M. and M. Keloharju, 2001, Distance, language, and cultural bias: the role of investor sophistication, Journal of Finance 46, 1053-1073.

Grinblatt, M. and S. Titman, 1989, Mutual fund performance: an analysis of quarterly portfolio holdings, Journal of Business 39, 393-411.

Huberman, G., 2001, Familiarity breeds investment, Review of Financial Studies 14, 659-680.

Jensen, M., 1968, The performance of mutual funds in the period 1945-1964, Journal of Finance 23, 389-416.

Karlsson, A., 2005, Risk preferences and investment decisions among non-professional investors, Working Paper, School of Business, Stockholm University.

Karlsson, A. and L. Nordén, 2004, Home sweet home: home bias and international diversification among individual investors, Working Paper, School of Business, Stockholm University.

Klayman, J., J. Soll, C. González-Vallejo and S. Barlas, 1999, Overconfidence: it depends on how, what and whom you ask, Organizational Behavior and Human Decision Processes, 79:3, 216-247.

Madrian, B. and D. Shea, 2001, The power of suggestion: inertia in 401(k) participation and savings behavior. Quarterly Journal of Economics 116, 1149-1187.

Oberlechner, T. and C. Osler, 2003, Overconfidence in currency markets, Working Paper, Brandeis University.

Sharma, S., 1996, Applied multivariate techniques, John Wiley & Sons, Inc.

Sharpe, W., 1966, Mutual fund performance, Journal of Business 39, 119-138.

Shiller, R., 2003, From efficient markets theory to behavioral finance, Journal of Economic Perspectives, 17:1, 83-104.

Säve-Söderbergh. J., 2003, Gender, risk and portfolio choices of retirement wealth, Working Paper, The Swedish Institute for Social Research, Stockholm University.

Theil, H., 1969, A multinomial extension of the linear logit model, International Economic Review 10, 251-259.

Wermers, R., 2000, The value of active mutual fund management, Journal of Financial and Quantitative Analysis.

Zellner, A., 1962, An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias, Journal of American Statistical Association 57, 348-368.

Table 1: Extract from the information folder, fund example

Fund number	Fund name, Management company	Information regarding the funds	Fund fee (%)	Percentage return 99-12-31 (after fees)						Total risk (last 3 years)
				In the year					Last 5 years	
				95	96	97	98	99		
191080	Baring Global Emerging Markets Baring International Fund Managers (Ireland) Ltd	Emerging markets' equity and equity related assets	1.59	-32	10	25	-25	77	25.3	32 (Red)

The percentage return for the last five years equals the compounded annual growth rate of return for the years 1995 through 1999. The total risk corresponds to an annualised percentage standard deviation of three-year monthly historical fund returns. The total risk is also categorised into five different classes, and colours, with respect to standard deviation; Class 1: very low risk, dark green, percentage standard deviation in the range 0-2; Class 2: low risk, light green, 3-7; Class 3: average risk, yellow, 8-17; Class 4: high risk, orange, 18-24; Class 5: very high risk, red, 25-.

Table 2: Factor analysis, initial and rotated solution

Factor	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	307.81	68.555	68.5546	257.62	57.377	57.3766
2	34.359	7.6524	76.2069	31.668	7.0530	64.4296
3	20.602	4.5883	80.7952	30.850	6.8707	71.3003
4	14.000	3.1180	83.9132	24.522	5.4615	76.7617
5	10.611	2.3633	86.2765	23.891	5.3209	82.0826
6	8.6618	1.9291	88.2056	13.109	2.9196	85.0022
7	6.5648	1.4621	89.6677	9.1348	2.0345	87.0367
8	4.8645	1.0834	90.7511	7.6295	1.6992	88.7360
9	3.9579	0.8815	91.6326	5.3101	1.1827	89.9186
10	3.6782	0.8192	92.4518	4.3428	0.9672	90.8858
11	3.2362	0.7208	93.1725	3.7569	0.8367	91.7226
12	2.6210	0.5837	93.7563	3.5350	0.7873	92.5099
13	2.4844	0.5533	94.3096	3.3459	0.7452	93.2551
14	2.3359	0.5203	94.8298	2.7545	0.6135	93.8685
15	2.0904	0.4656	95.2954	2.2293	0.4965	94.3650
16	1.8268	0.4069	95.7023	2.1874	0.4872	94.8522
17	1.6572	0.3691	96.0713	1.9699	0.4387	95.2909
18	1.4795	0.3295	96.4009	1.9499	0.4343	95.7252
19	1.3349	0.2973	96.6982	1.9178	0.4271	96.1524
20	1.2471	0.2777	96.9759	1.7693	0.3941	96.5464
21	1.0987	0.2447	97.2206	1.7507	0.3899	96.9363
22	1.0639	0.2369	97.4576	1.6802	0.3742	97.3105
23	1.0114	0.2252	97.6828	1.6715	0.3723	97.6828

Table 3: Average communalities and factor loadings for the mutual funds

Category 1	Category 2	Category 3	#Funds	Communality	F1	F2	F3	F4	F5
Equity	Sweden	Sweden (normal)	28	0.9910	0.9449	0.0877	0.1294	-0.1155	0.1155
		Sweden small cap	6	0.9590	0.8294	0.1374	0.2857	-0.1762	0.0498
		Sweden index	7	0.9948	0.9518	0.0701	0.1137	-0.1053	0.1160
	Regional	Swedish equity and foreign equity	11	0.9933	0.9389	0.1677	0.1566	-0.0760	0.1527
		Nordic countries	12	0.9788	0.9044	0.1347	0.1658	-0.0798	0.1164
		Europe	36	0.9829	0.8662	0.1490	0.1590	0.0445	0.1461
		Euroland	8	0.9843	0.8879	0.1362	0.1457	0.0219	0.1292
		Europe small cap	9	0.9751	0.7258	0.2247	0.3757	0.0688	0.0844
		Europe index	7	0.9898	0.8979	0.1274	0.1198	0.0446	0.1413
		North America and USA	26	0.9810	0.8163	0.2158	0.2312	0.0337	0.2201
		Asia and Far East	18	0.9665	0.5860	0.2625	0.6176	0.0650	0.1291
		Global	32	0.9827	0.8311	0.2597	0.2326	0.0335	0.1849
		New markets	21	0.9714	0.6349	0.2712	0.5311	0.0098	0.0246
	Countries	Japan	20	0.9753	0.3086	0.8467	0.1556	0.1186	0.0657
		UK	6	0.9530	0.7041	0.2619	0.3251	0.1634	0.1207
		Other countries	19	0.9497	0.6838	0.2079	0.3135	0.0514	0.1101
	Industry	IT and Communication	19	0.9855	0.8447	0.1212	0.2016	-0.0811	0.0387
		Pharmaceutical	7	0.9560	0.5714	0.0978	0.0409	0.0793	0.1594
		Other industries	16	0.9482	0.6645	0.2385	0.2850	0.0651	0.1076
Mixture	Mixture	Swedish equity and fixed income	3	0.9697	0.8985	0.0785	0.0555	-0.1544	0.0277
		Swedish equity, Swedish and foreign fixed income	28	0.9863	0.9318	0.1628	0.1494	-0.0557	0.0653
		Foreign equity and fixed income	22	0.9767	0.6063	0.2314	0.1772	0.4410	0.0690
Generation	Generation	Pension in less than 10 years	5	0.9891	0.9193	0.1969	0.1896	-0.0006	0.1262
		Pension in less than 20 years	6	0.9940	0.9248	0.1983	0.2036	-0.0092	0.1579
		Pension in more than 20 years	21	0.9956	0.9289	0.1909	0.1949	-0.0208	0.1597
Fixed inc.	Fixed inc.	Sweden, short maturity	15	0.9496	-0.1614	-0.0730	-0.1003	0.1469	-0.3477
		Sweden, long maturity	15	0.9867	-0.1702	-0.0527	-0.0311	0.1361	-0.7750
		Europe and Euroland	18	0.9668	-0.1100	0.0433	0.0283	0.7297	-0.2030
		Others	15	0.9678	-0.0432	0.2319	0.1391	0.5068	-0.0440
Default			1	0.9974	0.9355	0.1854	0.1989	-0.0672	0.1103
All funds			457	0.9759	0.6661	0.1802	0.1928	0.0650	0.0499

Table 3: Average communalities and factor loadings for the mutual funds (cont.)

Category 1	Category 2	Category 3	F6	F7	F8	F9	F10	F11	F12	F13
Equity	Sweden	Sweden (normal)	0.0736	-0.0350	-0.0397	0.0423	-0.0302	0.0643	0.0021	0.0103
		Sweden small cap	0.0629	0.0494	-0.0756	0.0556	0.1019	0.1091	-0.0108	-0.0493
		Sweden index	0.1147	-0.0751	-0.0640	0.0605	-0.0496	0.0582	0.0014	0.0220
	Regional	Swedish equity and foreign equity	0.0844	-0.0017	0.0185	0.0252	-0.0083	0.0253	0.0253	0.0201
		Nordic countries	0.0812	-0.0032	-0.0452	0.0552	-0.0141	0.0350	0.0242	-0.0219
		Europe	0.1125	0.2386	-0.0174	0.0559	-0.0296	0.0100	0.0549	-0.0039
		Euroland	0.1056	0.2736	-0.0148	0.0567	-0.0242	0.0061	0.0183	-0.0299
		Europe small cap	0.2125	0.2218	-0.1353	0.0716	-0.0036	0.2088	0.0152	0.0320
		Europe index	0.0910	0.2856	0.0185	0.0667	-0.0355	-0.0108	0.0620	-0.0081
		North America and USA	0.0647	0.0355	0.2151	-0.0128	0.1005	-0.0014	0.0321	0.0953
		Asia and Far East	0.1308	0.0436	0.0688	0.0142	0.0506	0.0425	0.0054	0.0490
		Global	0.0872	0.1079	0.1297	0.0135	0.0507	-0.0016	0.0531	0.0516
		New markets	0.0525	0.0498	0.1097	-0.0139	0.0339	0.0333	0.2511	-0.0030
	Countries	Japan	0.0664	0.0374	0.0332	0.0406	0.0109	0.0295	0.0265	0.0116
		UK	0.1271	0.2667	0.0039	0.0547	-0.0638	0.0646	0.0526	0.1128
		Other countries	0.1232	0.1425	-0.0226	0.0615	-0.0037	0.0585	0.0301	0.0154
	Industry	IT and Communication	0.0326	-0.1085	0.0344	-0.0587	0.3212	0.0057	0.0930	0.0719
		Pharmaceutical	0.0978	0.0503	0.1071	0.0784	-0.0340	-0.0255	-0.0016	0.3533
		Other industries	0.1463	0.2015	0.0240	0.0504	-0.0335	0.0298	0.0530	0.0223
Mixture	Mixture	Swedish equity and fixed income	0.0098	-0.0624	-0.0695	0.0588	-0.0586	0.0279	0.0031	-0.0348
		Swedish equity, Swedish and foreign fixed income	0.0538	-0.0233	0.0158	0.0429	0.0037	0.0352	0.0165	0.0277
		Foreign equity and fixed income	0.0412	0.1345	0.0515	0.0387	0.0193	0.0261	0.0341	0.0260
Generation	Generation	Pension in less than 10 years	0.0604	0.0052	0.0891	0.0430	0.0018	0.0330	0.0211	0.0528
		Pension in less than 20 years	0.0616	0.0257	0.0643	0.0071	-0.0006	0.0153	0.0137	0.0466
		Pension in more than 20 years	0.0683	0.0350	0.0709	0.0128	0.0038	0.0223	0.0131	0.0449
Fixed inc.	Fixed inc.	Sweden, short maturity	-0.7078	-0.0210	0.0105	0.0606	-0.0142	0.0049	-0.0014	-0.0322
		Sweden, long maturity	-0.1407	-0.0022	-0.0311	0.0402	0.0028	0.0153	-0.0022	-0.0121
		Europe and Euroland	-0.0565	0.0130	-0.0104	0.0507	-0.0185	0.1100	-0.0244	-0.0067
		Others	-0.0597	-0.0172	0.3534	0.1821	-0.0125	-0.0145	0.0405	0.0001
Default			0.1078	0.0460	-0.0198	0.0200	0.0098	0.0330	0.0271	0.0719
All funds			0.0413	0.0644	0.0308	0.0433	0.0092	0.0351	0.0311	0.0298

Table 4: Factor identification: the mutual funds with the highest factor loading for each factor

Factor	Highest absolute loading	Mutual fund with highest absolute loading	Factor identification
1	0.9687	Nordbanken Allemansfond Beta	World equity market portfolio
2	0.9323	JPM Japan Equity Fund	Japan equity
3	0.7645	Skandia Fond Aktiefond Far East	Far East equity
4	0.9208	BL - Short Term Euro	Euroland fixed income
5	-0.9263	Alfred Berg Obligationsfond	Swedish long term fixed income
6	-0.8896	EP Likviditetsfond Sverige	Swedish short term fixed income
7	0.5069	MSDW SICAV European Property Fund	European real estate
8	0.7291	MSDW SICAV US Bond	US Bonds
9	0.7882	Industrifinans Obligasjon/Obl. Utland	With Industrifinans only
10	0.4361	UBS (Lux) Equity Fund - Technology	IT
11	0.7336	Fleming European High Yield Bond Fund	High yield bonds
12	0.5178	Nomura Global Fund - Eastern European Sub-Fund	Eastern Europe
13	0.6734	Pictet G.S.F Compartiment Biotech	Biotech

Table 5: Two-step Heckman regression (SUR) results for individual factor communalities

	z_k	$\overline{\alpha}_{k,1}$	$\overline{\alpha}_{k,2}$	$\overline{\alpha}_{k,3}$	$\overline{\alpha}_{k,4}$	$\overline{\alpha}_{k,5}$	$\overline{\alpha}_{k,6}$	$\overline{\alpha}_{k,7}$	$\overline{\alpha}_{k,8}$	$\overline{\alpha}_{k,9}$	$\overline{\alpha}_{k,10}$	$\overline{\alpha}_{k,11}$	$\overline{\alpha}_{k,12}$	$\overline{\alpha}_{k,13}$
Constant	-1.4530	107.40	5.4119	-2.9839	0.4966	3.8815	-0.1723	-0.1769	0.3476	1.3144	-5.0750	-1.8433	-0.4221	-8.3490
	0.0000	0.0000	0.0750	0.3776	0.7135	0.8256	0.9645	0.8974	0.7900	0.2854	0.0006	0.0000	0.6073	0.0070
EDU_1	-0.1273	1.5157	-0.0758	-0.1486	-0.0708	-0.6410	-0.5260	0.0251	0.0492	-0.0039	0.0138	-0.0736	0.0011	-0.2011
	0.0000	0.0187	0.6174	0.3789	0.2947	0.0661	0.0064	0.7144	0.4493	0.9492	0.8510	0.0013	0.9792	0.1932
EDU_3	-0.0459	0.4701	0.1856	0.1083	-0.0187	-0.5432	-0.1740	-0.0646	-0.1451	0.0566	-0.1158	-0.0120	0.0163	0.0595
	0.0712	0.1653	0.0200	0.2220	0.5973	0.0030	0.0862	0.0725	0.0000	0.0796	0.0228	0.3178	0.4505	0.4635
MONEY	0.1945	-0.9487	-0.1274	0.2060	-0.0157	0.7235	0.5452	-0.0534	-0.0828	-0.0231	-0.1172	0.1283	-0.0568	0.2688
	0.0000	0.2772	0.5353	0.3676	0.8637	0.1255	0.0369	0.5650	0.3480	0.7812	0.2400	0.0000	0.3057	0.1988
INCOME	0.0016	-0.1559	0.0027	0.0223	0.0063	-0.0104	0.0274	0.0060	0.0037	0.0106	-0.0014	0.0011	-0.0026	0.0173
	0.7894	0.0148	0.8597	0.1908	0.3584	0.7668	0.1587	0.3833	0.5739	0.0859	0.8489	0.6290	0.5370	0.2665
WEALTH	0.0096	-0.0786	-0.0131	0.0153	0.0007	0.0623	0.0264	-0.0034	-0.0085	-0.0038	-0.0093	0.0081	-0.0056	0.0178
	0.0000	0.0929	0.2330	0.2111	0.8824	0.0137	0.0596	0.4997	0.0716	0.3945	0.0805	0.0000	0.0584	0.1106
RISKY	0.3054	-2.6164	-0.1716	0.3446	0.0483	1.3841	1.0785	0.0227	0.0026	-0.1302	-0.0299	0.2217	-0.0731	0.4294
	0.0000	0.0476	0.5808	0.3191	0.7270	0.0527	0.0064	0.8712	0.9846	0.3008	0.8428	0.0000	0.3838	0.1748
NONRISKY	0.0363	-0.1152	-0.0393	0.1458	-0.0509	-0.0193	0.1497	-0.0079	-0.0540	0.0027	0.0067	0.0213	0.0047	0.1230
	0.1404	0.7056	0.5844	0.0678	0.1111	0.9067	0.1011	0.8083	0.0798	0.9257	0.8466	0.0493	0.8095	0.0924
OCC_2	0.0217	-0.3074	0.0694	0.0962	0.0446	0.1849	-0.0074	-0.0218	-0.0831	0.0665	-0.0751	0.0321	-0.0097	0.1264
	0.4218	0.3003	0.3205	0.2158	0.1515	0.2494	0.9335	0.4891	0.0056	0.0186	0.0267	0.0024	0.6056	0.0756
OCC_3	-0.2089	2.7531	0.4632	0.4376	-0.0937	-2.0478	-0.8688	-0.0472	-0.0043	0.0987	0.0781	-0.1799	0.1360	-0.8593
	0.0001	0.0144	0.0803	0.1375	0.4266	0.0008	0.0099	0.6930	0.9697	0.3574	0.5435	0.0000	0.0572	0.0014
OCC_4	-0.2228	1.8231	0.5067	-0.3636	-0.0352	-0.5972	-0.9685	0.0269	0.0015	0.0405	-0.1627	-0.1563	0.0824	-0.4439
	0.0000	0.1176	0.0646	0.2332	0.7729	0.3432	0.0055	0.8277	0.9902	0.7150	0.2214	0.0002	0.2659	0.1118
MEN	-0.1431	-0.3895	0.3539	0.1501	0.0543	-0.6610	-0.0734	0.0929	0.1768	0.0777	0.0442	-0.1326	0.0634	-0.4033
	0.0013	0.6448	0.0752	0.4975	0.5394	0.1481	0.7718	0.3009	0.0384	0.3342	0.6468	0.0000	0.2379	0.0464
MARRIED	0.2331	-1.8280	-0.1172	0.4658	-0.0198	0.9427	1.0292	0.0014	0.0021	-0.0501	-0.1038	0.1468	-0.0654	0.2660
	0.0000	0.0902	0.6443	0.0992	0.8610	0.1062	0.0014	0.9901	0.9848	0.6256	0.3997	0.0001	0.3404	0.3035

Table 5 (cont.): Two-step Heckman regression (SUR) results for individual factor communalities

	z_k	$\overline{\alpha}_{k,1}$	$\overline{\alpha}_{k,2}$	$\overline{\alpha}_{k,3}$	$\overline{\alpha}_{k,4}$	$\overline{\alpha}_{k,5}$	$\overline{\alpha}_{k,6}$	$\overline{\alpha}_{k,7}$	$\overline{\alpha}_{k,8}$	$\overline{\alpha}_{k,9}$	$\overline{\alpha}_{k,10}$	$\overline{\alpha}_{k,11}$	$\overline{\alpha}_{k,12}$	$\overline{\alpha}_{k,13}$
MANMAR	0.0633	0.0200	-0.1514	-0.0431	0.0053	0.4746	-0.1450	-0.0849	-0.1417	-0.0615	0.0349	0.0901	0.0087	0.2239
	0.2075	0.8806	0.3334	0.8047	0.9392	0.1871	0.4663	0.2294	0.0350	0.3322	0.6458	0.0001	0.8379	0.1601
AGE	-0.0067	0.0429	0.0049	-0.0162	0.0001	-0.0362	-0.0339	0.0034	0.0003	0.0021	0.0146	-0.0054	0.0044	0.0003
	0.0000	0.1513	0.4869	0.0383	0.9759	0.0253	0.0002	0.2850	0.9135	0.4701	0.0000	0.0000	0.0220	0.9701
D2	-	-2.4729	-0.6763	-0.8628	0.2455	1.8413	0.8092	0.1594	0.2553	0.0850	-0.1741	0.0690	-0.0395	-0.0156
		0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0005	0.0000	0.0396	0.0004	0.0000	0.1519	0.8803
D3	-	-5.1606	-0.8622	-1.1240	0.3144	3.6718	1.1434	0.3715	0.3891	0.0399	-0.0530	0.0673	-0.0552	-0.1167
		0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2933	0.2448	0.0000	0.0295	0.2221
D4	-	-4.9928	-0.8487	-1.2057	0.4012	2.9725	1.3780	0.4937	0.4562	0.0248	-0.0084	0.1255	-0.0509	-0.2119
		0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.5339	0.8605	0.0000	0.0556	0.0345
D5	-	-6.0833	-0.5177	-0.9278	0.4027	3.0565	1.3938	0.5934	0.4666	0.0566	-0.0916	0.1254	0.0061	-0.0018
		0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1357	0.0440	0.0000	0.8086	0.9849
FEE	-	-22.012	0.9489	4.2832	0.0162	0.3128	1.2457	0.6101	0.7671	0.4298	0.8761	0.1104	0.6728	3.9228
		0.0000	0.0000	0.0000	0.7464	0.2254	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
RISKCAT	-	-2.5687	0.6657	1.9574	0.0078	-3.4036	-2.8167	0.5065	0.5568	-0.2455	0.2937	0.0156	0.4511	1.4163
		0.0000	0.0000	0.0000	0.8156	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1671	0.0000	0.0000
RET	-	8.7115	-1.3420	-2.7826	-0.1192	-1.1221	0.3546	-0.4099	-0.5173	0.0013	2.3849	-0.0604	-0.2813	-1.3872
		0.0000	0.0000	0.0000	0.0004	0.0000	0.0002	0.0000	0.0000	0.9658	0.0000	0.0000	0.0000	0.0000
λ_k	-	-18.297	-1.8338	2.6203	0.6407	10.720	7.1617	-0.1727	-0.3986	-0.4074	-0.2156	1.4283	-0.4244	2.9925
		0.0225	0.3313	0.2121	0.4455	0.0135	0.0029	0.8393	0.6227	0.5938	0.8139	0.0000	0.4051	0.1194
$\overline{R}^2$	0.0641	0.2996	0.0742	0.2442	0.0442	0.1558	0.1486	0.1323	0.1516	0.0437	0.5759	0.0533	0.1893	0.2292

Table 6: Results from the multinomial logit model

	Pr(y = 2)	Pr(y = 3)	Pr(y = 4)	χ^2 -statistic
CONSTANT	1.5345 (0.0158)	-0.0348 (0.9672)	4.3186 (0.0001)	-
EDU_1	-0.1232 (0.0659)	0.1505 (0.2374)	0.1421 (0.0361)	7.346 (0.0254)
EDU_3	0.1957 (0.0007)	0.1661 (0.1801)	0.2236 (0.0003)	11.58 (0.0031)
MONEY	0.0645 (0.0954)	-0.2414 (0.0017)	-0.2955 (0.0001)	19.29 (0.0001)
INCOME	-0.0072 (0.6154)	-0.0357 (0.1540)	-0.0099 (0.4933)	2.056 (0.3577)
WEALTH	0.0178 (0.0002)	0.0240 (0.0238)	-0.0021 (0.6772)	14.76 (0.0006)
RISKY	0.4545 (0.0001)	0.1000 (0.3929)	-0.1797 (0.0016)	73.96 (0.0001)
NONRISKY	-0.0550 (0.3188)	-0.2966 (0.0093)	-0.1171 (0.0454)	6.777 (0.0338)
OCC_2	-0.0374 (0.5263)	0.2827 (0.0363)	-0.0503 (0.4238)	6.315 (0.0425)
OCC_3	0.7228 (0.0001)	1.0605 (0.0001)	0.9332 (0.0001)	26.36 (0.0001)
OCC_4	0.0757 (0.4362)	0.4903 (0.0097)	0.4399 (0.0001)	6.724 (0.0347)
MALE	-0.2038 (0.0723)	0.7245 (0.0024)	0.1339 (0.2320)	18.51 (0.0001)
MARRIED	-0.0683 (0.4514)	0.0350 (0.8704)	-0.4319 (0.0001)	0.743 (0.6897)
MAR_MALE	0.2481 (0.0449)	-0.3287 (0.2089)	0.0522 (0.6740)	8.369 (0.0152)
AGE	-0.0303 (0.0001)	0.0087 (0.0939)	-0.0096 (0.0002)	189.9 (0.0001)

Table 5 contains results from the estimation of the multinomial logit model in Equation (10). The dependent variable y_k, has four possible outcomes (m = 1, …, 4), where each of the first three corresponds to an "active" choice, and an alpha in a range according to $y_k = 1$ if $-0.002 < a_k \le 0.002$, $y_k = 2$ if $a_k \le -0.002$, $y_k = 3$ if $a_k > 0.002$, and $y_k = 4$ represents the "passive" default. $\Pr(y_k = m \mid \mathbf{w}_k)$ is the probability of observing outcome m given **w**. The variables in **w** are EDU_1 (a dummy variable equal to 1 if the education level of the individual is below high school), EDU_3 (dummy variable equal to 1 if the education level is above high school, the base case represents high school education), MONEY (total initial investments in pensions funds for each individual in SEK), INCOME (individual's disposable income in SEK), WEALTH (market value in SEK of financial assets and real estate holdings, net of debt for each individual), RISKY (dummy variable equal to 1 if the individual has risky holdings), NONRISKY (dummy variable equal to 1 if the individual has holdings with low risk), OCC_2 through OCC_4 are dummy variables for individuals occupation (OCC_2 represents private sector employment, OCC_3 self-employment, OCC_4 unemployment, whereas the base case represents government employment), MALE (dummy variable equal to 1 if the individual is male), MARRIED (dummy variable equal to 1 if the individual is married), MAR_MALE (MALE× MARRIED) and AGE (in years). The probabilities are modeled as:

$$\Pr(y_k = m \mid \mathbf{w}_k) = \frac{1}{1+\sum_{j=2}^{J}\exp(\mathbf{w}_k\boldsymbol{\beta}_j)} \quad \text{for } m = 1, \quad \Pr(y_k = m \mid \mathbf{w}_k) = \frac{\exp(\mathbf{w}_k\boldsymbol{\beta}_m)}{1+\sum_{j=2}^{J}\exp(\mathbf{w}_k\boldsymbol{\beta}_j)} \quad \text{for } m > 1$$

where $\boldsymbol{\beta}_1 = 0$ for the first outcome. The model is estimated using the maximum likelihood technique outlined in Berndt et al. (1974), and the heteroskedasticity-consistent covariance matrix according to White (1980). The estimated coefficients are presented for each probability and explanatory variable, with *p*-values in parentheses. Each χ^2-statistic results from a Wald test for the hypothesis that each explanatory variable does not affect the likelihood of outcomes $y_k = 2$ and $y_k = 3$, relative the first outcome $y_k = 1$, and is χ^2-distributed with four degrees of freedom.

Figure 1: Individual performance measured as Jensen's alpha (monthly basis)