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Ownership of Stocks and Mutual Funds: A Panel Data Analysis*

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Abstract

In many industrial countries, ownership rates of risky assets have risen substantially over the past decade. This trend has potentially wide–ranging implications for the intertemporal and cross–sectional allocation of risk, and for the macro economy, establishing the need for understanding ownership dynamics at the micro level. This paper offers one of the first such analyses using representative panel survey data. We focus on the two main types of risky financial assets, mutual funds and individual stocks. We extend existing univariate dynamic binary choice models to the multivariate case and take account of interactions between the two types of assets. The models are estimated on data from the 1993–1998 waves of the Dutch CentER Savings Survey. We find that both unobserved heterogeneity and state dependence play a large role for both types of assets. Most of the positive relation between ownership of mutual funds in one period and ownership of individual stocks in the next period or vice versa, is explained by unobserved heterogeneity: if we account for correlation between the household specific effects in the two binary choice equations, we find a negative effect of lagged ownership of stocks on the ownership of mutual funds. These findings can be explained by adjustment costs that make it optimal to stick to one type of asset.

Keywords: household portfolio choice, panel data

JEL classification: *C33, C35, D12, D91*

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1 Introduction

In many industrialized countries including the Netherlands, the percentage of private households that own some type of risky financial assets has increased substantially during the nineties. In the US for example, the fraction of households owning some risky financial assets increased from 31.9% in 1989 to 49.2% in 1998. In Italy, the ownership rate increased from 12.0% to 22.1% in the same time period.[1] Similar trends exist in many other countries.

To quote The Economist of March, 2001: "Wider share ownership is profoundly important." It spreads wealth, changes attitudes to economic freedom and lowering business taxes, and leads to greater shareholder activism. This puts pressure on managers to improve their performance and promises to raise productivity and economic growth. Household stock ownership becomes more and more important with all kinds of implications for financial markets and macro-economic policy. According to the Financial Times of August 30 2000, the wider share ownership has reversed the public opinion on the US Federal Reserve's policy of cutting interest rates: while in the past, the majority of the public would be concerned about lower returns to their savings accounts, most households will now applaud an interest rate cut since it increases the expected returns to their shares portfolio. On the other hand, the same Financial Times article states, referring to the group of retail investors in risky assets, that "one problem for policy makers analyzing this growing group of Americans is that useful data on the identity of the average investor is hard to come by." This illustrates the need for empirical work on portfolio choice at the level of the individual households.

The forthcoming volume by Guiso *et al.* (2001) provides an overview of the current state of the art in this field. This volume links portfolio choice theory to empirical research and contains empirical studies for several countries. While many countries have some survey data on ownership and amounts invested for several types of assets, this data is often limited to one or more cross–sections. Though useful for many purposes, such data is insufficient to analyze the dynamics of portfolio choice behavior. This requires panel

[1] These numbers are taken from Guiso *et al.* (2001), Table 3.

data. Household panels with information on portfolio composition are currently available for Italy and the Netherlands only.

Existing empirical studies typically focus on broadly defined asset groups, including all risky financial assets as one category. Important differences between various risky financial assets, however, will not be revealed in an analysis at this high level of aggregation. Although it is infeasible to use survey data to analyze ownership of every single financial product in the market, it seems worthwhile to distinguish a few subcategories of risky financial assets and to investigate the dynamics in the ownership patterns of these categories as well as the interactions between these patterns. In particular, we think it is useful to consider the two largest categories, individual stocks and mutual funds. The theoretical argument to treat these separately is that one mutual fund can provide the level of diversification which would require a large number of different stocks. Thus mutual funds seem very attractive for the small, non–expert investor who wants to invest a limited amount with relatively low transaction costs. On the other hand, since transaction costs for stocks will be less than proportional with the amounts held, holding individual stocks may be more attractive for the large investors. An empirical argument to distinguish between the two types of risky assets is that in many countries including the Netherlands, the mutual funds market has grown even more than the market for individual stocks.

In this paper, we use dynamic binary choice panel data models to explain the dynamics of the ownership structure of asset portfolios. Existing univariate random effects panel data models are extended to the bivariate case, accounting for interactions between two types of assets. One of the main features of the univariate dynamic binary choice model with random effects is that it can distinguish between unobserved heterogeneity and genuine state dependence. In addition, the bivariate model can explain correlation between ownership of one type of asset and lagged ownership of the other type of asset from correlated unobserved heterogeneity as well as from state dependence across assets. The correlation between random effects in the ownership equations captures correlated unobserved heterogeneity. Dummies for lagged ownership of each asset type in each equation capture genuine state dependence effects. To investigate the sensitivity of the results for the random effects assumption, we compare our model with a fixed effects dynamic linear probability model.

The empirical analysis considers ownership of stocks and mutual funds, using the 1993–1998 waves of the CentER Savings panel survey of Dutch households. This is one of the few existing household panel surveys with detailed information on ownership of many types of assets and debts. The sample consists of a sub-sample designed to be representative for the Dutch population, and of a (smaller) sub-sample from the highest income decile. Since ownership of risky assets is much more common among the rich than among others, this makes the data particularly useful for our purposes.The estimation sample is an unbalanced panel with 2861 households who, on average, participate in 3.4 waves.

Our aim is to increase insight in how households adjust the structure of their asset portfolios, addressing questions such as the following. Who are the people who have invested in mutual funds or stocks? Do background variables such as income, age, education level, and labor market status affect ownership rates of the two types of assets in the same way? Can changes in these background variables explain the increasing trends in the ownership rates? Why has the ownership rate of individual stocks increased less than the ownership rate of mutual funds? Have most new investors gone into mutual funds, or have people replaced individual stocks by mutual funds? If people hold mutual funds to diversify their risk, there seems no reason to hold individual stocks in addition. Still, the raw data show a positive correlation between ownership of mutual funds and ownership of individual stocks. Is this spurious correlation, or is there genuine state dependence across asset types, which could, for instance, be due to learning effects? Or is it because the new mutual funds owners simply keep their individual stocks?

The remainder of this paper is organized as follows. In the next section, the econometric models are presented. The data are described in Section 3. Section 4 contains estimation results. Section 5 concludes. Appendix A contains some additional estimation results. More details on the model and the estimation procedure are given in Appendix B.

2 Models

Following Hyslop (1999), we use two kinds of models. In Subsection 2.1, the random effects probit model is presented. This model explicitly incorporates the binary nature of the dependent variables and produces predicted ownership probabilities between zero and one. On the other hand, it relies on the assumption that individual effects are uncorrelated with regressors. Since this assumption is hard to relax in a discrete choice framework, in Subsection 2.2 a linear probability model is presented that allows for fixed effects, but has the drawback that predicted ownership probabilities may be outside the zero/one interval.

2.1 Random Effects Probit Model

In this subsection we introduce a multivariate discrete choice model for panel data, to explain ownership of different types of assets. For the sake of notational convenience, we present the bivariate case, but the generalization to the case of more than two asset types is straightforward. Since we will apply the model to ownership of stocks and mutual funds, we will refer to asset type 1 as stocks and to asset type 2 as mutual funds. We use the following notation, where the index for the household is suppressed.

y_{jt}: dependent variables; ownership dummies for stocks ($y_{1t} = 1$ if the household owns stocks in year t, $y_{1t} = 0$ otherwise) and mutual funds ($y_{2t} = 1$ if the household owns mutual funds in year t, $y_{2t} = 0$ otherwise); $t = 1, \ldots, T$.

$\boldsymbol{x}_t$: vector of independent variables, assumed to be strictly exogenous. The same independent variables are used in the two ownership equations.

α_j: random individual effects ($j = 1, 2$); (α_1, α_2) is assumed to be bivariate normal with variances $\sigma^2_{\alpha_1}$ and $\sigma^2_{\alpha_2}$ and covariance $\sigma_{\alpha_1}\sigma_{\alpha_2}\rho_\alpha$.

u_{jt}: error terms ($j = 1, 2;\ t = 1, \ldots, T$); (u_{1t}, u_{2t}) are assumed to be bivariate standard normal with covariance ρ and to be independent over time.[2]

[2] We have estimated specifications allowing for first order autocorrelation in the u_{jt} but found insignificant values of the autocorrelation coefficient for both assets.

We assume that (α_1, α_2), $\{u_{jt};\ j = 1, 2;\ t = 1, \ldots, T\}$ and $\{\boldsymbol{x}_t;\ t = 1, \ldots, T\}$ are independent (which implies that $\boldsymbol{x}_t$ is strictly exogenous).

The following specification will be used in the sequel.[3]

$$y^\star_{1t} = \boldsymbol{x}'_t\beta_1 + y_{1,t-1}\gamma_{11} + y_{2,t-1}\gamma_{12} + \alpha_1 + u_{1t} \qquad (1)$$

$$y^\star_{2t} = \boldsymbol{x}'_t\beta_2 + y_{1,t-1}\gamma_{21} + y_{2,t-1}\gamma_{22} + \alpha_2 + u_{2t} \qquad (2)$$

$$y_{jt} = \begin{cases} 1 & \text{if } y^\star_{jt} > 0 \\ 0 & \text{else} \end{cases} \qquad j = 1, 2;\ t = 1, \ldots, T \qquad (3)$$

Some special cases are worth mentioning. If $\gamma_{12} = 0$, the equation for stocks (1) does not contain the lagged mutual funds ownership dummy. In that case, the parameters β_1, γ_{11} and $\sigma^2_{\alpha_1}$ can be estimated consistently by considering only equation (1). This would be the standard univariate panel data probit model for binary choice, with state dependence ($y_{1,t-1}$ is included) as well as unobserved heterogeneity (the random effect α_1). See Heckman (1981a) for a discussion of this model. Similarly, the equation for mutual funds (2) can be estimated as a univariate model if $\gamma_{21} = 0$.

If $y_{2,t-1}$ enters the first equation but error terms and random effects in the first equation are independent of error terms and random effects in the second equation, then $y_{2,t-1}$ is weakly exogenous in the equation for y_{1t}. In this case the first equation could be treated as a univariate model with (weakly) exogenous regressors only.

One of the main issues in the univariate version of this dynamic model, is the distinction between unobserved heterogeneity (random effects) and state dependence (the lagged dependent variable). Both phenomena can explain why ownership of stocks in period t is positively correlated with ownership of stocks in period $t + 1$ (conditional on observed background variables $\boldsymbol{x}_t$ and $\boldsymbol{x}_{t+1}$). The model estimates will tell us to which extent the correlation is due to either of the two. In the bivariate model, a similar issue can be addressed, concerning the "spill–over effects" from one asset type on the other. If ownership

[3] Adding interactions of the two lagged dependent variables or of lagged dependent variables with $\boldsymbol{x}_t$ would make the model as flexible as a transition model with four different ownership states (both assets owned, stocks only, mutual funds only, neither of the two; the standard transition model would not include the random effects, however). We experimented with interaction terms but found they did not change the qualitative conclusions and were mostly insignificant.

of stocks in period $t+1$ is correlated to ownership of mutual funds in period t, this can be due to correlated unobserved heterogeneity (i.e., a non–zero covariance between α_1 and α_2) or due to state dependence across asset types, i.e., a non–zero value of γ_{12}. This is important for understanding the dynamics of the asset ownership decisions. For example, a positive value of γ_{12} could mean that mutual funds – which are easily accessible and advertised on a large scale – may have a learning effect in the sense that their acquisition changes people's attitudes to holding risky assets in general. People may then be induced to start buying individual stocks. On the other hand, a positive correlation between the random effects would simply mean that the same people who find it attractive to hold stocks in general also have a preference for holding mutual funds.

Initial Conditions and Estimation

This subsection is an informal discussion of how to estimate the model. Details can be found in Appendix B. In a short panel, there is a problem with the initial conditions (cf. Heckman (1981a)). One way to deal with this problem is to add static ("reduced form") equations for the first time period similar to the dynamic equations, but without the lagged dependent variables. The coefficients are allowed to be different from the coefficients in the dynamic equations, the random effects are linear combinations of the random effects in the dynamic equations, and the error terms are allowed to have a different covariance structure. This is the straightforward generalization of the solution that was given by Heckman (1981b) for the univariate case. In principle, the static equations can be seen as linearized approximations of the true reduced form (obtained by recursively eliminating y_{t-1} until $t = -\infty$). Heckman's simulations suggest that the procedure already works well in short panels, i.e. the approximation error does not lead to a large bias on the parameter estimates.[4]

[4] An alternative solution is explored by Lee (1997), who treats the initial values as fixed. Lee's simulation evidence suggests that this does not lead to any serious bias if the panel consists of 20 waves, but it does if the panel has only eight waves. It therefore seems less appropriate for our panel of six waves. Chay and Hyslop (2000) compare various ways to deal with the initial conditions problem in logit and probit models. They find that the probit model with the Heckman procedure performs better than other random effects models.

The complete model can then be estimated by Maximum Likelihood (ML), including the "nuisance" parameters of the static equations. Conditional on the random effects, the likelihood contribution of a given household can be written as a product of bivariate normal probabilities for all time periods. Each bivariate normal probability is then the probability of the observed ownership state, conditional on the ownership state in the previous year ($t \geq 2$) or unconditional ($t = 1$).

Since random effects are unobserved, the actual likelihood contribution is the expected value of the conditional likelihood contribution, with the expected value taken over the two individual effects. This is a two-dimensional integral. It can be approximated numerically using, for example, Gauss–Hermite–quadrature. Instead, we use simulated ML: bivariate errors are drawn from $N(0, I_2)$, they are transformed into draws of the random effects using the parameters of the random effects distribution, the conditional likelihood contribution is computed for each draw, and the mean across R independent draws is computed. If $R \to \infty$ with the number of observations, this gives a consistent estimator; if draws are independent across households and $R \to \infty$ faster than $\sqrt{N}$, then the estimator is asymptotically equivalent to exact ML (see Hajivassiliou and Ruud (1994), for example).[5]

In practice, the data at hand are an unbalanced panel, due to attrition, non–response, and refreshment. We assume that attrition and item non–response are random. We will use the complete unbalanced sub–panel. This is more efficient than using the balanced panel only.[6]

2.2 Linear Probability Model

This subsection presents standard linear dynamic panel data models as discussed in numerous places. See, for example, Verbeek (2000, Section 10.4) for an accessible overview. To formulate the linear probability model, two types of covariates are distinguished: $\boldsymbol{x}_t = (\boldsymbol{x}_t^1, \boldsymbol{x}^2)$, where covariates in $\boldsymbol{x}_t^1$ are time varying and (strictly) exogenous, and

[5] In the application, we found $R = 100$ to be sufficiently large in the sense that results did not change if R was increased further.

[6] There are some observations with "gaps" (observed for $t = 1, 2, 4, 5, 6$ for example). For computational convenience, these will be used only partially (i.e., in the example above, use $t = 4, 5, 6$ only). This leads to a reduction of the size of the sample by about 2% of all observations and 1% of all households.

covariates in $\boldsymbol{x}^2$ are time invariant.[7] The model has the following structure:

$$\begin{aligned} y_{1t} &= \boldsymbol{x}_t'\beta_1 + y_{1,t-1}\gamma_{11} + y_{2,t-1}\gamma_{12} + \alpha_1 + u_{1t} \quad (4) \\ y_{2t} &= \boldsymbol{x}_t'\beta_2 + y_{1,t-1}\gamma_{21} + y_{2,t-1}\gamma_{22} + \alpha_2 + u_{2t} \quad (5) \end{aligned}$$

where we make the following assumptions:

1. $\{\boldsymbol{x}_t^1; t = 1, \ldots, T\}$ uncorrelated to $\{(u_{1t}, u_{2t}); t = 1, \ldots, T\}$ (strict exogeneity)

2. $\boldsymbol{x}^2$ uncorrelated to α_1 and α_2 and to $\{(u_{1t}, u_{2t}); t = 1, \ldots, T\}$

3. $\{u_t, t = 1, \ldots, T\}$ are mutually uncorrelated.

The assumption on the time invariant regressors is in line with a Hausman–Taylor (1981) approach. Not considering any time invariant regressors at all would correspond to the common practice of not using time invariant regressors in a fixed effects model.

Define, for $t = 3, \ldots, T$,

$$\begin{aligned} \epsilon_{1t} &= y_{1t} - [\boldsymbol{x}_t'\beta_1 + y_{1,t-1}\gamma_{11} + y_{2,t-1}\gamma_{12}](= \alpha_1 + u_{1t}) \quad (6) \\ \epsilon_{2t} &= y_{2t} - [\boldsymbol{x}_t'\beta_2 + y_{1,t-1}\gamma_{21} + y_{2,t-1}\gamma_{22}](= \alpha_2 + u_{2t}) \quad (7) \end{aligned}$$

and

$$\Delta\epsilon_{jt} = \epsilon_{jt} - \epsilon_{j,t-1}(= u_{jt} - u_{j,t-1});\ j = 1, 2. \quad (8)$$

The model assumptions imply the following moments

- $\mathrm{E}[\Delta\boldsymbol{x}_s^1\Delta\epsilon_{jt}] = 0;\ j = 1, 2; s = 2, \ldots, T;\ t = 3, \ldots, T$ (strict exogeneity)

- $\mathrm{E}[y_{is}\Delta\epsilon_{jt}] = 0;\ i, j = 1, 2;\ s = 1, \ldots, t-2;\ t = 3, \ldots, T$ (lagged dependent variables)

- $\mathrm{E}[\boldsymbol{x}^2\epsilon_{jt}] = 0;\ j = 1, 2;\ t = 3, \ldots, T$ (time invariant regressors)

It is well–known that the small sample performance of GMM can deteriorate if many moments are used. To avoid this problem, we will only use the following moments, in which regressors and error terms are "as close as possible":

[7] In the empirical part, $\boldsymbol{x}^2$ will also include some variables that only vary systematically over time such as age.

- $\mathrm{E}[\Delta \boldsymbol{x}_t^1 \Delta\epsilon_{jt}] = 0;\ j = 1, 2;,\ t = 3, \ldots, T$ ((strict) exogeneity)
- $\mathrm{E}[y_{i,t-2} \Delta\epsilon_{jt}] = 0;\ j = 1, 2;,\ t = 3, \ldots, T$ (lagged dependent variables)
- $\mathrm{E}[\boldsymbol{x}^2 \epsilon_{jt}] = 0;\ j = 1, 2;\ t = 3, \ldots, T$ (time invariant regressors)

For a given specification, i.e., given choices of $\boldsymbol{x}_t^1$ and $\boldsymbol{x}^2$, these moments can be used for standard GMM estimation, separately for the equations for stocks and mutual funds.[8] Any type of heteroskedasticity is allowed for, including that implied by the binary nature of the dependent variable. Sargan tests for overidentifying restrictions are used to test the validity of the moment restrictions. The assumption that the errors u_{jt} are uncorrelated error terms seems quite strong, but is common in this type of model. This assumption will be tested by checking for second order autocorrelation in the residuals in the differenced equations.[9]

3 Data

We use six waves of the CentER Savings Survey (CSS), drawn from 1993 until 1998. Nyhus (1996) describes the set up of this data set and its general quality. The panel consists of two samples. The first is designed to be representative of the Dutch population (REP), but, due to survey non-response, the actual REP samples are not completely representative. The REP contains approximately 2000 households in each wave, including refreshment samples compensating for panel attrition. The second sample was drawn from high-income areas and should represent the upper income decile (HIP). Initially, it consisted of about 900 families. It is available in each wave except the final one. For our analysis, we combine REP and HIP samples. In the descriptive statistics, we correct for non-random sampling by using sample weights that are based upon income and home ownership. These weights are constructed using information from a much larger data

[8] According to Blundell *et al.* (2000), additional moment restrictions based upon a mean stationarity assumption can be used to improve efficiency. Specifications imposing these additional restrictions were strongly rejected, however, and are therefore not discussed.

[9] To estimate the linear probability model, we use the DPD98 software as described in Arellano and Bond (1998).

set (Housing Needs Survey (WBO)) collected by Statistics Netherlands, which is close to representative for the Dutch population. For observations with missing income, we predict income from background variables such as family size and education level and age of the head of the household.

The CSS data were collected via on-line terminal sessions, where each family was provided with a PC and modem. The answers to the survey questions provide general information on the household and its members, including work histories and labor market status, health status, and many types of income. Important for our purposes are the questions on assets and debts. For most of the forty asset and debt categories, respondents first indicate whether they own the type. If they do, they get a series of questions on amounts and the precise nature of each asset in that category. Non–response in the ownership questions is negligible, but non–response in some of the questions on the amounts is substantial. On average, about 20% of those who own stocks do not know or refuse to give the value of their stocks. Mutual funds have a lower non–response rate of around 13% per year. For some descriptive statistics (such as shares of specific asset types in total financial assets, see below), the item non-response creates a problem. We have therefore imputed the amounts for those who reported to be owners but did not provide an amount. See Alessie *et al.* (2001), who also provide an extensive description of all categories of assets and debts in the survey.

In the current paper, we focus on two types of risky financial assets: stocks and mutual funds. The CSS distinguishes between two types of stocks: stocks from substantial holding and (other) shares of private companies. There are very few people who hold the former type, but these people typically hold high amounts. The two types of stocks are different for tax purposes, since income from a substantial holding is treated as business capital. Dividends from other shares and from mutual funds are liable to income tax to the extent that they exceed an exemption threshold (Dfl 2,000 for couples, Dfl 1,000 for singles). Capital gains on these are not taxed. The thresholds on dividends are separated from the thresholds on interest on savings, creating a tax incentive for holding stocks or mutual funds as well as saving accounts.

The first two columns of Table 1 show how ownership rates of the two types of assets have developed during the years of the survey. The ownership rate of stocks has risen from about 11% to more than 15%. Mutual funds were more often held than stocks, with an even higher growth rate during the sample period. Many financial institutions have been successful in presenting mutual funds as a low threshold asset, available to many individual investors. Still, the majority of Dutch households held neither stocks nor mutual funds in 1998. This lack of participation can be explained by monetary transaction costs and information costs, both of which can be substantial.[10]

The remaining columns of Table 1 show the time path of amounts invested in stocks and mutual funds, as shares of total financial assets.[11] While the ownership rate of stocks is always lower than the ownership rate of mutual funds, the reverse is true for the shares of stocks and mutual funds in total financial wealth. This is because the few people who hold stocks typically hold high amounts of them. The growth of the shares is less spectacular than the growth of the ownership rates. The shares may be strongly influenced by some large amounts, due to the skewed distribution of wealth and its components. Some rich people hold large amounts, and there are very few of these in the sample, particularly in 1998, the year without high income panel. This may explain why some of the time patterns are not as pronounced as in aggregate data produced by Statistics Netherlands (see Alessie *et al.* (2001)). In the remainder of the current paper, we will not use the amounts data and focus on ownership rates.

In Figures 1 and 2, we present (head of household) age and cohort patterns of the ownership rates of stocks and mutual funds, based upon the six waves of the survey. We use five year–of–birth cohorts, with birth years 1915–1919 for the oldest cohort, until birth years 1970–1974 for the youngest cohort. Cohort labels indicate the middle year-of-birth.

[10] In the Netherlands, explicit transaction costs are low (about 0.5% of the investment) but implicit costs (entry and exit fees incorporated in the buying and selling price of the fund) are higher. The maximum entry fee is about 2.5% of the investment, and the maximum exit fee is about 1.5% (see Consumentenbond (1999)). Apart from the transaction costs, most mutual funds charge a management fee of about 0.5% per year and apply minimum investment restrictions. These implicit costs are comparable to the substantial transaction costs in Italy discussed by Guiso and Jappelli (2001). It is not clear, however, whether Dutch investors are aware of the implicit costs.

[11] This is defined as the total amount invested in each asset by all households (weighted with the sample weights), divided by (weighted) total financial wealth of all households.

Each figure gives the raw ownership rates for each cohort in each wave; the six points for each cohort represent the six average age levels at the times of the six interviews, and form a "cohort curve". The jumps between the cohort curves show that, apart from age effects, there are cohort or time effects. The cohort curves are not horizontal, implying that there are time and/or age effects; the fact that not all cohort curves are the same shows that there is more than just time effects. As usual, cohort, time and age effects cannot be identified without further assumptions. A plausible interpretation of both figures, assuming that cohort effects are zero, is that ownership rates increase with age and that there are positive effects of calendar time, particularly for the older cohorts. King and Leape (1987) have found a similar positive effect of age, which they attribute to accumulation of financial knowledge with age. Alessie *et al.* (2001) find a similar increasing age pattern for the category of all risky financial assets. This deviates from the pattern for some other countries. Italy and the US, for example, have a hump shaped pattern.

Table 2 describes the dynamics of the ownership patterns of stocks and mutual funds separately. It presents transition rates from ownership to non–ownership and vice versa.[12] This gives a partial view on mobility of stocks and mutual funds, since we only look at transitions for people that sell all their stocks or mutual funds or enter the market of stocks or mutual funds. We do not consider changes in (positive) amounts held or changes within the stocks or mutual funds portfolio. For example, 4.2% of households that do not own stocks in 1993, own stocks in 1994. On the other hand, 22.7% of those who owned stocks in 1993, no longer own stocks in 1994. Thus ownership mobility is substantial, for stocks as well as mutual funds. In particular, the fractions of owners selling their mutual funds or stocks are larger than expected, given the high returns on these assets in the nineties. On average, 21.2% of all stock owners no longer own stocks one year later, and 26.3% of mutual fund owners no longer own mutual funds one year later. Still, the large transition rates are in a similar order of magnitude as those reported for the US and Italy.[13]

[12]These rates are not weighted. Numbers of observations on which transition rates are based are mentioned in parentheses. The numbers hardly change if observations with very small amounts are excluded.

[13]Vissing–Jørgensen (1999, p. 13) finds that in the Panel Study of Income Dynamics, 28.1% of all

In Table 3, we present some evidence of correlation between holding one asset type in one period, and holding the other asset type in the next period. For all years, the ownership rate of stocks in year $t+1$ is larger for those with mutual funds in year t than for those without mutual funds in year t – conditional on not owning stocks in year t. For example, 9.4% of those without stocks and with mutual funds in 1993 owned stocks in 1994. On the other hand, only 3.5% of those who had neither stocks nor mutual funds in 1993, owned stocks in 1994. Thus there is some positive correlation across ownership of the two asset types. The same conclusion is obtained when ownership rates of mutual funds are considered. Whether this positive correlation reflects some genuine state dependence effect (such as learning) or (observed or unobserved) heterogeneity, is one of the issues we will analyze in the next section, using the models in Section 2.

4 Results

The results of the random effects probit model and the linear probability model are discussed in the first and second subsection, respectively. In the final subsection, the implications of these results for explaining the growth in ownership rates of stocks and mutual funds is presented. This is based on predicted probabilities, which are not always between 0 and 1 in the linear probability models, and will therefore be done on the basis of the probit results only.

4.1 Random Effects Probit

Tables 4a and 4b give the results for the bivariate probit model. The same explanatory variables are used in both equations. Financial wealth is not included, since it may not be strictly exogenous. In Appendix A, results are presented where lagged log financial wealth

households hold stocks in 1989 but not in 1994 or vice versa. Kennickell and Starr-McCluer (1997, p. 455) consider ownership of one category consisting of stocks, mutual funds, managed investment accounts or trusts in the Survey of Consumer Finances 1983–1989, and report transition rates of 10% from ownership to non–ownership and 19% from non–ownership to ownership. Miniaci and Ruberti (2001) report two-years transition rates from ownership to non-ownership between 32% and 42% using the SHIW survey of the Bank of Italy.

and its own household specific average (over the observation window) are included. This specification was chosen to control for the potential correlation between lagged financial wealth and the individual effects (see Hausman and Taylor (1981), for example).[14] We do not discuss the results in Appendix A since most of them are qualitatively similar to those in Tables 4a and 4b.

To avoid correlation with random effects and endogeneity of income and the marginal tax rate, income is non-capital income and the marginal tax rate is the maximum of the within–household imputed marginal rate applied to pseudo–taxable income, in which individual capital income is replaced with its cross–sectional average (following Agell and Edin (1990)). The effects of income and the marginal tax rate are hard to disentangle, due to the strong (positive) correlation between these variables. We find that both effects are positive for both types of assets. For stocks, the income effect is significant (at the two-sided 5% level), while for mutual funds, the tax effect is significant. An explanation for the stronger income effect for stocks than for mutual funds may be that high income households will typically have more to invest, making the relatively large fixed costs component of acquiring or holding individual stocks less important.

The income tax rules for stocks and mutual funds are the same (see Section 3). The fact that capital gains are not taxed creates an incentive to hold stocks or mutual funds, which increases with the household's marginal tax rate.[15] This explains the positive effect of the marginal tax rate. The larger tax effect for mutual funds could be due to the fact that suppliers of these funds strongly advertise their tax favored nature.

Labor market status variables for the head of household are jointly significant in both equations. The most striking result is the enormous effect of self–employment on ownership of stocks: a self–employed head has a more than 25%-points higher probability to own stocks than an employee (the reference group), *ceteris paribus*. Part of the explanation could be that the self–employed often hold shares in their own firm which will often be shares from a substantial holding. Excluding stocks from a substantial holding from the analysis, however, hardly changes the size of the effect. Thus our result seems

[14] Including an arbitrary linear combination as in Hyslop (1999) is not possible due to the unbalanced nature of the panel.

[15] See Poterba (2001) for a general discussion of the impact of tax rules on portfolio choice.

rather different from what Heaton and Lucas (2000) find for the US: self–employed hold more stocks in their own business, but hold less common stock, which is consistent with precautionary behavior insofar as they assume less risk from other firms. The retired are significantly more likely to own stocks or mutual funds than employees.

Since Figures 1 and 2 in the previous section have a plausible interpretation without cohort effects, we have included age and time effects but no cohort effects. This identifies the age and time patterns. Age is significantly positive for stocks as well as mutual funds. This is in line with findings for risky assets ownership by King and Leape (1987), who attribute the age effect to the accumulation of information about investment opportunities. This information argument seems particularly relevant for individual stocks, since these are the more "information intensive" type of risky assets. The time effects are similar for the two asset types and show that the assets have become more popular during the last few years of the survey (1997 and 1998; 1994 is the reference year).

The education variables are jointly significant in the equation for stocks only, indicating that stocks are more often held by the higher educated. Again, this could be interpreted as an effect of financial knowledge or interest in personal finance matters. If financial wealth is included, however, the effects of education vanish (see Appendix A), implying that the education effects in Table 3 might pick up wealth effects. A similar interpretation can be given for the dummy "High Income Panel." The positive significant effect of this dummy for both asset types largely vanishes if financial wealth is included (Appendix A). The way the high income sample is drawn makes it plausible that selection into this panel is not only based upon income but also on wealth, explaining why the dummy variable serves as a wealth proxy.

The estimated standard deviations of the random effects are 1.44 and 1.20 for stocks and mutual funds, respectively. The standard deviations of the error terms are normalized to one. Thus unobserved heterogeneity plays a major role, explaining more than half of the unsystematic variation in the model.

In both equations, the lagged dependent variables concerning ownership of the same asset type are significantly positive. To interpret these results, predicted ownership probabilities for the various lagged ownership states are presented in Table 4b. Exogenous variables are set to their (weighted) sample means and random effects are set to zero. Owners of stocks are about 16.7%-points more likely to own stocks next period than non–owners with the same (observed and unobserved) characteristics if they do not own mutual funds, and 15.4% points if they do hold mutual funds. For mutual funds, the differences are even larger (20.1%-points if no stocks are held, 17.4% points if stocks are held). Explanations for positive state dependence are the costs of acquiring stocks or mutual funds (i.e., genuine transaction costs, not the costs of holding the assets)[16] and the information argument: once they own the asset, people are more familiar with it, and are more aware of its risk and return characteristics.

All the results discussed so far relate to the dynamics of each of the two types of assets separately. In most respects, these results are similar to what would be predicted by separate univariate models. The bivariate model, however, also gives insight in the relation between the two ownership decisions.

The "cross–effects" of lagged ownership of one asset type on ownership of the other asset type are both negative and one of them is significant at the 5% level: *ceteris paribus*, those who do not own stocks are significantly more likely to own mutual funds in the next period than those who own stocks. According to Table 4b, the differences are 4.4%-points and 2.9%-points for those who did and did not own mutual funds in the previous period. If financial wealth is controlled for, the other cross–effect becomes significantly negative also (see Tables A1a and A1b in Appendix A).

The negative cross–effects cannot be explained by a generic learning effect: if ownership of one asset type would improve knowledge about the other asset type, a positive cross–effect would result. On the other hand, these are consistent with the same adjustment cost arguments that explained the strong positive effects of lagged ownership of the same asset type. People who own stocks but no mutual funds have an incentive to remain focused on stocks to avoid the adjustment costs, while people who own neither stocks nor mutual funds and who consider investing in risky assets, face adjustment costs anyhow. Adjustment costs thus give an explanation for own as well as cross state dependence

[16]Hyslop (1999) formalizes this in a stylized dynamic optimization model; a similar model can be used here for each of the two assets separately.

effects, while learning can only explain the univariate effects. These adjustment costs may reflect the actual (monetary) transaction costs involved with buying or selling an asset, but may also include non-monetary components such as the required effort, the need to collect information, etc.

The estimated correlation coefficient between the two random effects is large: 0.659 (with standard error 0.055). This suggests that the people who have a large preference for holding stocks (given their observed characteristics), tend to be the same people who have a preference for holding mutual funds. These may be the people with lower degrees of risk aversion or higher interest in financial markets. The positive correlation between holding stocks and holding mutual funds in the data, is to a large extent due to this positive correlation in unobserved heterogeneity.[17]

Allowing for correlation in the individual effects in the two equations has a major impact on the estimates of the cross–effects of ownership of one type of asset on ownership of the other type of asset in the next time period. If we estimate the model with the correlation between the random effects restricted to zero, we find significant positive estimates for both cross–effects. Not allowing for correlation between unobserved heterogeneity terms would thus lead to a large upwards bias on the effect of ownership of one asset type on ownership of the other type.

The correlation between the error terms in the two equations is small and insignificant. A negative correlation could point at fixed holding costs for each asset type (such as monitoring costs) that would be an incentive for specialization. Vissing–Jørgensen (1999) finds evidence of such costs. A positive correlation could point at a common element in monitoring both assets, or at benefits of diversification. Apparently, the positive and the negative effects cancel or do not play a role.

4.2 Linear Probability Model

Several specifications of the linear probability model of Section 2.2 are estimated, with different choices for $\boldsymbol{x}_t = (\boldsymbol{x}_t^1, \boldsymbol{x}_t^2)$. On the basis of Sargan tests for the over–identifying

[17]The correlation drops somewhat if financial wealth is included, but remains significant (see Table A1b).

restrictions, we selected the specification presented in Table 5. For stocks, the over–identifying restrictions are not rejected at the 2% level although they are rejected at the 5% level. For mutual funds, the overidentifying restrictions are not rejected at any conventional significance level. Moreover, the hypothesis of no second order autocorrelation in the residuals of the differenced equations is not rejected for either type of assets, supporting the assumption of no autocorrelation in the u_{jt}. We will briefly discuss some results of alternative specifications at the end of this subsection.

The same explanatory variables are used as in the probit model in Tables 4a and 4b. Education, age and gender are included in $\boldsymbol{x}_t^2$ since they do not vary over time or vary over time in a systematic way (i.e., the age variation is collinear with the time dummies). The other, time varying, variables are assumed to be (strictly) exogenous and are included in $\boldsymbol{x}_t^1$. Thus the main difference with the random effects specification in the previous subsection is that these time varying variables are allowed to correlate with the individual effects.

The results are largely in line with the findings in Subsection 4.1. Income is positively significant for stocks ownership, while the marginal tax rate has a significantly positive effect on owning mutual funds. The large effect of self–employment on the probability of holding stocks is again the most salient finding among labor market state effects. We can now conclude that this is not an individual effect, since correlation between individual effects and regressors is controlled for. Apparently there is something that makes holding stocks more attractive while in self–employment. Age, gender and education effects are also comparable to those in Table 4a, with the same signs, significance levels, and similar marginal effects.

In both equations, the lagged dependent variables concerning ownership of the same asset type are again significantly positive. The estimates of the marginal effects in this linear model are equal to the parameter estimates, and are still somewhat larger than the marginal effects in Table 4b.[18] Owners of stocks are about 17.3%-points more likely than

[18]The interaction term between the two lagged dependent variables was insignificant in both equations so that the hypothesis that the marginal effect does not depend on ownership of the other asset type is not rejected.

otherwise identical non-owners of stocks to own stocks next period. Owners of mutual funds are about 20.4%-points more likely than non-owners of mutual funds to own mutual funds in the next period.

The main difference with Table 4b is the estimated "cross–effect" of lagged ownership of stocks on ownership of mutual funds. In Table 5, the effect is positive and insignificant, whereas it was negative and significant in the random effects probit model. This confirms that no evidence of learning is found, but does not support the adjustment costs argument given in the previous subsection.

Detailed results for alternative specifications are available upon request. One alternative is to exclude age, education and gender variables completely. This would correspond to the pure fixed effects model. Results for this model are similar to those in Table 5. For stocks as well as mutual funds, Sargan tests do not reject the over-identifying restrictions (significance probabilities 0.110 and 0.087) and tests for second order autocorrelation do not reject the assumption of error terms that are uncorrelated over time (significance probabilities 0.872 and 0.226). This specification gives similar effects of the time varying regressors as Table 5, and similar effects of lagged ownership of the asset type itself (0.181 for stocks and 0.191 for mutual funds, both significant). The main difference is that the effect of lagged ownership of mutual funds on ownership of stocks is now significantly negative (-0.084, with standard error 0.039), while that of lagged stocks on ownership of mutual funds remains insignificant and positive (0.009 with standard error 0.051).

Models which make more restrictive assumptions on the relation between error terms and time varying explanatory variables (such as zero correlation with individual effects or mean stationarity) are clearly rejected by the Sargan tests for over-identifying restrictions, although they give similar qualitative conclusions on the ownership dynamics. A model that includes lagged log financial wealth as a weakly exogenous variable in $\boldsymbol{x}_t^1$ also gives similar results to those in Table 5, particularly concerning the dynamics. These results imply a significantly negative effect of financial wealth on future ownership of stocks and mutual funds, as in the probit model in Table A1a in Appendix A.

The main purpose of the linear probability models is to perform a sensitivity check on the findings on the basis of the probit models. The conclusion is that most findings are very similar: the tax and income effects, the effect of labor market position, in casu self–employment, and the effects of lagged ownership of stocks on ownership of stocks and of lagged ownership of mutual funds on ownership of mutual funds. The only differences concern the cross–effects of lagged ownership of stocks on ownership of mutual funds and of lagged ownership of mutual funds on ownership of stocks. Still, we always find a significant negative effect or an insignificant effect, and we do not find significant positive effects unless we impose a zero correlation of unobserved heterogeneity terms for the two equations — a restriction that is always fiercely rejected. This confirms that cross–effects due to learning cannot be established, while there is some evidence of cross–effects due to adjustment costs.

4.3 Explaining the Growth in Ownership Rates

The probit model results presented in Table 4a can be used to predict ownership probabilities for individual households and aggregate ownership rates for groups of households under different scenarios. Such predictions can be used to analyze how much the explanatory variables in the equations contribute to the changes in the aggregate ownership rates of stocks and mutual funds over time. The idea is similar to the Oaxaca decomposition that is commonly used in studies on wage differentials (Oaxaca, 1973).

The results are presented in Table 6. The top panel refers to stocks, the bottom panel to mutual funds. The first row of each panel presents observed changes in mean predicted ownership rates (in percentage points), using common samples for the two years considered. Random effects are set to zero. Since time dummies for all years are included, these sample changes reflect the increasing trend in aggregate ownership rates over the same years reasonably well.[19] The other rows compare two sets of predicted aggregate ownership rates: those using the observed explanatory variables and those in which one or more explanatory variables are replaced by their lags. Take, for example, the change in the stocks ownership rate from 1997 to 1998 of about 3.48%-points. If in the 1998 sample age is replaced by its lagged value (i.e., age in 1997), the predicted mean ownership rate

[19]This should still improve if random effects were integrated out instead of set to zero, but then the correlation between random effects and lagged ownership dummies should be accounted for.

falls by 0.26%-points. Thus the age effect explains 0.26%-points of the total rise of 3.48% points. Similarly, changes in marginal tax rates (which become somewhat larger, on average) explain a 0.16%-points rise of the ownership rate. All exogenous regressors (not including time dummies or lagged dependent variables) explain a rise of about 0.44%-points. The lagged dependent variables explain a rise of 0.11% points. This is mainly due to the rise in the ownership rate of stocks from 1996 to 1997. In total the regressors in the model (time dummies not included) thus explain 0.55%-points of the 3.48%-points rise in ownership of stocks. The remainder is not explained by the regressors and mainly captured by the time dummies. The contribution of the time dummies can be seen as the (residual) part of the change in ownership that cannot explained by the economic variables in the model.[20] We find that the economic variables age referring to labor market status, and lagged ownership explain part of the rise in ownership, but most of it is a time trend not captured by the explanatory variables in the model. The results for mutual funds are similar. The conclusion is that age is the only exogenous variable which consistently positively contributes to explaining the rising ownership rates. The main reason is that age is not only significant in the probits but also systematically increases over time. Self-employment, for example, is very important for ownership of stocks, but the fraction of self–employed in the sample does not vary systematically over the years.

5 Conclusions

As the stockholder base has widened considerably over the last decade in many countries, understanding how households make their portfolio decisions over time has wide–ranging implications for understanding the allocation of risk in financial markets, the distribution of wealth, and pricing relationships for individual assets. This paper is one of the first studies of the dynamics of individual households' (multivariate) investment strategies using representative panel survey data.

We have estimated dynamic models explaining ownership of the two main types of

[20]This can be compared to the changes "explained by" parameter changes in the usual Oaxaca decomposition; in this model with time dummies, only the constant term can vary over time.

risky financial assets in the Netherlands: stocks and mutual funds. The main difference between the two is that mutual funds are an easy way to attain diversification, at the cost of a premium paid to the mutual funds provider. This makes mutual funds particularly attractive for small investors with little financial knowledge. Our results confirm this to some extent, since we find that the probability to own stocks increases significantly with income while the probability to own mutual funds does not. Tax incentives, on the other hand, play a larger role for mutual funds than for stocks. Self–employed are much more likely to hold stocks than others, while they do not have a different ownership rate of mutual funds. An explanation could be that the self–employed are interested in specific stocks to hedge against their larger income uncertainty. The alternative explanation that the self–employed simply have different preferences and care less about diversification, is unlikely since the effect remains the same if unobserved (preference) heterogeneity is allowed to be correlated with background variables in a fixed effects setting.

We find that the dynamics of ownership of either type of risky assets are driven by state dependence as well as unobserved heterogeneity. Both explain part of the persistence of ownership of both types of assets in the data. The state dependence can be explained from the adjustment costs of buying or selling the asset. On the other hand, the positive sample correlation between ownership of one type of asset and lagged ownership of the other asset is explained from (observed and unobserved) heterogeneity only. One source of this could be a joint element in monitoring or other holding costs that makes it attractive to hold both asset types simultaneously. Another reason could be that combining stocks and mutual funds creates opportunities for diversification that cannot be attained by mutual funds alone (since these typically invest in certain sub-samples of stocks).

We find no evidence that households substitute one type of assets by the other, or that ownership of one type leads to more financial knowledge and a larger probability of buying the other type of assets. In contrast, we find some evidence of a negative effect of owning one type of assets on buying or keeping the other type. This can be explained by adjustment costs, which imply that those who have acquired one specific asset will tend not to reallocate their money to the other type of assets. Such adjustment costs will comprise the actual transaction costs involved with portfolio adjustment, but may also contain non–monetary or perceived costs components, reflecting the required effort, the costs of acquiring information, etc.

Classical papers like those of Merton (1969) and Samuelson (1969) assume that agents live in a frictionless world and have HARA preferences. They predict myopic optimal behavior (i.e. a constant fraction of risky assets in the portfolio) for a given individual. To make such models more realistic, it would be useful to introduce dynamic features. Our results suggest that adjustment costs are particularly relevant.

Future research can go in several directions. First, we have not modelled the amounts held. Although this is not without measurement problems, it certainly seems a relevant extension. It could also help analyze the importance of fixed costs of holding, buying, and selling assets, extending the work of Vissing–Jørgensen (1999). Second, if data for a longer time period become available, it seems useful to relate the ownership dynamics to the trends in the financial markets or to relevant macro variables such as unemployment, inflation or expected inflation, consumer confidence, etc. Third, straightforward extensions of our models could be used to analyze other asset and debt types, or to analyze assets at a less aggregate level. For example, to understand the dynamics and in particular the underlying cost structure driving these, it seems relevant to distinguish people who substitute one stock for the other from people who do not trade at all.

Finally, it would be interesting to extend the analysis with data on the recent time period with falling asset returns. The rationale for people then not venturing into risky assets seems to be that the return foregone is too low compared to the costs saved. In times when returns are high (1993-1998), this may make sense, and the time dummies in our models seem to pick up the sluggishness in the adjustment. On the other hand, there is some asymmetry in the sense that once adjustment costs are incurred, part of them will be sunk (at least the information acquisition costs). Selling the assets will therefore not be associated with the same costs. It therefore seems interesting to see what happens if times are bad.

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Tables and Figures

Table 1: Ownership Rates and Portfolio Shares

	ownership rate		portfolio share	
year	stocks	mutual funds	stocks	mutual funds
1993	11.4	11.8	21.3	5.4
1994	9.9	12.8	20.6	6.7
1995	11.4	12.9	22.0	6.2
1996	13.5	14.7	24.0	7.0
1997	14.4	16.2	25.3	7.1
1998	15.4	18.4	23.8	10.0

Note: weighted statistics; portfolio share: ratio of wealth held in stocks or mutual funds to total financial assets

Table 2: Transition Rates (Univariate)

	ownership → non–ownership		non–ownership → ownership	
years $t/t+s$	stocks	mutual funds	stocks	mutual funds
1993/94	22.7	26.5	4.2	6.8
	(309)	(310)	(1768)	(1767)
1994/95	26.7	32.5	5.5	6.1
	(288)	(335)	(1592)	(1545)
1995/96	21.2	20.1	6.1	5.7
	(274)	(298)	(1406)	(1382)
1996/97	19.7	26.1	6.0	8.2
	(239)	(253)	(1172)	(1158)
1997/98	15.7	26.3	4.4	7.6
	(159)	(190)	(838)	(807)
1993/97	25.8	36.2	11.6	12.4
	(128)	(138)	(673)	(663)

Note: unweighted statistics; transition rate ownership → non–ownership, $t/t{+}s$ = 100 (number of households who own in year t but not in year $t+s$)/(number of owners in year t). Total cell sizes (corresponding to 100%) in parentheses.

Table 3: Transition Rates (Bivariate)

	ownership year t		ownership probability in $t+s$	
years $t/t+s$	stocks	mutual funds	stocks	mutual funds
1993/94	no	no	3.5	5.4
	yes	no	75.3	17.8
	no	yes	9.4	73.9
	yes	yes	81.3	72.9
1994/95	no	no	4.5	5.8
	yes	no	72.5	8.4
	no	yes	12.0	65.8
	yes	yes	74.6	70.9
1995/96	no	no	4.4	5.0
	yes	no	78.7	11.0
	no	yes	17.6	77.7
	yes	yes	79.1	83.6
1996/97	no	no	5.3	7.1
	yes	no	78.7	16.9
	no	yes	10.7	70.0
	yes	yes	82.5	79.6
1997/98	no	no	3.0	6.9
	yes	no	87.7	13.6
	no	yes	13.4	71.4
	yes	yes	80.8	76.9
1993/97	no	no	9.4	10.9
	yes	no	74.4	22.1
	no	yes	25.0	64.6
	yes	yes	73.8	61.9

Note: See Table 2

Table 4a: Bivariate Random Effects Probit

	Stocks		Mutual Funds	
Variable Name	Estimate	Std.Err.	Estimate	Std.Err.
constant	–4.8132	0.4400	–3.4065	0.3213
stocks_{t-1}	1.1909	0.1077	–0.2540	0.1232
$\text{mutual funds}_{t-1}$	–0.1401	0.1073	1.1144	0.0946
age	0.0210	0.0054	0.0091	0.0044
education				
intermediate	0.3623	0.1797	0.0491	0.1547
vocational	0.0372	0.1375	0.0225	0.1124
high	0.4054	0.1628	0.2161	0.1307
Wald (p–value)		*0.0028*		*0.2039*
log income	0.0522	0.0182	0.0219	0.0171
HH marg. tax rate	0.6158	0.3408	1.2520	0.2623
high–income panel	1.0030	0.1414	0.5981	0.1027
labor market status				
unemployed	0.1552	0.3431	–0.0121	0.2814
retired	0.3142	0.1519	0.3857	0.1274
disabled	–0.5144	0.3592	0.1424	0.2316
self–employed	1.5511	0.1695	0.1317	0.1538
other	0.4810	0.2371	–0.0329	0.1889
Wald (p–value)		*0.0000*		*0.0487*
female	–0.4962	0.1536	–0.0736	0.1117
year				
1995	0.0614	0.0855	–0.0661	0.0739
1996	0.2101	0.0966	0.0483	0.0904
1997	0.3542	0.1090	0.2106	0.0872
1998	0.6144	0.1378	0.3089	0.1039
Wald (p–value)		*0.0001*		*0.0021*
σ_α	1.4446	0.1602	1.2027	0.1241
ρ_α	0.6590	0.0549		
ρ	0.0260	0.0653		
Number of households	2861			
Number of observations	9680			
Log–likelihood	–5706.42			

Note: Estimates of the initial conditions equations are available upon request.

Table 4b: Bivariate RE Probit: Predicted Probabilities

Combination	Stocks (s)	Mutual Funds (m)
$(s_{t-1}, m_{t-1}) = (0, 0)$	9.322	11.872
$(s_{t-1}, m_{t-1}) = (0, 1)$	8.062	31.957
$(s_{t-1}, m_{t-1}) = (1, 0)$	26.000	8.951
$(s_{t-1}, m_{t-1}) = (1, 1)$	23.482	26.391

Note: the numbers are ownership rates (in %) as predicted from the model for an "average" household: exogenous variables are set to their weighted sample means, random effects are set to zero, and the lagged ownership dummies are set to 0 or 1.

Table 5: Linear Probability Models

	Stocks		Mutual Funds	
Variable Name	Estimate	Std.Err.	Estimate	Std.Err.
constant	–0.1403	0.0540	–0.1368	0.0566
stocks_{t-1}	0.1734	0.0541	0.0102	0.0503
mutual funds_{t-1}	–0.0640	0.0392	0.2044	0.0494
age	0.0025	0.0009	0.0035	0.0009
education				
intermediate	0.0603	0.0270	0.0063	0.0249
vocational	0.0148	0.0178	–0.0028	0.0171
high	0.0747	0.0259	0.0442	0.0243
log income	0.0073	0.0034	0.0015	0.0032
HH marg. tax rate	–0.0436	0.0444	0.1284	0.0621
high–income panel	0.1439	0.0211	0.0849	0.0212
labor market status				
unemployed	0.0070	0.0290	0.0230	0.0283
retired	0.0476	0.0293	–0.0263	0.0321
disabled	0.0257	0.0386	0.0048	0.0395
self–employed	0.2239	0.0580	0.0105	0.0369
other	0.0461	0.0232	–0.0197	0.0260
female	–0.0395	0.0160	–0.0164	0.0170
year				
1996	0.0176	0.0074	0.0033	0.0077
1997	0.0347	0.0093	0.0365	0.0109
1998	0.0638	0.0124	0.0539	0.0147
Number of households	1870			
Number of observations	5950			
Sargan, 14df ($p-$value)	26.7231	*0.021*	19.1600	*0.159*
AR(2) test ($p-$value)	0.094	*0.925*	1.336	*0.181*

Table 6: Oaxaca Decompositions of Changes in Ownership Rates (in %-points)

years	1993/94	1994/95	1995/96	1996/97	1997/98	1993/97
Change in ownership rate			Stocks			
Total change	n.a.	1.40	1.87	1.85	3.48	n.a.
exlained by						
change in ...						
stocks$_{t-1}$ & mutual fds.$_{t-1}$	n.a.	0.09	0.29	0.17	0.11	n.a.
education	0.00	0.04	0.00	–0.00	0.01	0.02
age	0.19	0.21	0.23	0.24	0.26	1.10
log income	0.16	–0.02	–0.02	–0.22	0.16	–0.02
tax rate	0.08	–0.03	–0.02	–0.12	0.06	–0.20
tax & income	0.23	–0.07	–0.05	–0.36	0.20	–0.25
labor market	0.00	0.50	–0.02	0.02	–0.02	0.69
all x-s	0.42	0.70	0.18	–0.09	0.44	1.62
time dummies	0.00	0.60	1.57	1.61	3.03	n.a.
Change in ownership rate			Mutual Funds			
Total change	n.a.	–0.71	1.71	2.29	1.80	n.a.
exlained by						
change in ...						
stocks$_{t-1}$ & mutual fds.$_{t-1}$	n.a.	0.27	–0.25	0.12	0.16	n.a.
education	0.00	0.04	–0.00	0.00	0.01	0.04
age	0.12	0.12	0.13	0.14	0.14	0.60
log income	0.07	0.00	0.00	–0.10	0.07	0.03
tax rate	0.13	–0.08	–0.10	–0.34	0.15	–0.56
tax & income	0.18	–0.09	–0.11	–0.47	0.20	–0.59
labor market	0.00	0.18	0.12	0.14	0.06	0.65
all x-s	0.29	0.25	0.13	–0.18	0.43	0.74
time dummies	0.00	–0.88	1.55	2.35	1.49	n.a.

Note: Based on weighted means of (univariate normal) ownership probabilities as predicted from equations (1) and (2), with random effects set to zero; presented are the differences in such means between the baseline case and the case where some regressors are lagged: "total change": all right hand side variables are lagged, including ownership dummies and time dummies; "all x-s": all regressors except time dummies and lagged ownership dummies are lagged.

Figure 1: Ownership by Cohort: Stocks

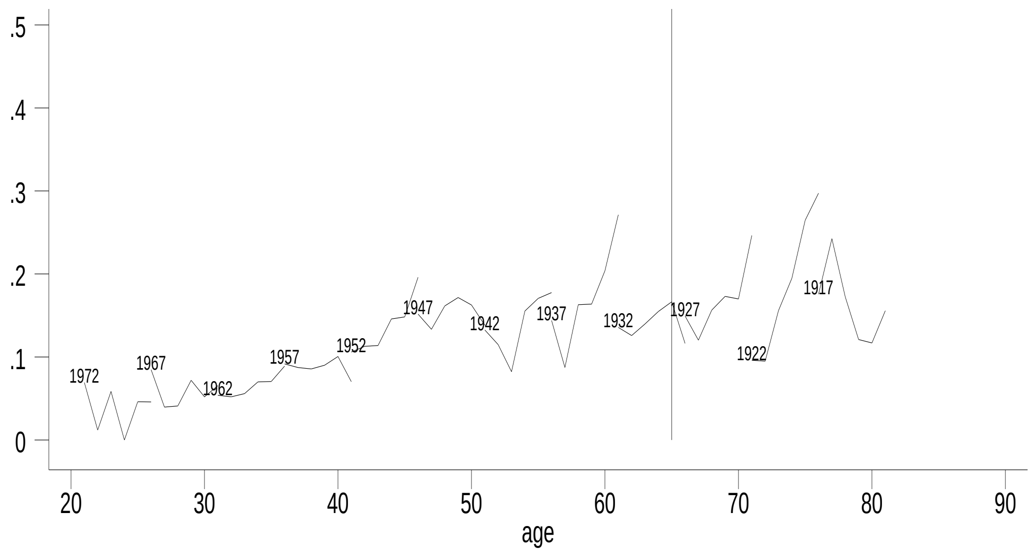
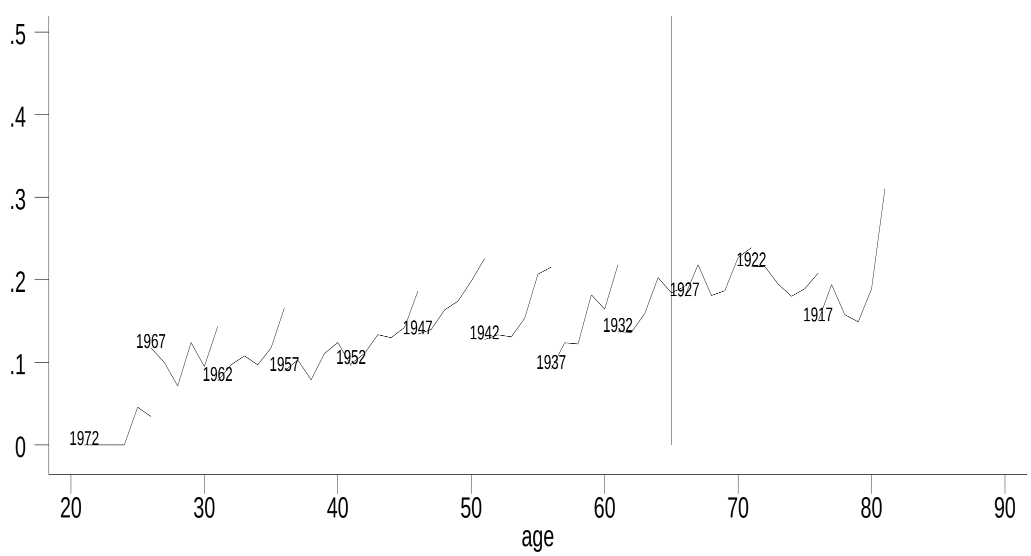


Figure 2: Ownership by Cohort: Mutual Funds



A Alternative Specification

Table A1a: Bivariate Random Effects Probit (Alternative Specification)

	Stocks		Mutual Funds	
Variable Name	Estimate	Std.Err.	Estimate	Std.Err.
constant	–12.5107	1.6092	–9.4148	1.0226
stocks_{t-1}	1.1531	0.1575	–0.4358	0.1831
$\text{mutual funds}_{t-1}$	–0.4175	0.1630	0.9944	0.1415
age	0.0008	0.0074	–0.0124	0.0062
education				
intermediate	–0.0216	0.2592	0.0152	0.1984
vocational	0.0307	0.2001	–0.0268	0.1508
high	0.2577	0.2305	0.0789	0.1738
Wald (p–value)		*0.4469*		*0.8696*
log income	0.0824	0.0267	0.0123	0.0230
HH marg. tax rate	0.1087	0.4680	0.9149	0.3561
high–income panel	0.1288	0.1454	–0.0711	0.1195
$\text{log. fin. wealth}_{t-1}$	–0.1089	0.0504	–0.0925	0.0554
log. fin. wealth (avg.)	0.9535	0.1235	0.8048	0.0992
labor market status				
unemployed	0.5903	0.4752	–0.1068	0.4148
retired	0.4507	0.2079	0.4781	0.1789
disabled	–0.1927	0.5550	0.2038	0.3207
self–employed	1.3236	0.2428	–0.4412	0.2180
other	0.5131	0.3815	0.2807	0.3226
Wald (p–value)		*0.0000*		*0.0219*
female	–0.1328	0.1794	0.2111	0.1520
year				
1996	0.1406	0.1065	0.1288	0.1006
1997	0.2737	0.1294	0.3247	0.1012
1998	0.5503	0.1705	0.4428	0.1247
Wald (p–value)		*0.0123*		*0.0011*
σ_α	1.4101	0.2223	1.1605	0.1787
ρ_α	0.6074	0.0995		
ρ	–0.1169	0.0910		
Number of households	1871			
Number of observations	5953			
Log–likelihood	–3401.50			

Note: see Table 4a.

Table A1b: Bivariate RE Probit: Predicted Probabilities

Combination	Stocks (s)	Mutual Funds (m)
$(s_{t-1}, m_{t-1}) = (0,0)$	5.638	7.440
$(s_{t-1}, m_{t-1}) = (0,1)$	3.382	21.339
$(s_{t-1}, m_{t-1}) = (1,0)$	17.909	4.197
$(s_{t-1}, m_{t-1}) = (1,1)$	12.295	14.026

Note: see Table 4b.

B Details on Model and Estimation Technique

This appendix presents some details of the econometric model described in Section 2.1. This is a bivariate random effects probit model with Gaussian errors. It is estimated by Simulated Maximum Likelihood.

Model

For a household (the index of the household will be suppressed) that is observed in waves $t = 1, \ldots, T$, the latent variable model for time periods $t = 2, \ldots, T$ is given by

$$\begin{aligned} y_{1t}^{\star} &= \boldsymbol{x}_t'\beta_1 + y_{1,t-1}\gamma_{11} + y_{2,t-1}\gamma_{12} + \alpha_1 + u_{1t} \\ y_{2t}^{\star} &= \boldsymbol{x}_t'\beta_2 + y_{1,t-1}\gamma_{21} + y_{2,t-1}\gamma_{22} + \alpha_2 + u_{2t} \end{aligned} \tag{B1}$$

We observe $y_{jt} = \mathbf{1}[y_{jt}^{\star} > 0]$, cf. (3). The β's and γ's are unknown parameters. The regressor vector $\boldsymbol{x}$ includes a constant term. Note that it would be straightforward to extend this model by adding interaction terms involving the lagged dependent variables. For instance, $y_{1,t-1}\gamma_{12}$ can be replaced by $y_{1,t-1}\boldsymbol{x}_t' ga\tilde{m}ma_{12}$, where $\tilde{\gamma}_{12}$, terms $y_{1,t-1}y_{2,t-1}\delta_j, j = 1, 2$ can be added to the first and second equation, etc. The model as it is presented here is the model for which we present the results.

We assume that the errors u_{jt} are independent over time, and that u_{1t}, u_{2t} follows a normal distribution, with unit variances and a cross–equation correlation $\mathrm{Cov}(u_{1t}, u_{2t}) = \rho$. The random effects α_j are assumed to be normally distributed with covariance matrix

$$\Sigma_\alpha = \begin{pmatrix} \sigma_{\alpha_1}^2 & \sigma_{\alpha_1}\sigma_{\alpha_2}\rho_\alpha \\ \cdot & \sigma_{\alpha_2}^2 \end{pmatrix}. \tag{B2}$$

For the initial period $t = 1$, Model (B1) would imply

$$\begin{aligned} y_{11}^{\star} &= \boldsymbol{x}_1'\beta_1 + y_{1,0}\gamma_{11} + y_{2,0}\gamma_{12} + \alpha_1 + u_{11} \\ y_{21}^{\star} &= \boldsymbol{x}_1'\beta_2 + y_{1,0}\gamma_{21} + y_{2,0}\gamma_{22} + \alpha_2 + u_{21} \end{aligned} \tag{B3}$$

Data at times $t = 0, -1, -2, \ldots$ are not available, however. For the univariate case, Heckman (1981b) suggests to replace the equation for $t = 1$ by a static equation with different regression coefficients and arbitrary linear combinations of the random effects. This can be seen as an approximation to the "reduced form". For the bivariate model, this yields

$$\begin{aligned} y_{11}^{\star} &= \boldsymbol{x}_1'\kappa_1 + \lambda_{11}\alpha_1 + \lambda_{12}\alpha_2 + \varepsilon_{11} \\ y_{21}^{\star} &= \boldsymbol{x}_1'\kappa_2 + \lambda_{21}\alpha_1 + \lambda_{22}\alpha_2 + \varepsilon_{21} \end{aligned} \tag{B4}$$

In a univariate framework, Chay and Hyslop (2000) also discuss an alternative specification that imposes a relation between the parameters in these equations and the parameters in model (B1), but they find that the estimator based upon this specification performs not as good as the specification without these restrictions. We will therefore not impose such restrictions and allow the parameters in the initial equations to be completely different from the parameters in the dynamic equations. The error terms ε_{11} and ε_{21} in (B4) are standard normal with correlation coefficient ρ_ε.

Estimation

The likelihood contribution for a given household can be written as the expected value of the log likelihood contribution conditional on the random effects. It is of the form

$$F = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} h(\alpha_1, \alpha_2)\; g_2(\alpha_1, \alpha_2, \Sigma_\alpha)\; \mathrm{d}\alpha_1 \mathrm{d}\alpha_2 \tag{B5}$$

where $g_2(\cdot)$ is the bivariate normal density of the random effects (α_1, α_2). See (B8) below for the exact expression of the function h.

Standard approaches of numerically integrating out the random effects are feasible but difficult.[21] Instead, we approximate the expectation in (B5) with the simulated average

$$F = \frac{1}{R} \sum_{r=1}^{R} h(\alpha_1^r, \alpha_2^r). \tag{B6}$$

where the random effects (α_1, α_2) are replaced by independent random draws (α_1^r, α_2^r), constructed as follows:

If N is the number of households in the sample, $2RN$ independent draws from the standard normal distribution are taken (using a pseudo–random number generator). For each household, this gives $2R$ independent draws $\tilde{\alpha}_1^r, r = 1, \ldots, R$ and $\tilde{\alpha}_2^r, r = 1, \ldots, R$ from the univariate standard normal distribution. These draws remain fixed during the estimation process.

To approximate the likelihood at given parameter values, the $(\tilde{\alpha}_1^r, \tilde{\alpha}_2^r)$ are transformed into draws from a bivariate normal distribution with zero means and covariance matrix Σ_α, using a Cholesky decomposition of Σ_α. This step is performed inside the likelihood routine because the parameters in Σ_α are updated at every iteration. The link between $\tilde{\alpha}_j^r$ and α_j^r is

$$\begin{aligned} \alpha_1^r &= \sigma_{\alpha_1} \tilde{\alpha}_1^r \\ \alpha_2^r &= \sigma_{\alpha_2} \rho_\alpha \tilde{\alpha}_1^r + \sigma_{\alpha_2} \sqrt{1 - \rho_\alpha^2}\, \tilde{\alpha}_2^r \end{aligned} \tag{B7}$$

The resulting estimator will be asymptotically equivalent to Maximum Likelihood if $R/\sqrt{N} \to +\infty$ (see Hajivassiliou and Ruud (1994), for example). For maximization of the log–likelihood function, we use the BHHH algorithm, based on first derivatives.

Likelihood contributions

A given household is observed in T waves. Hence the likelihood contribution (B5) is a function of

$$\begin{aligned} h(\alpha_1, \alpha_2) = {} & \Phi_2\Big(\tilde{y}_{11}\mu_{11}, \tilde{y}_{21}\mu_{21}, \tilde{y}_{11}\tilde{y}_{21}\rho_\varepsilon \Big| \boldsymbol{x}_1\Big) \times \\ & \times \prod_{t=2}^{T} \Phi_2\Big(\tilde{y}_{1t}\mu_{1t}, \tilde{y}_{2t}\mu_{2t}, \tilde{y}_{1t}\tilde{y}_{2t}\rho \Big| y_{1,t-1}, y_{2,t-1}, y_{1,t-2}, y_{2,t-2}, \ldots, \boldsymbol{x}_t\Big) \end{aligned} \tag{B8}$$

[21] The most popular method, Gauss–Hermite quadrature, can prove numerically unstable since the result depends non–monotonically on the number of quadrature points chosen.

Here $\Phi_2(\cdot, \cdot, \rho)$ is the bivariate cumulative density function of a bivariate normal distribution with means zero, unit variances, and covariance ρ, and we have defined

$$\tilde{y}_{jt} = 2y_{jt} - 1.$$

μ_{11} and μ_{21} are the right–hand sides of the two equations in (B4) excluding the error terms ε_{11} and ε_{21}, and, for $t = 2, \ldots, T$, μ_{1t} and μ_{2t} are the right–hand sides of the equations in (B1) excluding the error terms u_{1t} and u_{2t}.