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CAN HUMAN CAPITAL AND ASSET MANAGEMENT IMPROVE THE FINANCIAL PERFORMANCE OF OLDER AGE GROUPS? EVIDENCE FROM EUROPE

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Abstract

Extending Ehrlich et al.'s (2008, 2011) labor-theoretic, rational-expectations model of asset management (AM), we investigate the interplay between AM and portfolio choices of older-age households in a sample of 11 European countries plus Israel over 5 waves of the SHARE longitudinal data in the period 2004-2015. Our analysis shows that education, health, and other components of human capital, generally determine the reduced-form demand for, or portfolio shares of, risky assets, the derived-demand for asset management time, and the household's portfolio returns. Moreover, we find that education and underlying health conditions affect these portfolio outcomes largely through proxies of time household heads devote to asset management. Our key findings hold up against a battery of robustness and internal validation tests based on reduced-form and structural IV regressions, alternative regression specifications, and alternative groups of investors. We also find that the effects of education on the demand for AM time, risky financial assets, and portfolio returns, become larger as the opportunity costs of AM fall with age, which supports the mechanism of the asset management hypothesis.

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1. Introduction

To what extent do various components of human capital and household asset management activity affect portfolio choices and portfolio returns among older investors? This question is also related to the growing concerns about the financial independence of older age groups in aging populations. Policy makers in many developed countries are worried that it would be increasingly difficult to sustain the current level of social security programs and public health benefits for older households in countries with aging populations because of rapid demographic shifts caused by decreased fertility and increased longevity. In order to assess the comprehensive financial status of older households, it is also important to understand the mechanism determining the households' investment decisions as well as the dynamics of their wealth accumulation as they age. In this paper, we explore these issues from the perspective of the "asset management hypothesis (AMH)".

Building on Ehrlich and Ben-Zion (1976), Ehrlich et al. (2008, 2011), and Ehrlich and Shin (2010), we use a labor-theoretic, rational expectations framework to develop a testable micro-founded model of financial information acquisition. Unlike the empirical analysis offered in these earlier papers, however, we focus in this paper on portfolio choices of older age groups, including retirees, and explore the role of education and other components of human capital including health conditions and cognitive and non-cognitive abilities in determining time allocation into asset management (AM) and the selection of optimal portfolio allocations.

Our point of reference is that the market prices of financial assets are not fully revealing of all the relevant information about these assets, which leaves room for individual "asset management". By this term we mean the allocation of time and effort into a broad range of activities which aim to improve investors' knowledge and understanding of the expected performance of individual assets aside from their trading prices. Real world examples include following technological developments in specific sectors, reading financial outlook reports, incorporating diverse opinions of informed financial advisors, and conducting own research. To model the financial management challenge, we assume for simplicity that investors manage just two types of assets: a risky and a safe asset, and have the option of allocating some of their total productive time to AM activities in order to increase the precision of their beliefs about the future prospects of the risky asset in their portfolio.[1] We assume that investors rationally update their prior information-based beliefs using private and public signals to form a posterior belief about the risk and return profile of the risky asset, consistent with Bayes' theorem. By raising the precision of an investor's subjective assessment of the riskiness of the portfolio, effective AM activities can increase the investor's *expected demand* for the risky asset.

Our model predicts that human capital broadly defined to include education, or "knowledge capital", as well as additional indicators of health and ability (See Ehrlich and Murphy, 2007 and Ehrlich and Yin 2017), increases the expected demand for risky assets and the expected return on the overall portfolio of financial assets. Moreover, the asset management activity works, in practice, through time and effort devoted to managing the portfolio. The optimal allocation of time to AM is influenced by both the opportunity costs of such time and its effectiveness in providing private information and expected financial rewards, both of which are affected by education, or prior accumulated knowledge, and underlying physical health conditions.

There are three major testable implications emanating from this theoretical model:

First, the model suggests that the reduced form versions of investors' derived demand for asset management time and effort, *AMT*, as well as the expected demand for risky assets, *DEMAND* and expected portfolio return, *RETURN*, are determined by proxies of educational attainments and underlying health conditions~~,~~ as well as direct and opportunity cost of asset management time. Since we have only limited data about investors' wage rates, we use in some of the analysis proxy indicators

[1] The analysis can be generalized to allow for multiple risky assets, as we have done in a previous study where our data allowed for a distinction between domestic and foreign assets (see Ehrlich and Shin, 2010 and Ehrlich, Shin, and Yin, 2011).

of the opportunity costs of time, including individuals' age and market experience. We also approximate the direct costs of asset management by the households' portfolio size.

Second, the effectiveness of educational attainments, measured as years of education (*YEDU*), in explaining the main endogenous variables of the model - *AMT*, *DEMAND* and *RETURN* - should intensify when the opportunity costs of time start falling as investors approach retirement age. This is because the total effect of *YEDU* on effective asset management confounds both the positive effects of greater knowledge, and the negative effects of higher wages, thus opportunity cost of time it accounts for. For age groups that are closer to retirement, the opportunity cost of AM implicit in *YEDU* should considerably diminish, thus accentuating the favorable effect of *YEDU* on effective asset management.

Third, and more important, the model also produces a structural equation linking the optimal demand for risky assets to the investor's optimal information precision, which, in turn, is produced by the optimal allocation of time into AM activity. Identifying a causal relation between asset management time and the expected demand for risky assets, and thus the overall portfolio return, would confirm the main theoretical channel through which effective asset management, or information collection, can enhance the financial performance of informed investors.

We implement and test empirically the theoretical model from which these hypotheses are derived, using a sample of aging households (50 years old and over) in 11 European countries and Israel over 5 waves covering the period 2004-2015, drawn from the Survey of Health, Aging and Retirement in Europe (SHARE)[2]. Specifically, we estimate the model's reduced-form equations linking our main

[2] We use data from SHARE Waves 1, 2, 4, 5 and 6. DOIs: 10.6103/SHARE.w1.611 - 10.6103/SHARE.w6.611), see Börsch-Supan et al. (2013) for methodological details. SHARE data collection has been primarily funded by the European Commission through FP5 (QLK6-CT-2001-00360), FP6 (SHARE-I3: RII-CT-2006-062193, COMPARE: CIT5-CT-2005-028857, SHARELIFE: CIT4-CT-2006-028812) and FP7 (SHARE-PREP: N°211909, SHARE-LEAP: N°227822, SHARE M4: N°261982). Additional funding from the German Ministry of Education and Research, the Max Planck Society for the Advancement of Science, the U.S. National Institute on Aging (U01_AG09740-13S2, P01_AG005842, P01_AG08291, P30_AG12815, R21_AG025169, Y1-AG-4553-01, IAG_BSR06-11, OGHA_04-064, HHSN271201300071C) and from various national funding sources is gratefully acknowledged (see www.share-project.org).

endogenous variables with the model's exogenous and predetermined variables, primarily proxies of human capital and household wealth. We also test the internal validity of our theoretical model and major assumptions by estimating the basic structural equations of the model, which link the same dependent variables with our measures of asset management time (*AMT*). Since the latter variable is vulnerable to simultaneity bias, we estimate its effects using IV estimation methods.

The rest of the paper is organized as follows. Section 2 contains a short review of earlier literature on the general topic of our study and outlines our distinct approach and findings. Section 3 presents our theoretical model and its behavioral predictions. Section 4 contains the empirical implementation of the model and provides detail about our data and econometric specification, and Section 5 presents the empirical results. Section 6 offers robustness analysis and diagnostic tests. Section 7 concludes.

2. Related Literature

A. Financial literacy, human capital, and portfolio choices

There is a growing literature dealing with the captioned topics. This section covers just a selected number of studies that are more relevant for our paper. Bernheim et al. (2001, 2003) find positive and significant long-term effects of exposure to financial education and savings and wealth accumulation. Van Rooij et al. (2011) show a positive causal relationship between participation in the stock market and financial literacy. Jappelli and Padula (2013) build a life cycle model concerning investment in financial literacy and portfolio choice and estimate the relation between the two using the first two waves of SHARE and SHARELIFE. Behrman et al. (2012) report similar results based on analysis of the causal effect of financial literacy on wealth accumulation using Chilean data. Ameriks et al. (2003) report that households with higher propensity to plan spend more time developing financial plans, resulting in more savings. Banks and Oldfield (2007) and Banks et al. (2010) use the English Longitudinal Study of Aging to document the effect of cognitive abilities such as numeracy on the level and trajectory of wealth and retirement savings. Likewise, Christelis et al. (2010), using the first wave of SHARE, find that cognitive abilities such as mathematical skills, verbal fluency and recall skills are positively related to stock market participation.

Concerning the relevance of asset management and human capital to portfolio decisions, we should mention that, to our knowledge, Ehrlich and Ben-Zion (1976) has been the first attempt in the literature to develop a theoretical model emphasizing the trade-off between time allocated to "asset management" and labor market activities. Examples of more recent contributions based on these ideas include Ehrlich et al. (2008, 2011), Ehrlich and Shin (2010), Kim et al. (2016) and Lusardi et al. (2017).

B. Health and asset allocation

Another strand of the literature has focused on the effect of health indicators on wealth accumulation of older adults. Using HRS data, Edwards (2008) finds that perceived health risk explains about 20% of decline in financial risk exposure after retirement. Cardak and Wilkins (2009) show that "background risk" stemming from income uncertainties and health risk are important factors in explaining the holding of risky financial assets by Australian households. Love and Smith (2010) find a strong correlation between health conditions and financial and non-financial portfolios which disappears, however, when individual heterogeneity is controlled for. In contrast, Fan and Zhao (2009) show a positive relationship between adverse health shocks and safer asset holdings, even after controlling for individual heterogeneities. Atella et al. (2012) and Bressan et al. (2014) report a positive effect of self-perceived health on portfolio allocation in European countries using SHARE data.

Poterba et al. (2013) explores the relationship between education and the evolution of wealth after retirement and demonstrate the existence of positive effects of education and health on wealth accumulation using the HRS household data. Ehrlich and Yin (2017) address a similar topic and the same HRS data through the lens of the asset management hypothesis. They show that more schooling and better health status increase older age group's willingness to participation in risky financial markets as well as their demand for risky assets and the returns from their financial portfolios.

C. Retirement and cognitive abilities

Another line of research has investigated the effect of aging and retirement on cognitive abilities (e.g. Rohwedder and Willis (2010), Bonsang et al. (2012), Mazzonna and Peracchi (2012), Mazzonna and Peracchi (2017), Celidoni et al. (2017)). They generally find evidence that retirement reduces cognitive abilities. Korniotis and Kumar (2011), using a dataset from a large US discount broker for 1991-96, show that older and experienced investors exhibit investment patterns reflecting greater financial knowledge. But they also find that older investors apply such knowledge less effectively as they age.

Our study complements some of the findings reported by the various studies we reviewed in this section, but also deviates from them in important respects, as our results indicate. We base our empirical analysis on a theoretical model that builds on the "asset management hypothesis". The model identifies the specific channels through which asset management efforts, augmented by prior educational attainments and health status, affects portfolio choices and portfolio returns. We thus account for the simultaneous determination of the demand for risky assets, the derived-demand for asset management time and effort, and identify the impact of *AMT* on the key portfolio outcomes.

3. The Formal Model

Our model builds on the noisy rational expectations equilibrium literature pioneered by Hellwig (1980) and Verrecchia (1982). Their approach stresses the heterogeneity of investors to justify the role of private information in financial markets. We follow closely Ehrlich et al. (2008, 2011) which extended this approach by applying the Ehrlich and Ben-Zion (1976) labor-theoretic framework to allow for variations in asset management efforts by investors with heterogeneous human capital attainments to affect the precision of their private information about the posterior distribution of the returns on risky assets. Like the latter studies, we attribute investor heterogeneity largely to differences in human capital endowments, here defined more broadly to consist of prior educational attainments, differences in health conditions, and ability. More important, we go beyond those studies to establish a direct causal link between time allocation to asset management activity and asset management performance.

3.1 Compact Exposition of the Model

In an economy where the financial market is informationally complete and asset prices reveal all relevant information about returns on risky assets, individual private information would be redundant, since perfectly revealing prices leave no incentives for costly production of private information. In such equilibrium with zero private information, however, market prices should reveal no more than trivial information (see, e.g., Grossman & Stiglitz, 1980). Following the literature on asymmetric information and noisy prices, we assume the existence of random supply shocks in financial markets, which provides a simple justification for our more realistic assumption that asset prices cannot be fully revealing, leaving room for private information collection, or “asset management.”

Specifically, we assume that each investor, living through two periods, is endowed with human capital, H_i, distributed by a cumulative distribution $F: [H_L, H_H] \rightarrow [0, 1]$. The investor also has an initial financial wealth endowment consisting of x_i units of risky assets and B_{0i} units of risk-free bonds. For convenience, the price of risk-free bonds is fixed at unity for both periods, and thus its net return is zero. The risky asset, which is traded in a centralized market, offers a payoff μ in the 2nd period, which follows a normal distribution,

$$\mu \sim N(\bar{\mu}, h^{-1}). \tag{1}$$

The *average* risky asset supply, $x = \frac{1}{N}\sum_{i=1}^{N} x_i$, is random, subject to the normal distribution

$$x \sim N(\bar{x}, t^{-1}). \tag{2}$$

We assume that the parameter set $(\bar{\mu}, h, \bar{x}, t)$, including the means and variances of the corresponding variables, and the joint distribution of assets supply and payoff (x, μ) are commonly known to all investors. However, investors do not observe the realization of x or μ when they trade. Instead, they acquire a private information signal (z_i) that forecasts the risky asset’s payoff as follows:

$$z_i = \mu + \epsilon_i \ , \tag{3}$$

where

$$\epsilon_i \sim N(0, s_i^{-1}) \tag{4}$$

denotes a random forecasting error. Note that the acquired signal consists of the *sum* of μ and ϵ_i in eq. (3), not of μ and ϵ_i separately.[3] This implies that investors possess ex-post *diverse* private signals. The inverse variance of the private information signals s_i in eq. (4), has a special role in our model since it represents what we call the *"precision"* of the private information signal the investor acquires.

But what explains the degree to which investors can improve their private information precision? Our key assumption is that investors can devote part of their productive time to increase their current knowledge and understanding of the financial market. They may acquire information signals by following the direction of the economy or specific sectors and enterprises, including privately owned enterprises that are not traded in the financial markets; by interacting with selected financial advisers and traders, or by gaining experience through their own market trading.[4] Each of these information signals may reduce their subjective assessments of the variance of their forecasting errors of future market payoff on the risky asset. This is what we mean by *asset management* (AM).

Specifically, we assume that each investor is endowed with T units of productive time, which can be split into AM (q_i) and labor market activities ($T - q_i$). For simplicity, we abstract from leisure or alternative household production activities.[5] For each unit of time spent in AM, investor i faces an opportunity cost equaling the foregone wage rate, w_i, which is an increasing function of the investor's endowed human capital or $\partial w_i/\partial H_i \geq 0$. But human capital also works as an efficiency parameter which increases the productivity of time devoted to non-market activities of which AM is a distinct example. In this context, we assume that the stock of human capital, formed through prior investments in education and health, can independently raise private information precision, s_i. The latter variable can thus be specified as an outcome of the *asset management production function*,

$$s_i = g(q_i;\ H_i, W_{0i}). \tag{5}$$

[3] For simplicity, but without the loss of generality, we also assume that the stochastic variables μ, x and ϵ_i are unrelated.
[4] Hiring the services of financial advisers does not eliminate the investor's need to select advisers with varying limited knowledge to monitor their performance, and to make decisions on the extent of wealth they manage.
[5] Allowing for these additional activities would complicate the analysis by precluding the derivation of closed-form solutions for optimal asset management and demand for risky assets, but would not alter the model's testable propositions.

In equation (5), asset management time, q_i, serving as the direct input producing private information signals, is subject to diminishing marginal productivity, i.e., $g' > 0$, $g'' < 0$, and $W_{0i} = Px_i + B_{0i}$ denotes the investor's initial financial wealth. The latter consists of a risky asset, x_i, with P denoting the risky asset's variable price, and a riskless bond, B_{0i}, assumed to have a fixed price $P_B = 1$. By our key assumption concerning the role of human capital as an efficiency parameter in producing knowledge precision, $\partial g(q_i;\cdot)/\partial H_i > 0$ for all q_i, implying that the productivity of AM time, q_i, is enhanced by one's human capital stock. We also assume that portfolio size may independently help raise information precision, or $\partial g(q_i;\cdot)/\partial W_{0i} > 0$ for all q_i, because it captures the investor's experience in building a portfolio of assets, or economies of scale in asset management. Relatedly, we also assume that a higher initial portfolio lowers investors' average transaction costs.

The investor's problem involves two choices. The first concerns the optimal allocation of initial wealth (including earnings from time allocated to work) between the risky asset D_i and the riskless asset B_{1i}. The second, and closely related choice, is to determine the optimal allocation of productive time T into asset management (q_i) and work. Both choices, taking place in the model's first period, must satisfy the investor's initial wealth constraint:

$$W_{0i} + w_i(T - q_i) = PD_i + B_{1i}. \tag{6}$$

Terminal wealth, W_{1i}, thus becomes

$$W_{1i} = \underbrace{\mu D_i}_{\substack{\text{payoff from} \\ \text{risky asset}}} + \underbrace{B_{0i} + P(x_i - D_i) + w_i(T - q_i)}_{\substack{\text{payoff from} \\ \text{riskless bond}}}. \tag{7}$$

We define the investor's objective function to be the maximized utility from terminal wealth in eq. (7), representing the utility from potential consumption or bequest (s)he obtains in the model's second period. For analytical simplicity we assume that the utility function exhibits constant absolute risk aversion (CARA):

$$U(W_{1i}) = -exp\left(-\frac{W_{1i}}{r}\right), \tag{8}$$

where r denotes the constant absolute risk tolerance parameter. [6]

3.2 Portfolio Allocation, AM Time and Equilibrium

The model's optimal portfolio solution involves heuristically a two-step optimization procedure. In the first step, investors choose optimal asset management time, q_i given their optimal risky asset demand. In the second step, investors solve for the latter after observing the realization of their private signals, z_i, the precision of which, s_i, depends on their allocation of productive time into asset management in the first step.[7]

To solve the 2nd step, investors need to know the joint distribution of the stochastic market payoff, the private information signal, and the risky asset's market price, (μ, z_i, P). To this end, we first specify a linear conjecture for the risky asset's equilibrium market price:

$$P = \theta + \lambda\mu - \nu x. \tag{9}$$

Applying Bayes' theorem, the mean and variance of μ conditional on the private and market signals (z_i, P) are then given by the following equations, respectively:

$$\mu_i = E[\mu|z_i, P] = V_i\,[h\,\bar{\mu} + s_i z_i + t(\lambda/\nu)^2\lambda^{-1}(P - \theta + \nu\bar{x})] \tag{10}$$

$$V_i = Var[\mu|z_i, P] = [h + s_i + t(\lambda/\nu)^2]^{-1}. \tag{11}$$

Using eqs. (10) and (11), the demand for the risky asset, conditional on the investor's optimal information precision s_i and the resulting private information signal can be shown to be:

$$\begin{aligned} D_i^* &= D(z_i, P) = rV_i^{-1}(\mu_i - P) \\ &= r(h\bar{\mu} + s_i z_i + t(\lambda/\nu))^2[\lambda^{-1}(P - \theta - \nu\bar{x})] - [h + s_i + t(\lambda/\nu)^2]P). \end{aligned} \tag{12}$$

To arrive at the equilibrium solution for eq. (12), however, we must also solve for the coefficients of the conjectured equilibrium market price in eqs. (9)-(11). Under rational expectations equilibrium

[6] To simplify the exposition of our model, we assume that the risk tolerance parameter r is constant and equal across investors. We take this approach to stress the role of the main mechanism of our model – the asset management channel – which attributes the observed heterogeneity in investors' portfolio decisions to objective parameters, such as predetermined human capital, rather than subjective preferences. It is straightforward to introduce heterogeneity in both human capital and attitude toward risk. Our key theoretical findings and empirical specifications are not affected by such generalization.
[7] See Ehrlich et al. (2008) for the technical details of the solution using a Cobb-Douglas specification of the production function of information precision in equation (5).

conditions, the conjectured risky asset price must be consistent with the market clearing price. The conjectured coefficients (θ, λ, ν) must then satisfy the equilibrium condition,

$$\sum D(z_i, P) = \sum x_i. \tag{13}$$

We can show that this is indeed the case.

Using equations (9) and (12), we can now solve for the investor's demand for information precision, s_i^*, which must satisfy the optimality condition for maximizing eq. (8), subject to eqs. (5)-(7):

$$r(h + s_i^* + (rs)^2 t)^{-1} = 2C_i'(s_i^*; H_i, W_{0i}, w_i), \tag{14}$$

where the marginal revenue from asset management is equated to its marginal cost. Equation (14) suggests that the individual investor's optimal demand for private information must take into consideration the average private information precision in the economy, $s = \frac{1}{N}\sum_{i=1}^{N} s_i^*$, since the market price of risky asset aggregates the private information and partially reveals it.[8]

The minimized cost function of asset management, in turn, can be derived as follows:

$$C_i(s_i; H_i, W_{0i}, w_i(\cdot)) = w(H_i; \tau_i) f(s_i; H_i, W_{0i}), \tag{15}$$

where $f(s_i; H_i, W_{0i}) = g^{-1}(s_i; \cdot)$ is *the minimum* asset management time (q_i) required to achieve a given level of information precision, s_i. The wage rate $w_i(\cdot) = w(H_i; \tau_i)$ is an increasing function of human capital, H_i , and τ_i represents a vector of other determinants of the wage rate, which include labor market conditions and demographic factors.

The solution to the implicit function (14) yields the *optimal* demand for information precision, s_i^*:

$$s_i^* = s(H_i, w_i, W_{0i}, r). \tag{16}$$

Likewise, the derived demand for asset management time q_i is obtained by utilizing (5) and (16) as a function of the same underlying parameters:

$$q_i^* = q(H_i, w_i, W_{0i}, r). \tag{17}$$

[8] The existence of such a rational expectations competitive equilibrium is established by applying the fixed-point theorem. See Verrecchia (1982).

Equations (16) and (17) play a key role in deriving the testable propositions of the model.

3.3 Optimal Demand for Risky Assets, Portfolio Return, and Comparative Statics

Given the optimal demands for risky assets and information precision in equations (12) and (16), the expected demand, or "long-term" average demand, for the risky asset by investor i, which we henceforth term *DEMAND*, can be shown to have the following closed form:

$$E[D_i^*] = \bar{x}\,\frac{h + s_i^* + r^2 s^2 t}{h + s + r^2 s^2 t} > 0\,.^{9} \tag{18}$$

Similarly, the expected return on risky assets assumes the following form:

$$E[D_i^*(\mu - P)] = r\,\frac{h + s_i^* + r^2 s^2 t}{(h + s + r^2 s^2 t)^2}\,[\{h + (r^{-1} + rst)^2\, t^{-1}\} + \bar{x}^2 / r^2] > 0\,. \tag{19}$$

This expression can be also interpreted as the return on all financial assets, which we henceforth term *RETURN*, because the return on safe bonds is assumed for convenience to be nil. Equations (18) and (19) imply that both *expected* demand and portfolio returns of our heterogeneous investors are increasing functions of their private information precision (s_i^*), which is the basic outcome of our model.

Two important features of equations (18) and (19) are worth stressing. First, eq. (18) implies that it is the *absolute* demand for the risky asset that is expected to rise with the investor's information precision. This prediction does not apply directly to the optimal *share* of financial wealth allocated to risky asset, although by eq. (16) optimal information precision is a function of initial wealth, which needs to be accounted for in explaining optimal *DEMAND*. Second, eq. (19) implies that it is the *total portfolio return* that is expected to increase with the investor's information precision, rather than the *rate of return* on the risky asset in the portfolio. This is because in our model, one cannot 'beat the market', as is the case in the conventional CAPM, where all investors obtain the equilibrium market-

[9] While expected demand for the risky asset is positive, as eq. (18) implies, realized demand could be zero or even negative if $\mu_i < P$ at a point in time (see eq.(12)). Thus, in our baseline empirical analysis, we use the entire sample of investors, including those reporting zero risky asset holdings. In our robustness tests, we also perform subgroup analysis by restricting our sample to include only those households reporting positive financial or risky assets. For the derivation of Eq. (18) see Ehrlich et al. (2008). Eq. (19) is derived in Mathematical Appendix.

determined returns, $(\mu - P)$, on the risky assets they hold**.** Put differently, it is the demand for risky vs. risk-free assets that determines the expected return on the investor's total portfolio. However, investors who engage in more intensive AM activities are expected to obtain more precise private information. This lowers their perceived, private-information based riskiness of the risky asset, as measured by the Bayesian posterior variance (eq. 11) which, in turn, increases the expected demand for risky assets (eq. 18) and thus the expected portfolio returns due to the market-determined risk premium on these assets. Eqs. (18)-(19) thus imply that information precision s_i^* is the sufficient statistics which can fully account, on average, for the cross-sectional variation in households' portfolio allocations and returns, as summarized below:

Lemma 1. (*Sufficiency of s_i^*) The expected demand for risky assets and its expected return are fully explained by the investor's information precision, s_i^*.*[10]

Lemma 1 indicates that in order to empirically implement equations (18) and (19), we need to rely on the effects of the theoretical determinants of optimal information precision s_i^* as specified in eq. (16), and indirectly on the derived demand for asset management time (*AMT*), q_i^* as specified in equation (17). By eq. (5), or eqs. (14) and (15), *AMT* is the direct input affecting information precision, and human capital, H_i, is the fundamental parameter affecting its productivity. In addition, the initial total portfolio, W_{0i} and the investor's wage rate, $w_i = w(H_i, \tau_i)$ affect the optimal asset management time and information precision, (q_i^* and s_i^*) through their underlying respective impacts on the economies of scale and the opportunity costs of producing information precision (s_i^*). The risk tolerance parameter (r), in turn, affects s_i^* through its impact on the demand for risky assets. Lemma 2 summarizes the related comparative statics effects:

Lemma 2. (*Comparative statics: parameter changes affecting optimal s_i^* and q_i^**).

[10] The sufficiency of s_i is an artifact of the constant absolute risk aversion (CARA) utility function and an assumed common constant risk tolerance parameter, *r*. We take this simplified approach to obtain closed form solutions and to highlight the asset management mechanism. In our empirical analysis, however, we control for other factors which may have an impact on the demand for risky assets, such as individual risk tolerance and other demographic characteristics of household heads.

(a) An exogenous increase in the investor's wage rate or the common risk aversion ($1/r$) of all investors, or a decrease in the investor's initial wealth, W_{i0}, are all expected to decrease the investor's demand for information precision s_i^* and asset management time q_i^*.

(b) (Conditional effects of H_i) An exogenous increase in the investor's human capital (H_i) conditional on the investor's wage rate, w_i, raises the derived demand for optimal information precision s_i and possibly asset management time q_i as well.[11]

(c) (Unconditional effects of H_i) The net effect of an exogenous increase in H_i unconditional on w_i is smaller in magnitude than the conditional effect of H_i.

Proof: See Ehrlich et al. (2008) for a more detailed analysis.

Lemma 2 implies that, given the values of all other parameters of the model, including the wage rate, w_i, investors who are endowed with more wealth and human capital would demand a higher precision of private information, and thus *DEMAND* and *RETURN*.

Since the wage rate is a monotonic function of human (knowledge) capital, an exogenous increase in the latter will also raise the opportunity costs of time, w_i, which works in the opposite direction on the demand for optimal precision. The *unconditional* impact of human capital on the demand for information precision, and thus *DEMAND*, would therefore be positive only if it is not offset by the opposite effect it imparts on the opportunity cost of asset management time.

Regardless of what the net impact of the *unconditional* effect of human capital may be, its effect on *DEMAND* and thus also the derived-demand for asset management time (*AMT*) would be lower (algebraically) than its *conditional* demand for both, given the wage rate. Based on this analysis, we propose the following testable behavioral predictions:

Proposition 1 (*+stable implications of the asset management hypothesis): DEMAND* and *RETURN* are functions of the basic determinants of the derived-demand for *AMT*, which includes human capital H_i, initial wealth, W_{0i} and the constant relative risk tolerance, parameter, r, as follows:

[11] The comparative statics results concerning the effects of shifts in H_i and W_{0i} on q_i are based on the sufficient assumption that the elasticity of q_i with regard to s_i exceeds one. Standard constant returns to scale production functions such as Cobb-Douglas and CES satisfy this condition.

(a) Conditional on the household head's wage rate, *DEMAND* and *RETURN* increase with optimal information precision, s_i, and thus, indirectly by *AMT*, q_i.

(b) The unconditional effects of H_i on *DEMAND*, *RETURN* and *AMT* decrease with the elasticity of the wage rate with respect to human capital, ϵ_{w_i,H_i} (see the Mathematical Appendix for proof). This can be viewed as a generalization of our prediction concerning the conditional vs. unconditional effects of human capital.

(c) The implications of Lemma 2 are also part of our empirically testable hypotheses.

4. Empirical Implementation

4.1 Sample Construction

Our sample is drawn from the Survey of Health, Aging and Retirement in Europe (SHARE). This is a cross-country longitudinal data concerning individuals aged 50 and over. As of 2018, SHARE has released five waves of regular survey datasets. Completion of data collection in each wave is roughly 2 years apart. Our dataset is constructed based on Release 6.0.0 made available in July, 2017. Our total sample covers the micro survey data on demographics, socio-economic status, health, etc., of more than 120,000 individuals.

The decision maker in our unit of analysis is the household head. The survey also reports information about the spouses of the respondents. In order to avoid possible double counting of the same households and to ensure accurate responses to financial queries, we retain in our analysis only the observations linked with the same financial respondents in all waves and discard the rest.

To focus on the older population, we remove a handful of households where the financial respondents are younger than age 50. Those households are included in the initial file, because their spouses are 50 and over. We then delete the observations with invalid responses to queries concerning key demographic information including years of education (*YEDU*), gender, age, and immigration status (*IMMIG*). We also remove the few observations ($\simeq 3\%$) without test scores capturing intellectual abilities (*FLUENCY, NUMERACY*). Finally, we constrain the sample to include all the following variables: *AMT* (asset management time), *RISKAVS* (risk aversion), *RASST* (risky assets = stock, mutual funds and bonds), *FASST* (total financial assets), and *NFASST* (non-financial assets). This leaves slightly fewer than 8000 observations. To guard against the possibility that our results are impacted by extreme outliers, all variables are winsorized to 1st and 99th percentiles. However, the results are broadly similar if the original non-winsorized values are used. Table 1.A reports the breakdown of the sample size by country and wave. Table 1.B presents the descriptive statistics of key variables and brief explanations.

A. Description of key variables in our econometric implementation

The concept of human capital, H_i in our model: For simplicity of exposition, we have modeled the role of human capital in asset management as a single efficiency parameter, H_i. We recognize, however, that human capital encompasses distinct components which may not have the same effects on the demand for asset management time and efforts or the opportunity cost of time. Empirically, we therefore break down the theoretical human capital into three major components, as below.

a. Knowledge component of human capital (YEDU): Years of schooling serves as our major proxy, capturing the general knowledge component of human capital, which is assumed to serve as a key efficiency parameter which raises the productivity of asset management time (*AMT*) in accumulating new knowledge. At the same time, however, *YEDU* also raises individual wages and thus their opportunity cost of asset management time. For the age groups in our sample, *YEDU* represents completed years of formal schooling and is thus treated as a predetermined variable.

b. Health component of human capital, self-perceived health (SPH): The literature in section 2 suggests that individuals' health may complement the knowledge component of human capital (*YEDU*) by enhancing both asset management activity and wealth accumulation (see e.g., Poterba et al., 2013, Ehrlich and Yin, 2013, 2017). Good health may enhance the effort and energy associated with time devoted to asset management and also relax the time constraints limiting AM through random incidents of morbidity. Both channels impart a positive impact on private knowledge precision, s_i^*, and may independently enhance the demand for risky and other assets since those having less medical bills can also invest more of their disposable income on financial and non-financial assets. We use the SHARE survey's self-perceived health (*SPH*) index as a predetermined discrete index of overall mental and physical health, falling monotonically from 1 (excellent) to 5 (poor) - see Appendix C. We place a negative sign before the original numerical categories to assure that a higher value of *SPH* indicates a better health condition. Atella et al. (2012) and Bressan et al. (2014) show that *SPH* dominates other overall health measures in the survey in terms of their relevance for making financial decisions.

c. Other components of human capital – ability indicators (NUMERACY, FLUENCY): As section 2 of our paper indicates, there is a growing literature suggesting that innate ability measures contribute to households' financial management effectiveness. We use *NUMERACY* and *FLUENCY* to control for these effects. *NUMERACY* is the sum of test scores involving basic algebra. In some studies (e.g. Lusardi and Mitchell 2007, Jappelli and Padula, 2013), such variables are also considered to be relevant for measuring financial literacy. *FLUENCY* is designed to capture verbal fluency, and is measured by the number of animals one can name in one minute. While both skills capture primarily cognitive skills, they may also reflect noncognitive skills, since fluency, e.g., can be acquired through practice. [12]

Asset management time (AMT) – q_i^* in the model: Since *AMT* is jointly determined with *DEMAND*, it is our main endogenous variable. The first wave of the SHARE survey reports data on the time used for asset management as a categorical variable measuring investors' self-reported frequency of time they spend reviewing their financial statements per year (*AMFREQ*): 1=never, 2=about once a year, …6=every day (see Appendix C for details).[13] Treating *AMFREQ* as a continuous variable, we use its logarithmic transformation to form our empirical proxy for asset management time, *AMT*, since the skewness of the distribution of *AMFREQ* appears to resemble a log-normal distribution. Clearly, *AMT*,

[12] We have run a large number of robustness tests with other measures of cognitive/non-cognitive abilities including self-rated intellectual characteristics and short-and medium-term memory scores, in all our regression models. Our key results are virtually unchanged, and in general, these variables have less explanatory power and lower statistical significance than Numeracy and Fluency. In the interest of saving space, we do not report these results.

[13] $AMFREQ$ also has an extra category of 7 - delegation to a third party - which is reported, however, only in the French survey. To maintain international comparability, we drop a small number of such French households from the sample.

is not a perfect proxy for q_i. Yet, if *AMFREQ* is proportional to q_i, the factor of proportionality affects just the estimated constant term of regressions in which this variable is the dependent variable.[14]

Risk aversion (*RISKAVS*) - $1/r$ *in our model*: We use a self-assessed measure of risk aversion, or inverse of risk tolerance, to disentangle the effects of attitude toward risk from asset management effects. *RISKAVS* is available in the SHARE data as a self-reported measure of personal risk aversion.

Risky Asset Demand (DEMAND) – $E[D_i^*]$ *in our model:* The SHARE sample reports the total value of household's risky financial portfolio, which include stocks, mutual funds and all bonds. We use the log transformation of this variable, $\ln RASST$, as a proxy for the expected demand for risky assets. The inclusion of government bonds in this variable is likely to reduce the power of our AM indicators in explaining the demand for risky assets and may work against our asset management hypothesis, since government bonds are often considered a proxy for risk-free assets.

Participation in risky financial asset market (PARTICIPATION): While *DEMAND* captures the intensive dimension of the demand for risky assets, it also justifies looking separately at the willingness to hold risky assets or enter the markets for risky assets. *PARTICIPATION* is thus measured as a dummy variable, which takes the value of 1 if the household currently has positive risky financial assets ($RASST > 0$), and zero otherwise.

Expected portfolio return (RETURN) – eq. (19) *in our model*: The SHARE survey reports a related variable – the returns from total financial assets (*RTFASST)*, which consists of realized dividends from stocks and mutual funds, and interest income from bank accounts and bonds. We use $\ln RTFASST$ as our empirical proxy for the expected returns from the total risky portfolio. This variable is subject to potentially severe measurement errors. First, it measures realized returns, not expected returns. Second, it includes neither realized nor unrealized capital gains. This may introduce non-random errors to the measurement of this variable, which would bias downward the estimated effects of asset management

[14] The logarithm transformation we use for all our dependent and independent variables is strongly supported by the Box-Cox tests.

time on the *RETURN* variable. This is because by the logic of the asset management hypothesis, more informed investors would tend to invest in riskier financial assets, which typically yield more return in the form of capital gains rather than dividends and interest income.

Wealth/Portfolio size (FASST, NFASST), W_{0i} in our model: We construct a proxy for W_{0i} based on two variables comprising wealth. Total household financial assets (*FASST*) measures the size of the financial portfolio, including *RASST*, bank savings accounts, personal retirement accounts, and whole life insurance. In general, investors hold part of their wealth in the form of real assets as well. For this reason, we also use *NFASST* (household non-financial assets) to account for investors' portfolio sizes. *NFASST* consists of the value of homes, business assets, cars, and other real assets net of mortgages owned by the households. We use the logarithmic transformations of these two measures [15] ($\ln FASST$, $\ln NFASST$) separately to account for our hypothesized economies of scale in financial asset management.[16] But both variables may also capture any potential wealth effects on investors' risk tolerance we abstract from in our model.

Underlying Chronic Health Conditions: BMI and EYE. These predetermined variables are used as instrumental variables in our structural equations linking asset management time (*AMT*) with the simultaneously determined demand for risky assets and total portfolio returns. *BMI* and *EYE* are selected as IVs since they limit the productive time available for work and AM activities, but not directly the demand for risky assets and portfolio returns**.** A more detailed discussion of their relevance and validity as IVs is given in section 5.3. They are defined technically as follows:

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[15] We apply $\ln X = \ln(1+X)$ for X =*RASST, RETURN, FASST* and *NFASST* to retain observations with zero values.

[16] In our empirical analysis, we treat the total values of $\ln FASST$ and $\ln NFASST$ as predetermined variables, since they reflect the value of assets accumulated as a result of past saving and investment decisions. Since all of our continuous dependent variables are log-transformed, in this specification, we essentially estimate the effect of our key explanatory variables on the share of the total portfolio spent on risky assets, but allow for the possibility of differences in the effects of $\ln FASST$ and $\ln NFASST$ on the demand for risky assets. In unreported empirical analyses, however, we perform robustness checks under alternative specifications of the total portfolio by using the 'initial' portfolio values reported in wave 1, initial or contemporaneous values of total assets (= *FASST* + *NFASST*) and total household consumption expenditures in lieu of our baseline measures of the portfolio size. Our empirical findings are largely unaffected by these alternative specifications.

The body mass index (BMI) measures a person's weight in relation to height and is reported in the SHARE survey as a continuous variable. *Eyesight for reading (EYE) is* reported in SHARE as a self-assessed measure of visual acuity in a close range (using regularly glasses or contact lenses). *EYE* is measured as a discrete index falling monotonically from 1 (excellent) to 5 (poor) - see Appendix C. We place a negative sign in front of the values of *EYE* to assure that a higher value of the index implies a better eyesight for reading.

B. Data challenges

Apart from the limitations of our *RETURN* measure due to the partial measure of returns on risky assets, other key variables also face some measurement challenges. Time devoted to asset management (*AMT*) is surveyed only in wave 1, while individuals' attitude toward risk (*RISKAVS*) is reported only in wave 2. In order to use our entire longitudinal sample, we assign the available values of these variables to the same investor in all other waves. This procedure inevitably introduces random errors of measurement in the construction of these variables.

To control for the possible effects of non-random bias, we include demographic variables, such as age (*AGE*), and dummy variables for gender (*MALE*), marriage status (*MARRIED*), and immigration status (*IMMIG*), in addition to our proxies for wealth and cognitive and non-cognitive ability measures (*NUMERACY, FLUENCY*). When *AMT* is used as a key explanatory variable in the structural regressions, we further attempt to minimize the effects of random measurement errors by using instrumental variable (IV) regression methods to project the relevant measures of *AMT*. Remaining random errors, however, are likely to bias downward the estimated coefficients of *AMT* relative to their true values.

Also, the proxy for predetermined knowledge human capital, *YEDU* is time-invariant for the majority of households in our sample. Although a small fraction of households appears to report changes in formal education, this appears to be largely the result of changes in the coding used to measure the total years of education. To minimize the impact of measurement errors, we use the average value of *YEDU* for the same individual over all data waves in our regression analysis.

The restrictions we impose to enable the use of *AMT* and *RISKAVS* further penalizes our empirical analysis in two ways. First, it reduces the number of observations available for analysis, as the investors in our sample must be surveyed in both of the first two waves. This excludes use of the refreshment samples for the twelve countries surveyed in the initial two waves.[17] Moreover, we are unable to utilize the observations surveyed in 15 European countries that were added in later waves. This removes about 80% of the observations available in all 5 waves. Second, this procedure limits the variability of time-invariant explanatory variables such as *YEDU*, *AMT* and *RISKAVS*, as we are forced to follow the same individuals across all waves. This is likely to raise the standard errors of our estimated regression coefficients. Yet, as the following sections indicate, the empirical results appear to support our model.

4.2. Econometric Model Specification

A. Baseline reduced form model

Our theoretical model indicate that the endogenous variables, *DEMAND*, *RETURN* and the derived AM time, q_i^*, are explained by the same reduced form exogenous determinants of asset management activities, including investors' human capital's knowledge component, H_i, and health, as summarized in Lemma 2 and Proposition 1.

We use the following baseline *reduced form* specifications to test this proposition:

$$Y_{it} = \beta_0 YEDU_i + Z_{it}'\gamma \;\; + \mu_c + \eta_t + u_{it} \tag{20}$$

where i, t and c denote the individual household, time (wave) and country, respectively; μ_c and η_t stand for country and wave fixed effects; and u_{it} represents the individual household random error. The dependent variables set, Y_{it}, represents *DEMAND*, *PARTICIPATION*, *RETURN*, and *AMT*,

[17] The 12 countries surveyed in the initial two waves are Austria, Germany, Sweden, Netherlands, Spain, Italy, France, Demark, Greece, Switzerland, Belgium, and Israel.

respectively. The vector of control variables other than *YEDU* – our key proxy for the knowledge component of human capital – is denoted by Z_{it}. It includes *SPH*, *RISKAVS*, $\ln FASST$, $\ln NFASST$, and other demographic characteristics such as age (*AGE*), immigration (*IMMIG*) and marriage (*MARRIED*) status. In some regressions, Z_{it} also includes *FLUENCY* and *NUMERACY*.

In eq. (20), β_0 represents the *unconditional effect* of education (*YEDU*), since we cannot control for the effect of investors' wage rates - the opportunity costs of asset management. This is because only 35.8% of respondents in our sample report that they are not retired and much fewer report their wage income. We are thus unable to accurately estimate the *conditional effect* of human capital. Although our theoretical model predicts that the sign of the unconditional effect, β_0 , is ambiguous, our earlier studies (see Ehrlich et al., 2008, 2011), based primarily on the US working age investors, show that the unconditional effect of human capital is positive. In light of Proposition 1(b), we expect β_0 to be positive in our sample as well. The flipside is that our estimate of β_0 in eq. (20) represents a lower bound of the true conditional effect of investors' human capital, H_{i0}.

B. Structural model

The reduced-form regression model tests the implicit effect of human capital as a key determinant of effective asset management in the absence of any indicators of asset management activity as captured theoretically by the effect of asset management time q_i^* or information precision s_i^*. Our SHARE sample allows us to go one step further and test our AM hypothesis directly by specifying the effects of our empirical measures of asset management time on the model's dependent variables as per proposition 1(a). The proposition leads to the following specification of our empirical structural model as expressed in equations (16)-(19):

$$Y_{it} = \beta_0 YEDU_i + \beta_1 AMT_i + Z_{it}'\gamma + \mu_c + \eta_t + u_{it}, \tag{21}$$

where Y_{it} stands for *DEMAND*, *PARTICIPATION* and *RETURN* . In this specification (*structural equation*), we expect that $\beta_1 > 0$ but the sign of β_0 is ambiguous.

While *AMT* captures the effect of asset management's length of time, which is the direct input in the production of information precision, there may still exist a residual effect of *YEDU* as an efficiency parameter in the knowledge precision production function (5), because we do not fully control for the knowledge precision variable itself - s_i^* in equation (18). Furthermore, in the absence of the wage variable, w_i, in the estimated regression equation (21), *YEDU* captures the effect of the opportunity costs of time as well. As these effects work in opposite directions, the unconditional sign of *YEDU* in equation (21) is ambiguous. Generally, however, since we control for the expected positive effect of *AMT*, we anticipate the magnitude of the *YEDU* effect, β_0, to be *smaller* than its estimated value in the reduced-form model, eq. (20) due to the effect of the missing opportunity cost of time. These considerations allow us to propose supplementary empirical hypotheses as a test of the mechanism underlying our "asset management hypothesis".

Proposition 2 (The main testable implications of the structural model)

(a) In the structural equation (21), we expect *AMT* to have a positive effect on the outcomes of effective asset management, or $\beta_1 > 0$.

(b) The magnitudes of the estimated effect of *YEDU*, and possibly all other components of human capital, on the demand for all specific outcomes of AM activity, are expected to be lower in absolute value in the (second-stage) structural regressions relative to those in the reduced-form regressions, since the impacts of the human capital components work in various degrees through that of the projected value of *AMT*.

C. Estimation issues

Our theoretical model implies that *AMT*, *DEMAND*, and *RETURN* are determined simultaneously. It is thus possible that investors demand higher asset management time or intensity because they have larger demand for risky assets (and thus a risky portfolio) rather than the other way around. Therefore, the OLS estimates of equation (21) capture essentially associative relationships, not causal ones. We address the potential simultaneity bias using an instrumental variable approach.

Since key explanatory variables in our baseline equations (20) and (21) – *AMT*, *RISKAVS* and *YEDU* – are time invariant, we cannot use the fixed-effects estimation method to estimate these equations, as this would fully absorb the distinct effects of these key variables. To enable the estimation of their predicted effects by propositions 1 and 2, we therefore apply the OLS method with clustered standard errors to account for the panel structure of our data.[18]

5. Empirical Results

5.1 Reduced Form Regressions

Table 2 presents the estimated coefficients of the reduced form regressions of our model, as specified in eq. (20), which show the unconditional effects of human capital and wealth components on the dependent variables of our model –*DEMAND*, *PARTICIPATION*, *RETURN* and *AMT*.

DEMAND: In columns (1)-(3) of Table 2.A, the dependent variable is the logarithm of our proxy for the demand for risky financial assets, *RASST*. The explanatory variables include the basic determinants of asset management and a gradually expanding demographic and ability measures. The results indicate that *YEDU*, *SPH*, and $\ln FASST$ have positive and significant effects on *DEMAND*, in line with our hypotheses. *RISKAVS* also exerts negative effects, as expected. In column (2), we introduce demographic characteristics and an additional measure of wealth, $\ln NFASST$ as control variables to capture the effect of the total portfolio size on *DEMAND*. In column (3), we further include variables capturing cognitive and non-cognitive abilities. $\ln NFASST$, like $\ln FASST$, has a positive and significant effect. Among demographic variables, *AGE* has a positive and significant effect – this an issue we explore further in this section. Among the indicators of ability, only *FLUENCY* has positive and significant effects on *DEMAND.* The inclusion or exclusion of these variables does not alter markedly the predicted effects of the basic variables of our model qualitatively.

[18] We have also estimated all of our empirical models using a random effects model. We find that our key results are highly consistent across these different estimation methods.

PARTICIPATION: While our theoretical model predicts that *expected demand* (*DEMAND)* should be positive for all households (see eq. 18), Table 1.B shows that only 24% of households in our sample participate in risky financial markets.[19] This prediction relies, however, on the model's simplifying assumption of costless participation in risky financial assets: the model overlooks investments in non-financial assets (real estate) that also involve some risk, as well as any direct fixed costs of participation, or prohibitive time, effort, or knowledge constraints on the ability to access and trade in risky financial markets. In view of these fixed costs, which we skipped for simplicity, the expected participation decision becomes a special dimension of *DEMAND*. We therefore expect the determinants of *DEMAND* in Proposition 1 and Lemma 2 to explain the participation decision as well, recognizing that both may be positive only above a threshold level, subject to positive participation costs.

In columns (4)-(6), we use the linear probability model (LPM) to estimate our expected theoretical effects. The results are broadly similar to those in the baseline *DEMAND* regressions. *YEDU*, ln *FASST*, ln *NFASST* and *SPH* all exert positive and significant effects on participation, while *RISKAVS* has a negative and significant effect. The addition of other control variables including cognitive and non-cognitive abilities, as well as demographic variables and country/wave fixed effects, do not change our results qualitatively. As in the *DEMAND* regressions, *FLUENCY* has a positive and significant effect. It is interesting to note that the positive effect of *AGE* turns significant when cognitive and non-cognitive skill proxies are controlled for.

RETURN: To examine the impact of the determinants of AM on total financial returns, we use a proxy for *RETURN*, (acronym $\ln RTFASST$), which includes the reported returns on financial assets in SHARE, as the dependent variable in columns (1)-(3) in Table 2.B. Despite the significant limitations of our returns data we discussed in the preceding section, *YEDU*, *SPH* and ln *FASST* exert positive and significant effects on *RETURN*, consistent with their effects on *DEMAND* and *PARTICIPATION* in

[19] This rate is very close to the participation rate in the US. Ehrlich et al. (2011) document that the average participation rates are 25% for salaried workers and 26% for all investors, based on the Survey of Consumer Finance (SCF) dataset over 1992-2007.

eq. (20). Also, ln *NFASST* (capturing the effect of total wealth) and *RISKAVS* exhibit their expected signs. These basic results are again not affected by the inclusion or exclusion of additional control variables**.**

AMT: Derived demand for AM time, q_i^*: Our model predicts that the derived-demand for AM time has the same fundamental determinants as *DEMAND*, *PARTICIPATION* and *RETURN*.[20] Columns (4)-(6) indicate that this is indeed the case. As before, *YEDU*, ln *FASST* and ln *NFASST* all exhibit positive and significant effects, and *RISKAVS* exerts negative effects. The self-perceived health, *SPH*, however, is statistically insignificant at conventional levels. This result is not inconsistent with our model, since *SPH*'s interaction with *AMT* in the production of information precision s_i^* may be different from that of *YEDU.* Good health may enhance the energy and effort accompanying asset management time, and thus its effectiveness in identifying information signals and the demand for risky assets without necessarily enhancing the derived demand for its quantity, while *YEDU* may be a complement to *AMT* in generating knowledge and thus more likely to enhance both the demand for risky assets as well as the derived demand for *AMT*. The results also indicate that married investors (*MARRIED*) tend to spend more time in asset management, which appears to be a reflection of division of labor within a household**.** The indicators of ability and financial literacy, however, are all insignificant.

5.2. The Implicit Effect of the Opportunity Cost of Asset Management

As previously emphasized, there exist two distinct channels through which human capital affects asset management and portfolio decisions and returns. On the one hand, human capital increases the efficiency of *AMT*. Thus, other things equal, higher human capital would lead to more precise information and greater demand for risky assets. On the other hand, higher human capital increases the opportunity costs of time. These effects work in opposite directions. Proposition 1(b) shows that

[20] In this regression model, we use the sample drawn from wave 1 only, as our dependent variable *AMT* is reported only in wave 1. See also the first stage regression results shown in Table 5, which utilize the full sample information. Our main findings are not affected by the sample construction.

the unconditional effect of human capital on *DEMAND*, *RETURN* and *AMT* decreases with the elasticity of wages rate with respect to human capital, ϵ_{w_i,H_i}.

To test this implication, we use the investor's age to trace the variations in ϵ_{w_i,H_i}. Specifically, we expect that the individual's 'wage rate' becomes less sensitive to the predetermined terminal level of education, so its elasticity with respect to education gets smaller as they get older in the SHARE survey, and especially as they enter the retirement phase. Hence, we expect the unconditional positive effects of *YEDU* to become larger as investors get older.

To implement this empirical design, we sort our sample by age to form three roughly equal-sized age groups and run subgroup regressions to estimate eq. (20).[21] Table 3 reports the results. Corroborating Proposition 1(b), the unconditional effect of *YEDU* is larger in the oldest group (G3) than the youngest group (G1) in all the reduced-form regressions concerning *DEMAND, PARTICIPATION* and *AMT* models. These results appear to support the implicit influence of the opportunity costs of time on our dependent variables. Although *YEDU* does not have a significant effect on *RETURN* in these subgroup regressions, this is not surprising in view of the smaller sample sizes of each of the age groups and the limitations of our *RETURN* proxy, which is devoid of any capital gains.

Note that this pattern of increasing quantitative impact of *YEDU* on the first three outcome of asset management is not observed in connection with any of our other explanatory variables, which may add further credence to Proposition 1(b) since the effects of these variables is not expected be dependent on the opportunity cost of AM time. In particular, *FLUENCY* is found to have a positive effect on the bulk of the dependent variables, but its effect does not seem to be increasing with age. Although the estimated effects of *NUMERACY* do appear to rise from the younger to the older age

[21] The cut-off ages are 65 and 75 except for *AMT* regressions in which these are 60 and 70. Thus, the youngest group (group 1, G1) includes investors aged between 50 and 64 (50 and 59 for *AMT*). The intermediate age group (group 2, G2) and the oldest group (group3, G3) consist of investors in the age bands 65-74 and 75 and over (60-69 and 70+ for *AMT*), respectively.

groups in some of the regressions, none of the estimated coefficients of *NUMERACY* is statistically significant.

5.3. Structural Equations: Estimating the Direct Effect of Asset Management

A. Associative effects

To test the internal validity of our model, we first present the regression results for the structural equation (21) based on the non-IV, random effects OLS estimation method. Table 4 reports the results. We find that the results are broadly and fully consistent with the theoretical *DEMAND* and *RETURN* we derive in equations (18) and (19) and Proposition 1. *AMT*, the direct input into asset management and our knowledge precision variable (s_i^*) has a positive and statistically significant effects in all the corresponding structural models. The overall effects of self-perceived health (*SPH*) and the size of financial and real portfolios remain positive and significant while those of *RISKAVS* remain negative and significant. Also, the effect of *AGE* is mostly positive and significant. *NUMERACY* and *FLUENCY* have positive and significant effects in some of the regression models. Importantly, the inclusion of these variables does not change our key results.

B. The causal effect of *AMT*

a. Baseline IV regression model (eq. 21). Our theoretical model implies that *AMT*, *DEMAND* and *RETURN* are determined simultaneously. This implies that the estimated regression coefficients reported in Table 4, although providing strong support to the internal validity of our model, are likely to be subject to endogeneity biases concerning the true causal effects running from *AMT* to the reported outcome variables. We address the bias by using instrumental variable estimation methods.

We assume that variables representing endowed health limitations or chronic health conditions can serve as appropriate instruments, since they are directly related to asset management time, but not to portfolio allocation decision directly. In this context, we have selected the individual body mass index (*BMI*) as a relevant IV. It is well-established in the medical literature that obesity measured by *BMI* is associated with functional limitations in physical activities, locomotive abilities, and chronic health conditions among older adults, which affect actual and self-perceived individual health. Thus, older persons with higher *BMI*s may experience more difficulty discharging productive activities, including asset management related activities, than those with normal or "healthy" *BMI*s by the CDC definition.[22] They are also more likely to resort to sick time, which lowers their productive time endowment (e.g. Chen and Guo, 2008; Peytremann-Bridevaux, and Santos-Eggimann, 2008; Kearns et al. 2014), hence the time available for asset management. While *SPH* reflects both mental and physical conditions, obesity *per se* is not directly correlated with cognitive abilities (see e.g. Sturman et al. 2008, Atti et al. 2008) which affect AM productivity, and thus portfolio allocation and the demand for risky assets.[23] For this reason, the household head's *BMI* may serve as a valid IV for estimating the effects of *AMT* on *DEMAND*, *PARTICIPATION,* and *RETURN*. We also restrict the individuals' *BMI* variable to include just its values in wave 1 in order to derive a valid link with our *AMT* proxy, since the latter variable is reported only in that wave.

Table 5.A presents the 1st stage structural regression results in which *BMI* is serving as the only IV. Columns (1)-(2) correspond to the 2nd stage estimated *DEMAND* and *PARTICIPATION* equations shown in Table 6, whereas **c**olumns (3)-(4) are associated with the 2nd-stage estimated *RETURN* equation. As expected, in all columns the effect of *BMI* on *AMT* is negative and statistically significant at the conventional levels. The estimated effects of included variables are comparable to those reported in the derived demand for *AMT* regressions in Table 2.B. The proxy for knowledge capital, *YEDU,* has a positive and significant effect on *AMT* but it loses its significance in the second stage. This suggests

[22] For details, see https://www.cdc.gov/healthyweight/assessing/index.html.
[23] There may be concerns that investors with severe obesity may save less, thus have smaller portfolios, and select less risky assets due to increased health risks. Although in the structural regression equation (21) and the first-stage regressions used to obtain projected values of *AMT* we control for a proxy for perceived health conditions, portfolio size, and risk aversion as part of the vector Z'_{it}, there may still be some residual effects of high values of *BMI* on the dependent variables in these regressions. To assess the potential bias associated with high values of *BMI* as an IV, we have run a series of alternative estimates of eq. (21) by sequentially dropping morbidly obese (with *BMI*≥40) and severely obese investors (with *BMI*≥35). These estimates are broadly similar to our baseline estimates, which are based on the full sample.

that the effect of *YEDU* on portfolio choice works mainly through its complementary relations with asset management time. The marriage status also remains positive and significant, which could reflect the division of labor within a household.

As is the case in reduced-form derived demand for *AMT*, our overall health measure, *SPH* has positive but insignificant effects in the first stage regressions indicating that its association with *AMT* is less complementary than that of *YEDU*, as we noted in our analysis of Table 2's *AMT* results in section 5.1. In addition, the presence of *BMI* as a correlate in the stage-1 regressions already captures the effect of health on loss of productive time due to illness, which is more prevalent as a result of chronic health conditions.

The proxies for cognitive and non-cognitive abilities do not explain *AMT.* Neither *NUMERACY* nor *FLUENCY* is significant in the first stage. But the effect of the financial portfolio's size on *AMT*, as reflected by both $\ln FASST$ and $\ln NFASST$ is positive and significant in the 1st stage regressions.

Table 6 shows our baseline IV estimates of structural equation (21). Consistent with our model, *AMT* exerts positive and significant effects at the 5% level on all the portfolio outcomes, especially *DEMAND* and *PARTICIPATION*. In the *RETURN* regression, however *AMT*'s effect, while positive, is insignificant. In light of the limitations in the measurement of our *RETURN* variable, this result is not surprising. Since *RETURN* is dominated by safe assets and imprecisely reflects returns on risky assets, the estimated causal effect of *AMT* on the observed *RETURN* is subject to significant random and non-random errors, and thus larger standard errors.

Nonetheless other human capital components, such has *SPH* and *NUMERACY* turn significant (1% and 10%, respectively) in the 2nd stage regressions of *RETURN*. This result contrasts with those in the *DEMAND* and *PARTICIPATION* regression models, where only *FLUENCY* is found significant among the human capital proxies. This indicates that perhaps some components of human capital may have direct but heterogeneous impacts on asset management efforts and the resulting portfolio decision and returns, independent of that of the AM time input.

Moreover, the results for *DEMAND* and *PARTICIPATION* in Tables 6 corroborate the basic mechanism underlying our model, as summarized in Proposition 2(b). The results indicate that the impact of both the knowledge and health components of human capital (*YEDU* and *SPH*) on the outcomes of AM works mainly via their impact on the projected value of *AMT* obtained from stage 1 of the IV regressions in Table 5. In the second stage of the 2SLS analysis, the unconditional effect of *YEDU, given AMT*, declines and becomes insignificant compared to its positive and significant effects in the reduced-form regressions of Tables 2. In particular, the partial negative (but insignificant) effect of *YEDU* in most of the regression models in Table 6 may also reflect the higher opportunity costs of *AM* due to any residual effect of education, in line with proposition 1. While the size of the financial portfolio, ln *FASST,* has significant effects in Table 6, *RISKAVS* loses its significance in all models. Apparently, the residual role of risk aversion is captured by the projected *AMT* variable, as is generally the case for the human capital components.

To test the relevance of our 2SLS-IV estimation, we compute the effective first stage *F* statistic developed by Olea and Pflueger (2013), which corrects for general non-homoscedasticity. The values of the *F* statistics are all below the conventional threshold of 10. Thus, there is a concern that inferences based on 2SLS may be subject to size distortions. To address this issue, we employ weak instrument robust inference methods**.** Specifically, we use the test inversion method based on Anderson-Rubin (AR, 1949) test statistics, which do not depend on the strength of the first stage regression and are thus fully robust to weak instrument problems, to construct the confidence intervals associated with our key explanatory variable in eq. (21).[24]

[24] In this method, we perform a series of hypothesis tests using the Anderson-Rubin (AR) test over a fine grid of potentially true values of the parameters of our endogenous explanatory variables and include the values that are not rejected by the test in the confidence set. Moreira (2009) argues that the AR test is optimal relative to a set of other weak instrument robust estimation methods in the sense that it is uniformly most accurate, unbiased and asymptotically efficient when the model is just-identified, as is the case in our baseline model. Also, the AR confidence set is asymptotically equivalent to the two-sided confidence interval based on a t-test in just identified models when instruments are strong (see e.g. Andrews et al., 2019).

The estimated robust confidence sets, based on the AR test are reported at the bottom row of Table 6. Corroborating our 2SLS estimates, they show that the 95% confidence intervals of the effects of *AMT* are positive in the *DEMAND* and *PARTICIPATION* regressions. Although the AR confidence sets in the *RETURN* regressions include small intervals of negative numbers, this is likely to be due to the severe limitations of our *RETURN* proxy as explained earlier.

In sum, all our estimated weak-IV robust confidence intervals support the respective 2SLS point estimates and the significance levels, and thus the validity of the predicted causal effects running from the asset management input (*AMT*) to the outcome variables. Although the *F*-values are not sufficiently high in the first stage regressions, the concerns about size distortions do not appear relevant in our case.

b. The IV model (eq. 21) estimated using an alternative set of IV. Our baseline IV estimates are based on just-identified models where the instrumental variable is *BMI*. To examine the validity of our choice of the instrumental variable and the robustness of our results, we introduce an additional IV – eyesight relevant for reading (*EYE*), thus applying an over-identified IV model. Arguably, visual acuity is another endowed human capital component that can be used to process documented information, but is unlikely to affect portfolio decision directly. Indeed, as shown in Table 7, Hansen's *J* statistics indicate that the null hypothesis that both IVs can be excludable from the 2^{nd} stage regression model cannot be rejected. This result provides further support for our choice of *BMI* as an instrumental variable both in this application as well as in our benchmark IV analysis shown in Table 6.

Table 5.B shows the first stage results for this over-identified model. As in Table 5.A, columns (1)-(2) are associated with the 2^{nd} stage regressions concerning *DEMAND* and *PARTICIPATION* reported in Table 7 whereas columns (3)-(4) correspond to *RETURN* regressions. The estimates are by and large similar to those based on the just-identified model reported in Table 5.A. As expected, the new instrumental variable *EYE* is positive and significant.

The over-identified IV specification allows us to estimate the effect of our endogenous variable more precisely. In the *DEMAND* and *PARTICIPATION* regressions, the statistical significance of *AMT* increases to 1% from 5% in the just-identified model while in the *RETURN* regressions, it turns from insignificance to significance at the 5% level. Estimates of other variables are qualitatively and quantitatively comparable to those based on the just-identified model, except that *NUMERACY* in the *RETURN* regression turns insignificant.

Despite the introduction of the extra IV, the first stage *F* values are still below 10. Accordingly, we report the weak-instrument robust statistics too. Since we apply an over-identified IV model, the Anderson-Rubin (AR) test may not be optimal. We therefore report the confidence intervals based on both the AR and the conditional likelihood ratio (CLR) tests. The latter is found to be superior to the AR test over wide ranges of parameters and 'nearly optimal' (Moreira 2003, Mikusheva 2010). The 95% confidence sets produced by both tests include only positive intervals, and are consistent with our 2SLS point estimates. Overall, the results based on the alternative set of IVs used in this application corroborates our baseline IV estimates of equation (21).

6. Robustness Analysis and Corroborating Tests

This section presents a set of robustness analysis and some diagnostics tests, which corroborate the main empirical results reported in the previous section.

6.1. Limiting the sample to exclude investors with zero financial and risky assets (FA and RA)

Our baseline sample includes all households who provided complete responses to key survey questions we use in our empirical analysis, which include zero values of *FASST* and *RASST*. This is because while the expected demand for risky assets in eq. (18) requires positive values, the realized demand for these assets may include zero values (see fn. 9). In this section we offer robustness tests where we allow for separate subsamples for FA-holders (*FASST*>0) and RA-holders (*RASST*>0) to see if the hypotheses included in Lemma 2 and Proposition 1 hold for these groups as well.

Panel A in Table A1 shows the reduced form estimates of *DEMAND*, *RETURN* and *AMT* in all samples. While the FA-holders subsample lowers the full sample size by about 10%, the RA-holders subsample reduces the sample by over 75%. Despite this limitation, the results in Table A1 are by and large similar qualitatively to those based on the full sample in Table 2 in terms of the signs and statistical significance of the estimated effects of the key determinants of AM. The only exception is found in the *AMT* regressions based on the RA-holders subsample. In this case, however, the sample size drops to just 540 observations, as we can use only the observations available in the wave 1 survey (see Table A1, Panel A, columns 5-6). This explains the large standard errors associated with the positive but statistically insignificant estimates of *YEDU*.

In light of this severe sample size limitation, we focus below just on the FA-holders sample to check the robustness of our baseline models. The results in Panel B indicate that our baseline estimates concerning the implicit opportunity cost of time (Table 3) are robust to the exclusion of investors reporting zero financial asset holding: it shows that the unconditional effects of *YEDU* are generally greater in the oldest (G3) relative to the younger (G1) group. Panel C replicates the structural IV regression analysis using just the FA-holders sample. As in the full sample results reported in Table 6-7, the causal effect of *AMT* on the portfolio outcomes in the FA-holders subgroup is found to be positive and significant, except for the *RETURN* regressions corresponding to the just identified model.

6.2. Probit estimation of *PARTICIPATION* models

As the participation regression set in Tables 2-7 involves a binary outcome, one may be worried that the use of the linear probability model (LPM) may distort our findings. To address this concern, we repeat our analysis of participation using the Probit model. As shown in Table A2 in Appendix, the Probit estimates are qualitatively similar to those based on the LPM estimation method.

6.3. Corroborating tests concerning the implicit opportunity cost of time effect

a. Approximating the implicit wage variable using Mincer's earnings function: Proposition 1(b) predicts that the unconditional effect of *YEDU* is inversely related to the elasticity of wage rate with respect to *YEDU*. In the baseline analysis of the implicit opportunity cost of time, we form three similarly-sized subgroups based on the age levels of household heads under the assumption that the wage elasticity declines as investors get older and approach their retirement ages. However, our choices of distinct age groups and cut-off points are somewhat arbitrary. To test the robustness of our results, we run pooled regressions using direct proxies of the wage variable to parametrically estimate the unconditional effect of *YEDU* as a function of *AGE*. To this end, we specify the wage function using the Mincer earnings function: $f(YEDU, x) = c_0 + c_1 YEDU + c_2 x + c_3 x^2 + \epsilon$, where x = *AGE* - *YEDU* denotes job experience. Based on this specification, we modify the reduced form eq. (20), to include the implicit wage function as follows:

$$Y_{it} = \beta_0 + \beta_1 YEDU_i + \varphi f(\cdot) + Z_{it}'\gamma + \mu_c + \eta_t + e_{it}. \tag{22}$$

Substituting $AGE - YEDU$ for x, one can rewrite eq. (22) as below:

$$Y_{it} = \theta_0 + \theta_1 YEDU_i + \theta_2 YEDU_i^2 + \theta_3 AGE_{it} \times YEDU_i + \theta_4 AGE_{it}^2 + \delta Z_{it} + \mu_c + \eta_t + u_{it}. \tag{23}$$

This model enables us to recover the average marginal effect of $YEDU$ associated with investors in different age group: [25]

$$\frac{\partial E[Y]}{\partial YEDU} = \theta_1 + 2\theta_2 YEDU + \theta_3 AGE. \tag{24}$$

To examine the theorized effect of investor's implicit opportunity costs on the unconditional effect of *YEDU*, we plot *YEDU*'s average marginal effect on portfolio outcomes against *AGE* in Figure A1, using estimates based on equations (23)-(24). Consistent with the baseline results, the unconditional effect of *YEDU* on *DEMAND*, *PARTICIPATION* and *RETURN* increases with *AGE* in each of the corresponding regressions. The 95% confidence band shows that *YEDU*'s positive effects are significant for most age groups.[26]

[25] Note that θ's are mongrel parameters (e.g. $\theta_1 = \beta_1 + \varphi(c_1 - c_2)$), which have no clear interpretations. Hence these estimates are not reported.

[26] We have also explored the average marginal effects as function of both $YEDU$ and AGE using 3-dimensional plots, which show similar results.

b. Capturing the opportunity costs of time by retirement status: So far, our test of Proposition 1(b) was based on using the household head's age or experience to account for the latter's implicit wage. To explore the robustness of our results, we here use the household head's retirement status to estimate the impact of the missing wage variable. Essentially, we assume that the household heads' market wage drops significantly once they retire. We therefore expect the unconditional effects of *YEDU* to be larger for retired investors than non-retired investors. Table A3 indicates that this is indeed the case. The estimated unconditional effect of *YEDU* is always larger for the retired group than for the non-retired group. To some extent, *SPH* shows a similar pattern, but other components of human capital do not exhibit such pattern.

6.4. Measuring DEMAND as the Portfolio Share of Risky Assets

As we have already noted in section 3.3, theoretically, asset management is expected to raise the expected absolute demand for risky assets (*DEMAND*) rather than the latter's portfolio share. For this reason, the portfolio size is included as a control variable in equations (20) and (21), rather than as the denominator of *DEMAND*. Wealth is also subject to errors of measurement for two reasons: it consists of both financial and non-financial assets, whereas our focus is on financial assets, and the errors of measurement corresponding to non-financial assets may be especially large since their prices are not determined in a centralized market. Nevertheless, in Table A4, we report the results of regressions where, *DEMAND* in eqs. (20) and (21) is replaced by the portfolio share of risky assets:

$$PSHRA = \frac{RASST}{FASST + 1} \times 100$$

Overall, we find the effects of *AMT* and its determinants on the portfolio share of risky assets (*PSHRA)* are comparable to those on *DEMAND*. Column (1) presents the estimates based on the reduced form eq. (20). Like the *DEMAND* regression models reported in Table 2, the effects of *YEDU*, *SPH*, ln $FASST$, ln $NFASST$, *AGE* and *FLUENCY* are all positive and significant while *RISKAVS* is negative and significant. Column (2) shows the non-instrumental OLS estimates of the structural eq. (21), which is quite comparable to the corresponding *DEMAND* models shown in Tables 4. Columns (3)-

(4) report the instrumental variable estimation of (21). Both the 2SLS and the weak IV robust 95% CS indicate that the effect of *AMT* on portfolio share of risky asset is positive.

6.5. Alternative panel data estimation methods

So far, we have relied primarily on the OLS model with standard errors clustered at the individual level in estimating equations (20) and (21), since our key endogenous variable, *AMT*, as well as our key determinant of effective asset management, *YEDU* (and *RISKAVS* too) are time-invariant variables. Although we control for various individual characteristics as well as proxies for cognitive abilities, there may still be some concern that there exists residual unobserved individual heterogeneity that might be correlated with the explanatory variables. This violation of the OLS assumption could result in biased regression estimates. To test the robustness of our results against unobserved individual heterogeneity, we employ hybrid models which combine the virtues of fixed effects and random effects models.[27] Panel A of Table A6 presents the results based on the Hausman-Taylor (HT) model [28] where we specify *YEDU* as an endogenous variable on the assumption that it can be potentially correlated with the unobserved individual heterogeneity. The results show that the effects of *YEDU* on *DEMAND*, *PARTICIPATION* and *RETURN* are positive and significant at the 1% level, confirming qualitatively the estimated reduced-form regressions using the random-effects OLS model reported in Table 2.

We also use the correlated random effect model *à la* Mundlak (1978) and Chamberlain (1980). In this model, the individual heterogeneity is assumed to be correlated with the average of the time varying variables. The results are reported in Panel B. They are again similar to the baseline results qualitatively.

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[27] This robustness test is performed for the reduced form equation only. To estimate the structural equation, we use IV estimation methods which address biases due to the general omitted variable issue, including unobserved individual heterogeneities.

[28] Hausman and Taylor (1981) have developed an instrumental variable approach in which exogenous tine-invariant variables as well as the cross-section averages and within-variations (deviation from group-mean) of time varying variables are used as the instrumental variables. Due to the latter requirement, however, we are unable to apply this HT technique in estimating the derived-demand equation.

7. Concluding Remarks

It has already been documented in our earlier studies (Ehrlich et al. 2008, 2011) and Ehrlich and Shin (2010) that education and the measures of the direct and opportunity cost of asset management have significant effects on the demand for risky financial assets (*DEMAND*), the holding of such assets (*PARTICIPATION*), and portfolio returns (*RETURN*). This study provides distinct support for the earlier findings by indicating that more education and better health contribute to a greater demand for risky assets even by older workers and retirees. The main innovation of this study, however, lies in our attempt to (a) validate the mechanism through which these variables affect the household heads' allocation of time into asset management activity, and (b) provide some evidence, consistent with Propositions 1 and 2, that the asset management time input (*AMT*) may play an important role in causally determining individual *DEMAND* and *PARTICIPATION*, as indicated by Tables 6 and 7.

We recognize that in the 2-asset case, where investors can choose between only a risky and a riskless asset, our basic findings may be consistent with an alternative hypothesis: to the extent that a higher level of human capital is associated with greater risk tolerance (r), the observed effects of education and health on portfolio selection could be ascribed to greater risk tolerance. We have therefore considered this possibility as an implicit null hypothesis in our empirical tests and proceeded to verify the internal validity of our AMH via several measures.

First, we add as control variables the self-reported measure of individual risk aversion and wealth, which are also relevant for asset management, as well as other components of human capital capturing ability indicators and demographic variables. We find that neither addition nor exclusion of the latter controls alters the qualitative significance of years of education (*YEDU)* as a driver of asset management and its portfolio outcomes. Second, we estimate separately the derived demand for asset management time (*AMT*). This equation constitutes the essence of the AMH, by which time inputs into asset management are expected to play a critical role in determining simultaneously knowledge precision (s_i^*), hence *DEMAND* and *RETURN*. The estimated results verify the role of education and underlying health conditions as the basic determinants of *AMT*.

Third, we establish the internal validity of the model by estimating the parameters of the model's structural equations, where *AMT* acts as the direct input into the production of information precision (s_i^*) and its portfolio outcomes. We then complete testing the logic of our model by estimating the causal effects of *AMT* on *DEMAND* and *RETURN* using IV methods. Despite the weak instrument issues we encounter, the significance (at 1 or 5%) of the estimated coefficients of *AMT* in the 2nd-stage of our IV regressions (Tables 6-7), are corroborated by the weak instrument robust confidence sets we derive. By these results, *AMT* appears to be causally enhancing the holding of, and demand for, risky assets via their impact on the derived-demand for *AMT* in the 1st stage of the IV regressions. They also show that *YEDU* and other components of human capital influence the demand for risky assets through their effects on the projected value of *AMT*. All three test measures appear to support our model, despite many limitations of our data, which generally work against our hypotheses (see section 4).

In section 6, we subject the results obtained from the reduced-form baseline regressions as well as from our IV structural regressions to a battery of robustness and corroborating diagnostic tests based on alternative subgroups of investors, alternative econometric estimation models, and alternative specifications of key variables. The test measures we apply suggest that the results corroborate the basic propositions of the model concerning the key input and output of asset management – *AMT, PARTICIPATION, DEMAND,* and *RETURN.*

One caveat is that the effect of *AMT* on the *RETURN* regressions estimated via our IV methods is positive but statistically insignificant in our just-identified model in Table 6. We believe that the weaker effect stem from inherent limitations of our data. Our *RETURN* proxy includes neither realized nor unrealized capital gains, and mainly captures the reward from safe investments, which do not require extensive asset management time. Also, the sample size drops considerably to enable use of the *RETURN* data for our analysis. However, our IV regression models – both the just-identified and over-identified regression models - show consistently that the effect of *AMT* on *RETURN* is consistent with a positive effect of *AMT* on *RETURN*, as is the case for *DEMAND* and *PARTICIPATION*, by the 95% weak instrument robust confidence sets in both our baseline regressions and our robustness checks**.**

An important limitation of the SHARE data is that they lack complete information about the market wages of household heads. Thus, in our baseline reduced form results, we derive estimates of unconditional effects of *YEDU*, which reflect its dual effect as both an efficiency parameter in information production and an indicator of higher opportunity cost of time. To test the implication of missing opportunity costs on the unconditional effects of *YEDU*, we conduct a regression analysis based on population subgroups stratified by age or retirement status**.** The results indicate that the unconditional positive effects of the education component of human capital on risky asset demand and portfolio returns become significantly larger when the opportunity costs of asset management time start declining as the household heads approach, or reach, the retirement phase (see Tables 3 and A3).

An important implication of our findings concerns the effect of *AGE* on *DEMAND* and *RETURN*. The conventional recommendation to investors is to reduce their exposure to risky financial assets as they age. Typical justifications are that older investors may lack sufficient wealth to smooth their consumption and recoup losses when financial markets become bearish. Our findings indicate that the asset management channel could partly offset these concerns. While our model offers no direct implications about the intrinsic effect of age on demand for risky assets, it suggests that "age" indirectly captures age-related opportunity costs of time. When investors get older and/or retire, their opportunity costs of asset management fall, raising their demand for *AMT* and *DEMAND*. This may explain why participation in risky asset markets falls just mildly across our age groups (see Table B3)

Our study also adds to the literature on the role of health in portfolio choices. Our empirical findings indicate that underlying chronic health conditions in particular, such as *BMI* and *EYE*, which we use as IVs in our analysis affect portfolio choices through their impact on sick time, which lowers the productive time available for asset management. Indeed, both exert significant effects on *AMT* in our first stage IV regressions. Self-assessed health (*SPH*), in contrast, while having a positive and significant effects on *DEMAND*, *PARTICIPATION*, and *RETURN* in the reduced-form regressions (Table 2), has a generally insignificant effect in the reduced-form *AMT* regressions and the 1st and 2nd stage of the IV regressions (Tables 5-7), except for its impact on *AMT* in the subsample including the oldest age group (Table A4). This may be because perceived health generally has a milder effect on sick time relative to *BMI* and *EYE*, and it enhances the demand for risky assets directly by increasing the effectiveness of the AM production process.

The proxies of alternative human capital components, such as *NUMERACY* and *FLUENCY*, do not have consistent effects in our regressions as do *YEDU* and health conditions. Generally, *FLUENCY* has a generally positive and significant effect in regression concerning *DEMAND* or *PARTICIPATION*, whereas *NUMERACY* has a positive and significant effects on *RETURN* in both the reduced-regressions and the 2nd stage structural equations.

The point estimates of the unconditional effect of human capital on the demand for risky financial assets are surprisingly close to those reported in Ehrlich et al. (2008) using the Survey of Consumer Finances (US) data. In the current study, based on the European sample, we find that the elasticity of *DEMAND* with respect to *YEDU* is 0.781 in our full sample regression analysis (column 3 in Table 2.A) while Ehrlich et al. (2008) show that it is 0.764 in their full sample regression.[29]

The impact of *AMT* appears to be significant quantitatively as well. Since *AMT* is an endogenous variable, we can illustrate its impact on *DEMAND* as if it were triggered by an increase in *YEDU*, using the estimated coefficients of *YEDU* and *AMT* in the IV regression models reported in Tables 6 and 7, respectively. By this approach, a one-year increase in *YEDU*, is found to increase the dollar amount of

[29] Ehrlich et al. (2008) uses a log-log specification, while in this study we use a log-linear format concerning the human capital variables. In our study, the elasticity is therefore computed at the mean level of schooling where it is found to be 0.781 (=0.074×10.56).

risky financial asset held in our portfolio by 5.2 or 8.2% while also increasing the risky financial market participation by 0.5 or 0.6% through the influence of the asset management channel as measured by our over-identified or just-identified structural regressions, respectively. Also, a one-year increase in *YEDU* raises the annual portfolio return by 2% through the AM channel using the over-identified model.[30]

Finally, our theory and empirical evidence suggest that human capital plays a decisive role not just in determining individual wage income and income distribution, but the returns to individual portfolios as well through the willingness to hold and manage risky financial assets. Given the renewed interest in understanding the determinants of apparently rising wealth inequality, it would be interesting to see how much of the cross-section and time series variation in wealth inequality could be explained by the returns to human capital and asset management activities. We leave this topic for future research.

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[30] Using the just-identified model, a one-year increase in *YEDU* increases *AMT* by 0.010 (Table 5A, column 2), which in turn leads to an increase in *DEMAND* ($ln\ RASST$) by 0.079 $=0.010 \times 7.140$ (Table 6, column 2). The increase in the dollar value of *DEMAND* is thus given by $\exp(0.079) - 1 = 0.082$. All other quantitative estimates are similarly calculated. We use just the over-identified model to calculate the implied effect of *AMT* on *RETURN* in Table 7.

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