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ASSET MANAGEMENT, HUMAN CAPITAL, AND THE MARKET FOR RISKY  
ASSETS

Isaac Ehrlich  
William A. Hamlen Jr.  
Yong Yin

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**ABSTRACT**

Risky-asset prices are conventionally modeled as "fully (information-) revealing". Much less work has been done on how prices get to reveal information. Following the "noisy-prices", rational-expectations approach, our answer focuses on the micro-foundations of information acquisition and the role of human capital in asset, or risk, management. We derive testable propositions on how education and other determinants of asset management affect its intensity, risky-asset demand, and portfolio returns. We derive related insights concerning determinants of the level and volatility of asset prices and equity premiums. Using micro-level data on portfolio choices, we find that education raises both the portfolio share of risky assets and overall portfolio returns, while a measure of the opportunity cost of asset management has the opposite effects. Our results indicate a non-trivial return to education in generating non-wage income. They suggest that educational attainments directly affect the distribution of income as well as earnings.

Isaac Ehrlich  
415 Fronczak Hall  
University of Buffalo  
Box 601520  
Buffalo, NY 14260-1520  
and NBER  
mgtehrl@buffalo.edu

Yong Yin  
State University of New York at Buffalo  
415 Fronczak Hall  
Box 601520  
Buffalo, NY 14260  
yyin@buffalo.edu

William A. Hamlen Jr.  
The State University of New York  
School of Management  
University at Buffalo  
244 Jacobs Management Center  
Buffalo, NY 14260-4000

## Introduction

The standard assumption that equilibrium prices of financial assets reveal all the relevant information about the profitability of these assets raises a puzzle at the micro level: It leaves no incentive for individuals to collect any private information (cf., Grossman and Stiglitz, 1980). But how, then, do prices become “fully revealing”? Indeed, as recent stock market scandals indicate, information gleaned from security prices is often inaccurate, if not misleading, and certainly incomplete. To resolve the puzzle, it is necessary to augment the equilibrium theory of efficient markets by pertinent micro foundations. This is what we aim to do in this paper.

The idea is that individuals’ demand for risky assets are partly influenced by effort and ability to gather and assess information about likely realizations of future returns. For centrally traded homogeneous assets, the hypothesis is that the public information revealed by market prices is incomplete or imperfect, leaving room for “asset, or risk, management”.<sup>1</sup>

This hypothesis is a natural extension of the costly-information, or “noisy-prices”, rational expectations literature. Early contributions include Darby (1976), Grossman and Stiglitz (1980), Hellwig (1980), Verrecchia (1982), Admati and Ross (1985), and Kim and Verrecchia (1991a, b). More recent studies, e.g., Wang (1994), de Fontnouvelle (2000), Allen, Morris and Shin (2006), and Veldkamp (2006) apply a similar methodology to multi-period models. Existing studies allow for noisy prices which justify private information collection, but assign such activity to a distinct group of homogeneous agents, or allow agents with diverse risk preferences to collect information at identical costs of unspecified origin. This literature has not led so far, however, to the development of discriminating propositions involving the role of asset management at the micro or market levels. We attempt to do so by specifying the information cost function and linking its major determinants – human capital endowments, opportunity costs, and information-collection technology – with endogenous asset management, risky asset

demand, portfolio returns, asset-price volatility, and equity premiums.<sup>2</sup>

As in earlier costly information papers, the market for risky assets in this paper retains its efficiency under a competitive equilibrium. But since prices are subject to exogenous “supply” shocks which convey no information, an incentive remains to collect private information. The incentive is a reduction in **conditional** risk bearing. Investors who are more productive at asset management wind up bearing lower subjective risk. They thus tend to hold objectively riskier portfolios and reap higher expected portfolio returns. To sharpen the empirical relevance of our model we identify the relevant human capital endowments with education and specific knowledge. We then implement the model quantitatively at both the micro and macro levels and test some of its distinct implications empirically, and against alternative hypotheses as well.

We expect education and specific knowledge to raise the demand for risky assets and thus portfolio income. We expect the opportunity costs of asset management to have the converse effects. At the market level we expect higher average human capital to raise the relative price of risky assets and lower the equilibrium “equity premium” as perceived by the average investor, but the volatility of risky assets’ prices may rise or fall as a result, depending on the relative magnitudes of information precision and assets’ supply and return variances. Our analysis offers new insights about the “equity-risk-premium puzzle”. It also enables us to assess the rate of return to education from asset management. Our empirical findings suggest that educational attainments play a direct role in explaining the distribution of total income as well as earnings.

The rationale for individual asset management applies even when potential economies in information-collection generate specialized agents, or “analysts”, who sell their services to less specialized investors. But heterogeneous analysts offer information signals of varying precision. Learning about their reliability and precision thus becomes part of individual asset management. Furthermore, successful asset managers have an incentive to internalize potential externalities

from information-sharing by selling equity in their enterprises, rather than the information itself (cf. Leland and Pyle, 1977). Investors then need to assess the information value of such equities.

Our model builds on the basic analysis of asset pricing under costly information offered by Hellwig (1980), Verrecchia (1982), and Kim and Verrecchia (1991a). In sections I and II we extend their framework by specifying the production and cost functions governing asset management and the role of human capital. In Sections III and IV we derive our novel behavioral propositions and simulate the extended model at the individual and market levels. In section V we test some of these propositions using nine independent micro-level data sets. The conclusion summarizes our results and assesses the value added of this paper.

## **I. The Economy, Opportunities, and Preferences**

Like Hellwig (1980) and Verrecchia and Kim (1991a), we model a competitive exchange economy with a continuum of heterogeneous investors-traders ( $i = 1, \dots, n$ ), but unlike them we ascribe the basic individual heterogeneity mainly to different endowments of human capital,  $H_i$ , related market wages,  $w_i$ , and initial wealth endowments,  $W_{0i}$ , rather than risk tolerance.<sup>3</sup> We do so in order to ascribe differences in personal risk-taking **behavior** to objective indicators of personal human capital and labor market returns, rather than subjective risk **preferences**.

There are two assets in the economy: a risky asset and a safe bond. Both the returns on, and the endowed supply of, the risky asset are stochastic. The existence of random supply fluctuations or “noise” implies that the equilibrium risky asset price – the public information channel - is not fully revealing of information collected by investors, which leaves investors an incentive to devote resources to acquire private information. Specifically, investors are assumed to be operating in two sectors – a market sector, where they obtain labor earnings, and a household sector, where they “manage” their risky assets by seeking information signals to better forecast related future returns – over two periods of time. In the first, they make all resource

allocation decisions, including portfolio choices, and in the second, market realizations of portfolio returns dictate the outcomes of these choices.

The varying human capital, or educational attainments  $H_i$ , across investors are elements of the compact set  $[\underline{H}, \bar{H}]$  and their distribution is characterized by the density function

$f : [\underline{H}, \bar{H}] \rightarrow \mathbf{R}_+$  such that for all  $H_i \in [\underline{H}, \bar{H}]$ ,  $f(H_i) \geq 0$  and  $\int_{\underline{H}}^{\bar{H}} f(H_i) dH_i = 1$ . The assumed

distinct attribute of human capital in our model is that it enhances the productivity of working time devoted to information collection, or “asset management”, as well as to earning generation.<sup>4</sup>

Each trader possesses an endowment of an independently and normally distributed risky asset,  $\tilde{x}_i$ . The **average** supply is commonly known to be normally distributed,

$$(1) \tilde{x} \sim N(\bar{x}, t^{-1}),$$

with mean  $\bar{x}$  and inverse variance  $t$ .<sup>5</sup> Its realized market return is likewise normally distributed,

$$(2) \tilde{\mu} \sim N(\bar{\mu}, h^{-1}),$$

with mean  $\bar{\mu}$  and inverse variance  $h$ . While the realized return  $\tilde{\mu}$  (price plus dividend) is not observable at the time of purchase, investors can devote asset management time to identify a private information signal ( $\tilde{z}_i$ ), which will help forecast it:

$$(3) \tilde{z}_i = \tilde{\mu} + \tilde{\varepsilon}_i,$$

where  $\tilde{\varepsilon}_i \sim N(0, s_i^{-1})$  denotes a normally distributed random forecast error with mean zero and inverse variance or "precision",  $s_i$ , assumed to be independent of both  $\tilde{\mu}$  and  $\tilde{x}_i$ .

Initial wealth,  $W_{0i}$ , consists of the risky-asset endowment,  $\tilde{x}_i$ , valued at the initial market price  $\tilde{P}$ , a riskless bond,  $B_{0i}$ , and a safe level of wage income,  $w_i(T-q_i)$ . Total productive time,  $T$ , can be used as an input into asset management,  $q_i$ , or earning generation ( $T-q_i$ ) at a non-stochastic wage rate,  $w_i$ . For simplicity, we abstract from leisure.<sup>6</sup> The return on, and price of,

bonds, viewed as a numeraire, are normalized as 1. The investor chooses implicitly between risky assets and bonds, as well as between asset management and work. The budget constraint is:

$$(4) \tilde{W}_{0i} \equiv \tilde{P}\tilde{x}_i + B_{0i} + w_i(T - q_i) - C_0 = \tilde{P}\tilde{D}_i + B_{1i},$$

where  $\tilde{D}_i$  is investor  $i$ 's demand for risky assets, and  $[w_i(T - q_i) - C_0]$  is the investor's labor income net of the fixed cost of asset management (see equation 7 below). Since this is a single-generation, two-period model we assume that realized wealth is consumed in the second period.

Terminal wealth or consumption is given by  $\tilde{W}_{1i} = \tilde{\mu}\tilde{D}_i + \tilde{B}_{1i}$ , which can be re-written:

$$(4a) \tilde{W}_{1i} = B_{0i} + \tilde{P}(\tilde{x}_i - \tilde{D}_i) + \tilde{\mu}\tilde{D}_i + w_i(T - q_i) - C_0.$$

Bond holdings are thus given by  $\tilde{B}_{1i} = B_{0i} + \tilde{P}(\tilde{x}_i - \tilde{D}_i) + w_i(T - q_i) - C_0$ , where  $\tilde{B}_{1i}$  is stochastic, since both the endowment of, and demand for, the risky asset are stochastic.

Consistent with human capital theory, we specify the wage rate,  $w_i$ , as an exponential function of an investor's attained level of education,  $H_i$ , and a vector of idiosyncratic factors,  $\delta = (\delta_1, \delta_2)$ , such as health, labor market experience or idiosyncratic labor market conditions:

$$(5) w_i = w_i(H_i, \delta) = w_0(\delta_1) \exp\{\eta(\delta_2) [H_i - H(0)]\},$$

where  $H(0)$  is a minimal level of knowledge and  $\eta$  is the labor-income rate of return on  $H_i$ .

We think of asset management as a quest for information signals that can improve one's forecast of the risky asset's future returns. The idea is that while all investors know the probability distribution of  $\tilde{\mu}$ , private information can help forecast its realization with greater **precision**,  $s_i$ , thus reducing its conditional risk. The signal could vary from a specific, publicly available data composite, a sharp financial analyst, or "inside information" about corporate performance. By "inside information", however, we do not mean information available to technical insiders who are legally proscribed from disseminating it. We take private information acquisition to result, more generally, from tracking relevant information sources, including

reliable analysts. Educational attainments,  $H_i$ , including ability and specialized knowledge, and an external search technology ( $A(\tau)$  below) augment the productivity of search time,  $q_i$ .

The information-precision production function is of the Cobb-Douglas variety:

$$(6) \quad s_i = F(q_i, H_i) = A(\tau)q_i^\alpha H_i^\beta, \quad \text{where } A > 0, \quad 0 < \alpha, \beta \leq 1,$$

and  $\tau$  is a vector comprising all factors affecting asset management's external technology. The actually employed asset management time technically becomes:

$$(6a) \quad q_i = s_i^{1/\alpha} A(\tau)^{-(1/\alpha)} H_i^{-(\beta/\alpha)}.$$

Using (5) and (6a), the total cost of asset management is thus given by the convex function

$$(7) \quad C(s_i) = w_i q_i + C_0 = w_i(H_i, \delta) [s_i^{1/\alpha} A(\tau)^{-(1/\alpha)} H_i^{-(\beta/\alpha)}] + C_0,$$

where  $C_0$  includes possible fixed monetary costs or fees associated with asset management.

With this opportunity set, the investor determines both optimal asset management and risky-asset demand by maximizing the expected utility of terminal consumption or wealth,  $\tilde{W}_{ii}$  in (4a).

In line with earlier literature, utility is specified as an exponential function of terminal wealth,

$$(8) \quad U(W_{ii}) = -\exp(-W_{ii}/r),$$

where  $W_{ii}$  is a realized value of  $\tilde{W}_{ii}$ , and  $r$  denotes risk tolerance, or the inverse value of one's absolute risk aversion. As indicated earlier, to keep the analysis focused on the main theme of the paper, we assume that risk tolerance  $r$  does not vary across investors (see footnote 3).

## II. Asset Demand and Management under Rational Expectations

In the context of the preceding basic framework, investors' optimizing behavior can be viewed **heuristically** as a two-step process. In the second step, the investor choose the demand for the risky asset,  $D_i^*$ , conditional on optimal asset management intensity  $q_i$  and the information precision it yields,  $s_i$ , as well as the observed market price,  $P$ . Each investor forms rational expectations about the stochastic properties of  $\tilde{P}$  as both market-clearing price and public



information signal. In the first step the investor chooses optimal asset management,  $q_i^*$ , conditional on the second-step solutions for the asset demand. These choices are shown to be consistent with the existence of rational-expectations equilibrium.

### A. Conditional Individual Demand and the Equilibrium Price for the Risky Asset

In step 2 of the optimization process, the investor makes use of the realized public price signal  $P$  and (optimal) private information signal  $z_i$  to derive the posterior probability distribution of future returns and the conditional expected utility function. The investor then determines the conditional demand for the risky asset by solving the objective function:

$$(9) \text{Max}_{D_i} E[U(\tilde{W}_{1i} | z_i, P)].$$

To solve equation (9) investors must know the joint probability distribution of the stochastic variables  $(\tilde{\mu}, \tilde{z}_i, \tilde{P})$ . A simplifying assumption is that under a rational-expectations-equilibrium (REE), investors **conjecture** that the competitive market-clearing price,  $\tilde{P}$ , is linearly related to the asset's future return,  $\tilde{\mu}$ , their acquired private information signals,  $\tilde{z}_i$  (or  $\tilde{\varepsilon}_i$ ), and the supply shock,  $\tilde{x}$ . Since by equations (1)-(3),  $\tilde{\mu}$ ,  $\tilde{z}_i$ , and  $\tilde{x}$  are normally distributed, the triplet  $(\tilde{\mu}, \tilde{z}_i, \tilde{P})$  would be normally distributed as well. The conjecture can be further simplified to show that the REE price would converge **in probability** to<sup>7</sup>:

$$(10) \tilde{P} = \theta + \lambda \tilde{\mu} - \nu \tilde{x},$$

where  $\tilde{x} \equiv (1/n) \sum_{i=1}^n \tilde{x}_i$ . By this conjecture, investor  $i$ 's posterior distribution of the return,

conditional on the observed price and private signal, is also normally distributed with mean

$$(11a) \mu_i = E(\tilde{\mu} | z_i, P) = [h\bar{\mu} + s_i z_i + t(\lambda/\nu)^2 (1/\lambda)(P - \theta + \nu \bar{x})] / [h + s_i + (\lambda/\nu)^2 t],$$

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

Investor  $i$ 's conditional demand for the risky asset can then be derived using (11a) and (11b):

$$(12) D_i(z_i, P) = r \frac{\mu_i - P}{V_i} = r \{h\bar{\mu} + s_i z_i + [t(\lambda/\nu)^2][(1/\lambda)(P - \theta + \nu\bar{x})] - [h + s_i + t(\lambda/\nu)^2]P\}.$$

To arrive at the equilibrium solution for equations (12), however, we must also solve for the conjectured coefficients  $\theta$ ,  $\lambda$ , and  $\nu$ , in equation (10). The assumption underlying the REE analysis is that the conjectured asset prices are consistent in probability with the market-clearing prices. The coefficients  $\theta$ ,  $\lambda$ , and  $\nu$  must then satisfy the equilibrium condition:

$$(12a) \frac{1}{n} \sum_{i=1}^n D_i(\tilde{z}_i, \tilde{P}) = \frac{1}{n} \sum_{i=1}^n \tilde{x}_i \equiv \tilde{x}.$$

This is indeed the case. The parameter  $(\lambda/\nu)$  in equations (11a)-(12) can be shown equal to  $(rs)$ .<sup>8</sup>

The stochastic market clearing price and individuals' risky-asset demands thus become:

$$(13) \tilde{P} = \{h\bar{\mu} + rst\bar{x} + (s + r^2s^2t)\tilde{\mu} - [(1/r) + rst]\tilde{x}\} / \{h + s + r^2s^2t\},$$

$$(14) \tilde{D}_i = r [h\bar{\mu} + rst\bar{x} + s_i \tilde{z}_i + r^2s^2t\tilde{\mu} - rst\bar{x} - \tilde{P}(h + s_i + r^2s^2t)],$$

where  $s = \int_{\underline{H}}^{\bar{H}} s_i f(H_i) dH_i$  is the weighted average of all investors' information precision.<sup>9</sup> Note

that by equation (12) or (14) a higher precision  $s_i$  may either **increase** or **lower** optimal risky-asset holding in period 1, depending on  $s_i(\tilde{z}_i - \tilde{P})$ , i.e., whether one's realized private signal exceeds or falls short of the realized price, and such periodic adjustments in risky-asset holdings would be larger the higher is one's information precision.<sup>10</sup> In section II.A we show, however, that the **expected** demand level for the risky asset will unambiguously rise with  $s_i$ .

## B. Derived-Demand for Asset Management

Having thus determined the demand for the risky asset,  $\tilde{D}_i$ , conditional on given values of asset management time,  $q_i$ , we can solve for the latter by maximizing the expected utility of terminal wealth,  $\tilde{W}_{1i}$  conditional on  $\tilde{D}_i$ , with respect to  $q_i$ . Since by equation (6) information precision is a monotonically increasing function of asset management,  $s_i = s_i(q_i)$ , we proceed for

convenience to maximize the expected utility of final wealth with respect to  $s_i(q_i)$ , (as in Verrecchia, 1982, and Kim and Verrecchia, 1991a), and then extricate our model's solution for  $q_i$ . We rewrite first the terminal wealth in equation (4a) as  $\tilde{W}_{it} = W_{0i} + \tilde{P}\tilde{x}_i + \tilde{D}_i(\tilde{\mu} - \tilde{P}) - C(s_i)$ , where  $W_{0i} \equiv B_{0i} + w_i T$ . The expected utility to be maximized can then be derived from equations (8) and (9), using the properties of the log-normally distributed mean return  $\tilde{\mu}$ ,

$$(15) \text{Max } E \left\{ -\exp \left[ -\frac{1}{r} (W_{0i} - C(s_i) - \tilde{P}\tilde{x}_i) - \frac{1}{2} (\mu_i - \tilde{P})^2 / V_i \right] \right\},$$

with the expected utility operator defined over the bivariate normal distribution of the  $\tilde{z}_i$  and  $\tilde{P}$ .

We can now state our solutions for information precision and asset management as follows:

$$(16) s_i = \max \left\{ 0, s_i \mid \frac{1}{2(h + s_i + (rs)^2 t)} - \frac{C'(s_i)}{r} = 0 \right\}.$$

An interior optimum requires equalizing the relevant marginal cost and revenue

$$(16a) C'(s_i) = (1/\alpha) w_i(H_i, \delta) s_i^{(1-\alpha)/\alpha} A(\tau)^{-1/\alpha} H_i^{-\beta/\alpha} = .5r (h + s_i + r^2 s^2 t)^{-1}.$$

The marginal cost,  $C'(s_i)$ , is derived from equation (7). The corresponding marginal revenue is inversely related to the variance of investor  $i$ 's posterior distribution of the risky return,  $V_i$  (see equation 11b and footnote 8).<sup>11</sup> Rearranging terms, we obtain an implicit, non-linear solution:

$$(17) MR(s_i) \equiv s_i^{(1-\alpha)/\alpha} (h + s_i + r^2 s^2 t) = MC(s_i) \equiv .5r A(\tau)^{1/\alpha} H_i^{\beta/\alpha} \alpha w_i(H_i, \delta)^{-1}.$$

An interior solution for  $s_i$  necessarily exists if  $0 < \alpha < 1$  in equation (6) and there are no fixed asset management costs, or  $C_0=0$  in (7). If  $\alpha = .5$ , e.g., (17) becomes quadratic in  $s_i$ :

$$(18) s_i^* = .5 \{ [(h + r^2 s^2 t)^2 + (rA(\tau)^2 H_i^{2\beta} w_i(H_i, \delta)^{-1})]^{.5} - (h + r^2 s^2 t) \} > 0, \text{ and}$$

$$(19) q_i^* = .25 \{ [(h + r^2 s^2 t)^2 + (rA(\tau_i)^2 H_i^{2\beta} w_i(H_i, \delta)^{-1})]^{.5} - (h + r^2 s^2 t) \}^2 A(\tau)^{-2} H_i^{-2\beta} > 0.$$

Alternatively, if we let  $\alpha = 1$ , the cost function in equation (7) becomes linear. Here, if a positive solution for optimal asset management time exists, it is given by<sup>12</sup>

$$(20) q_i^* = .5r w_i^{-1} - (h + r^2 s^2 t) A(\tau)^{-1} H_i^{-\beta}.$$

### III. Behavioral Implications at the Micro Level

#### A. Expected demand for the risky asset

Equations (13) and (14) identify the basic determinants of demand for risky assets and derived demand for asset management at any point in time. To derive testable propositions concerning these determinants, which are new to the literature, we first insert equation (13) into (14) to derive the **expected** individual demand for the risky asset and its market price:

$$(21) \quad E(\tilde{D}_i) = r [(s_i - s)(\bar{\mu} - E(\tilde{P})) + (1/r)\bar{x}] , \text{ where}$$

$$(22) \quad E(\tilde{P}) = \bar{\mu} - [(1/r)\bar{x} / (h + s + r^2s^2t)] .$$

Alternatively, by inserting equation (22) into (21) the latter can be rewritten:

$$(21a) \quad E(\tilde{D}_i) = \bar{x} [(h + s_i + r^2s^2t) / (h + s + r^2s^2t)] > 0.$$

By equation (21a) all investors have some positive **expected** demand for the risky asset which rises monotonically with the precision of the investor's private information ( $s_i$ ) relative to the collected public information embedded in the market price ( $r^2s^2t$ ). The ratio  $[s_i/r^2s^2t]$  is inversely related to the variance of the posterior distribution of the return as perceived by investor  $i$  relative to the average investor,  $\{[1/(h + s_i + r^2s^2t)]/[1/(h + s + r^2s^2t)]\}$  (see equation 11b and footnote 8). Clearly, the lower the perceived riskiness of the asset, the greater is the tendency to hold it.

By equation (22), the expected future return or price,  $\bar{\mu}$ , is always greater than the expected equilibrium purchase price of the asset due to risk aversion. Equation (21) also implies that, abstracting from any systematic differences in risk tolerance, investors who are better informed relative to the average ( $s_i > s$ ) can be expected to have relatively greater demand for the risky asset. So while at any point in time, those with superior knowledge may use it to either buy or sell the risky asset, as equation (14) indicates, over many periods or independent groups of informed investors, risky asset demand would **average out** to be relatively larger for the better informed, as their **conditional** risk from holding risky assets, given private information, is lower.

## B. Participation in asset management

If the elasticity of information production with respect to search time were unitary, or  $\alpha = 1$ , then equation (17) would allow for a corner solution whereby the marginal benefit from asset management is below its marginal cost, and investor  $i$  would eschew asset management i.e.,  $q_i = s_i = 0$ , even if there were no fixed entry costs in information collection. Here, by equation (21a)

$$(23) E(D_i)^0 \rightarrow \bar{x} [(h + r^2 s^2 t) / (h + s + r^2 s^2 t)], \text{ as } q_i, \text{ hence } s_i \rightarrow 0.$$

A fraction of investors with expected demand at or below the threshold level  $E(D_i)^0$  would then eschew asset management and rely just on the market price as information signal. Our numerical simulation of this case, using equation (5) and the baseline parameters in Table 1, sets this fraction at 30% of all investors.

In the more general case where  $0 < \alpha < 1$ , the marginal cost is increasing and convex from the origin, absent any fixed costs, which implies that investors allocate at least some nonzero time to manage assets. In this case, we can estimate numerically the fraction of “minimally informed investors” whose private information  $s_i$  is at least one standard deviation below the average,  $s$ . Using our baseline parameters, this fraction is 19.48%. The fraction could be much higher if fixed costs were nonzero. (A related survey estimate is given in section V.B.)

## C. Comparative-statics and testable implications at the micro level

For interior solutions for asset management, we can derive analytically or via numerical simulations testable propositions about the impact of basic parameter shifts on the demand for information,  $s_i^*$ , the derived-demand for asset management,  $q_i^*$ , the expected demand for risky assets,  $E(\tilde{D}_i)$ , and the rate of return to human capital in wage and financial income at different education levels. Table 1 illustrates the results using a specified parameter set and an assumed truncated log-normal distribution of educational attainments  $H_i$ .<sup>13</sup>

*a. Shifts in human capital endowments, ( $H_i$ ):*

We take educational attainments – our proxy for human capital – to be of the “general” type - raising the productivity of time in both the labor market and asset management. Assuming that shifts in idiosyncratic individual parameters do not affect equilibrium market prices or average information precision, the impact of shifts in  $H_i$  can be determined by differentiating equation (17) with respect to  $H_i$ , using equations (5) and (7) (see Appendix 1 for proofs):

$$(24a) \quad \text{sgn } ds_i^*/dH_i = \text{sgn } d[E(\tilde{D}_i)^*/dH_i] = \text{sgn } [(\beta/\alpha) - \varepsilon_{w_i, H_i}]; \quad \varepsilon_{w_i, H_i} \equiv (dw_i^*/dH_i)(H_i/w_i^*) > 0;$$

$$(24b) \quad \text{sgn } dq_i^*/dH_i = \text{sgn } (\varepsilon_{s_i, H_i} - \beta); \quad \varepsilon_{s_i, H_i} \equiv (ds_i^*/dH_i)(H_i/s_i^*);$$

$$(24c) \quad \text{sgn } (\partial s_i^*/\partial H_i)|_{w_i=const} = \text{sgn } \partial[E(\tilde{D}_i)^*/\partial H_i]|_{w=const_i} > 0;$$

$$(24d) \quad \text{sgn } (\partial q_i^*/\partial H_i)|_{w_i=const} = \text{sgn } (E_{s_i, H_i} - \beta); \quad E_{s_i, H_i} \equiv [(\partial s_i^*/\partial H_i)(H_i/s_i^*)]|_{w_i=const} > 0.$$

**Proposition 1:** An “unconditional” increase in individual human capital which allows wages to rise with  $H_i$ , would increase private information precision,  $s_i^*$ , thus expected demand for the risky asset,  $E(\tilde{D}_i)^*$ , if the elasticity of the wage rate with respect to  $H_i$ ,  $\varepsilon_{w_i, H_i}$ , is lower than  $(\beta/\alpha)$  - the ratio of the elasticities of  $s_i$  with respect to  $H_i$  and  $q_i$  in production (see equation 6). It would increase asset management time  $q_i^*$ , however, only if an unconditional increase in  $H_i$  had a larger percentage impact on the **demand** for  $s_i^*$  than on its **production**, or  $\varepsilon_{s_i, H_i} > \beta$  in elasticity terms.

**Proposition 2:** A “conditional” increase in  $H_i$ , that left the wage rate  $w_i(H_i, \delta)$  intact would unambiguously raise  $s_i^*$ , and  $E(\tilde{D}_i)^*$ . A conditional increase in  $H_i$  thus generates a larger increase in  $s_i^*$  and  $E(\tilde{D}_i)^*$  than an unconditional one, but the derived demand for asset management time would again rise only if the conditional elasticity of  $s_i^*$  with respect to  $H_i$  in demand is larger than that in production, or  $E_{s_i, H_i} > \beta$ .

The ambiguity regarding the impact of an unconditional increase in individual educational endowment stems from its opposing effects on the marginal benefit from information

precision and the opportunity cost of management time,  $w_i$ . The latter effect is absent when  $w_i$  is held constant. Therefore, a conditional increase in  $H_i$  leads to an unambiguous increase in desired information precision and the demand for the risky asset (by 21a). The impact on the derived-demand for asset management time,  $q_i^*$ , however, is still ambiguous because a higher  $H_i$  also raises the productivity of any unit of time already spent managing assets. In our simulations,  $\varepsilon_{w_i, H_i}$  and  $E_{s_i, H_i}$  are found to be sufficiently low and high, respectively. Indeed, optimal information precision  $s_i^*$  is found to be a monotonically increasing function of  $H_i$ , while time devoted to asset management ultimately falls at higher levels of  $H_i$  (see Figure 1).

*b. Idiosyncratic shifts in the opportunity cost  $w_i(\delta_i)$  and “technology”  $A(\tau)_i$  of asset management:*

The vector  $\delta$  represents individual attributes or labor market conditions for specific occupations or locations that affect individual wages and thus the opportunity cost of asset management time at any given level of educational attainments. Likewise, the vector  $\tau$  represents various external or internal cost-saving “technologies” that augment the productivity of education and time inputs in acquiring information. These include indicators of “specific” human capital, such as experience in financial transactions, as opposed to “general” human capital (schooling), and technological innovations that affect the efficiency of information acquisition.

Although our equilibrium solutions in equations (13) and (14) assumed a uniform  $A(\tau)$  and  $\delta$  across investors, we can here allow for idiosyncratic shifts in  $w(\delta)_i$  and  $A(\tau)_i$  which do not alter the average private information level,  $s$ . Differentiating equation (17) with respect to  $A(\tau)_i$  or  $w(\delta)_i$  and using equations (7) and (21), we prove in Appendix 1 that:

**Proposition 3:** A higher opportunity cost of time  $w(\delta)_i$  will lower asset management and demand for risky assets. The converse holds for improved efficiency in information production,  $A(\tau)_i$ .

$$(25a) \text{sgn}(ds_i^*/dw_i) = \text{sgn} d[E(\tilde{D}_i)/dw_i] = \text{sgn}(dq_i^*/dw_i) < 0, \text{ as long as } s_i^* > 0.$$

$$(25b) \text{sgn}(ds_i^*/dA_i) = \text{sgn} d[E(\tilde{D}_i)/dA_i] = \text{sgn}(dq_i^*/dA_i) > 0, \text{ as long as } s_i^* > 0.^{14}$$

*c. “Initial Wealth” effects:*

The exponential utility function (8) exhibiting constant absolute risk aversion inherently precludes any initial “wealth effects” on the demand for risky assets. Also, the formal model does not recognize any borrowing constraints or bankruptcy costs that impose lump-sum costs on risky-asset holdings. Consequently, the model also precludes any impact on the demand for risky assets stemming from higher (safe) earnings or the value of human capital as a safe asset in a larger portfolio that includes both human and nonhuman wealth (but see our analysis of this issue in section V.B.a). However, the size of one’s financial wealth, or financial portfolio can act as a distinct idiosyncratic “efficiency” factor,  $A(\tau)_i$ , since larger portfolios, accumulated or inherited, signal greater past experience or scale economies in portfolio management.<sup>15</sup> By equation (25b), a larger portfolio size is therefore expected to enhance the expected demands for asset management, private information, and risky assets,  $q_i^*$ ,  $s_i^*$ , and,  $E(\tilde{D}_i)^*$  respectively.

*d. Returns to human capital in generating wage and non-wage income:*

Proposition 4: Propositions 1-3 concerning the impact of human capital on the demand for risky assets hold for its impact on overall portfolio returns as well.

The rationale is that any returns to human capital from asset management may occur in our model strictly via shifts in portfolio composition from “bonds” to “stocks”, i.e., from higher  $E(\tilde{D}_i)^*$  induced by information precision. Thus our DEMAND and RETURN regression results in section V should be qualitatively similar if estimated using the same regression specification. We can also simulate our model numerically to estimate expected premiums on unconditional increments in human capital from, which generate both higher wage earnings and added portfolio returns. In Table 1 the impact of  $H_i$  on log earnings is assessed by simulating equation (5), and its impact on the expected net return on financial investments is assessed by simulating  $d \ln \{E[\tilde{D}_i(\tilde{\mu} - \tilde{P}) - C(s_i)]\} / dH_i$  at different levels human capital endowments.<sup>16</sup>



## IV. Market-Level Implications

### A. Private information, Price level, and Price Volatility

Under our competitive setting, changes in idiosyncratic individual parameters do not alter average private information,  $s$ , or the risky asset's expected market price and volatility. Changes in investors' common parameter levels would affect all of these variables.

From equation (13), price realization is linearly related to “supply” and “return” shocks:

$\tilde{P} = \theta + \lambda\tilde{\mu} - v\tilde{x}$ , where  $\theta = [1/(h + s + r^2s^2t)][h\bar{\mu} + rst\bar{x}]$ ;  $\lambda = [(s+r^2s^2t)/(h+s+r^2s^2t)]$ ; and  $v = [(1/r)+rst]/(h+s+r^2s^2t)$ . From (22), expected price is  $E[\tilde{P}] = \bar{\mu} - [(1/r)\bar{x} / (h + s + r^2s^2t)]$ . It

follows that under a fixed supply of the risky asset, changes in average parameter levels that affect exclusively average information precision ( $s$ ) will increase the expected price level by virtue of enhanced demand. The price **variance**, in turn, is given by

$$(26) \text{Var}(\tilde{P}) = \lambda^2 \text{Var}(\tilde{\mu}) + v^2 \text{Var}(\tilde{x}) - 2\lambda v \text{Cov}(\tilde{\mu}, \tilde{x}),$$

where  $\text{Var}(\tilde{\mu}) \equiv (1/h)$ , and  $\text{Var}(\tilde{x}) \equiv (1/t)$ . Since “return shocks” ( $\tilde{\mu}$ ), are not linked to unpredictable “supply” shocks ( $\tilde{x}$ ),  $\text{Var}(\tilde{P})$  simplifies to

$$(26a) \text{Var}(\tilde{P}) = \lambda^2 (1/h) + v^2 (1/t) = \lambda^2 \{ (1/h) + [1/(r^2s^2t)] \},$$

and price volatility, defined as the ratio of variance to expected price, becomes

$$(27) v(\tilde{P}) \equiv \text{Var}(\tilde{P}) / E(\tilde{P}) = [\lambda^2 (1/h) + v^2 (1/t)] / [\theta + \lambda\bar{\mu} - v\bar{x}].$$

Movements in all three price-related measures are thus seen to be controlled by our model's basic parameters either directly or through their influence on private information collection.

Our simulations in Table 2 offer comparative static implications about the effects of common parameters shifts on three sets of market-level outcomes: average asset management intensity and information precision,  $\bar{q}$  and  $s$ ; the risky asset's expected price, price variance and volatility,  $E(\tilde{P})$ ,  $\text{Var}(\tilde{P})$  and  $v(\tilde{P})$ ; and the expected risk premium  $R^e$  (discussed in section B).

a. *The impact of improvements in the efficiency of asset management:  $\bar{H}$  and  $A(\tau)$*

Consider first “unconditional” shifts in average human capital and information production “technology”,  $\bar{H}$  and  $A(\tau)$ , which shift  $Var(\tilde{P})$  and  $v(\tilde{P})$  just through their impact on average information precision,  $s$  (see equation 26a). Increases in  $\bar{H}$  stemming from a uniform increase in schooling would monotonically raise average private information,  $s$  (provided that  $\varepsilon_{w\bar{H}} < \beta/\alpha$  in equation 24b) and thus the risky asset’s expected price,  $E(\tilde{P})$ . They also lower average asset management intensity  $\bar{q}$  in our simulations, partly because of a feedback effect owing to higher average private information,  $s$ , which lowers the derived-demand for  $q_i$  by the relatively more informed investors. Increments in the external technology of information production,  $A(\tau)$ , have similar effects: they raise  $s$  and  $E(\tilde{P})$ , and lower  $\bar{q}$  (contrary to outcomes for  $q_i$  at the individual level), because of the feedback effect of  $s$  on  $q_i$ .

How do shifts in  $\bar{H}$  or  $A$ , affect the risky asset’s price variance and volatility,  $Var(\tilde{P})$  and  $v(\tilde{P})$ ? The answer depends on basic-parameter levels and the magnitude of  $s$ . Three cases are relevant: a. If  $r^2ht < 1$ , as would be the case if the variances of supply and unconditional return are sufficiently high,  $Var(\tilde{P})$  would be a U-shaped function of  $s$  as it rises from zero; b. If  $1 < r^2ht < (5/4)$ , as would be the case if  $Var(\tilde{x})$  and  $Var(\tilde{\mu})$  are lower,  $Var(\tilde{P})$  will assume a humped shape: first rising, then falling, then rising again as  $s$  increases; c. If  $r^2ht > 5/4$ , which would be the case if  $Var(\tilde{x})$  and  $Var(\tilde{\mu})$  were sufficiently low,  $Var(\tilde{P})$  would be continuously rising.<sup>17</sup> The common feature in all cases is that as higher  $\bar{H}$  or  $A$  increases, at least beyond some positive level,  $Var(\tilde{P})$  would begin rising monotonically. Since an increasing  $s$  also raises the expected price,  $E(\tilde{P})$ , the behavior of price volatility  $v(\tilde{P}) = Var(\tilde{P}) / E(\tilde{P})$  is in principle uncertain. However, in all our experiments with alternative parameter sets,  $v(\tilde{P})$ , mimics the shape of

$Var(\tilde{P})$ , essentially because expected price rises at a lower rate than price variance.

The rationale is that increasing average precision,  $s$ , has two competing effects: on the one hand it lowers the incentive to trade on price fluctuations which convey no information; on the other hand, it raises the incentive to take advantage of acquired information signals by trading on the strength of these signals (by adjusting up or down the risky assets' portfolio shares). The second effect becomes more pronounced as  $s$  rises sufficiently. If  $Var(\tilde{x})$ , or  $Var(\tilde{\mu})$  in equation (26a) are high, such that  $r^2ht < 1$ , optimal  $s$  would be quite low at low levels of  $\bar{H}$  or  $A$  (see Table 2). The first effect may thus dominate initially, but the second takes over as  $\bar{H}$  or  $A$ , hence  $s$ , continue to rise (See Figure 2.A). The inference is that higher levels of human capital and private information can ultimately increase observed market volatility, especially in more developed financial markets, while the average subjective risk to individuals actually falls.

*b. The Impact of increments in the means and variances of supply and return distributions:*

Fiscal and policy changes that affect firms' incentives to float stocks or the price of bonds could alter the distributions of the risky asset's supply and returns,  $\tilde{x}$  and  $\tilde{\mu}$ , respectively.

Upward shifts in just their mean levels,  $\bar{x}$ ,  $\bar{\mu}$ , have no impact on mean asset-management time,  $\bar{q}$ , but they respectively lower and raise the asset's market expected price  $[E(\tilde{P})]$ .

Lower variances of  $\tilde{x}$  and  $\tilde{\mu}$ , i.e., higher  $t$  and  $h$ , in contrast, have more complex effects on  $E(\tilde{P})$  and  $Var(\tilde{P})$ . On the one hand they lower average asset management and information

precision,  $\bar{q}$  and  $s$ , but raise the expected price  $E(\tilde{P})$ : From equation (17) we can prove that higher  $t$  or  $h$  lower the marginal benefits from information collection, so optimal  $\bar{q}$  and  $s$  fall.

Expected demand rises, however, because the higher  $t$  and  $h$ , which lead to a lower variance of the posterior distribution of returns in equation (11b), raise the willingness to hold stocks.

Expected price must then rise to ration expected demand to the given mean supply level,  $\bar{x}$ <sup>18</sup>. On

the other hand, higher  $t$  and  $h$  directly contribute to a lower variance of the market price in equation (26a). In our simulations, the latter effect dominates that of the decline in information precision,  $s$ , when  $h$  continuously rises, causing the variance and volatility to fall. A rising  $t$ , in contrast, causes the price variance to first fall but then rise as  $t$  increases, essentially because of the decline in  $s$  (see Figure 2.B). Price volatility, however, tends to fall as variances of supply and demand shocks ( $1/t$  and  $1/h$ ) fall. By implication, asset prices are expected to fall and their volatility to rise as a result of adverse supply shocks and recessions.

### **B. Asset management, equity premium, and the equity-risk-premium puzzle**

Since we assume for convenience that the return on bonds is zero, the expected equity premium as conventionally defined is given by:

$$(28) \rho^e = E\{[\tilde{\mu} - \tilde{P}]/\tilde{P}\}, \text{ which can be rewritten,}$$

$$(28a) \rho^e = \rho - \text{Cov}\{R^e, [\tilde{P}/E(\tilde{P})]\},$$

where  $\rho \equiv [E(\tilde{\mu}) - E(\tilde{P})]/E(\tilde{P})$ . The value of  $\rho$  has a precise interpretation in our model: it is the relative gap between the expected value of the posterior distribution of returns, conditional on average private information and expected market price, or alternatively from equation (22):

$$(28b) \rho = \{[(1/r)\bar{x}]/[(h + s + r^2s^2t)\bar{\mu} - (1/r)\bar{x}]\} > 0.$$

The covariance term in equation (28a) is generally ambiguous in sign. Our numerical simulations using the parameters of Table 1 find it to be negative but small in magnitude, and little affected by changes in average information precision  $s$ . By equation (28b), however, there is an inverse relationship between  $\rho$  and  $s$ . By our numerical simulations this relationship applies to  $\rho^e$  as well. Higher  $\bar{H}$  or  $A$  are thus expected to lower the equilibrium equity premium for investors because the variance of the posterior distribution of returns to the average investor is monotonically decreasing with the greater information precision they generate.

This analysis also offers new insights concerning the “equity-risk-premium puzzle”. The conventional literature interprets  $\rho^e$  in equation (28) as equilibrium compensation for pure risk bearing. By our model, however,  $\rho^e$  overstates that compensation, since a component of the equity risk premium must account for the cost of asset management rather than pure risk bearing. The analysis below offers a way to pin down this component using our model.

A representative investor faces two competing options: a. cashing out her endowed average supply of the risky asset ( $\bar{x}$ ) and converting it to safe bonds at the going market price  $\tilde{P}$ ; or b. purchasing an optimal amount of the risky equity consistent with optimal asset management ( $q_i^*$ ). Since her information precision is the same as the average precision,  $s_i=s$ , by equation (21) her expected demand for the risky asset indeed equals her endowed average supply,  $E(\tilde{D}_i) = \bar{x}$ .

Second-period wealth associated with option A would then be:

$$\tilde{W}_{1A} = B_0 + wT + \tilde{P}\bar{x}, \text{ while option B's would be } \tilde{W}_{1B} = B_0 + w(T - q_i^*) + \tilde{P}\bar{x} + (\tilde{\mu} - \tilde{P})\bar{x}.$$

The compensating differential  $N^*$  required to compensate this investor for selecting the inherently riskier option B over A can be determined from

$$(28c) \text{ EU}(\tilde{W}_{1A} + N^*) = \text{EU}(\tilde{W}_{1B}).$$

As computed in equation (28c), however,  $N^*$  understates the full compensation required for bearing the added risk from holding the endowed risky asset over bonds, as option B also entails bearing the opportunity cost of asset management  $C^*=wq_i^*$ . Absent any fixed management costs ( $C_0=0$ ), the required **full** compensation would therefore be  $G^*=N^*+C^*$ .

By this analysis, a fraction  $c^*=C^*/G^*$  of the equilibrium compensation for holding stocks over safe bonds must be ascribed to asset management rather than pure risk bearing, and exactly the same inference applies to equation (28) defining the equilibrium compensation per dollar invested in the risky asset. This inference can resolve at least part of the “equity risk-premium puzzle” discussed in the literature (see Mehra and Prescott, 2003).

To illustrate the quantitative value of  $c^*$ , we have assessed  $N^*$ ,  $C^*$  and  $c^* = C^*/G^*$  numerically by simulating equation (28c). Based on the model parameters used to derive Table 1, we estimate the portion of  $R^e$  due to information costs,  $c^*$ , to be 10.44%. This result is just illustrative; it ignores fixed information costs and is sensitive to the model's parameter values.<sup>19</sup>

## **V. Empirical Evidence**

Some of our key predictions are testable empirically. At the individual level we expect that:

1. Consistent with our comparative-static propositions, “conditional” increases in personal educational attainments (EDU), with personal wage rate held constant, will raise the expected demand for risky assets, and hence the overall portfolio return on financial assets.
2. Indicators of “technological efficiency”, such as a management-related occupation or accumulated portfolio size which decreases the marginal cost of asset management, will also raise risky-assets demand and management time, and hence overall portfolio returns.
3. In contrast, higher “conditional” wage rates, given education, will unambiguously lower asset management time and expected demand for risky assets, thus overall portfolio returns.
4. “Unconditional” increases in educational attainments will have weaker effects on risky- assets demand and management, as they also raise the opportunity cost of asset management.

We test the preceding implications using two data sets, the first of which includes 8 samples.

### **A. First Data Set: Risky Asset Demand and Portfolio Returns**

The first set consists of data from eight surveys of individual asset holdings and realized returns for the years, 1963-64, 1983, 1989, 1992, 1995, 1998, 2001, and 2004 that are reported in the *Survey of Consumer Finances* of corresponding years based on separate national probability samples. These data sets, spanning four decades, contain data critical to testing our specific hypotheses. All data sets contain information about household initial portfolio composition by asset categories, realized portfolio returns in the same year (for 1963-1964 the returns are on the

previous year's holdings), household wage income, and personal characteristics of household heads and their spouses. The national probability samples from the early years (through 1989) represent relatively affluent and older investors, as these are more likely to own marketable assets, but in the later years attempts were made to sample the entire population. Since there are also differences in the personal characteristics included in different samples, we analyze them separately. We report the results in a single table, however, to facilitate qualitative comparisons.

A number of empirical studies sought to identify factors that explain household decisions to hold risky assets. Several of these rely on data sets similar to ours, and although they use different specifications, some of their results are similar to ours (see especially Bertaut (1998)).<sup>20</sup> Also, like other studies we define as risky assets corporate and international stocks and bonds.

Where we differ is in our model specification, which is designed to test specific implications of our comparative static analysis concerning the effects education, experience in managing assets and, especially the opportunity cost of time on risky-assets demand. While some studies also include disposable income as a regressor, they do not ascribe a theoretical justification for it. They also treat this variable as exogenous, although earnings are a product of the wage rate and time allocated to labor-market activities, which are endogenous to our model.

In this section we restrict our sample to include only investors who have positive risky asset holdings and positive total assets (net worth). This is in conformity with our theoretical analysis requiring that all investors have positive expected demands for the risky asset as well as initial financial wealth (see equation 21a). Moreover, it is only under these conditions where all our key propositions (1-4) are expected to hold. We thus estimate risky-assets demand and total portfolio returns functions **conditional** on non-zero values, and in log format for most variables after testing for the efficient regression format. In the following section, however, we relax this assumption and include investors with zero holdings of risky assets as well.

We base our specification of the risky assets demand (“DEMAND”) regression on our theoretical analysis. The dependent variable is the log value of risky assets holdings, defined as all publicly tradable stocks and corporate and foreign bonds,  $\ln RASST$ . We choose this definition since our model applies to a centrally-traded security (portfolio subset) subject to unambiguous risk. The remainder of the total portfolio (TASST) is thus treated as a “safe” asset.<sup>21</sup> The explanatory variables account for determinants of productivity at, and opportunity cost of, asset management by household heads, as implied by our model. They include, the household head’s number of years of schooling  $EDU$  (average schooling of husbands and wives yields similar results), the log value of the investor’s portfolio size,  $\ln TASST$ , as an indicator of experience in managing assets, or lower fixed costs of asset management, and the log value of the predicted wage rate of the household’s head (see below),  $\ln WAGE^*$ . They also include an indicator of “managerial and professional-specialty occupations” lumping together managers of all types, and specialty occupations varying from speech therapists to nuclear engineers, some of which might be conducive to asset management ( $PROF$ ), and self-employment vs. salaried status which may need to be examined separately for reasons we explain later in this section. Investors also provide self-assessments of their relative risk aversion intensity ( $RAV$ ) in 7 of our annual samples (the only exception is 1963-64) using 4 categories (1-4) in ascending order of risk aversion. We therefore introduce this categorical variable as a robustness check on the validity of our hypotheses, which do not rely on differences in attitudes toward risk in explaining risky assets demand and management. However, it is difficult to ascertain whether  $RAV$  measures genuine risk preferences, or just mimics the risk-taking **behavior** of individual investors. And although our model abstracts from life-cycle dynamics, we add the investor’s age ( $AGE$ ) as a regressor to account for the “vintage” effect of schooling or see if one’s life-cycle position has an independent effect on risky asset demand. The basic regression model is thus:



$$(29) \lnRASST = a_0 + a_1 \ln EDU + a_2 \ln TASST + |a_3 \ln WAGE^*| + a_4 AGE + a_5 PROF + a_6 RAV + |a_7 SELF|.$$

Equation (29) allows for two basic specifications: one that excludes WAGE in the regression, to allow for estimation of the theoretical “unconditional” effect of EDU on DEMAND, and one that includes WAGE to allow for conditional effects of both education and wage effects. It also allows for regressions based on just wage and salary workers or for all investors, by including the dummy variable SELF as a separate regressor. While the exact functional form of equation (29) cannot be pinned down theoretically, our theoretical simulations indicate that the effect of education on the demand for information-precision, and hence the demand for risky assets, may be subject to diminishing returns, which is why we enter EDU in log form. Variables defined in continuous dollar values are also introduced in log form, while those defined as discrete-step variables are entered in natural form. Extensive Box-Cox tests support the log transformation of the dependent variables and other dollar variables in both equations (29) and (30) below. As for the education variable, the Box-Cox tests support a logarithmic, or other non-linear transformations of EDU in most sample years. We have thus chosen  $\ln EDU$  as the regressor in our benchmark specification.

We employ a similar specification to test if the realized overall portfolio returns (“RETURN”) likewise responds to the theoretical determinants of asset management.<sup>22</sup> This reported measure misses, of course, unrealized capital gains, which our two-period model abstracts from, so our implicit assumption is that the realized gains are monotonically related to the unrealized gain:

$$(30) \ln RETURN = b_0 + b_1 \ln EDU + b_2 \ln TASST + |b_3 \ln WAGE^*| + b_4 AGE + b_5 PROF + b_8 RAV + |b_7 \ln SHARE| + |b_6 SELF|.$$

Equation (30) includes another distinct regression variant where SHARE, denoting the

share of risky assets in the portfolio (RASST/TASST), is introduced as a proxy for portfolio composition. Recall that by our model, more effective asset management is expected to raise overall portfolio returns **only** through its impact on the demand for a single risky asset, which yields a higher return than the safe assets (our theoretical “bonds”) in the overall portfolio (see equation 28). The empirical counterpart we use, however, is an **aggregate** portfolio of risky financial assets. If we could actually control for precise portfolio composition in terms of all specific risky assets, the impact of our determinants of asset management might vanish. But since lnSHARE distinguishes between broad composites of risky and non-risky assets, asset management could still raise the overall portfolio returns, but to a **lesser** degree than when lnSHARE is accounted for.

There are important reasons to separate self-employed from all investors in both our DEMAND and RETURN regressions for two main reasons: first, wage and non-wage income reported by members of this group may be arbitrary, as they are determined largely by the person’s decision to declare business income as either wages or business profits. This difficulty can be alleviated by projecting the expected wage of self-employed persons based on the conventional human-capital earnings function (see below). Another difficulty, however, is that the self-employed are also heavily invested in their own business assets, which represent non-financial manageable risky assets in which salaried workers have comparatively trivial shares. We therefore pursue two types of regressions: for all investors, and just for salary workers.

Measuring the opportunity cost of asset management presents a special challenge. The conventional proxy we seek is the person's wage rate, but no consistent “wage rate” data are reported. The surveys report consistently annual wage and salary income, WAS, for all investors. This measure is, in principle, the product of the wage rate and hours worked. Our challenge thus is to produce an effective measure of the individual’s wage rate that would

eliminate measurement and simultaneity errors. This would be especially important in the case of retired persons who report zero earnings, workers in high managerial positions, whose wage earnings may contain bonuses based on company profits, and self-employed persons who make arbitrary decision how to divide their total compensation between profits and wage income. Also, since asset management time is an endogenous variable, hours worked is in principle also an endogenous variable, and the estimated coefficient of WAS (or the earnings rate) may thus be subject to biases stemming from simultaneity and measurement errors.

We provide two alternative estimation methods to overcome these potential biases: 2SLS and a “projected wage rate” [PW] method. In the 2SLS method we derive a predicted wage rate ( $\ln WAGE^*$ ) from first-stage regressions incorporating as instruments EXP (job experience = AGE – EDU – 6), EXP<sup>2</sup>, GENDER (of household head), RACE (of household head), MARRIED (marital status of household head), and HEALTH status (available in all samples other than 1963-4). In the PW method we estimate an “extended Mincer model” (regressing  $\ln WAS$  on EDU, EXP, EXP<sup>2</sup>, GENDER, RACE, MARRIED, and HEALTH) just for active salaried workers, i.e., excluding self-employed, retirees and people not in the work force. We then use the estimated coefficients of this model to **project**  $\ln WAGE^*$  for **all investors**.<sup>23</sup> The advantage of this projected wage method is that it helps overcome both the simultaneity of wage and DEMAND or RETURN variables and potentially distorted wage data for the self-employed. The estimated regression equations (29) and (30) are summarized for the three basic variables of interest: EDU,  $\ln WAGE^*$  and  $\ln TASST$  (portfolio size) in Tables 3 – 5 for each of our 8 sample years as well as in a pooled (“all) regression model using all 8 samples. In these “all” regressions, we restrict the coefficients of EDU,  $\ln WAGE^*$ , and  $\ln TASST$  to be identical while estimating all other coefficients freely. The full regression results are illustrated for our annual samples in Tables A.1-A.6 of Appendix 2.

These results support our theoretical predictions. We rely on the regressions for wage and salary workers as our benchmark case because both our definition of risky assets and our expected wage projections,  $\ln WAGE^*$  are more accurate for salaried workers than the self-employed. The qualitative results, however, are similar for salaried, as well as all, investors.

**Education effects:** In all DEMAND regressions for salaried workers, all  $\ln EDU$  coefficients are positive and significant in the regressions estimated via the 2SLS and the PW methods and the same holds in virtually all the OLS regressions. The estimates derived via OLS are typically smaller in magnitude than those based on 2SLS and the PW method, which are often similar. The unconditional estimates (not controlling for  $\ln WAGE^*$ ) are generally **smaller** in magnitude than the conditional estimates. This supports our propositions 1 and 2, since an increase in education is expected to raise the wage rate, which produces an offsetting (opportunity cost) effect on asset management and the demand for risky assets. The same qualitative effects are obtained in the “all investors” regressions in all years, where the OLS estimates are insignificant. The estimates derived from the 2SLS and the PW method, however, are significant everywhere. The results imply that investors with more education hold higher shares of risky financial assets in their portfolios. From the estimated coefficients for  $\ln EDU$  and  $\ln Wage^*$  of equation (29) in the pooled 2SLS regression in Table 3, e.g., we estimate that salaried investors with 16 years of schooling hold about 20% more risky financial assets than those with 12 years.

In the RETURN regressions, where we do not control for SHARE, the “unconditional” as well as “conditional” effects of EDU (i.e., controlling for  $\ln WAGE^*$ ) are significant, as predicted, for both salaried workers and all investors. Note that our predicted effects of EDU on the overall portfolio returns are not conditional on our definition of “risky manageable assets”, which are likely to be different in practice for self-employed v. salaried workers. In the case of the self-employed, the returns are thus coming from both the realized returns on stocks and

bonds, as well as business assets. Again, the “conditional” education effects are larger in absolute magnitudes than the “unconditional” effects in **all** the RETURN regressions.

As expected by our theoretical analysis, adding lnSHARE to the RETURN equation **lowers** the estimated coefficient of EDU, significantly in the case of salaried workers (in the 1963/64 regression EDU becomes insignificant), essentially because controlling (perfectly) for portfolio composition can eliminate the mechanism – a change in portfolio composition – through which superior private information can yield larger portfolio returns. Since SHARE is a crude proxy for the exact share of risky manageable assets in the portfolio (especially for the self-employed), however, education can still induce larger portfolio returns for investors.

**Wage effects:** Our theoretical proposition that an increase in the wage rate, education held constant, would **lower** the demand for, hence the returns on, risky assets, is our most discriminating hypothesis stemming from the asset management hypothesis. As Tables 3 and 4 show, this prediction is confirmed in all of our 16 DEMAND and RETURN samples with no exception for salaried workers as well as for all investors (except for the 2001 RETURN results). Specifically, the predicted wage rate affects the demand and return equations in an opposite direction to that of a compensated increase in EDU.

**Portfolio size effect:** Portfolio size as defined by ln(TASST), unambiguously and significantly enhances both the demand and returns on risky assets. Note that although TASST includes RASST, since both variables are entered in logs, our regressions implicitly estimate the impact of TASST on the **fraction** of the total portfolio held in stocks, which minimizes spurious effects. We have also obtained similar regression results, however, using (TASST-RASST) as portfolio-size measure. The results are consistent with our conjecture that accumulated portfolio size captures size economies or is a proxy for “on the job” experience in asset management, both of which are expected to enhance the demand for and returns on risky assets.

The complete regression results for the other regressors entering equations (29) and (30) are reported in Tables A.1-A.6 in the appendix. We here provide a summary for each.

**Risk aversion:** This self-assessed variable has somewhat inconsistent effects across different annual samples, albeit a positive one in the pooled regression combining all years. However, its introduction or exclusion from the regression model (29) and (30) has virtually zero effects on the estimated effects of education. The results are compatible with the role assigned to education by our asset management hypothesis, and are inconsistent with the **competing hypothesis** that education increases the demand for stocks essentially because of a positive correlation between education and risk preference. The inconsistent effects of RAV in different years, however, may also indicate that the self-reported measure of risk aversion does not capture a “pure” attitude toward risk, partly mimicking risk-taking behavior, not preferences.

**Age:** Although mostly negative, the AGE coefficients fluctuate in sign across pre-1990s samples, and even in the same sample year based on different estimation techniques. In contrast, in most of the 1992-2001 samples, AGE has a consistently negative and significant coefficient in the DEMAND equations. A similar, though not identical, pattern is seen in the RETURN equations. Our model does not offer testable implications for AGE, which we control for essentially as a robustness check. The inconsistent pattern of results for AGE may be due to changes in the composition of investors in the post-1989 samples when SCF surveys attempted to target an increasingly representative sample of the entire population, as opposed to the tendency in earlier years to sample wealthy individuals, who tend to be older in age. Also, AGE in the RETURN equations may account for age differences in the incentive to realize capital gains.

**Professional status:** The effect of PROF is generally insignificant and inconsistent in the DEMAND regressions. In the RETURN regressions, its coefficients are positive and significant in 1995 and 2001, but negative and significant in 1989, 1992, 1998, and 2004. The reason is that

this variable does not offer a sharp and consistent distinction between occupational and professional status which represents experience in asset management.

***Self-employment:*** The coefficients associated with SELF in the full sample do not exhibit a consistent pattern as well in the DEMAND and RETURN equations. Our explanation is that since the self-employed invest heavily in own business assets, identifying financial assets with variable returns as the relevant measure of “risky assets” is not suitable for the self-employed. It is largely for this reason that wage and salary workers serve as our benchmark group.

***The impact of education on added portfolio returns:*** In Table 6, we report estimated “education premiums” measured alternatively as proportional or absolute increments in the rates of return on investments in financial assets due to an annual, unconditional increase in schooling. These education premiums are computed by using an interval estimation approach – 12 to 16 years of schooling – since average schooling in our annual sample tends to fall within this interval.

Accordingly, we first estimate the rates of return on financial investments,  $R^*(EDU_j)$ , for the two levels of schooling framing this interval,  $EDU_1 = 12$  and  $EDU_2 = 16$ , relative to the observed rate of return on financial assets realized by the sample’s average investor,  $R(\text{ref})$ , serving as a reference point. The estimates are based on the coefficients of  $\ln EDU$  and  $\ln WAGE^*$  in equation (30), as reported in our pooled regressions of Tables 3 and 4, as well as an estimate of the conventional internal rate of return to education in generating wage income,  $\hat{\eta} = 0.086$ , which we obtain from an extended “Mincer Model” used to estimate our projected wage rate variable [PW].<sup>24</sup> The ratio of the estimated  $\{[R^*(EDU_{16})/ R^*(EDU_{12})] - 1\}$  indicates the proportional increment in the financial rate of return on 4 years of schooling over the range 12-14; dividing this figure by 4 yields the “proportional education premium” per schooling year. The absolute education premium, in turn, is estimated as the absolute difference between the estimated rates of return to investors with 16 versus 12 years of schooling divided by 4.

To indicate the robustness of the results, Table 6 presents alternative estimates of relative or absolute education premiums, based on our three estimation methods and the two investor groups included in Tables 3 and 4. We have also computed Table 6 based on the regression results for each of the 8 sample years. While the estimated education premiums fluctuate from year to year, as is to be expected, the variations are consistent across the alternative regression methods. The relative education premium we estimate for all salary workers in Table 6 varies from 9.98% to 13.83% implying an absolute education premium of .54 to .71 percentage points per school year above the average portfolio return to salary workers of 6.63%. For all investors the corresponding education premium varies from .59 to .68 above a portfolio return of 7.72%. These estimated premiums are illustrative since the return data available in our SCF samples is limited to just realized gross returns, and they are not adjusted for the cost of asset management as are our estimated net premiums in table 1.

## **B. Alternative Hypotheses and Robustness Checks**

### *a. Human capital as a non-tradable asset*

Our model views human capital as a store of knowledge which raises the wage flow and asset management efficiency (hypothesis 1), but it can also be viewed as a non-tradable component of one's **total** portfolio. If its implicit value – discounted future earnings – is treated as a safe asset, like the wage income entering initial wealth in equation (4), then our model implies that it would have no impact on the demand for risky assets. The result follows, however, from the assumed CARA utility function, which is needed to solve the model analytically. If the utility exhibited CRRA, e.g., it is plausible to expect that initial wealth, and thus human capital as a safe (albeit non-tradable) asset would increase the willingness to allocate a larger portion of the financial portfolio to risky assets (hypothesis 2). Since this is also the implication of optimal asset management (hypothesis 1), can one distinguish between the two hypotheses?



One distinction is implicit in the discriminating propositions developed in section III. While both hypotheses imply that more schooling would raise the expected demand for risky assets and portfolio returns, they offer conflicting wage effects. By the alternative hypothesis 2, a higher wage level should enhance the demand for risky assets and portfolio returns, while our hypothesis 1 implies just the opposite, since a higher wage rate raises the opportunity cost of asset management time (proposition 3). Indeed, this is what we find empirically. We also find that the conditional effect of education (with the wage rate held constant) is larger in elasticity terms than its unconditional effect, consistent just with hypothesis 1 (proposition 4).

Another way to distinguish between the two hypotheses empirically is via a direct test of proposition 2. Since the discounted value of human capital must ultimately fall at older ages, hypothesis 2 implies that the demand for risky assets would taper off at older ages. To test this implication we have introduced in our DEMAND and RETURN regressions an interaction term of education and a discrete-step variable distinguishing ages higher than 55 (EDU-55) from younger ages to see whether the estimated coefficient becomes weaker or negative. The results are inconsistent with this hypothesis: The interaction effect assumes a positive and significant value (but not the converse) in some annual samples and is insignificant statistically in other years. All other estimated coefficients remain largely unaffected. While this test is not conclusive, it is nevertheless consistent with our asset management hypothesis.<sup>25</sup>

*b. Including investors with zero “risky-asset holdings” in Demand and Return regressions*

Our model does not allow for zero risky-asset holding essentially because we do not allow for borrowing constraints or fixed “entry costs” to investing in risky asset (such as minimum investments, or employer-subsidized 401K plans). More important, we have selected stocks and tradable corporate and foreign bonds as an efficient proxy for “risky assets” that involve asset management, implicitly treating all other assets as “safe”, since our model applies

to centrally-traded risky securities. But business and real estate assets, including homes, could be “risky” as well. Indeed, in a large fraction of cases of zero security holdings, investors specialize in the holding of these other assets – this is especially true for self-employed investors who hold a significant fraction of the portfolio in business assets, but even for wage earners whose major investments may be homes. In these cases our portfolio-size variable (TASST) may also be zero or negative because of large debt. Moreover, our discriminating proposition 3 - the “opportunity cost of time (wage)” effect - applies only if investors actually engage in asset management. At low levels of risky asset holding, or when asset management entails large fixed entry costs, our model predicts that investors may do no asset management. For these reasons we have focused on the estimation of demand functions conditional on positive values of RASST and TASST.

Nevertheless, we have also run our regressions by including all those with zero risky securities in the sample (assuming that  $\ln RASST = -10$ ), provided they have positive “total assets” (at least \$ 1,000 or \$10,000) to avoid spurious correlation between TASST and RASST and to enable a meaningful test of our discriminating hypotheses. In these “full-sample” regressions, the estimated effects of our key variables: EDU,  $\ln Wage^*$ , and  $\ln ASSTS$  exhibit the same hypothesized signs and statistical significance as our reported results for the conditional DEMAND and RETUEN regressions in section A. In fact, the positive education in the full sample for all years is significantly larger than the one estimated in section A, while the wage effect is lower in magnitude. As expected, the results are more pronounced for investors with at least \$10,000 in total net assets and for salaried workers relative to all investors and.

### **C. Second Data Set: Time Spent at Asset Management**

This data set contains the results of a national survey conducted by Barlow et al. in 1966. The survey of 1051 households of high income and wealth contains mostly qualitative information about individual portfolio holdings by different types of assets as well as a set of

personal characteristics. In this regard, the survey is similar to data set 1. It also contains, however, a unique datum: a proxy measure of a key variable in our theoretical analysis which data set 1 lacks. Individuals were asked to respond to the question: "how frequently do you review where your savings are invested to determine if you would like to make any changes?" The response options range from never (1) to daily (7), which comprise a polychotomous, ordered-response variable we name AMT. Since monitoring portfolio holdings is time consuming and may lead to portfolio adjustments, especially higher categorical values of AMT may be a meaningful proxy for our theoretical "time spent at asset management",  $q$ . Establishing direct links between this variable and the household head's education, business-related occupation, or portfolio size, would provide **direct** support to the asset management hypothesis.

The survey gives the overall value of individual portfolios as a categorical variable (by 5 classes), and the reported portfolios generally contain the same range of assets included in the FRB data, but excluding own homes. We thus refer to the portfolio size measure as TASST'. The survey also reports the schooling level attained by the family head (EDH), and the head's "proximity" to a business-related occupation. We define the latter by distinguishing distinctly business-related occupational categories (businessmen, corporate officials, traders, stock brokers, auditors and financial consultants) (BUS=1) from all other occupations. We also have information on whether they are self-employed (SELF=1) or salaried, and the household head's age (AGE). Insufficient information is provided in the survey, however, about wage income, personal risk aversion or portfolio returns to duplicate those available in data set 1.

In Table 7 we have implemented the basic comparative-static predictions of our model concerning the derived demand for asset management time (AMT), by running ordered-probit regressions of AMT on a set of covariates including the net worth proxy TASST', and indicators of human capital, experience, age and occupational status:

$$(31) \text{AMT} = a_{0j} + a_1\text{TASST}' + a_2\text{EDH} + a_3\text{AGE} + |a_4\text{BUS}| + |a_5\text{SELF}|,$$

where  $a_{0j}$  denotes a categorical constant term associated with the different AMT categories.

Note that our model predicts that education may increase the demand for asset-management **time** only if the elasticity of information acquisition with respect to human capital is larger than  $\beta$ . Thus it is not necessary to find that EDU would unambiguously or significantly increase AMT for all investors, especially those with the highest education levels, as our simulations indicate. However, evidence that EDH significantly increases asset management time, would certainly be consistent with the asset management hypothesis, as our numerical simulations are consistent with such effect for most education levels. Also, indicators of skills conducive to information production or economies of scale in asset management (as indicated by BUS and TASST') should, by proposition 3, unambiguously increase AMT. This is generally what we find using our ordered-probit regressions.

In column 1 of Table 7 we report the full-sample results for all individuals, including “all salaried” and self-employed workers. The estimated coefficients of TASST', EDH and BUS all have positive and significant signs. Self-employment status also raises asset management intensity, and AGE generally reduces it, although neither effect is significant at the 5 % level.

In column 2, the reported results are for strictly self-employed investors and in column 3 they cover all salaried workers. For the self-employed, portfolio size is statistically significant, although education and professional status are not significant, in enhancing time spent at asset management. For the salaried employees, however, portfolio size, education, and managerial status are all significant. These different results are to be expected, since the self-employed own their businesses, and are more likely to acquire business-management skills through learning-by-doing rather than formal education, or via training for a specific occupation. This weakens the importance of “general” schooling (EDH) as a determinant of asset management efficiency by

the self-employed. However, business-related training does have a significant effect (at the 10% level) on the desired AMT even for the self-employed.

Column 4 reports the results for salaried workers in business-related occupations, while column 5 shows the results for all other salaried workers. For the small sample of workers in business-related occupations, schooling has a favorable but insignificant effect on asset management time, AMT. These results are due partly to the small variability in the categorical regressor in this sub-sample, especially in schooling attainments among the business-related salaried workers, which all have relatively high levels of education. (The average categorical value of EDH for the BUS workers is 5.39 while it is 4.53 for non-BUS workers, where 4 stands for 12 graders with non-college training, 5 stands for college training with no degree, and 6 stands for college degree). Indeed, even portfolio size is significant only at the 10% level. For non-managerial salaried workers, in contrast, EDH has a favorable and significant impact on asset management intensity, along with portfolio size (TASST'). As is the pattern in Tables 3 and 4, the AGE effect is generally insignificant and inconsistent in Table 7.

Data set 2 allows us also to directly estimate the proportion of investors with negligible levels of AMT i.e., those reporting that they never engage in monitoring their savings, or seldom do it. The combined percentage of these investors is 21.25%. This fraction is surprisingly close to the fractions of those with zero or trivial amounts of asset management in our simulations (see section III.A.) In contrast, those reporting active monitoring (daily or weekly) constitute 60% of the sample. The average educational attainments and business-oriented occupational status of the latter group are substantially higher than those of the former group.

## **Conclusion**

The role of information collection and information channels in financial markets has received little attention in the financial economics literature partly because existing models of

“noisy prices” and costly information have not offered well-defined empirically testable hypotheses. We attempt to fill this void by basing the analysis of equilibrium in financial markets on richer micro foundations forming the “asset management hypothesis”. By offering explicit specifications of the technology and cost functions of information acquisition, where human capital endowments play a critical role, we are able to derive an array of testable implications concerning portfolio composition and returns, asset management intensity, level and volatility of market prices, equity premiums, and the return to education from asset management.

Our model suggests that more informed investors obtain added expected returns on their overall portfolios of financial assets essentially because over time, they tend to allocate a larger portion of these portfolios to risky assets. They do so not necessarily because of greater tolerance for risk – our hypothesized education effects hold in our regression analyses even when we control for a risk tolerance measure – but because private information precision acquired through asset management reduces relative personal risk by lowering the perceived variance of the posterior distribution of returns on risky assets. Human capital augments, however, both one’s productivity at asset management and its opportunity costs – a higher wage rate. Therefore, more schooling does not necessarily lead to greater time allocation to asset management. But if schooling is a dominant input in producing information precision, as suggested by the constraints specified in equation (24a), more schooling would produce more precise information. Indeed, numerical simulations of our model produce a strict monotonic relation between unconditional increases in educational attainments and private information precision (see figure 1).

There is an alternative channel through which education might enhance demand for risky assets. If human capital is perceived as a safe asset in a grand portfolio encompassing both human and nonhuman portfolios, then people with more human capital may be inclined to hold more risky financial portfolios in their grand portfolio to achieve optimal diversification. While

our formal model specification rules out this alternative hypothesis, a more general specification could support it. In section V.B.a we attempt to test the diversifying role of human capital empirically by allowing the education effect to diminish at old age. The results, although inconclusive, do not support this hypothesis. In contrast, our findings based on nine independent samples are consistent with discriminating implications of the asset management hypothesis.

To wit: the prediction that expected demand for risky assets and total portfolio returns will rise especially with a conditional increase in educational attainments ( $\ln\text{EDU}$ ), holding constant the predicted wage and portfolio size, is overwhelmingly supported in regressions based on 8 independent annual Surveys of Consumer Finances (data set 1), as is the corollary prediction that an unconditional increase in educational attainments, allowing the wage rate to rise with EDU, would yield a comparatively **smaller** increment in the demand for risky assets and total portfolio returns because of the role of wage rates as measures of the opportunity cost of asset management (propositions 1 and 2). Indeed, the most discriminating hypothesis of the model, that a rise in the predicted wage rate of individual investors would **lower** the demand for risky assets and total portfolio returns (proposition 3), is confirmed in all our regressions without exception (see section V.A). In contrast, the “diversifying role of human capital”, suggests that higher wages should produce the opposite effects. The wage effect we estimate is robust not just to use of alternative methods of deriving predicted individual wage rates, but also to use of alternative raw wage and salary data: annual, monthly, or hourly wage data.

Similarly the prediction that higher educational attainments may also raise the derived-demand for asset-management time for most workers is confirmed for wage and salary workers using data set 2 (section V.C). Proposition 3 predicting the effects of portfolio size and indicators of “specific human capital”, such as occupational status conducive to asset management, on the expected demand and returns for risky assets are supported by regression results based on both

data sets 1 and 2. Moreover, the pattern of the regressions results linking total portfolio returns to educational attainments and initial wealth as well as the opportunity cost of time measure, are remarkably symmetrical to the pattern of regressions linking demand for risky assets to these same variables using identical specifications, confirming proposition 4.

At the market level we offer some new insights concerning the impact of human capital and private information on the level and volatility of risky asset prices. We show that at given risky-asset supplies, increments in education and information-producing “technology”, which increase average information precision ( $s$ ), are likely to exert upward pressure on market prices and ultimately on price volatility as well because of greater willingness of investors to trade on the power of superior information. At the same time, the individually-perceived risk from holding stocks falls. Indeed, this result accounts for the related inference that higher levels of education and private information are likely to lower the representative investor’s required equity premium, and thus its equilibrium magnitude. More intriguing, perhaps, is the new insight we propose concerning the “equity-risk-premium puzzle” by which the large observed magnitudes of equity premium cannot be reconciled by reasonable magnitudes of personal risk aversion. By our analysis, observed equity premiums cannot be ascribed solely to risk aversion. A portion must be ascribed to asset management costs, which may account for 10.44% of the premium.

Perhaps the most intriguing results of our analysis are our estimates of the rate of return to education in generating financial income. To our knowledge, this may be the first attempt in the literature to come up with estimated rates of return to education in generating non-wage income or other benefits – the topic of a recent study published in this journal (see Becker and Murphy, 2008). We find that the premium per school year in terms of financial income is not trivial. Using the projected wage [PW] estimation procedure in Table 6, the absolute premium we estimate for all salary workers in all years is .54 percentage points per school year above the



average overall portfolio return for salary workers of 6.63%. For all investors the corresponding premium is .59 percentage points on an overall portfolio return of 7.72%. These estimates are largely illustrative, however, since our empirical financial returns include only realized gains.

Clearly, the results of this paper are subject to important caveats. Theoretically, we pursue a partial-equilibrium, two-period model where the supply of assets, initial portfolio sizes, and human capital endowments are exogenous variables. We also explore the role of human capital in a pure exchange economy, although the information value of asset management extends to the real economy as well, and we abstract from multiple risky assets, leisure, and the separate role of specialized agents who offer asset management services for sale. These limitations also apply, however, to the standard finance models which do not recognize any private information collection. Empirically, the limitation of the Surveys of Consumer Finances is that they report asset holdings only for broad asset categories, including non-centrally traded assets, at market values assessed by the investors, and the reported portfolio returns include only realized returns. More detailed information on individual assets and unrealized returns would certainly make our tests of the asset-management hypothesis more compelling.

Yet the overall consistency of our analysis with empirical evidence derived from nine independent samples indicates that the line of thought we pursue in this paper can produce new insights about both specific features of investors' choices, such as "home-bias" or "own company bias" in investment decisions, the volatility of asset prices in different financial markets, and the rate of return to human capital in generating non-wage income – a heretofore largely neglected topic in the human capital literature. This work suggests that the monetary return to education may have been understated, and that educational attainments may play a direct role in explaining not just the distribution of earnings, but that of income as well.

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## ENDNOTES

<sup>1</sup> The term is borrowed from Ehrlich and Ben-Zion (1976). Ehrlich and Hamlen (1995) invoke costly asset management to justify portfolio-consumption choices under pre-commitments.

<sup>2</sup> Some recent studies using a "behavioral finance" approach to portfolio choices have also relied on "partially revealing" asset prices – see e.g., Shleifer (2000). We offer an alternative approach that does not rely on assumed variations in unobserved risk preferences and is thus testable empirically. We eschew a full review of the preceding literature to focus on the value added of our extended model, especially our analysis in sections III –V.

<sup>3</sup> Our analysis can be generalized, however, to allow for heterogeneity in both human capital and risk preferences. In principle,  $H_i$  can stand for both knowledge and ability, but to sharpen the empirical content of our model, we identify it with schooling and general training. The distribution of the initial endowments of stocks  $x_i$ , or bonds  $B_{0i}$  and hence initial wealth is treated as uniform across investors, but this assumption plays no role in our simulations or comparative static analysis since the assumed utility function does not allow for any pure wealth effects.

<sup>4</sup> For analytical simplicity, we treat human capital as a single-type asset, although empirically it is reasonable to distinguish "general", from "asset-management-specific" human capital, such as training in the interpretation of financial statements, which would have a differentially higher effect on productivity at asset management, relative to alternative labor market activities.

<sup>5</sup> The assumption that  $\tilde{x}$  is normally distributed, which is common to the literature we follow, is an approximation intended to allow for closed-form solutions of the model, as it allows for potentially negative average supply values. In our simulations, however, we set  $\bar{x}=1$  and variance  $(1/t) = 1/40$ , yielding a 99% confidence interval ranging from .52 to 1.48. As 0 is not in that range (let alone a negative number) the assumed normal distribution is an acceptable approximation by the "three sigma" rule.

<sup>6</sup> Since our objective function in equation (8) involves the maximization of **terminal** wealth, or terminal consumption (see equation 8), it is not warranted to specify current leisure as a separate commodity in this model. Indeed, the wealth concept we model - both initial and terminal – can be interpreted as "full wealth", incorporating the full value of time. Thus,  $T$  in equations (4) and (4a) becomes total time available, and terminal wealth represents both consumption and the value of leisure time, or time devoted to producing all household commodities.

<sup>7</sup> Following Hellwig's derivation of the REE competitive price, we can write the conjecture as: (9a)

$$\tilde{P}(n) = \theta(n) + \sum_{i=1}^n \lambda_i(n) \tilde{\mu} + \sum_{i=1}^n \lambda_i(n) \tilde{\varepsilon}_i(n) - v(n) \tilde{x}(n). \text{ The second and third terms on the RHS of (9a)}$$

are the weighted averages of traders' perceptions of the public information on returns, and the private information signals they pursue, respectively. As the number of traders,  $n$  approaches infinity, the term involving the random private signals vanishes and equation (9a) converges in probability to:

$$\tilde{P} \rightarrow \theta + \lambda \tilde{\mu} - v \tilde{x}, \text{ where } \lambda = \lim_{n \rightarrow \infty} (1/n) \sum_1^n \lambda_i.$$

<sup>8</sup> The variance of the posterior distribution of the risky-asset returns, conditional on the observed price and private signal in equation (11b) thus becomes  $V_i \equiv Var(\tilde{\mu} | z_i, P) = 1/[h + s_i + r^2 s^2 t]$ . In equilibrium, this conditional variance is thus inversely related to the investor's own private information,  $s_i$ , and the collected public information embedded in the market price,  $r^2 s^2 t$ .

<sup>9</sup> These solutions do not precisely match those of KV (1991a), since in our analysis, the mean supply of the risky asset is assumed to be positive,  $\bar{x} > 0$ , while KV assumed  $\bar{x} = 0$ . Note that by equations (13),  $\tilde{P}$  is determined partly by the specific (non-stochastic) distributions of  $H_i$  and  $w_i(H_i, \delta)$  across investors,

which determine the distribution of private precision levels,  $s_i$ .

<sup>10</sup> As  $s_i$  approaches an infinite value for a single investor (measure zero), optimal demand would approach holding or short selling the entire market supply of the risky asset.

<sup>11</sup> The second-order conditions are thus assured by virtue of the concavity of the objective function and the convexity of the cost function with  $0 < \alpha \leq 1$ .

<sup>12</sup> Note that our solutions for optimal  $s_i$  and  $q_i$  are deterministic, since the production and earnings functions in equations (5) and (6) are non-stochastic.

<sup>13</sup> These simulations are calibrated to approximately produce the overall portfolio return (7.81%) and average ratio of non-wage to wage income for all investors, as documented in the Surveys of Consumer Finances used in our empirical analysis (18.24%). In Tables 1 and 2 we assume that  $H_i$  has a truncated lognormal distribution over the interval  $[1, 5]$ , with parameters  $M$  and  $\sigma$ , and  $a$ . The probability density function is:

$$f(H_i) = \frac{1}{G\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{[\ln(H_i - a) - M]^2}{2\sigma^2}\right\}, \text{ where } G = \int_1^5 g(u)du \text{ is a normalization factor and}$$

$$g(u) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{[\ln(u - a) - M]^2}{2\sigma^2}\right\}$$

<sup>14</sup> The proof is illustrated for a change in  $A_i$  but the same analysis applies to a shift in  $w_i(\delta_i)$ . We can also allow for idiosyncratic shifts in the risk-tolerance parameter,  $r$ , across investors. From equations (14) or (15) we can see that an upward shift in  $r$  for a specific individual or group  $i$  that does not affect  $s$  would result in unambiguous upward shifts in  $s_i^*$ ,  $q_i^*$ , and  $E(\tilde{D}_i)^*$ .

<sup>15</sup> This would be the case if we allow the fixed cost component of the cost function in equation (8),  $C_0$  to be a decreasing function of one's total portfolio size because of economies of scale in obtaining financial services, although for convenience we do not consider this formally. In either interpretation, portfolio size affects the demand for risky assets through its impact on the cost of asset management.

<sup>16</sup> While  $d\ln(w_i)/dH_i = \eta$ , based on equation (5), represents the conventional "internal rate of return to human capital" in terms of wage income, the proportional net education premium over  $R$ ,  $d\ln\{E[\tilde{D}_i(\tilde{\mu} - \tilde{P}) - C(s_i)]\}/dH_i$ , is not the rate of return on financial investment in risky assets but the proportional net addition to it (after netting asset management's opportunity costs,  $C(s_i)$ ) owing to an unconditional rise in  $H_i$ .

<sup>17</sup> In all cases, as  $\bar{H}$  (thus  $s$ )  $\rightarrow \infty$ ,  $\text{Var}(\tilde{P}) \rightarrow 1/h$  and  $v(\tilde{P}) \rightarrow 1/(h\bar{\mu})$ , while as  $\bar{H} \rightarrow 0$ ,  $\text{Var}(\tilde{P}) \rightarrow (1/r^2h^2t)$  and  $v(\tilde{P}) \rightarrow 1/(r^2h^2t\bar{\mu} - rht\bar{x})$ . Thus, if  $r^2ht < 1$ , e.g., both  $\text{Var}(\tilde{P})$  and  $v(\tilde{P})$  are higher when  $\bar{H} = 0$  than as  $\bar{H} \rightarrow \infty$ . In this case,  $\text{Var}(\tilde{P})$  is a U-shaped function of  $s$ , and  $v(\tilde{P})$  likewise first falls with  $\bar{H}$  and **ultimately** rises toward  $1/(h\bar{\mu})$  as  $s \rightarrow \infty$ . Since  $E(\tilde{P})$  is continuously rising with  $\bar{H}$ , the shape of  $v(\tilde{P})$  is indeterminate whenever  $\text{Var}(\tilde{P})$  is also rising with  $\bar{H}$ , but in our simulations it mimicked the shape of  $\text{Var}(\tilde{P})$  at all values of  $\bar{H} > 0$ . The parameter values used in the simulations shown in Figure 2A with  $r^2ht < 1$  are:  $h=0.033$ ,  $r=1$ ,  $t=30$ ,  $A(\tau) = 0.04$ ,  $\bar{\mu}=160$ , and  $\bar{x}=1$ .

<sup>18</sup> From equation (17) a higher  $t$  or  $h$  initially raises  $MR(s_i)$  but leaves  $MC(s_i)$  unchanged. It can easily be shown that in equilibrium, desired private information precision,  $s_i$ , must then necessarily fall for all

investors, hence  $s$  falls as well. Technically, this is because the component of MR reflecting public information precision ( $h + r^2s^2t$ ) must necessarily rise. Consequently, both  $s$  and  $\bar{q}$  fall. In contrast, from equation (22), since  $(h + r^2s^2t)$  rises,  $E(\tilde{P})$  must go up.

<sup>19</sup> The estimated value of  $c^*$  fluctuates between 8.94% and 12.05% when the base wage income,  $w_0=1$  changes from 0.5 to 2. It increases from 10.44% to 14.56% when  $A$  rises from 0.2 to 0.4, and from 10.44% to 22.55% when  $r$  rises from 2 to 4.

<sup>20</sup> These include studies by Uhler and Cragg (1971), Friend and Blume (1975), Feldstein (1976), Agell et. al., (1990), Ioannides (1992), Haliassos and Bertaut (1995), Bertaut (1998), King and Leape (1998) and Perraudin and Sorensen (2000). The last study also reported an adverse wage effect on risky portfolio shares, but did not offer a systematic explanation.

<sup>21</sup> The total portfolio measure (net worth), TASST, incorporates six major categories of tradable (net) assets: liquid assets (checking and savings accounts and savings bonds), investment assets (all marketable securities, investment real-estate, and mortgages), business/professional assets, assets held in personal trusts, homes, and automobiles.

<sup>22</sup> RETURN is defined as the sum of taxable and non-taxable interests, dividend income, gains from sale of stocks/bond or real estate, and rent, trust income, royalties from other investment.

<sup>23</sup> In estimating and projecting the wage rate of workers by this method, we cap the job experience variable  $EXP=AGE-EDU-6$  at age 65 because of likely retirement.

<sup>24</sup> To derive estimated rates of return for the two education levels, we transform equation (30) to:  
 (30a)  $\ln[R^*(EDU)_j] \equiv \ln(Y/TASST)_j = b_0 + b_1 \ln(EDU_j) + (b_2 - 1) \ln(TASST) + b_3 \ln[WAGE(EDU_j)] + \dots$ ,  
 where  $Y$  denotes earnings. Viewing the observed rate of return on financial assets by the reference group,  $\ln[R(\text{ref})]$ , as a special case of (30a), we can compute  $\ln[R^*(EDU)] - \ln[R(\text{ref})]$  as  $\ln[R^*(EDU)_j/R(\text{ref})] = b_1 \ln(EDU_j/EDU^{\text{ref}}) + b_3 \eta (EDU_j - EDU^{\text{ref}})$ , which enables us to derive  
 (30b)  $R^*(EDU_j) = R(\text{ref}) \exp\{b_1 \ln(EDU_j/EDU^{\text{ref}}) + b_3 \eta (EDU_j - EDU^{\text{ref}})\}$ , where  $\eta$  is estimated from an extended Mincer model. We can thus estimate  $R^*(EDU_j)$  for  $j=1$  and  $j=2$  from (30b). The proportional education premium over the range  $EDU=12-16$  can now be computed as  $\{[R^*(COL)/R^*(HS)] - 1\}/4$  percent, and the absolute premium as  $[R^*(COL) - R^*(HS)]/4$  percent (see Table 6). The reason we measure the reference rate of return  $R(\text{ref})$  as a return on just financial investments is that the bulk of the **realized** returns in our sample stems from financial assets, while other assets are much less frequently traded or their gains realized. We thus use the rate of return on financial assets (excluding homes, business assets, and vehicles) as a proxy for that on all portfolio assets.

<sup>25</sup> It is also arguable that the wage flow, hence human capital, is stochastic. In this case, we can show that risky asset demand becomes a function of two additive effects: Human capital's impact on information precision, and the correlation between the wage flow and risky-asset returns. Hypothesis 2 then becomes more ambiguous: Zero correlation would be consistent with hypothesis 2. If the correlation were positive (negative) in specific occupations, however, unconditionally larger human capital would lower (increase) risky-asset demand.

**Table 1: Effects of Individual Parameter Shifts on Asset Management Outcomes at the Micro level**

AM outcomes at the micro level <sup>1</sup>	Educational Attainment Value ( $H_i$ ) <sup>2</sup>			
	1 (NHS)	2.159 (HS)	2.895 (CND)	5 (CWD)
$s_i$	0.0266	0.0726	0.1025	0.1781
$q_i$	0.0064	0.0140	0.0172	0.0200
$E(\tilde{D}_i)$	0.9576	0.9842	1.0016	1.0454
Wage income (level)	0.9936	1.2007	1.3564	1.9344
Financial income (level)	0.0957	0.1541	0.1920	0.2879
$ds_i/dH_i$	0.0365	0.0410	0.0399	0.0312
$\varepsilon_{w_i, H_i}$	0.17	0.367	0.492	0.85
$(\partial s_i / \partial H_i)  _{w_i = \text{const}}$	0.0394	0.0490	0.0511	0.0501
$dq_i/dH_i$	0.0076	0.0052	0.0034	-0.0002
$E_{s_i, H_i}$	1.3719	1.2205	1.1273	0.8756
$(\partial q_i / \partial H_i)  _{w_i = \text{const}}$	0.0094	0.0091	0.0081	0.0051
$ds_i/dA(\tau)_i$	0.2373	0.6322	0.8793	1.4764
$dq_i/dA(\tau)_i$	0.0850	0.1738	0.2046	0.2169
Rate of return on total financial investments ( $R$ ) <sup>3</sup>	4.59%	5.71%	6.53%	9.37%
Proportional net education premium over $R$ <sup>4</sup>	19.06%	18.44%	17.86%	16.60%
Absolute net education premium over $R$ <sup>5</sup>	0.87%	1.05%	1.17%	1.56%
ROR on education in wage income, $\eta$ <sup>6</sup>	16.24%	16.47%	16.66%	17.02%

Notes: 1. The outcomes are computed using a truncated log-normal distribution of  $H_i$  over the range 1-5 (see footnote 8) and the following set of underlying model parameters:  $h = 0.033$ ,  $t = 40$ ,  $\bar{\mu} = 4$ ,  $\bar{x} = 1$ ,  $\bar{B} = 20$ ,  $r = 2$ ,  $A(\tau) = 0.2$ ,  $\alpha = 0.4$ ,  $\beta = 0.9$ ,  $a = 1$ ,  $\sigma = 1$ ,  $M = 1$ ,  $w_0 = 1$ , and  $\eta = 0.17$ . 2. The educational attainment values were picked to match the percentage of people with no high school (NHS) (1), HS (2), college without a degree (CND) (3), and College with degree (CWD) (4) among salaried workers with positive risky assets holdings in the 2004 SCF sample. 3.  $R \equiv$  ratio of net financial returns on total financial assets for different education levels, net of asset management costs. 4. Proportional increment in the net rate of return ( $R$ ) on all financial investments due to an unconditional increase in education (%). See footnote 16 in the text for its measurement. 5. Absolute increment in the rate of return ( $R$ ) due to an unconditional increase in education. These proportional and absolute educational premiums are illustrative, as they are conditional on the parameters used in our numerical simulation. 6. Conventional internal rate of return on education in terms of wage income,  $\eta$ , as defined in equation (5).

**Table 2: Effects of Common Parameter Shifts on Asset Management Outcomes at the Market Level**

Upward Parameter Shifts	Outcomes*					
	$\bar{q}$	S	E(P)	Var(P)	v	R
t	-	-	+	-/+	-/+	-
h	-	-	+	-	-	-
r	-	-	+	+	-	-
$\alpha$	+	-	-	-	+	+
A( $\tau$ )	-	+	+	-/+	-/+	-
$\bar{\mu}$	0	0	+	0	-	-
$\bar{x}$	0	0	-	0	+	+
w <sub>0</sub>	-	-	-	-	+	+
$\eta$	-	-	-	-	+	+
$\bar{H}$ (unconditional)#	-	+	+	-/+	-/+	-

See note 1 in Table 1. Comparative statics are illustrated for the case where the variances of supply noise and unconditional return are sufficiently large so  $r^2ht < 1$ .

\* Negative (positive) signs indicate that increments in parameter values consistently lower (raise) the endogenous outcomes. Negative/positive signs indicate that increments in parameters first lower and then raise the endogenous outcomes.

# Outcomes are evaluated for “unconditional” increments in  $\bar{H}$  (allowing wages to increase with education) as a result of uniform increments in all  $H_i$



**Table 3: Regressions Results for Three Key Variables in Regression Equations (29) and (30) for Salaried Workers, Eight Independent SCF Samples**

Year	log(EDU)			log(WAGE)		log(TASST)		
	Uncon- ditional <sup>1</sup>	Conditional <sup>1</sup>		Conditional <sup>1</sup>		Uncon- ditional <sup>1</sup>	Conditional <sup>1</sup>	
		2SLS	PW <sup>2</sup>	2SLS	PW <sup>2</sup>		2SLS	PW <sup>2</sup>
<b>DEMAND for Risky Assets Regressions<sup>3</sup></b>								
1963	0.641 (3.34)	1.342 (5.64)	1.121 (4.96)	-0.312 (-5.43)	-0.705 (-3.87)	1.101 (17.1)	1.132 (16.8)	1.121 (17.6)
1983	1.304 (4.63)	1.286 (4.32)	1.845 (6.12)	-0.207 (-4.98)	-0.523 (-4.66)	0.613 (13.6)	0.712 (13.8)	0.693 (14.6)
1989	0.812 (4.57)	0.980 (5.41)	1.912 (9.63)	-0.239 (-11.6)	-0.775 (-11.5)	0.701 (23.8)	0.837 (26.0)	0.811 (26.7)
1992	1.580 (8.47)	1.880 (9.74)	2.096 (10.5)	-0.128 (-6.82)	-0.297 (-6.81)	0.746 (29.5)	0.800 (30.0)	0.795 (30.4)
1995	0.434 (2.66)	0.527 (3.21)	1.327 (7.14)	-0.166 (-9.68)	-0.565 (-9.58)	0.941 (39.2)	1.028 (39.8)	1.016 (40.6)
1998	0.162 (1.31)	0.375 (2.97)	0.732 (5.39)	-0.169 (-10.1)	-0.449 (-9.57)	0.934 (46.9)	0.998 (47.3)	0.992 (48.1)
2001	0.532 (4.35)	0.902 (7.04)	1.040 (8.02)	-0.236 (-14.1)	-0.544 (-10.7)	0.945 (45.7)	1.054 (46.7)	1.023 (47.2)
2004	1.026 (6.52)	1.237 (7.53)	1.995 (10.6)	-0.134 (-8.56)	-0.465 (-9.11)	0.787 (38.7)	0.828 (38.4)	0.835 (40.1)
All*	0.764 (12.5)	1.138 (17.6)	1.286 (19.7)	-0.237 (-21.9)	-0.583 (-20.8)	0.804 (74.4)	0.874 (75.8)	0.875 (78.0)
<b>RETURN on Total Portfolio of Assets Regressions<sup>3</sup></b>								
1963	0.523 (1.65)	1.572 (3.71)	1.397 (3.75)	-0.467 (-4.56)	-1.283 (-4.28)	1.081 (10.1)	1.127 (9.36)	1.117 (10.6)
1983	1.764 (4.05)	1.736 (3.86)	2.790 (6.02)	-0.323 (-5.15)	-0.991 (-5.74)	0.860 (12.4)	1.014 (13.0)	1.011 (13.8)
1989	1.641 (6.03)	1.925 (6.85)	3.583 (11.9)	-0.405 (-12.7)	-1.368 (-13.3)	1.128 (25.0)	1.359 (27.3)	1.323 (28.6)
1992	4.421 (13.2)	5.202 (14.9)	5.848 (16.4)	-0.334 (-9.77)	-0.819 (-10.6)	1.117 (24.6)	1.258 (26.0)	1.252 (26.8)
1995	2.160 (7.84)	2.303 (8.19)	3.221 (10.2)	-0.254 (-8.66)	-0.671 (-6.67)	1.315 (32.4)	1.448 (32.8)	1.405 (33.0)
1998	1.214 (4.47)	1.721 (6.20)	2.176 (7.24)	-0.402 (-11.0)	-0.757 (-7.29)	1.210 (27.6)	1.361 (29.4)	1.308 (28.7)
2001	0.869 (3.58)	1.258 (5.07)	1.209 (4.64)	-0.248 (-7.63)	-0.365 (-3.57)	1.288 (31.4)	1.403 (32.1)	1.340 (30.8)
2004	1.096 (3.15)	1.472 (4.18)	3.447 (8.29)	-0.238 (-7.10)	-1.127 (-10.0)	1.447 (32.2)	1.520 (32.9)	1.564 (34.1)
All*	1.388 (12.6)	1.946 (16.7)	2.092 (17.6)	-0.353 (-18.2)	-0.786 (-15.4)	1.125 (57.4)	1.230 (59.2)	1.221 (59.8)

Notes: 1. “Unconditional” (OLS) regressions exclude lnWAGE as regressor. “Conditional” ones include it. 2. PW denotes the projected-wage method. 3. Numbers in parentheses are z-values. 4. See corresponding tables in Appendix for full results. \*All = pooled regression restricting just coefficients of the 3 reported regressors to be identical.

**Table 4: Regressions Results for Three Key Variables in Regression Equations (29) and (30) for All Investors, Eight Independent SCF Samples**

Year	log(EDU)			log(WAGE)		log(TASST)		
	Unconditional	Conditional		Conditional		Unconditional	Conditional	
		2SLS	PW	2SLS	PW		2SLS	PW
<b>DEMAND for Risky Assets Regressions</b>								
1963	0.752 (4.84)	1.298 (6.75)	1.248 (6.73)	-0.312 (-6.07)	-0.722 (-4.74)	1.059 (20.4)	1.089 (19.1)	1.080 (21.1)
1983	1.574 (5.93)	1.607 (5.66)	2.135 (7.46)	-0.203 (-4.95)	-0.528 (-4.90)	0.629 (14.8)	0.718 (14.7)	0.706 (15.7)
1989	0.793 (5.72)	0.997 (6.88)	1.775 (11.4)	-0.222 (-12.9)	-0.673 (-13.0)	0.726 (33.0)	0.830 (34.2)	0.814 (35.9)
1992	0.762 (5.17)	1.180 (7.11)	1.116 (7.14)	-0.294 (-7.37)	-0.324 (-6.60)	0.791 (36.5)	0.825 (35.3)	0.832 (37.0)
1995	0.143 (0.91)	0.134 (0.80)	0.575 (3.38)	-0.256 (-6.37)	-0.380 (-6.45)	0.870 (42.6)	0.918 (39.8)	0.915 (42.5)
1998	0.468 (2.71)	0.966 (4.82)	1.270 (7.04)	-0.411 (-11.0)	-0.641 (-13.4)	0.847 (47.0)	0.914 (43.0)	0.929 (49.5)
2001	0.554 (4.81)	0.921 (6.56)	1.070 (8.87)	-0.564 (-11.1)	-0.619 (-12.7)	0.888 (50.3)	0.967 (43.8)	0.972 (52.1)
2004	0.894 (6.51)	0.987 (6.80)	1.372 (9.11)	-0.195 (-7.18)	-0.319 (-7.54)	0.797 (49.3)	0.831 (47.0)	0.834 (49.6)
All	0.831 (19.2)	1.076 (22.7)	1.338 (28.6)	-0.256 (-27.9)	-0.542 (-26.8)	0.819 (107)	0.883 (104)	0.882 (112)
<b>RETURNS on Total Portfolio of Assets Regressions</b>								
1963	0.521 (1.98)	1.263 (3.79)	1.347 (4.28)	-0.424 (-4.76)	-1.202 (-4.64)	0.970 (11.0)	1.011 (10.2)	1.004 (11.5)
1983	1.574 (3.88)	1.629 (3.76)	2.623 (6.03)	-0.331 (-5.29)	-0.987 (-6.03)	0.907 (13.9)	1.053 (14.1)	1.051 (15.4)
1989	1.709 (7.71)	2.057 (8.74)	3.546 (14.3)	-0.380 (-13.6)	-1.259 (-15.4)	1.113 (31.6)	1.291 (32.8)	1.277 (35.5)
1992	1.908 (7.17)	2.751 (9.15)	2.651 (9.42)	-0.593 (-8.21)	-0.680 (-7.70)	1.241 (31.7)	1.309 (30.9)	1.327 (32.8)
1995	2.148 (8.16)	2.146 (8.16)	2.307 (8.06)	-0.067 (-1.07)	-0.140 (-1.41)	1.478 (43.2)	1.490 (41.3)	1.494 (41.3)
1998	2.883 (7.55)	3.617 (8.75)	4.016 (9.99)	-0.606 (-7.86)	-0.907 (-8.50)	1.157 (29.1)	1.257 (28.7)	1.273 (30.5)
2001	1.877 (7.96)	1.918 (7.90)	1.854 (7.40)	-0.064 (-0.73)	0.028 (0.28)	1.152 (31.8)	1.161 (30.4)	1.149 (29.6)
2004	2.787 (8.81)	2.986 (9.11)	3.801 (10.9)	-0.413 (-6.76)	-0.676 (-6.94)	1.243 (33.4)	1.316 (33.0)	1.322 (34.1)
All	1.275 (16.0)	1.636 (19.2)	1.948 (22.4)	-0.378 (-22.9)	-0.720 (-19.2)	1.155 (82.1)	1.249 (81.6)	1.239 (84.5)

See notes to Table 3

**Table 5: Regressions Results for Three Key Variables in Regression Equation (30) with lnSHARE included as a regressor. Eight Independent SCF Samples**

Year	log(EDU)			log(WAGE)		log(TASST)		
	Uncon- ditional	Conditional		Conditional		Uncon- ditional	Conditional	
		2SLS	PW	2SLS	PW		2SLS	PW
<b>SALARIED WORKERS</b>								
1963	-0.033 (-0.12)	0.478 (1.33)	0.463 (1.40)	-0.213 (-2.46)	-0.696 (-2.64)	0.994 (10.9)	1.020 (10.4)	1.016 (11.1)
1983	1.177 (2.79)	1.203 (2.81)	2.025 (4.44)	-0.238 (-3.97)	-0.774 (-4.60)	1.034 (14.9)	1.133 (15.2)	1.139 (15.8)
1989	1.386 (5.19)	1.681 (6.11)	3.100 (10.3)	-0.345 (-10.9)	-1.172 (-11.3)	1.222 (27.2)	1.400 (28.7)	1.371 (29.9)
1992	3.735 (11.4)	4.439 (12.9)	5.000 (14.2)	-0.282 (-8.47)	-0.699 (-9.19)	1.227 (27.4)	1.339 (28.4)	1.335 (29.2)
1995	1.989 (7.42)	2.111 (7.74)	2.723 (8.76)	-0.194 (-6.72)	-0.459 (-4.62)	1.339 (33.8)	1.438 (33.6)	1.399 (33.7)
1998	1.164 (4.33)	1.624 (5.91)	1.970 (6.59)	-0.358 (-9.76)	-0.631 (-6.05)	1.231 (28.3)	1.362 (29.8)	1.311 (29.0)
2001	0.714 (2.97)	1.029 (4.17)	0.917 (3.53)	-0.188 (-5.72)	-0.211 (-2.06)	1.304 (32.1)	1.389 (32.1)	1.334 (30.9)
2004	0.657 (1.92)	0.974 (2.81)	2.670 (6.44)	-0.184 (-5.57)	-0.946 (-8.46)	1.539 (34.5)	1.590 (34.9)	1.628 (35.8)
All	1.072 (9.93)	1.513 (13.3)	1.590 (13.6)	-0.263 (-13.8)	-0.559 (-11.1)	1.206 (62.6)	1.278 (63.4)	1.270 (63.4)
<b>ALL INVESTORS</b>								
1963	-0.135 (-0.59)	0.175 (0.63)	0.291 (1.03)	-0.162 (-2.19)	-0.591 (-2.58)	0.918 (12.1)	0.936 (11.8)	0.936 (12.4)
1983	0.860 (2.18)	0.951 (2.32)	1.723 (4.02)	-0.245 (-4.16)	-0.765 (-4.80)	1.076 (16.7)	1.172 (16.6)	1.175 (17.5)
1989	1.448 (6.66)	1.781 (7.78)	3.056 (12.4)	-0.318 (-11.5)	-1.073 (-13.7)	1.203 (34.4)	1.338 (34.9)	1.329 (37.2)
1992	1.522 (5.95)	2.177 (7.68)	2.103 (7.73)	-0.450 (-6.61)	-0.521 (-6.11)	1.347 (35.5)	1.394 (34.8)	1.409 (36.0)
1995	2.111 (8.12)	2.111 (8.12)	2.158 (7.62)	-0.001 (-0.01)	-0.041 (-0.42)	1.511 (44.6)	1.512 (42.3)	1.516 (42.4)
1998	2.767 (7.29)	3.412 (8.40)	3.751 (9.33)	-0.519 (-6.76)	-0.773 (-7.15)	1.195 (30.0)	1.275 (29.6)	1.288 (30.9)
2001	1.749 (7.45)	1.703 (7.01)	1.599 (6.38)	0.068 (0.77)	0.118 (1.72)	1.178 (32.6)	1.169 (30.7)	1.155 (30.0)
2004	2.404 (7.70)	2.579 (8.07)	3.236 (9.40)	-0.333 (-5.58)	-0.545 (-5.65)	1.330 (35.9)	1.385 (35.5)	1.391 (36.1)
All	0.936 (12.0)	1.069 (14.8)	1.430 (16.6)	-0.250 (-22.2)	-0.510 (-13.8)	1.229 (88.8)	1.354 (104)	1.285 (89.3)

See notes to Table 3.

**Table 6: Education Premiums over Realized Average Rates of Return on Financial Investments based on the pooled regression results for all years in Tables 3 and 4**

Estimated realized rates of return (ROR*) & Education premiums	OLS	2SLS	PW
<b>SALARIED WORKERS</b>			
ROR* on financial investments R*(HS)	5.32	5.15	5.44
ROR* on financial investments R*(COL)	7.85	8.00	7.61
Average ROR on total financial investments, R(ref)	6.63	6.63	6.63
Proportional education premium $\{[R*(COL)/R*(HS)]-1\}/4$	11.93	13.83	9.98
Absolute education premium $[R*(COL)-R*(HS)]/4$	0.63	0.71	0.54
<b>ALL INVESTORS</b>			
ROR* on financial investments, R*(HS)	6.24	6.28	6.35
ROR* on financial investments, R*(COL)	8.94	8.84	8.72
Average ROR* on total financial investments R(ref)	7.72	7.72	7.72
Proportional education premium $\{[R*(COL)/R*(HS)]-1\}/4$	10.81	10.22	9.31
Absolute education premium $[R*(COL)-R*(HS)]/4$	0.68	0.64	0.59

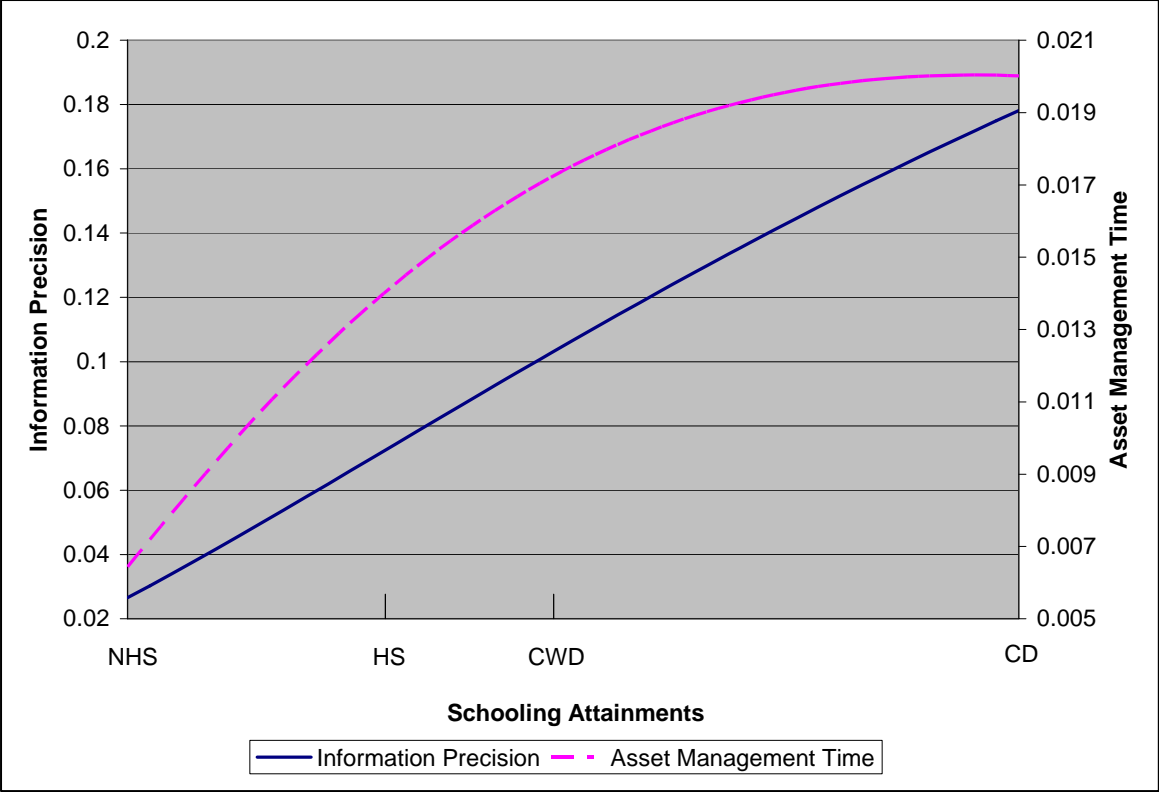
Notes: All reported rates of returns are in percentage terms. Our method of estimating realized rates of return and education premiums is based on estimates of the coefficients of EDU and  $\ln Wage^*$  in equation (30), which we obtain from the pooled (“All”) regression model in Tables 3 and 4, as well as on an estimate of the conventional rate of return on education in generating wage income,  $\hat{\eta} = 0.086$ , which we obtain from a pooled regression specification of the extended Mincer’s model used to estimate our projected wage [PW] variable. See footnote 24.

**Table 7: Ordered-Probit Regressions with Management Time as dependent variable**

	<b>Full Sample</b> All Investors	Self-employed Investors	<b>Salaried Workers</b>		
			All	BUS- related	Non-BUS related
TASST'	0.2764 (0.0506)	0.2554 (0.0621)	0.2867 (0.0880)	0.1779 (0.1195)	0.4447 (0.1314)
EDH	0.0594 (0.0222)	0.0289 (0.0278)	0.0852 (0.0402)	0.0269 (0.0830)	0.0795 (0.0469)
AGE	-0.0011 (0.0037)	-0.0010 (0.0044)	-0.0020 (0.0067)	0.0157 (0.0107)	-0.0140 (0.0088)
BUS	0.3440 (0.0830)	0.1912 (0.1056)	0.5297 (0.1443)		
SELF	0.0221 (0.0861)				
N	804	513	291	113	178

Notes: standard errors in parentheses

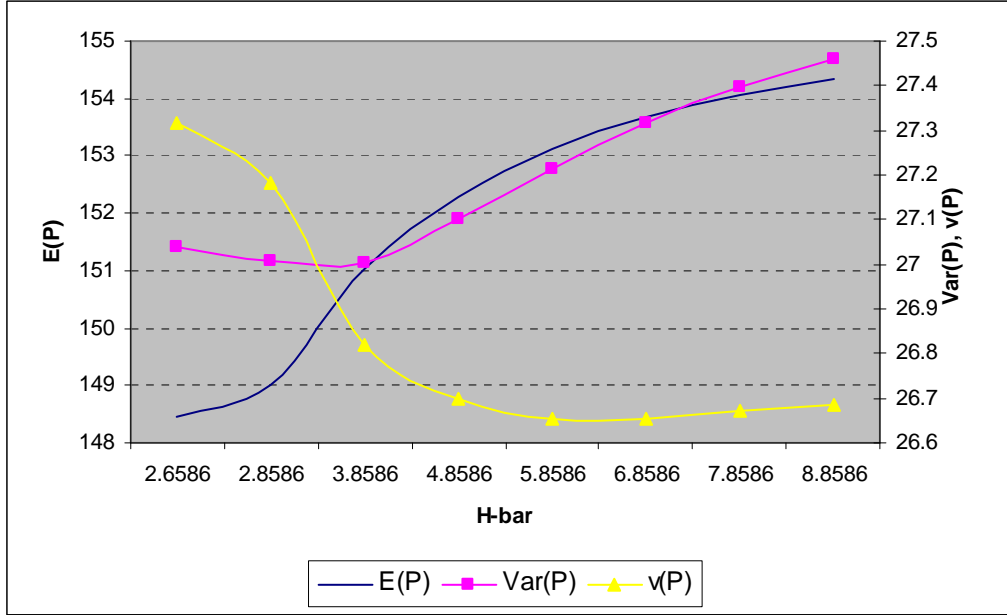
Figure 1: Optimal Information Precision and Asset Management Time as Functions of Alternative Schooling Attainments



Note: For variable definitions and parameter values, see Table 1.

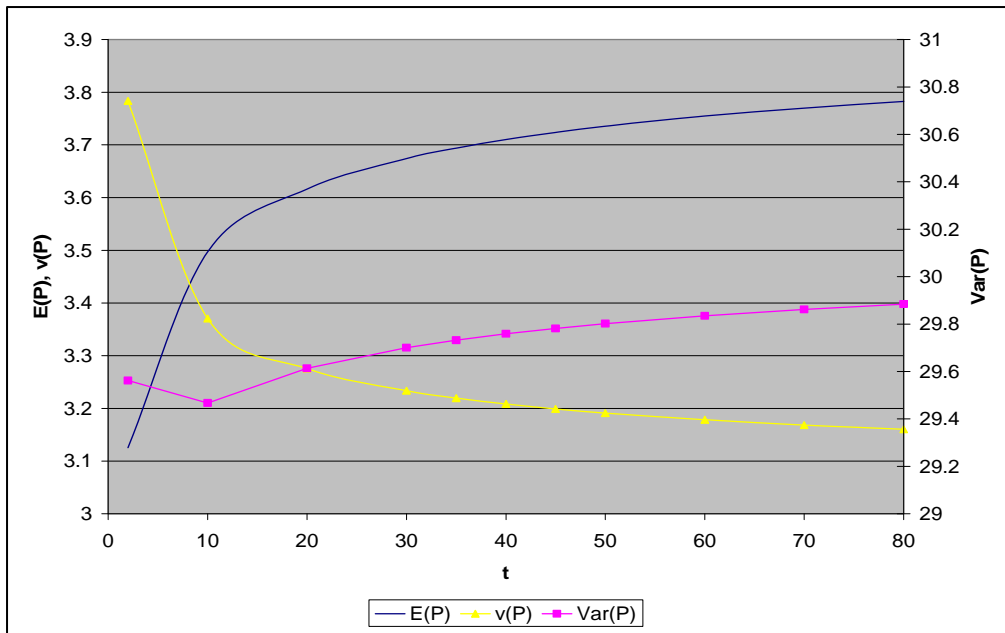
Figure 2: Private Information and Price Volatility: Effects of Unconditional Shifts in Determinants of Efficiency in Asset Management\*

A. Increments in Average Educational Attainments ( $\bar{H}$ )



The  $v(P)$  values are magnified 150 times their actual values to fit the scale. Parameter values used:  $h = 0.033$ ,  $t = 40$ ,  $\bar{\mu} = 160$ ,  $\bar{X} = 1$ ,  $r = 1$ ,  $\alpha = 0.4$ ,  $\beta = 0.9$ ,  $a = 1$ ,  $\sigma = 1$ ,  $M = 1$ ,  $w_0 = 1$ , and  $\eta = 0.17$  \* Illustrations conditional on  $r^2ht < 1$ .

B. Reductions in the variance of supply shocks (increments in  $t$ )



The  $v(P)$  values are reduced to 0.4 of their original values. For parameter values used see Table 1.

## Appendix 1: Comparative Statics at the Individual Level

### 1. The impact of shifts in individual human capital endowments $H_i$ on $s_i^*$ and $q_i^*$ .

a. We first differentiate equation (15) with respect to  $H_i$ , using equations (5) and (6), to derive its “uncompensated” effect on  $s_i^*$ . By collecting terms we obtain:

$$(A.1) \quad (1/\alpha) s_i^{(1-\alpha)/\alpha} [(1-\alpha) (h + r^2 s^2 t) s_i^{-1} + 1] (ds_i^*/dH_i) \\ = .5r A(\tau)^{1/\alpha} H_i^{\beta/\alpha} w_i(H_i)^{-1} [\beta H_i^{-1} - \alpha w_i(H_i, \delta)^{-1}] (\partial w_i / \partial H_i).$$

Since  $(1-\alpha) > 0$ ,

$$(A.2) \quad \text{sgn} (ds_i^*/dH_i) = \text{sgn} \{ \beta H_i^{-1} - \alpha w_i(H_i)^{-1} [\partial w_i / \partial H_i] \}.$$

The RHS of (A.2) would have a positive sign if

$$[\partial w_i / \partial H_i][H_i / w_i(H_i)] \equiv E_{w_i, H_i} < (\beta / \alpha). \text{ Thus,}$$

$$(A.3) \quad (ds_i^*/dH_i) > 0 \text{ if } E_{w_i, H_i} < (\beta / \alpha).$$

b. To derive the impact of an “uncompensated” shift in  $H_i$  on the optimal value of  $q_i^*$ , we substituting equation (7) into (15) and differentiate the latter with respect  $H_i$ :

$$(A.3) \quad (dq_i^*/dH_i) = (1/\alpha) s_i^{(1-\alpha)/\alpha} A(\tau)^{-1/\alpha} H_i^{-(\beta-\alpha)/\alpha} [H_i (ds_i^*/dH_i) - \beta s_i^*]; \text{ thus,}$$

$$(A.4) \quad (dq_i^*/dH_i) > 0 \text{ if } (d \ln s_i^* / d \ln H_i) \equiv E_{s_i^*, H_i} > \beta.$$

c. The “compensated” effects of  $H_i$ , on  $s_i^*$  and  $q_i^*$ , with  $w_i(H_i, \delta)$  held constant, are

$$(A.5) \quad \partial s_i^* / \partial H_i |_{w_i = \text{const}} > 0,$$

as can be seen directly from equation (A.2); while from (A.3) and (A.4):

$$(A.6) \quad (\partial q_i^* / \partial H_i) |_{w_i = \text{const}} > 0 \text{ if } (\partial \ln s_i^* / \partial \ln H_i) |_{w_i = \text{const}} \equiv \varepsilon_{s_i^*, H_i} > \beta.$$

### 2. The impact of shifts in idiosyncratic “technology” factors $A(\tau)_i$ on $s_i^*$ and $q_i^*$

a. Note that the first-order condition (15) can be expressed in terms of  $q_i$  as

$$(A.7) \quad A(\tau)^{(1-\alpha)/\alpha} q_i^{1-\alpha} H_i^{\beta(1-\alpha)/\alpha} (h + r^2 s^2 t) + A(\tau)^{1/\alpha} q_i H_i^{\beta/\alpha} - .5r A(\tau)^{1/\alpha} H_i^{\beta/\alpha} \alpha w_i^{-1} = 0.$$

Differentiating equation (A.7) with respect to  $A_i$  and collecting terms, we obtain:

$$(A.8) \quad [A(\tau)^{(1-\alpha)/\alpha} (1-\alpha) q_i^{-\alpha} H_i^{\beta(1-\alpha)/\alpha} (h + r^2 s^2 t) + A(\tau)^{1/\alpha} H_i^{\beta/\alpha}] (dq_i/dA) \\ = .5r A(\tau)^{(1-\alpha)/\alpha} H_i^{\beta/\alpha} w_i^{-1} - [(1-\alpha)/\alpha] A(\tau)^{[(1-\alpha)/\alpha]-1} q_i^{1-\alpha} H_i^{\beta(1-\alpha)/\alpha} (h + r^2 s^2 t) - (1/\alpha) A(\tau)^{(1-\alpha)/\alpha} q_i H_i^{\beta/\alpha}$$

Using (A.7), the RHS of (A.8) can be rewritten as  $A(\tau)^{(1-\alpha)/\alpha} H_i^{\beta/\alpha} [.5\alpha r w_i^{-1} - q_i]$

The RHS of (A.8) would be positive in sign if  $.5\alpha r w_i^{-1} - q_i > 0$ . Since coefficient of  $(dq_i/dA_i)$  on the LHS of (A.8) is positive in sign, it follows that  $(dq_i^*/dA_i) > 0$ , if

$$(A.9) \quad q_i < .5\alpha r w_i^{-1}.$$

We now prove that this condition is always satisfied at optimal values of  $s_i^*$ . From equation (15) in the text  $s_i^*$  must satisfy:

$$(15) \quad s_i^{(1-\alpha)/\alpha} (h + r^2 s^2 t) + s_i^{1/\alpha} - .5r A^{1/\alpha} H_i^{\beta/\alpha} \alpha w_i^{-1} = 0,$$

Multiplying (A.9) through by  $A^{1/\alpha} H_i^{\beta/\alpha}$  we obtain:

$$(A.10) \quad q_i A^{1/\alpha} H_i^{\beta/\alpha} < .5r A^{1/\alpha} H_i^{\beta/\alpha} \alpha w_i^{-1}$$

Inserting the value of  $q_i$  from equation (7) in the text into (A.10), the condition becomes:

$$(A.11) \quad s_i^{1/\alpha} < .5r A^{1/\alpha} H_i^{\beta/\alpha} \alpha w_i^{-1},$$

This equation necessarily holds for an optimal value of  $s_i^*$  since by equation (15),

$$s_i^{1/\alpha} < s_i^{(1-\alpha)/\alpha} (h + r^2 s^2 t) + s_i^{1/\alpha} = .5r A^{1/\alpha} H_i^{\beta/\alpha} \alpha w_i^{-1}. \text{ Thus, using (A.9) and (6):}$$

$$(A.12) \quad \text{sgn} (ds_i^*/dA_i) = \text{sgn} (dq_i^*/dA_i) > 0.$$



## APPENDIX 2: Full regression results

Table A.1. DEMAND for risky Assets: SALARIED WORKERS, Independent SCF Samples

Year	1963				1983				1989				1992			
	Original	No-wage	2SLS	PW	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW
Constant	-4.731 (-6.55)	-5.709 (-7.84)	-3.339 (-3.81)	-0.652 (-0.44)	-2.064 (-2.32)	-2.634 (-3.04)	-0.214 (-0.21)	0.676 (0.61)	-0.084 (-0.16)	-1.415 (-2.72)	0.788 (1.4)	3.150 (4.87)	-3.792 (-6.97)	-4.331 (-8.05)	-3.384 (-6.05)	-2.606 (-4.40)
log(EDU)	0.941 (4.89)	0.641 (3.34)	1.342 (5.64)	1.121 (4.96)	1.277 (4.55)	1.304 (4.63)	1.286 (4.32)	1.845 (6.12)	0.676 (3.86)	0.812 (4.57)	0.980 (5.41)	1.912 (9.63)	1.620 (8.71)	1.580 (8.47)	1.880 (9.74)	2.096 (10.46)
log(TA)	1.114 (17.86)	1.101 (17.05)	1.132 (16.75)	1.121 (17.58)	0.632 (13.95)	0.613 (13.64)	0.712 (13.82)	0.693 (14.55)	0.761 (25.72)	0.701 (23.81)	0.837 (26.04)	0.811 (26.70)	0.767 (30.12)	0.746 (29.48)	0.800 (29.98)	0.7952 (30.39)
log(WAGE)	-0.127 (-5.72)		-0.312 (-5.43)	-0.705 (-3.87)	-0.043 (-2.76)		-0.207 (-4.98)	-0.523 (-4.66)	-0.105 (-10)		-0.239 (-11.62)	-0.775 (-11.49)	-0.051 (-5.7)		-0.128 (-6.82)	-0.297 (-6.81)
AGE	0.001 (0.11)	0.020 (3.07)	-0.026 (-2.39)	0.014 (2.20)	0.025 (5.15)	0.033 (8.23)	-0.005 (-0.59)	0.026 (6.22)	0.006 (1.73)	0.027 (10.44)	-0.024 (-4.71)	0.014 (5.36)	0.012 (4.26)	0.022 (9.82)	-0.004 (-0.96)	0.0117 (4.29)
RAV	*	*	*	*	-0.319 (-4.65)	-0.319 (-4.62)	-0.314 (-4.3)	-0.326 (-4.77)	-0.478 (-10.35)	-0.513 (-10.97)	-0.461 (-9.64)	-0.543 (-11.82)	-0.322 (-8.46)	-0.319 (-8.35)	-0.329 (-8.54)	-0.350 (-9.14)
PROF	-0.379 (-2.26)	-0.338 (-1.94)	-0.192 (-1.05)	-0.233 (-1.34)	0.397 (2.76)	0.351 (2.45)	0.416 (2.73)	0.421 (2.95)	0.110 (1.34)	-0.183 (-2.36)	-0.026 (-0.33)	-0.091 (-1.19)	0.036 (0.52)	-0.058 (-0.85)	-0.023 (-0.33)	-0.055 (-0.82)

Year	1995				1998				2001				2004			
	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW
Constant	-2.853 (-5.77)	-3.874 (-8.01)	-1.963 (-3.74)	-0.539 (-0.91)	-1.651 (-4.33)	-2.632 (-7.1)	-0.806 (-1.94)	0.579 (1.17)	-2.804 (-7.3)	-3.855 (-10.18)	-1.824 (-4.4)	0.329 (0.61)	-3.209 (-6.88)	-3.483 (-7.72)	-2.020 (-4.07)	-1.088 (-2.10)
log(EDU)	0.387 (2.4)	0.434 (2.66)	0.527 (3.21)	1.327 (7.14)	0.201 (1.65)	0.162 (1.31)	0.375 (2.97)	0.732 (5.39)	0.537 (4.46)	0.532 (4.35)	0.902 (7.04)	1.040 (8.02)	1.009 (6.41)	1.026 (6.52)	1.237 (7.53)	1.995 (10.58)
log(TA)	0.977 (40.4)	0.941 (39.19)	1.028 (39.83)	1.016 (40.64)	0.947 (47.95)	0.934 (46.93)	0.998 (47.31)	0.992 (48.14)	0.986 (47.67)	0.945 (45.71)	1.054 (46.66)	1.023 (47.20)	0.792 (38.72)	0.787 (38.69)	0.828 (38.42)	0.835 (40.09)
log(WAGE)	-0.073 (-8.39)		-0.166 (-9.68)	-0.565 (-9.58)	-0.072 (-9.5)		-0.169 (-10.14)	-0.449 (-9.57)	-0.092 (-11.52)		-0.236 (-14.08)	-0.544 (-10.70)	-0.017 (-2.32)		-0.134 (-8.56)	-0.465 (-9.11)
AGE	-0.005 (-1.76)	0.010 (4.88)	-0.025 (-6.07)	-0.001 (-0.35)	-0.005 (-2.21)	0.007 (3.77)	-0.026 (-6.78)	-0.005 (-2.08)	-0.009 (-3.65)	0.007 (3.67)	-0.038 (-9.92)	-0.004 (-1.79)	0.015 (6.16)	0.018 (9.07)	-0.010 (-2.53)	0.008 (3.78)
RAV	-0.037 (-0.95)	-0.034 (-0.88)	-0.042 (-1.05)	-0.052 (-1.33)	-0.044 (-1.34)	-0.035 (-1.07)	-0.044 (-1.33)	-0.054 (-1.66)	-0.031 (-0.87)	-0.023 (-0.62)	-0.042 (-1.12)	-0.036 (-0.99)	-0.226 (-6.11)	-0.223 (-6.03)	-0.219 (-5.74)	-0.234 (-6.38)
PROF	-0.124 (-1.8)	-0.244 (-3.59)	-0.240 (-3.51)	-0.265 (-3.69)	0.103 (1.75)	-0.014 (-0.23)	-0.008 (-0.13)	-0.022 (-0.38)	0.035 (0.56)	-0.156 (-2.55)	-0.085 (-1.34)	-0.097 (-1.60)	0.061 (1.00)	0.010 (0.17)	0.059 (1.02)	0.034 (0.61)

<sup>1</sup> Model refers to the way the log(WAGE) measure is treated in the regression (see text). \* RAV is absent in the 1963-64 sample.

Table A.2. DEMAND for risky Assets: ALL INVESTORS, Independent SCF Samples

Year	1963				1983				1989				1992			
Model <sup>1</sup>	OLS	no-wage	2SLS	PW	OLS	no-wage	2SLS	PW	OLS	no-wage	2SLS	PW	OLS	no-wage	2SLS	PW
Constant	-5.083 (-8.75)	-5.772 (-9.93)	-3.013 (-3.86)	-0.623 (-0.51)	-3.184 (-3.81)	-3.571 (-4.35)	-1.353 (-1.37)	-0.236 (-0.22)	-0.991 (-2.35)	-1.852 (-4.47)	0.207 (0.45)	2.204 (4.30)	-2.543 (-5.55)	-2.579 (-5.69)	-0.440 (-0.79)	-0.154 (-0.26)
log(EDU)	0.927 (5.99)	0.752 (4.84)	1.298 (6.75)	1.248 (6.73)	1.573 (5.94)	1.574 (5.93)	1.607 (5.66)	2.135 (7.46)	0.740 (5.37)	0.793 (5.72)	0.997 (6.88)	1.775 (11.39)	0.775 (5.2)	0.762 (5.17)	1.180 (7.11)	1.116 (7.14)
log(TA)	1.086 (21.34)	1.059 (20.43)	1.089 (19.13)	1.080 (21.08)	0.640 (14.97)	0.629 (14.77)	0.718 (14.65)	0.706 (15.7)	0.755 (34.15)	0.726 (32.96)	0.830 (34.2)	0.814 (35.87)	0.792 (36.35)	0.791 (36.46)	0.825 (35.25)	0.832 (37.03)
log(WAGE)	-0.095 (-5.70)		-0.312 (-6.07)	-0.722 (-4.74)	-0.032 (-2.32)		-0.203 (-4.95)	-0.528 (-4.90)	-0.067 (-8.81)		-0.222 (-12.88)	-0.673 (-13.02)	-0.007 (-0.56)		-0.294 (-7.37)	-0.324 (-6.60)
AGE	0.009 (1.65)	0.024 (4.56)	-0.021 (-2.26)	0.019 (3.53)	0.028 (6.25)	0.033 (8.69)	-0.002 (-0.25)	0.027 (6.62)	0.015 (6.44)	0.028 (14.22)	-0.016 (-4)	0.016 (7.64)	0.017 (6.62)	0.017 (6.86)	0.006 (2.04)	0.009 (3.41)
RAV	*	*	*	*	-0.296 (-4.64)	-0.294 (-4.59)	-0.291 (-4.25)	-0.299 (-4.73)	-0.472 (-13.19)	-0.483 (-13.42)	-0.447 (-11.91)	-0.509 (-14.35)	-0.341 (-10.12)	-0.342 (-10.13)	-0.358 (-10.03)	-0.363 (-10.77)
PROF	-0.346 (-2.6)	-0.375 (-2.76)	-0.243 (-1.62)	-0.272 (-2.00)	0.234 (1.82)	0.215 (1.67)	0.273 (1.97)	0.277 (2.16)	0.085 (1.39)	-0.077 (-1.31)	0.032 (0.52)	-0.026 (-0.46)	0.114 (2.02)	0.113 (2.01)	0.118 (1.99)	0.126 (2.24)
SELF	-0.983 (-5.49)	-0.652 (-3.76)	-1.680 (-6.61)	-0.615 (-3.60)	-0.710 (-4.34)	-0.603 (-3.84)	-1.293 (-5.92)	-0.563 (-3.62)	-0.424 (-5.79)	-0.461 (-6.26)	-0.311 (-4.02)	-0.467 (-6.45)	-0.438 (-6.35)	-0.427 (-6.44)	-0.865 (-9.41)	-0.430 (-6.52)

Year	1995				1998				2001				2004			
Model <sup>1</sup>	OLS	no-wage	2SLS	PW	OLS	no-wage	2SLS	PW	OLS	no-wage	2SLS	PW	OLS	no-wage	2SLS	PW
Constant	-2.215 (-4.68)	-2.076 (-4.49)	0.409 (0.65)	0.541 (0.88)	-2.174 (-4.53)	-2.240 (-4.72)	0.728 (1.21)	2.339 (4.04)	-2.482 (-6.75)	-2.810 (-7.96)	2.179 (3.55)	2.099 (4.03)	-3.301 (-8.4)	-3.226 (-8.43)	-1.442 (-3.05)	-1.181 (-2.53)
log(EDU)	0.155 (0.98)	0.143 (0.91)	0.134 (0.8)	0.575 (3.38)	0.474 (2.74)	0.468 (2.71)	0.966 (4.82)	1.270 (7.04)	0.555 (4.83)	0.554 (4.81)	0.921 (6.56)	1.070 (8.87)	0.899 (6.54)	0.894 (6.51)	0.987 (6.8)	1.372 (9.11)
log(TA)	0.863 (41.34)	0.870 (42.6)	0.918 (39.75)	0.915 (42.54)	0.851 (46.02)	0.847 (47)	0.914 (43.01)	0.929 (49.53)	0.896 (50.25)	0.888 (50.26)	0.967 (43.75)	0.972 (52.13)	0.795 (48.76)	0.797 (49.32)	0.831 (47)	0.834 (49.58)
log(WAGE)	0.014 (1.37)		-0.256 (-6.37)	-0.380 (-6.45)	-0.010 (-0.96)		-0.411 (-10.98)	-0.641 (-13.40)	-0.034 (-3.17)		-0.564 (-11.12)	-0.619 (-12.71)	0.007 (0.83)		-0.195 (-7.18)	-0.319 (-7.54)
AGE	0.002 (0.68)	0.001 (0.47)	-0.005 (-1.71)	-0.003 (-1.07)	-0.003 (-1.21)	-0.002 (-1.03)	-0.016 (-5.84)	-0.017 (-7.30)	-0.010 (-4.39)	-0.009 (-3.95)	-0.024 (-8.09)	-0.019 (-8.32)	0.002 (0.9)	0.001 (0.76)	-0.006 (-2.73)	-0.005 (-2.39)
RAV	-0.028 (-0.8)	-0.028 (-0.82)	-0.020 (-0.54)	-0.028 (-0.81)	-0.009 (-0.33)	-0.009 (-0.31)	-0.025 (-0.77)	-0.039 (-1.37)	-0.018 (-0.6)	-0.016 (-0.53)	-0.018 (-0.5)	-0.018 (-0.60)	-0.014 (-0.46)	-0.014 (-0.45)	0.002 (0.07)	0.002 (0.07)
PROF	0.034 (0.62)	0.036 (0.66)	-0.004 (-0.07)	0.010 (0.19)	0.142 (2.83)	0.142 (2.84)	0.123 (2.17)	0.119 (2.41)	0.155 (3.05)	0.142 (2.81)	0.138 (2.31)	0.150 (3.01)	0.193 (4.04)	0.197 (4.16)	0.194 (3.89)	0.210 (4.48)
SELF	-0.033 (-0.44)	-0.080 (-1.19)	-0.878 (-6.07)	-0.131 (-1.94)	0.109 (1.75)	0.127 (2.15)	-0.522 (-5.85)	0.141 (2.42)	-0.151 (-2.42)	-0.091 (-1.53)	-0.982 (-9.22)	-0.153 (-2.61)	0.073 (1.34)	0.058 (1.13)	-0.339 (-4.39)	0.019 (0.37)

<sup>1</sup> Model refers to the way the log(WAGE) measure is treated in the regression (see text). \* RAV is absent in the 1963-64 sample.

Table A.3. RETURNS-on-Total-Portfolio-of-Assets: SALARIED WORKERS, Independent SCF Samples

Year	1963				1983				1989				1992			
	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW
Constant	-8.678 (-7.02)	-9.185 (-7.63)	-5.638 (-3.61)	0026 (0.01)	-7.969 (-5.84)	-9.446 (-7.04)	-5.666 (-3.61)	-3.173 (-1.85)	-11.245 (-13.83)	-13.263 (-16.6)	-9.530 (-10.91)	-5.203 (-5.28)	-19.182 (-19.7)	-20.481 (-21.19)	-18.020 (-17.74)	-15.72 (-14.9)
log(EDU)	0.678 (2.06)	0.523 (1.65)	1.572 (3.71)	1.397 (3.75)	1.696 (3.94)	1.764 (4.05)	1.736 (3.86)	2.790 (6.02)	1.436 (5.34)	1.641 (6.03)	1.925 (6.85)	3.583 (11.9)	4.518 (13.58)	4.421 (13.19)	5.202 (14.85)	5.848 (16.4)
log(TA)	1.088 (10.2)	1.081 (10.12)	1.127 (9.36)	1.117 (10.62)	0.909 (13.06)	0.860 (12.36)	1.014 (13.03)	1.011 (13.8)	1.220 (26.88)	1.128 (25.02)	1.359 (27.25)	1.323 (28.6)	1.167 (25.62)	1.117 (24.57)	1.258 (25.95)	1.252 (26.9)
log(WAGE)	-0.066 (-1.73)		-0.467 (-4.56)	-1.283 (-4.28)	-0.111 (-4.66)		-0.323 (-5.15)	-0.991 (-5.74)	-0.159 (-9.88)		-0.405 (-12.68)	-1.368 (-13.3)	-0.123 (-7.67)		-0.334 (-9.77)	-0.819 (-10.6)
AGE	0.012 (1.03)	0.022 (2.09)	-0.045 (-2.39)	0.012 (1.16)	0.025 (3.34)	0.046 (7.31)	-0.014 (-1.08)	0.033 (5.02)	0.006 (1.12)	0.037 (9.57)	-0.048 (-6.12)	0.016 (3.90)	0.016 (3.12)	0.039 (9.89)	-0.028 (-3.52)	0.011 (2.30)
RAV	*	*	*	*	-0.204 (-1.93)	-0.203 (-1.9)	-0.195 (-1.76)	-0.216 (-2.06)	0.219 (3.09)	0.166 (2.31)	0.254 (3.43)	0.114 (1.63)	-0.049 (-0.71)	-0.042 (-0.61)	-0.067 (-0.96)	-0.126 (-1.85)
PROF	-0.475 (-1.65)	-0.454 (-1.57)	-0.236 (-0.72)	-0.262 (-0.92)	0.375 (1.7)	0.256 (1.15)	0.357 (1.55)	0.389 (1.77)	-0.100 (-0.8)	-0.545 (-4.57)	-0.279 (-2.24)	-0.382 (-3.28)	-0.580 (-4.65)	-0.806 (-6.6)	-0.715 (-5.74)	-0.799 (-6.64)

Year	1995				1998				2001				2004			
	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW
Constant	-16.995 (-20.19)	-17.945 (-21.93)	-15.021 (-16.69)	-13.99 (-13.9)	-10.946 (-13.1)	-13.483 (-16.53)	-9.150 (-10.03)	-8.071 (-7.34)	-13.026 (-16.93)	-14.517 (-19.28)	-12.384 (-15.42)	-11.71 (-10.8)	-14.530 (-14.18)	-16.470 (-16.51)	-13.866 (-13.01)	-10.66 (-9.32)
log(EDU)	2.117 (7.7)	2.160 (7.84)	2.303 (8.19)	3.221 (10.2)	1.317 (4.92)	1.214 (4.47)	1.721 (6.20)	2.177 (7.24)	0.876 (3.63)	0.869 (3.58)	1.258 (5.07)	1.209 (4.64)	0.977 (2.83)	1.096 (3.15)	1.472 (4.18)	2.447 (8.29)
log(TA)	1.349 (32.75)	1.315 (32.36)	1.448 (32.78)	1.405 (33.0)	1.242 (28.71)	1.210 (27.62)	1.361 (29.42)	1.308 (28.7)	1.347 (32.52)	1.288 (31.35)	1.403 (32.06)	1.340 (30.8)	1.486 (33.06)	1.447 (32.2)	1.520 (32.89)	1.564 (34.1)
log(WAGE)	-0.068 (-4.58)		-0.254 (-8.66)	-0.671 (-6.67)	-0.187 (-11.21)		-0.402 (-10.96)	-0.757 (-7.29)	-0.130 (-8.16)		-0.248 (-7.63)	-0.365 (-3.57)	-0.121 (-7.49)		-0.238 (-7.1)	-1.127 (-10.0)
AGE	0.038 (8.4)	0.051 (15.04)	-0.002 (-0.33)	0.039 (9.96)	0.011 (2.17)	0.043 (10.14)	-0.035 (-4.24)	0.023 (4.51)	0.023 (4.73)	0.046 (11.54)	-0.001 (-0.2)	0.038 (8.49)	-0.014 (-2.62)	0.008 (1.96)	-0.040 (-4.95)	-0.014 (-2.98)
RAV	-0.308 (-4.66)	-0.306 (-4.61)	-0.317 (-4.69)	-0.326 (-4.94)	-0.381 (-5.36)	-0.359 (-4.98)	-0.380 (-5.23)	-0.391 (-5.45)	-0.325 (-4.51)	-0.313 (-4.31)	-0.334 (-4.59)	-0.322 (-4.44)	-0.058 (-0.71)	-0.036 (-0.44)	-0.030 (-0.36)	-0.062 (-0.77)
PROF	0.771 (6.58)	0.659 (5.74)	0.665 (5.68)	0.634 (5.55)	0.098 (0.76)	-0.203 (-1.59)	-0.189 (-1.47)	-0.217 (-1.71)	0.986 (7.87)	0.715 (5.87)	0.790 (6.47)	0.755 (6.18)	0.037 (0.28)	-0.324 (-2.6)	-0.235 (-1.88)	-0.265 (-2.15)

<sup>1</sup> Model refers to the way the log(WAGE) measure is treated in the regression (see text). \* RAV is absent in the 1963-64 sample.

Table A.4. RETURNS on Total Portfolio of Assets: ALL INVESTORS, Independent SCF Samples

Year	1963				1983				1989				1992				
	Model <sup>1</sup>	OLS	no-wage	2SLS	PW	OLS	no-wage	2SLS	PW	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW
Constant		-8.301 (-8.23)	-8.650 (-8.76)	-4.901 (-3.61)	-0.080 (-0.04)	-8.240 (-6.47)	-9.104 (-7.26)	-5.492 (-3.66)	-2.865 (-1.78)	-12.104 (-17.91)	-13.278 (-20.09)	-9.758 (-13.11)	-5.690 (-7.00)	-13.821 (-16.74)	-14.097 (-17.23)	-9.779 (-9.63)	-9.002 (-8.59)
log(EDU)		0.610 (2.27)	0.521 (1.98)	1.263 (3.79)	1.347 (4.28)	1.572 (3.9)	1.574 (3.88)	1.629 (3.76)	2.623 (6.03)	1.636 (7.42)	1.709 (7.71)	2.057 (8.74)	3.546 (14.34)	2.006 (7.46)	1.908 (7.17)	2.751 (9.15)	2.651 (9.42)
log(TA)		0.983 (11.13)	0.970 (11.01)	1.011 (10.23)	1.004 (11.53)	0.933 (14.31)	0.907 (13.94)	1.053 (14.09)	1.051 (15.38)	1.153 (32.58)	1.113 (31.64)	1.291 (32.78)	1.277 (35.48)	1.250 (31.81)	1.241 (31.7)	1.309 (30.88)	1.323 (32.79)
log(WAGE)		-0.048 (-1.67)		-0.424 (-4.76)	-1.202 (-4.64)	-0.070 (-3.38)		-0.331 (-5.29)	-0.987 (-6.03)	-0.091 (-7.50)		-0.380 (-13.57)	-1.259 (-15.35)	-0.053 (-2.41)		-0.593 (-8.21)	-0.680 (-7.70)
AGE		0.025 (2.54)	0.033 (3.65)	-0.029 (-1.77)	0.024 (2.65)	0.029 (4.27)	0.041 (7.01)	-0.017 (-1.31)	0.029 (4.68)	0.029 (7.68)	0.046 (14.82)	-0.028 (-4.41)	0.024 (7.30)	-0.007 (-1.5)	-0.005 (-1.05)	-0.027 (-4.88)	-0.021 (-4.24)
RAV		*	*	*	*	-0.257 (-2.64)	-0.252 (-2.57)	-0.247 (-2.37)	-0.262 (-2.73)	0.007 (0.13)	-0.008 (-0.15)	0.054 (0.89)	-0.057 (-1.01)	0.070 (1.16)	0.068 (1.11)	0.033 (0.52)	0.022 (0.36)
PROF		-0.246 (-1.07)	-0.261 (-1.13)	-0.082 (-0.31)	-0.089 (-0.39)	0.189 (0.96)	0.146 (0.74)	0.241 (1.14)	0.263 (1.35)	-0.014 (-0.14)	-0.234 (-2.5)	-0.048 (-0.48)	-0.139 (-1.51)	-0.013 (-0.13)	-0.018 (-0.18)	-0.007 (-0.07)	0.009 (0.09)
SELF		-0.861 (-2.77)	-0.693 (-2.35)	-2.090 (-4.74)	-0.631 (-2.17)	-0.607 (-2.44)	-0.370 (-1.54)	-1.492 (-4.48)	-0.295 (-1.24)	-0.252 (-2.16)	-0.303 (-2.58)	-0.046 (-0.37)	-0.314 (-2.73)	0.420 (3.38)	0.502 (4.20)	-0.382 (-2.30)	0.495 (4.16)

Year	1995				1998				2001				2004				
	Model <sup>1</sup>	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW
Constant		-18.673 (-23.59)	-19.364 (-25.01)	-18.709 (-19)	-18.40 (-17.83)	-16.056 (-15.17)	-16.319 (-15.58)	-11.942 (-9.65)	-9.844 (-7.63)	-14.599 (-19.34)	-14.745 (-20.36)	-14.180 (-13.35)	-14.965 (-13.84)	-18.291 (-20.2)	-18.934 (-21.47)	-15.147 (-14.18)	-14.594 (-13.53)
log(EDU)		2.092 (7.95)	2.148 (8.16)	2.146 (8.16)	2.307 (8.06)	2.906 (7.61)	2.883 (7.55)	3.617 (8.75)	4.016 (9.99)	1.878 (7.96)	1.877 (7.96)	1.918 (7.9)	1.854 (7.40)	2.743 (8.67)	2.787 (8.81)	2.986 (9.11)	3.801 (10.94)
log(TA)		1.507 (43.18)	1.477 (43.24)	1.490 (41.28)	1.494 (41.33)	1.173 (28.74)	1.157 (29.09)	1.257 (28.67)	1.273 (30.45)	1.156 (31.58)	1.152 (31.79)	1.161 (30.35)	1.149 (29.63)	1.258 (33.51)	1.243 (33.37)	1.316 (32.97)	1.322 (34.06)
log(WAGE)		-0.071 (-4.05)		-0.067 (-1.07)	-0.140 (-1.41)	-0.040 (-1.72)		-0.606 (-7.86)	-0.907 (-8.50)	-0.015 (-0.69)		-0.064 (-0.73)	0.028 (0.28)	-0.057 (-3.11)		-0.413 (-6.76)	-0.676 (-6.94)
AGE		0.006 (1.34)	0.009 (2.01)	0.007 (1.54)	0.007 (1.62)	0.011 (2.23)	0.012 (2.65)	-0.008 (-1.36)	-0.009 (-1.70)	0.028 (6.18)	0.028 (6.36)	0.027 (5.3)	0.029 (6.03)	0.005 (1.17)	0.008 (1.77)	-0.009 (-1.65)	-0.006 (-1.22)
RAV		0.135 (2.32)	0.138 (2.38)	0.141 (2.41)	0.138 (2.38)	-0.361 (-5.69)	-0.360 (-5.67)	-0.384 (-5.73)	-0.402 (-6.35)	-0.395 (-6.23)	-0.394 (-6.21)	-0.395 (-6.22)	-0.394 (-6.21)	0.059 (0.85)	0.056 (0.81)	0.089 (1.24)	0.089 (1.28)
PROF		0.750 (8.28)	0.738 (8.14)	0.727 (7.99)	0.728 (8.01)	0.073 (0.67)	0.075 (0.68)	0.046 (0.4)	0.042 (0.38)	0.700 (6.73)	0.694 (6.70)	0.694 (6.69)	0.694 (6.70)	-0.005 (-0.05)	-0.042 (-0.38)	-0.048 (-0.43)	-0.012 (-0.11)
SELF		-0.089 (-0.71)	0.143 (1.26)	-0.067 (-0.3)	0.124 (1.09)	0.107 (0.78)	0.180 (1.37)	-0.778 (-4.23)	0.200 (1.54)	0.087 (0.68)	0.113 (0.93)	0.013 (0.07)	0.116 (0.95)	0.396 (3.18)	0.523 (4.43)	-0.319 (-1.83)	0.440 (3.73)

<sup>1</sup> Model refers to the way the log(WAGE) measure is treated in the regression (see text). \* RAV is absent in the 1963-64 sample.

Table A.5. RETURNS on Total Portfolio of Assets Conditional on log(SHARE): SALARIED WORKERS, Independent SCF Samples

Year	1963				1983				1989				1992			
Model <sup>1</sup>	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW
Constant	-4.448 (-4.01)	-4.235 (-3.85)	-2.915 (-2.26)	0.569 (0.27)	-7.077 (-5.39)	-8.260 (-6.4)	-5.577 (-3.78)	-3.453 (-2.09)	-11.221 (-14.03)	-12.818 (-16.37)	-9.727 (-11.42)	-5.998 (-6.15)	-17.602 (-18.46)	-18.600 (-19.65)	-16.646 (-16.86)	-14.66 (-14.25)
log(EDU)	-0.163 (-0.56)	-0.033 (-0.12)	0.478 (1.33)	0.463 (1.4)	1.144 (2.73)	1.177 (2.79)	1.203 (2.81)	2.025 (4.44)	1.249 (4.72)	1.386 (5.19)	1.681 (6.11)	3.100 (10.3)	3.843 (11.75)	3.735 (11.37)	4.439 (12.93)	5.000 (14.2)
log(TA)	0.986 (10.78)	0.994 (10.87)	1.020 (10.38)	1.016 (11.1)	1.068 (15.42)	1.034 (14.92)	1.133 (15.19)	1.139 (15.8)	1.286 (28.5)	1.222 (27.24)	1.400 (28.68)	1.371 (29.9)	1.265 (28.2)	1.227 (27.44)	1.339 (28.35)	1.335 (29.2)
log(WAGE)	0.048 (1.42)		-0.213 (-2.46)	-0.696 (-2.64)	-0.092 (-4.02)		-0.238 (-3.97)	-0.774 (-4.60)	-0.130 (-8.09)		-0.345 (-10.85)	-1.172 (-11.3)	-0.102 (-6.49)		-0.282 (-8.47)	-0.699 (-9.19)
AGE	0.012 (1.14)	0.005 (0.56)	-0.025 (-1.58)	0.0004 (0.05)	0.014 (1.95)	0.031 (4.95)	-0.012 (-0.98)	0.022 (3.39)	0.004 (0.83)	0.029 (7.46)	-0.042 (-5.49)	0.012 (3.03)	0.011 (2.19)	0.030 (7.64)	-0.026 (-3.41)	0.006 (1.36)
RAV	*	*	*	*	-0.066 (-0.64)	-0.059 (-0.57)	-0.065 (-0.62)	-0.080 (-0.79)	0.351 (4.95)	0.327 (4.57)	0.369 (5.03)	0.251 (3.56)	0.086 (1.28)	0.097 (1.44)	0.067 (0.97)	0.016 (0.23)
PROF	-0.136 (-0.55)	-0.161 (-0.65)	-0.079 (-0.3)	-0.068 (-0.28)	0.203 (0.95)	0.098 (0.46)	0.184 (0.85)	0.214 (1.01)	-0.131 (-1.06)	-0.487 (-4.17)	-0.272 (-2.24)	-0.359 (-3.12)	-0.595 (-4.9)	-0.781 (-6.59)	-0.706 (-5.86)	-0.776 (-6.63)
log(SHARE)	0.894 (12.59)	0.867 (12.65)	0.816 (10.71)	0.833 (12.0)	0.432 (8.74)	0.450 (9.07)	0.414 (8.1)	0.415 (8.35)	0.276 (10.19)	0.314 (11.69)	0.249 (8.85)	0.253 (9.39)	0.417 (14.43)	0.434 (15.03)	0.406 (13.76)	0.405 (14.07)

Year	1995				1998				2001				2004			
Model <sup>1</sup>	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW
Constant	-15.900 (-19.3)	-16.420 (-20.46)	-14.304 (-16.39)	-13.79 (-14.04)	-10.511 (-12.64)	-12.662 (-15.58)	-8.942 (-9.91)	-8.234 (-7.55)	-12.305 (-16.03)	-13.395 (-17.78)	-11.922 (-14.99)	-11.81 (-11.0)	-13.183 (-13.04)	-14.979 (-15.2)	-13.053 (-12.51)	-10.24 (-9.08)
log(EDU)	1.968 (7.34)	1.989 (7.42)	2.111 (7.74)	2.723 (8.76)	1.264 (4.75)	1.164 (4.33)	1.624 (5.91)	1.970 (6.59)	0.738 (3.08)	0.714 (2.97)	1.029 (4.17)	0.917 (3.53)	0.554 (1.62)	0.657 (1.92)	0.974 (2.81)	2.670 (6.44)
log(TA)	1.358 (33.83)	1.339 (33.83)	1.438 (33.61)	1.399 (33.7)	1.256 (29.21)	1.231 (28.33)	1.362 (29.78)	1.311 (29.0)	1.350 (32.87)	1.304 (32.06)	1.389 (32.11)	1.334 (30.9)	1.573 (35.22)	1.539 (34.45)	1.590 (34.92)	1.628 (35.8)
log(WAGE)	-0.040 (-2.74)		-0.194 (-6.72)	-0.459 (-4.62)	-0.168 (-10.03)		-0.358 (-9.76)	-0.631 (-6.05)	-0.107 (-6.63)		-0.188 (-5.72)	-0.211 (-2.06)	-0.114 (-7.17)		-0.184 (-5.57)	-0.946 (-8.46)
AGE	0.040 (9.03)	0.047 (14.25)	0.007 (0.99)	0.039 (10.3)	0.012 (2.45)	0.041 (9.69)	-0.028 (-3.46)	0.024 (4.81)	0.025 (5.23)	0.044 (11.1)	0.008 (1.1)	0.039 (8.82)	-0.020 (-3.85)	0.001 (0.21)	-0.036 (-4.58)	0-0.018 (-3.69)
RAV	-0.294 (-4.56)	-0.292 (-4.53)	-0.302 (-4.61)	-0.307 (-4.76)	-0.370 (-5.23)	-0.348 (-4.88)	-0.369 (-5.13)	-0.376 (-5.28)	-0.317 (-4.43)	-0.307 (-4.27)	-0.323 (-4.49)	-0.312 (-4.34)	0.037 (0.46)	0.059 (0.74)	0.059 (0.73)	0.029 (0.36)
PROF	0.818 (7.17)	0.755 (6.75)	0.752 (6.62)	0.733 (6.56)	0.071 (0.56)	-0.199 (-1.57)	-0.187 (-1.47)	-0.211 (-1.67)	0.977 (7.86)	0.761 (6.31)	0.811 (6.72)	0.782 (6.47)	0.011 (0.09)	-0.328 (-2.69)	-0.259 (-2.12)	-0.278 (-2.30)
log(SHARE)	0.384 (14.35)	0.394 (14.83)	0.365 (13.38)	0.375 (13.99)	0.263 (7.82)	0.312 (9.27)	0.259 (7.55)	0.282 (8.32)	0.257 (8.64)	0.291 (9.87)	0.254 (8.4)	0.281 (9.42)	0.420 (12.71)	0.428 (12.9)	0.403 (12.05)	0.389 (11.7)

<sup>1</sup> Model refers to the way the log(WAGE) measure is treated in the regression (see text). \* RAV is absent in the 1963-64 sample.

Table A.6. RETURNS-on-Total-Portfolio-of-Assets: ALL INVESTORS, Independent Samples from Eight Years

Year	1963				1983				1989				1992			
	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW
Constant	-3.773 (-4.13)	-3.611 (-3.98)	-2.374 (-2.15)	0.448 (0.25)	-6.825 (-5.56)	-7.484 (-6.19)	-4.922 (-3.52)	-2.766 (-1.79)	-11.794 (-17.78)	-12.668 (-19.54)	-9.815 (-13.63)	-6.298 (-7.85)	-12.536 (-15.77)	-12.792 (-16.24)	-9.565 (-10.05)	-8.927 (-8.85)
log(EDU)	-0.216 (-0.91)	-0.135 (-0.59)	0.175 (0.63)	0.291 (1.03)	0.873 (2.22)	0.860 (2.18)	0.951 (2.32)	1.723 (4.02)	1.405 (6.48)	1.448 (6.66)	1.781 (7.78)	3.056 (12.38)	1.614 (6.24)	1.522 (5.95)	2.177 (7.68)	2.103 (7.73)
log(TA)	0.907 (11.93)	0.918 (12.13)	0.936 (11.78)	0.936 (12.37)	1.093 (16.95)	1.076 (16.71)	1.172 (16.56)	1.175 (17.54)	1.229 (34.99)	1.203 (34.41)	1.338 (34.93)	1.329 (37.22)	1.355 (35.58)	1.347 (35.49)	1.394 (34.84)	1.409 (35.99)
log(WAGE)	0.037 (1.43)		-0.162 (-2.19)	-0.591 (-2.58)	-0.056 (-2.82)		-0.245 (-4.16)	-0.765 (-4.80)	-0.070 (-5.85)		-0.318 (-11.54)	-1.073 (-13.07)	-0.049 (-2.34)		-0.450 (-6.61)	-0.521 (-6.11)
AGE	0.017 (1.96)	0.012 (1.5)	-0.011 (-0.84)	0.008 (1.02)	0.017 (2.51)	0.026 (4.48)	-0.016 (-1.34)	0.017 (2.90)	0.024 (6.52)	0.037 (11.91)	-0.024 (-3.84)	0.020 (6.03)	-0.015 (-3.47)	-0.013 (-3.08)	-0.030 (-5.79)	-0.026 (-5.37)
RAV	*	*	*	*	-0.126 (-1.33)	-0.119 (-1.26)	-0.125 (-1.27)	-0.136 (-1.46)	0.155 (2.71)	0.151 (2.63)	0.178 (2.98)	0.084 (1.49)	0.243 (4.12)	0.240 (4.07)	0.208 (3.38)	0.200 (3.39)
PROF	0.062 (0.31)	0.066 (0.33)	0.122 (0.58)	0.141 (0.70)	0.085 (0.45)	0.049 (0.26)	0.126 (0.64)	0.146 (0.78)	-0.040 (-0.42)	-0.209 (-2.27)	-0.057 (-0.58)	-0.132 (-1.46)	-0.070 (-0.72)	-0.075 (-0.77)	-0.065 (-0.64)	-0.053 (-0.54)
SELF	0.015 (0.05)	-0.124 (-0.48)	-0.681 (-1.85)	-0.111 (-0.44)	-0.291 (-1.21)	-0.096 (-0.41)	-0.947 (-3)	-0.057 (-0.25)	-0.120 (-1.04)	-0.152 (-1.31)	0.040 (0.33)	-0.185 (-1.63)	0.642 (5.36)	0.718 (6.23)	0.039 (0.25)	0.706 (6.15)
log(SHARE)	0.891 (15.45)	0.873 (15.49)	0.839 (13.78)	0.846 (14.84)	0.445 (9.9)	0.454 (10.1)	0.422 (8.92)	0.421 (9.37)	0.313 (14.02)	0.329 (14.82)	0.277 (11.75)	0.276 (12.44)	0.506 (20.19)	0.506 (20.2)	0.487 (18.6)	0.491 (19.6)

Year	1995				1998				2001				2004			
	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW	Original	no-wage	2SLS	PW
Constant	-18.092 (-23.08)	-18.823 (-24.55)	-18.815 (-19.3)	-18.542 (-18.18)	-15.519 (-14.73)	-15.764 (-15.11)	-12.096 (-9.97)	-10.334 (-8.03)	-14.027 (-18.63)	-14.096 (-19.48)	-14.691 (-13.89)	-15.47 (-14.4)	-16.873 (-18.86)	-17.552 (-20.13)	-14.553 (-14.02)	-14.11 (-13.3)
log(EDU)	2.051 (7.89)	2.111 (8.12)	2.111 (8.12)	2.158 (7.62)	2.789 (7.34)	2.767 (7.29)	3.412 (8.4)	3.751 (9.33)	1.750 (7.45)	1.749 (7.45)	1.703 (7.01)	1.599 (6.38)	2.357 (7.55)	2.404 (7.7)	2.579 (8.07)	3.236 (9.40)
log(TA)	1.543 (44.56)	1.511 (44.58)	1.512 (42.25)	1.516 (42.37)	1.210 (29.65)	1.195 (30.03)	1.275 (29.61)	1.288 (30.9)	1.180 (32.34)	1.178 (32.6)	1.169 (30.72)	1.155 (29.98)	1.347 (36.01)	1.330 (35.86)	1.385 (35.46)	1.391 (36.1)
log(WAGE)	-0.075 (-4.32)		-0.001 (-0.01)	-0.041 (-0.42)	-0.037 (-1.63)		-0.519 (-6.76)	-0.773 (-7.15)	-0.007 (-0.33)		0.068 (0.77)	0.175 (1.72)	-0.060 (-3.32)		-0.333 (-5.58)	-0.545 (-5.65)
AGE	0.005 (1.24)	0.008 (1.96)	0.008 (1.85)	0.008 (1.81)	0.011 (2.38)	0.013 (2.79)	-0.004 (-0.77)	-0.005 (-1.01)	0.030 (6.7)	0.030 (6.84)	0.032 (6.38)	0.033 (6.99)	0.005 (1.02)	0.007 (1.66)	-0.006 (-1.19)	-0.004 (-0.80)
RAV	0.142 (2.48)	0.146 (2.53)	0.146 (2.53)	0.146 (2.53)	-0.359 (-5.69)	-0.358 (-5.67)	-0.379 (-5.76)	-0.394 (-6.25)	-0.391 (-6.2)	-0.391 (-6.19)	-0.390 (-6.18)	-0.390 (-6.18)	0.065 (0.95)	0.062 (0.91)	0.088 (1.27)	0.088 (1.29)
PROF	0.741 (8.29)	0.728 (8.13)	0.728 (8.09)	0.726 (8.08)	0.038 (0.35)	0.040 (0.36)	0.020 (0.18)	0.017 (0.16)	0.664 (6.43)	0.661 (6.42)	0.661 (6.41)	0.658 (6.39)	-0.088 (-0.82)	-0.126 (-1.18)	-0.128 (-1.17)	-0.099 (-0.92)
SELF	-0.081 (-0.64)	0.164 (1.47)	0.161 (0.72)	0.158 (1.41)	0.080 (0.59)	0.148 (1.14)	-0.668 (-3.68)	0.170 (1.31)	0.122 (0.96)	0.134 (1.11)	0.243 (1.31)	0.153 (1.26)	0.365 (2.98)	0.498 (4.3)	-0.179 (-1.06)	0.432 (3.72)
log(SHARE)	0.263 (10.97)	0.261 (10.86)	0.261 (10.81)	0.260 (10.77)	0.247 (8.3)	0.248 (8.32)	0.212 (6.74)	0.209 (6.94)	0.231 (8.72)	0.231 (8.74)	0.234 (8.73)	0.238 (8.90)	0.430 (14.57)	0.429 (14.52)	0.412 (13.63)	0.412 (13.94)

<sup>1</sup> Model refers to the way the log(WAGE) measure is treated in the regression (see text). \* RAV is absent in the 1963-64 sample.