Industry-Specific Human Capital, Idiosyncratic Risk and the Cross-Section of Expected Stock Returns

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Abstract

This paper shows that industry-specific human capital impacts portfolio choice and expected stock returns. First, I find that the characteristics of human capital returns vary across industries. I show that the effect of an investor's nontradable human capital on her optimal stock portfolio depends on the industry in which she works. Next, I include industry-specific rather than aggregate labor income growth in a linear asset pricing model. This leads to a remarkable improvement in the model's ability to capture returns on size – idiosyncratic risk, size – BM and industry equity portfolios. Last, the paper relates human capital to the apparent premium for idiosyncratic risk that is documented by several empirical studies. Using the CRSP dataset, I find that portfolios with high idiosyncratic risk stocks not only have higher CAPM alphas, but they also have higher exposures to human capital returns. I show, both theoretically and empirically, that the observed cross-sectional relation between stocks' idiosyncratic volatilities and their expected returns is related to the hedging demand induced by human capital.

Keywords: Industry-specific human capital, nontradable assets, idiosyncratic volatility, cross-section of expected stock returns

JEL classification: G11, G12, J24

1 Introduction

According to traditional asset pricing theory, investors choose their optimal portfolios by maximizing the expected utility of their life time consumption. Next to investments in tradable assets such as stocks and bonds, part of their wealth may be tied up in nontradable assets. A nontradable asset that forms a significant fraction of the wealth of virtually all investors is human capital. When human capital returns are correlated with stock returns, investors are endowed with certain exposures to stocks. This affects their portfolio choice, as next to the usual speculative demand, investors also have hedging demands that arise due to their nontradable human capital. Consequently, human capital can impact the risk premium for stocks. Indeed, various papers recognize the importance of considering human capital returns when measuring systematic risk (e.g., Mayers, 1972, Shiller, 1995, Jagannathan and Wang, 1996, Campbell, 1996, Palacios-Huerta, 2003).

This paper re-examines the asset pricing implications of human capital. Existing papers mostly consider only aggregate, economy-wide human capital. However, the nature of human capital is investor-specific and may depend on, for instance, age, education, occupation, or the industry in which the investor works. Heterogeneity in human capital may induce different hedging demands for stocks, due to different correlations between equity returns and human capital returns. Also, if employees with certain occupations or working in certain industries would be less active on the stock market, their human capital would have a smaller effect on expected stock returns. Furthermore, in the labor economics literature several papers document the existence of significant inter-industry wage differentials (e.g. Krueger and Summers, 1988, Katz and Summers, 1989, Neal, 1995, Weinberg, 2001). This suggests that labor income and human capital are, in part, determined by industry affiliation. Accordingly, I focus on industry-specific human capital.

First, I examine the effect of industry-specific human capital on optimal portfolio choice. Using 30 industry equity portfolios, I estimate the hedging portfolio weights for investors working in five different broad industries. The results show that the portfolio adjustments for nontradable human capital are significant and they are industry-dependent. For instance, an investor who works in the goods producing industry should downweight stocks from her own industry by 5.43% (significant at the 1% level). On the other hand, an investor working in the service industry should overweight stocks from the fabricated products industry by 1.02% (which is statistically insignificant).[1]

Next, I investigate the asset pricing implications of industry-specific human capital. To this end, I derive a simple asset pricing model in which investors are endowed with fixed positions in

[1] This is in line with Davis and Willen (2000) and Fugazza, Giofré and Nicodano (2008) who show that occupation-specific and industry-specific human capital affects portfolio choice. Whereas these papers only consider portfolio implications, I go one step further and investigate implications for asset pricing.

nontradable assets. In line with Mayers (1972), this nontradable assets model shows that, next to the usual market beta, equity returns are affected by their exposures to the aggregate returns on all nontradable assets. Hence, in theory, there would be no need to distinguish between nontradable human capital from different industries for the purpose of asset pricing. However, empirically, it is very challenging to estimate the aggregate returns on human capital. Existing papers, such as Jagannathan and Wang (1996) and Lettau and Ludvigson (2001), measure aggregate human capital returns as the growth rate in aggregate US labor income. However, this is based on the assumption that labor income follows the same process in all industries (with the same growth rate and the same discount rate). This may be a rather stringent assumption when industry affiliation influences wages and human capital.

In contrast, this paper estimates industry-specific human capital returns as the growth rate in labor income for different US industries, thereby allowing discount rates and growth rates to vary across industries. I consider the following five industries: goods producing, manufacturing, service, distribution, and the government. Aggregating these industry-specific human capital returns is problematic, as it involves estimating the value of human capital in each industry. I avoid this in the nontradable assets model by allowing for different exposures to human capital returns from different industries. The resulting pricing equation includes a market beta as well as industry-specific human capital betas. This way I aim to identify those industries from which human capital matters most and to thereby obtain a better estimate of the full impact of human capital on the cross-section of expected stock returns.

I test the nontradable assets model for 25 size – idiosyncratic volatility sorted portfolios. In a robustness check I also consider 25 size – book to market portfolios and 30 industry portfolios. I compare the performance of this model with industry-specific human capital to the static CAPM, the human capital CAPM that includes the growth rate in aggregate labor income, the conditional CAPM (Jagannathan and Wang, 1996) and the Fama and French (1993) three-factor (FF3). The results show that the effect of human capital on the cross-section of expected stock returns is indeed industry-dependent. Except for the government, the coefficients of all types of industry-specific human capital are statistically significant. Importantly, the model outperforms all four benchmark models. The average absolute pricing error is almost twice as low compared to the other models. Also, the OLS cross-sectional adjusted R^2 for the model with industry-specific human capital is 85%, while it is only 19% for the static CAPM, 27% for the human capital CAPM with aggregate labor income growth, 55% for the conditional CAPM and 37% for the FF3 model. The model has a substantially higher GLS R^2 as well. Last, the industry human capital betas are robust for inclusion of the lagged yieldspread and the size and value factors. In sum, I find that a linear asset pricing model that includes growth rates in industry-specific rather than aggregate labor income better captures the cross-section of expected returns.

Next, I relate nontradable human capital to the apparent premium for idiosyncratic risk. An increasing number of papers provide empirical evidence of a cross-sectional relation between idiosyncratic risk and expected stock returns (e.g., King, Sentana and Wadhwani, 1994, Malkiel and Xu, 1997, 2004, Spiegel and Wang, 2005, Fu, 2007, Ang, Hodrick, Xing and Zhang, 2006, 2008).[2] This creates a puzzle, as true idiosyncratic risk should not be priced. Whereas several other explanations for this puzzle have been investigated in the literature, the link with human capital has so far received little attention.[3]

Papers documenting a cross-sectional relation between stocks' idiosyncratic risk and their expected returns typically measure idiosyncratic risk (IR henceforth) as the residual variance of an asset pricing model that does not include human capital. For example, the Fama and French (1993) three-factor model or the market model. Using the CRSP dataset, I find that portfolios consisting of high IR stocks (measured as the market model residual volatility) indeed have higher CAPM alphas than portfolios with low IR stocks, confirming a "premium " for idiosyncratic risk. However, precisely the high IR portfolios also have higher exposures to (industry-specific) human capital returns.

I use the nontradable assets model to explicitly show the link between nontradable human capital, idiosyncratic risk and expected returns. Intuitively, when systematic risk is measured using the market portfolio of tradable assets, the systematic risk due to nontradable human capital that is not captured ends up in the error term. Consequently, the residual risk affects expected returns and idiosyncratic risk appears to be systematically priced. The magnitude of this effect depends on the hedging demand due to human capital. My empirical results confirm this: the covariance between the CAPM residual and human capital returns significantly affects the cross-section of expected stock returns. The results are even stronger when industry-specific human capital is considered. This implies that the apparent premium for idiosyncratic risk is related to nontradable human capital.

[2] Ang *et al.* (2006, 2008) find a negative relationship between idiosyncratic volatility (estimated using daily returns over the past month) and expected returns. This result is puzzling, as theories such as Merton (1987) predict a positive relation when investors underdiversify. Fu (2007) shows that their lagged measure is not a good measure of expected idiosyncratic volatility due to its time-varying properties. Using an EGARCH model, he documents a positive relation between expected idiosyncratic volatility and expected returns, similar to, amongst others, Spiegel and Wang (2005). I follow this approach and confirm the positive relationship.

[3] Spiegel and Wang (2005) relate idiosyncratic risk to liquidity. Baker, Coval and Stein (2004) use idiosyncratic volatility as a proxy for differences in opinion. Some papers examine whether idiosyncratic volatility can predict market returns (e.g., Goyal and Santa Clara, 2003, Bali, Cakici, Yan and Zhang, 2005, Guo and Savickas, 2004). Other related papers are Campbell, Lettau, Malkiel and Xu (2001) and Brandt, Brav and Graham (2005), who examine the time series properties of idiosyncratic risk.

The remainder of this paper is structured as follows. Section 2 presents the nontradable assets model. Section 3 analyzes industry-specific human capital returns and the corresponding hedging portfolios. Section 4 discusses the empirical analysis of the impact of industry-specific human capital on the cross-section of stock returns. Section 5 reports several robustness checks. Section 6 investigates the link with idiosyncratic risk, both theoretically and empirically. Section 7 concludes. An appendix contains further details of the derivation of the model.

2 Asset pricing with nontradable human capital: a simple model

This section discusses the theoretical framework that serves as basis for examining the relation between industry-specific human capital and the cross-section of expected stock returns. In Section 6, I extend this framework to investigate the relation with idiosyncratic risk. First, I derive a simple asset pricing model in which I allow for multiple nontradable assets, corresponding to human capital from different industries. I treat human capital as nontraded, following amongst others, Mayers (1972), Bottazzi, Pesenti, and Van Wincoop (1996), Baxter and Jermann (1997), and Viceira (2001). While investors may borrow against their future labor income, most of them would not trade claims against future labor income due to adverse selection and moral hazard problems. This makes human capital essentially nontradable.

Consider a standard one-period mean-variance framework with $N + K$ risky assets, where N assets are tradable and K are nontradable. Their excess returns are given in vectors r^{tr} and r^{nt} (sizes $N \times 1$ and $K \times 1$ respectively), with expectations μ_{tr} and μ_{nt} and variance matrices Σ_{tr} and Σ_{nt} respectively. $\Sigma_{tr,nt}$ is the $N \times K$ matrix with covariances between returns on tradable (tr) and nontradable (nt) assets. It does not contain any variances. There is a risk free asset with return R_f.

Investor i has a fraction of her initial wealth $W_{0,i}$ tied up in the nontradable assets, which is denoted by the $K \times 1$ vector q_i. She determines her optimal portfolio of tradable assets x_i (as fractions of $W_{0,i}$) by solving the following portfolio optimization problem:[4]

$$\max_{x_i} E[W_{1,i}] - \frac{1}{2}\gamma_i Var[W_{1,i}]$$
$$s.t. \;\; W_{1,i} = W_{0,i}[x_i' r_{tr} + q_i' r_{nt} + (1 + R_f)].$$

γ_i denotes the coefficient of risk aversion of agent i and $W_{1,i}$ is her wealth at the end of the period. This leads to her optimal portfolio weights:

$$x_i = \gamma_i^{-1}\Sigma_{tr}^{-1}\mu_{tr} - \Sigma_{tr}^{-1}\Sigma_{tr,nt}q_i, \tag{1}$$

[4] This utility maximization corresponds to negative exponential utility with normally distributed future wealth. Without the existence of nontradable assets the optimization problem leads to the well-known CAPM.

Equation (1) shows that an investor's fixed positions in nontradable assets affect her demand for tradable assets, which now consists of two parts. The first part is the well-known Markowitz (1959) portfolio (i.e. speculative demand). The second part is the hedging demand induced by the investor's positions in nontraded assets.

Next, I define the market portfolio as the value-weighted portfolio of all N tradable assets in the economy, with weights α. Its expected return equals $\mu_{mkt} = \alpha' \mu_{tr}$ and its variance is $\sigma^2_{mkt} = \alpha' \Sigma_{tr} \alpha$. The covariances between the tradable assets' returns and the market portfolio returns are given by the $N \times 1$ vector $\Sigma_{tr,mkt} = \Sigma_{tr}\alpha$. It is now straightforward to derive the pricing equation for the expected excess returns on the tradable assets (for details, see appendix):

$$\mu_{tr} = \bar{\gamma}\Sigma_{tr,mkt} + \bar{\gamma}\Sigma_{tr,nt} q_{nt}, \tag{2}$$

where $\bar{\gamma}$ is the market aggregate risk aversion coefficient and q_{nt} is the $K \times 1$ vector of aggregate wealth due to the nontradable assets divided by the total value of the tradable assets. This expression shows that the expected excess returns on tradable assets depend on their covariance with the tradable market portfolio returns and their covariances with the nontradable asset returns. I refer to this model as the nontradable assets model.

In fact, the second term in the pricing equation depends on the covariance with the aggregate return on all nontradable assets, in line with Mayers (1972). This follows because q_{nt} contains the relative values of the K nontradable assets. However, for nontradable assets such as human capital, it is very difficult to estimate the value. I avoid the need to directly estimate q_{nt} by including different nontradable assets in the model separately, rather than estimating the exposure to their aggregate returns. In the empirical analysis I consider industry-specific human capital. By allowing for different exposures to human capital returns from different industries, I implicitly estimate the weights of the different industries in the aggregate human capital returns.[5]

The pricing equation of the nontradable assets model can be rewritten in a more familiar beta-form, which facilitates comparisons to alternative asset pricing models. I proceed as follows. First, equation (2) must also hold for the market portfolio itself, hence

$$\mu_{mkt} = \bar{\gamma}\sigma^2_{mkt} + \bar{\gamma}\alpha'\Sigma_{tr,nt} q_{nt}.$$

The tradable assets' exposures to the market portfolio is defined as usual: $\beta_{mkt} \equiv \frac{1}{\sigma^2_{mkt}}\Sigma_{tr,m}$. This allows me to write:

$$\mu_{tr} = \beta_{mkt}\mu_{mkt} + \bar{\gamma}\left(\Sigma_{tr,nt} - \beta_{mkt}\Sigma_{mkt,nt}\right) q_{nt}, \tag{3}$$

[5] Existing papers such as Jagannathan and Wang (1996) estimate aggregate human capital returns directly, as the growth rate in aggregate labor income. However, as I argue in the next section, if returns on human capital in different industries have different characteristics, this measure is less suitable as a measure of the aggregate human capital returns. Then, it is important to consider human capital returns from different industries separately.

where $\Sigma_{mkt,nt} \equiv \alpha' \Sigma_{tr,nt}$ is a $1 \times K$ vector with covariances between the market portfolio and the K nontradable assets. This implies that for each tradable asset i the expected excess returns equal[6]

$$E[r_{tr,i}] = \beta_{mkt,i} E[r_{mkt}] + \bar{\gamma} \sum_{k=1}^{K} \left(Cov[r_{tr,i}, r_{nt,k}] - \beta_{mkt,i} Cov[r_{mkt}, r_{nt,k}] \right) q_{nt,k}. \tag{4}$$

Next, I rewrite equation (4) such that it includes $\beta_{mkt,i}$ as well as $\beta_{nt,k,i}$ that measures the exposure of asset i with respect to the returns on nontradable asset k:

$$E[r_{tr,i}] = \beta_{mkt,i} \left(E[r_{mkt}] - \bar{\gamma} \sum_{k=1}^{K} Cov[r_{mkt}, r_{nt,k}] q_{nt,k} \right) + \bar{\gamma} \sum_{k=1}^{K} \beta_{nt,k,i} Var[r_{nt,k}] q_{nt,k}, \tag{5}$$

where $\beta_{nt,k,i} \equiv \frac{Cov[r_{tr,i}, r_{nt,k}]}{Var[r_{nt,k}]}$. The expression above can be estimated using the following cross-sectional regression model:

$$E[r_{tr,i}] = c_0 + c_{mkt} \beta_{mkt,i} + \sum_{k=1}^{K} c_k \beta_{nt,k,i}. \tag{6}$$

where the intercept c_0 should be zero. $\beta_{mkt,i}$ can be estimated as the slope of an OLS regression of $r_{tr,i,t}$ on a constant and on $r_{mkt,t}$. Similarly, $\beta_{nt,k,i}$ can be estimated as the slope of an OLS regression of $r_{tr,i,t}$ on a constant and $r_{nt,k,t}$, the excess returns on nontradable asset k.[7] By estimating separate betas for the different nontradable assets, q_{nt} does not need to be estimated explicitly (assuming it is constant over time). This is an important advantage, since I use this model to examine the asset pricing implications of industry-specific human capital. This implies that in the empirical analysis I do not have to estimate the values of nontradable human capital in different industries, I only have to estimate their returns.

3 Industry-specific human capital returns

I use the model derived in Section 2 to examine the impact of industry-specific human capital on the cross-section of expected stock returns. While two other important nontradable assets are housing and private businesses, I focus on human capital only, which forms a nonnegliglible fraction of wealth for virtually all investors. Using the Survey of Consumer Finances data, Heaton and Lucas (2000) report that about 48% of household wealth is due to human capital, while 23% is due to real

[6]This expression of the nontradable assets model is similar to De Roon (2002). The nontradable assets model is also in line with certain models from the international finance literature, for instance Errunza and Losq (1985) and De Jong and de Roon (2005). In these partial segmentation models domestic investors are restricted from investing in foreign assets.

[7]Note that the cross-sectional regression coefficient c_{mkt} is an estimate of $(\mu_{mkt} - \bar{\gamma}\Sigma_{mkt,nt} q_{nt})$ and not of the market price of risk alone. It also reflects the exposure of the tradable market portfolio to the nontradable assets returns. Hence, the coefficient c_{mkt} could in principle be negative in the nontradable assets model.

estate, 4.6% is due to private businesses and only 6.8% is invested in financial assets, mostly bonds and equity. Palia, Qi and Wu (2007) empirically show that whereas all three types of nontradable assets impact households' stock market participation and stock holdings, human capital dominates. These results suggest that households do take their human capital into account in their portfolio choice decisions.

Several papers show that the risk of human capital is related to stock returns. Amongst others, Mayers (1972), Shiller (1995), Campbell (1996) and Jagannathan and Wang (1996) argue that human capital should be taken into account when measuring market returns.[8] Lustig and Van Nieuwerburgh (2006) show that innovations in human capital returns are negatively correlated with innovations in stock returns. Davis and Willen (2000) report that while human capital returns are only weakly correlated with aggregate equity returns, they are more highly correlated with equity portfolios formed on size or industry. Additionally, a number of papers show that future equity returns can be predicted using variables that are related to human capital and labor income, such as Lettau and Ludvigson (2001), Julliard (2004) and Santos and Veronesi (2006).[9]

The aforementioned papers typically consider only aggregate human capital for the economy as a whole. In reality however, human capital is investor-specific. It depends on, for instance, the investor's education, occupation, work experience, age and the sector in which he or she is employed. Heterogeneity in human capital may induce different hedging demands for stocks, for instance due to different correlations between equity returns and human capital returns. Also, it could be the case that employees with certain occupations or in certain industries are less active on the stock market. This would imply that their human capital has a smaller effect on stock returns. Or, the risk that the investor's human capital becomes obsolete due to technological developments may depend on the industry in which she works. This suggests that heterogeneity in human capital may have important portfolio implications for individual investors. Indeed, Davis and Willen (2000) show that occupation-specific human capital influences the investor's optimal portfolio choice. Fugazza, Giofré and Nicodano (2008) argue that the optimal portfolios of occupational pension funds vary substantially depending on the industry in which the members work. In this paper, I go one step further by investigating the asset pricing implications of industry-specific human capital.

I focus this particular type of heterogeneity in human capital, since it is likely to affect investors'

[8] Fama and Schwert (1977) empirically test the model of Mayers (1972), which includes nontradable human capital. They do not find a significant impact on risk premia, which they attribute to the low covariance between equity and human capital returns. This contrasts with papers such as Jagannathan and Wang (1996), and Palacios-Huerta (2003) who show that human capital does matter. Stambaugh (1982) shows that the CAPM is not very sensitive to the proxy used for the market portfolio. However, he does not investigate the inclusion of human capital returns.

[9] Papers investigating the relation between labor income risk and market returns are amongst others, Constantinides and Duffie (1996) and Heaton and Lucas (1996).

optimal stock portfolios. In the labor economics literature, several papers document the existence of significant inter-industry wage differentials (e.g. Krueger and Summers, 1988, Katz and Summers, 1989, Neal, 1995, Weinberg, 2001). This suggests that labor income and human capital are, in part, determined by industry affiliation.[10]

Returns on human capital are difficult to estimate, since only the cash flow component is observed (labor income), but not the discount rate component that is used to calculate the present value of all future labor income, i.e. the value of human capital. The literature provides several approaches for estimating returns on aggregate human capital. However, these are based on fairly restrictive assumptions on the discount rate of human capital, such as a constant discount rate (Schiller, 1995, and Jagannathan and Wang, 1996), or a perfect correlation between the discount rates on human capital and stock returns (Campbell, 1996). Lustig and Van Nieuwerburgh (2006) investigate the extent to which these models can match consumption data. They find that, according to this metric, the Jagannathan and Wang (1996) measure outperforms the other two measures.

Therefore, in order to estimate returns on human capital, I follow the approach of Jagannathan and Wang (1996). The setup is as follows. Assume that the expected rate of return on human capital is constant and labor income L_t follows a first-order autoregressive process

$$L_t = (1+g)L_{t-1} + \varepsilon_t, \tag{7}$$

where g is the average growth rate in labor income and ε_t has mean zero and is independently distributed over time. Human capital wealth is regarded as the capitalized value of all future labor income:

$$W_t^{hc} = \frac{L_t}{r-g}, \tag{8}$$

where r is the discount rate, which is assumed to be constant. Under these assumptions the return on wealth due to human capital can simply be calculated as the growth rate in labor income. Labor income data are typically published with a one-month delay. I therefore adopt the dating convention of Jagannathan and Wang (1996) and use the lagged growth rate in labor income. Furthermore, in order to diminish the influence of measurement errors, a two-month moving average of L_{t-1} is

[10] An alternative way of disaggregating human capital is by looking at age-specific human capital. However, this is more likely to have implications for the choice between the risky and the riskless assets and its effect on the choice between different risky stocks is less clear. One could also consider occupation-specific human capital. However, in the nontradable assets model one additional factor is included for each type of human capital. Occupation-specific human capital would lead to a very large number of factors. By considering industry-specific human capital for five broad industries, I am able to allow for heterogeneity, and at the same time to include the full universe of human capital assets in the asset pricing model.

used. Hence, the returns on human capital in month t are estimated as follows:

$$R_t^{hc} = \frac{L_{t-1} + L_{t-2}}{L_{t-2} + L_{t-3}} - 1. \tag{9}$$

In this setup, if human capital from different industries have the same discount rate and the same growth rate, differences in human capital wealth across industries only arise due to differences in labor income. Total human capital wealth is equal to total labor income for all industries divided by $(r - g)$. Hence, the return on aggregate human capital can simply be calculated as the growth rate in aggregate labor income. This is the approach of, amongst others, Jagannathan and Wang (1996) and Lettau and Ludvigson (2001).

However, if the discount rates and growth rates are different for different industries, total human capital wealth is affected by these differences in discount and growth rates, which are unknown. Consequently, the return on aggregate human capital can no longer be calculated as the growth rate in aggregate labor income. In this case, using the growth rate in aggregate labor income as a measure of aggregate human capital returns may make it more difficult to capture the full impact of human capital on stock returns. Therefore, I allow for industry-specific human capital and I calculate the returns on human capital for each industry separately, by taking the growth rate in labor income from that industry. Aggregating the returns on human capital over all industries should lead to a more accurate measure of aggregate human capital returns. However, as argued in Section 2, the relative values of human capital in different industries are difficult to estimate. In other words, the weights of the different types of human capital in the aggregate returns are unknown. I avoid estimating these weights by considering human capital returns from different industries separately. To compare my results to the existing literature, I consider the growth rate in aggregate labor income as well.

3.1 Income data and summary statistics

I retrieve labor income data from the National Income and Product Accounts (NIPA) tables published by the Bureau of Economic Analysis. Aggregate US labor income comes from NIPA table 2.6. Similar to Jagannathan and Wang (1996) I define labor income as per capita total personal income minus total dividends. NIPA table 2.7 provides labor income data for the following five industries: goods producing (excluding manufacturing), manufacturing, distributive industries, service industries and government.[11] The table provides wages and salary disbursements per industry,

[11] The goods producing industry includes agriculture, forestry, fishing, hunting, mining and construction. Whereas until 2000 the industries are classified according to SIC codes, as of January 2001 they are classified according to NAICS codes. NIPA table 2.7A provides data until 2000, and table 2.7B provides data starting January 2001. The following three industries have the same classification before and after 2001: goods producing excluding manufac-

which is a subset of total personal income. Hence, for industry-level human capital I define labor income as per capita total wages and salary disbursements. I calculate monthly returns on human capital in excess of the one month T-bill rate (provided by CRSP) for the full sample period, that runs from April 1959 to December 2005 (a total of 561 monthly observations).

Table 1 Panel A presents a number of descriptive statistics for the returns on human capital. Note that the average of the time series of R^{hc} should be interpreted as the average growth rate in labor income rather than as the average return on human capital, due to the assumption that labor income follows an AR(1) process. The average growth rate in aggregate labor income for the US as a whole is 0.49% and its standard deviation is 0.38%. Labor income from the service industry has the highest average growth rate (0.64%) while labor income from the manufacturing industry has the lowest average growth rate (0.31%). This is not surprising, as the service industry appears to be more human capital intensive than the manufacturing industry. The returns to human capital for the government are least volatile, while those for the goods producing and manufacturing industries are most volatile.

In order to assess whether the observed differences in human capital returns from different industries are statistically significant, I perform three Wald tests. First, I test whether the mean growth rates in labor income are jointly equal to zero. Panel A of Table 1 shows that this hypothesis can be rejected at the 1% significance level. Second, I test whether the mean growth rates in labor income are equal across industries. Even though the differences in mean growth rates may seem relatively small, this hypothesis is rejected at the 1% level. Note that the growth rates in labor income have very low volatilities, which positively affects the accuracy of the estimates of their averages. Finally, I test whether the variances of the returns on human capital are equal. I estimate the asymptotic covariance matrix of the estimated variances that is derived in Gerard *et al.* (2006). I find that this hypothesis can be rejected at the 1% level. In sum, the means and variances of the returns on human capital differ across industries. Panel B reports the unconditional correlation matrix of the excess human capital returns. It shows that human capital returns from different industries typically exhibit significant positive correlations, ranging from 0.03 (between services and government) to 0.72 (manufacturing and distribution).

In sum, a preliminary look at the data reveals that human capital returns from different industries have different characteristics. This may have important portfolio and asset pricing implications. I start with an analysis of (some of) the portfolio implications.

turing, manufacturing and government. I match distributive industries (until 2000) with trade, transportation and utilities (after 2000) and service industries (before 2000) with other service-producing industries (after 2000).

3.2 Hedging demand due to human capital

This section empirically investigates the hedging demand for stocks that arises due to investors' nontradable human capital. This is a first step in the analysis of the impact of industry-specific human capital on equity returns. Expression (1) shows that the hedging portfolio weights of investor i are given by $-\Sigma_{tr}^{-1}\Sigma_{tr,nt}q_i$. When stock returns and human capital returns are positively correlated, stocks receive negative weights in the hedging portfolio. In other words, investors are endowed with initial exposures to those stock returns due to their nontradable human capital. Hence, in order to achieve their desired exposures, they underweight those stocks in their optimal portfolios. The effect of human capital on the composition of the optimal stock portfolio increases with the fraction of the investor's wealth that is due to human capital, q_i.

A natural set of equity portfolios for analyzing the hedging demand due to industry-specific human capital are industry equity portfolios. I download monthly returns on 30 US industry equity portfolios from French's website and I calculate excess returns by subtracting the one-month T-Bill rate. Part of the expression of the hedging portfolio weights, $\Sigma_{tr}^{-1}\Sigma_{tr,nt}$, can be estimated by regressing the excess returns on human capital (aggregate or industry-specific) on a constant and the excess returns on the 30 industry equity portfolios. The regression coefficients of this multivariate regression can be used to calculate the weights of the hedging portfolio. I multiply the coefficients with -1, and consequently, I estimate the hedging portfolio weights up to q_i.

Table 2 reports the results. The estimated weights are multiplied by 10^2 and they have a straightforward interpretation. Consider a young investor. She typically has little financial wealth and the main part of her wealth is due to her human capital. Hence, for this type of investor q_i will be close to one. If the investor works in the manufacturing industry, the optimal portfolio should be adjusted for her human capital as follows. For instance, stocks from the steel works industry should be underweighted by 2.47% and stocks from the retail industry should be overweighted by 2.30%. In fact, the column with hedging portfolio weights can be seen as the adjustments that an industry pension fund should incorporate for its members' human capital. Older investors typically have a lower q_i as a larger fraction of their wealth is usually invested in stocks. Their human capital will have fewer portfolio choice implications. If the same investor would have 50% of her wealth invested in stocks and 50% due to her human capital, she should only overweight the retail industry stocks by 1.15%. Young investors generally have a high hedging demand and little financial wealth, and they will want to borrow against the risk free rate in order to invest in stocks for speculative and hedging reasons.

The bottom row of the table reports the sum of the absolute values of the hedging portfolio weights. This ranges from 14.54% (for human capital from the government) to 31.22% (goods producing industry). For aggregate human capital returns the sum of absolute hedging portfolio weights is 17.29%. This suggests that investors' nontradable human capital can substantially change the composition of their optimal equity portfolios.

The table shows that next to their economic significance, the portfolio adjustments for investors' nontradable human capital are statistically significant as well. The p-values on the one but last row indicate that the null hypothesis that all hedging portfolio weights are equal to zero can be strongly rejected (at the 1% level) for aggregate human capital returns as well as human capital from all industries, except for the government. In addition, for all types of human capital, various individual hedging portfolio weights are significantly different from zero. This suggests that human capital has an important effect on optimal portfolio choice. Among the industry equity portfolios that most often have a significant weight in the hedging portfolio are steel works, petroleum and gas, and utilities.

Furthermore, the table shows that a hedging portfolio based on aggregate human capital returns (i.e. the growth rate in aggregate labor income) can be quite different from a hedging portfolio based on industry-specific human capital returns. (For ease of comparison, I assume $q = 1$ when discussing these results.) For instance, when considering aggregate human capital returns, stocks from the mining industry have an estimated weight of 0.49% in the hedging portfolio, which is statistically insignificant. On the other hand, in the hedging portfolios for human capital from the manufacturing and service industries, mining stocks have weights of 1.38% and 1.63% respectively, which are both highly statistically significant.

Furthermore, Table 2 illustrates that the hedging demand induced by human capital is indeed industry-specific. Consider the following striking example. An investor who works in the goods producing industry should adjust her optimal stock portfolio for her human capital by downweighting stocks from her own industry, fabricated products, by 5.43% (significant at the 1% level). On the other hand, an investor working in the service industry should overweight stocks from the fabricated products industry by 1.02% (which is statistically insignificant).

The nontradable assets model from Section 2 shows that the impact of human capital from a certain industry on the cross-section of expected stock returns depends, amongst others, on q_{nt}, the aggregate wealth that is due to human capital from that industry (over the value of all tradable assets). q_{nt} is very difficult to estimate, which is an important reason for focusing on industry-specific human capital. However, to gain some very preliminary insights in the relative human capital wealth in different industries, I perform a simple back-of-the-envelope calculation. NIPA tables 6.5 and 6.6 report the annual number of employees in the different industries (full time equivalent workers and self-employed persons). I calculate the average number of workers in each industry between 1959 and 2005, as a percentage of the total average number of employees.

Unreported results show that on average 28% of all workers are employed in the service industry, 26% in the distributive industry, 20% in the manufacturing industry, 16% works for the government and 10% works in the goods producing industry.[12] Note that the five industries under consideration are broad and none of them seems to be negligible in terms of human capital wealth. Hence, from these results it is difficult to infer which human capital industries will matter most for asset pricing. However, these back-of-the-envelope calculations suggest that human capital wealth varies across industries. In the next section I examine how industry-specific human capital affects the cross-section of expected stock returns.

4 Industry-specific human capital and the cross-section of stock returns

The results from the previous section show that human capital returns from different industries have different characteristics and they result in different hedging portfolios. This section goes one step further by testing the asset pricing implications of industry-specific human capital, using the nontradable assets model derived in Section 2. Moreover, I compare this model to various alternative asset pricing models, such as the Fama and French (1993) three-factor model.

I estimate these asset pricing models for three sets of equity portfolios. First, I consider 25 size – idiosyncratic risk sorted portfolios. I use these as the main test assets, because in Section 6 I examine how the cross-sectional relation between stocks' idiosyncratic volatilities and their expected returns is affected by human capital. In other words, for this research question I am specifically interested in the ability of the nontradable assets model with industry-specific human capital to capture the returns on stocks that have been sorted based on their idiosyncratic volatilities. Next, in a robustness check, I estimate all models for two alternative sets of portfolio returns, consisting of 25 size – book to market portfolios and 30 industry portfolios. In a first stage I estimate the time series human capital betas and I examine their significance. Then, using the Fama MacBeth (1973) approach, I perform cross-sectional regressions.

Before estimating the models, I first discuss the characteristics of the 25 size-idiosyncratic risk

[12] Alternatively, I calculate the average labor income over the full sample period for each industry, as a percentage of total average labor income. Under the stringent assumption that the discount rate and the growth rate of labor income are the same for all industries, differences in q_{nt} across industries stem from differences in the labor income in those industries (assuming that labor income follows an AR(1) process). The results are similar to those based on the number of workers: human capital from the service industry forms the largest fraction of total wealth due to human capital: 34%. Next are the distributive industry (22%), the manufacturing industry (19%) and the government (18%), and the goods producing industry (7%).

(size-IR) sorted portfolios. In order to construct their monthly returns, I use all common shares (excluding financial firms) traded on the NYSE, AMEX and NASDAQ from the return files of the Center for Research in Security Prices (CRSP) from April 1959 to December 2005. Idiosyncratic volatility is specified as the residual volatility of the market model, which I estimate using an Exponential GARCH model (Bollerslev, 1986, Nelson, 1991). Spiegel and Wang (2005) and Fu (2007) show that the EGARCH estimates outperform the simple moving window OLS estimates in forecasting realized idiosyncratic volatility for the current month. Similar to Fu (2007) I estimate an EGARCH model for every stock, using all available monthly returns, with a minimum of 60 return observations. Then, for a given month, I first sort the stocks into size quintiles, based on their market capitalization at the beginning of the month. I use five size groups in order to ensure that there is a sufficient number of stocks in each portfolio. Within each size group I sort stocks into idiosyncratic volatility quintiles, based on their idiosyncratic volatility for the current month. I calculate the 25 value-weighted portfolio returns and subtract the one-month T-Bill rate.[13]

Sorting stocks into 25 size-IR portfolios leads to substantial variability in the portfolio characteristics. Table 3 shows that the time series average excess returns range from -0.12 (S1-IR1; the small size - low IR portfolio) to an impressive 4.66 percent per month of the S1-IR5 portfolio. The standard deviation of the portfolio returns ranges from 3.65% per month (S5-IR1) to 13.54% per month (S1-IR5). Portfolios with higher idiosyncratic risk stocks typically have higher market betas. One portfolio clearly stands out: the small size - high IR portfolio. It has a remarkably high average return of 4.66% and it is the most volatile portfolio. Its size does not differ much from the average sizes of the other four portfolios in the same size quintile. Related papers, such as Spiegel and Wang (2005) and Fu (2007) show similar large returns for portfolios consisting of small size and high IR stocks. In the robustness checks I redo the analysis excluding this extreme portfolio.

4.1 Time-series human capital betas

Before performing cross-sectional asset pricing tests, I first test the significance of the time series human capital betas. Kan and Zhang (1999) show that when the asset pricing model is misspecified, betas with respect to useless factors (i.e. factors that have zero covariance with all asset returns)

[13]Since the EGARCH model is estimated over the full sample period, the 25 size-IR portfolios do not form a true trading strategy. This could be solved by estimating the EGARCH model for each stock for each month, using all returns prior to that month (as in Spiegel and Wang, 2005). However, this would require the estimation of a much larger number of EGARCH models. Also, the main purpose of the 25 size-IR portfolios is to test the nontradable asset model and not to design a trading strategy based on idiosyncratic volatility. In Section 5 I test the model for other sets of portfolio returns that are based on true trading strategies.

can still be significantly priced in the cross-sectional regressions.[14] They argue that it is important to first investigate whether the human capital betas are statistically different from zero, before including them in the cross-sectional regression model.

I estimate human capital betas for each of the 25 size-IR sorted portfolios, based on multiple univariate regressions over the full sample period. Table 4 reports the results. Section 6 discusses the individual betas in Panel A in greater detail, as they reveal a relation between idiosyncratic risk and exposure to human capital returns. In this section I merely focus on their joint significance (Panel B). In order to determine whether a factor is useless, I perform two types of Wald tests. First, I test whether the exposures to this factor are jointly equal to zero for all 25 portfolios. Then, I test whether the exposures are all equal for the 25 portfolios, since that would take away any power the factor might have in explaining the cross-sectional variation in expected returns. The null hypotheses can be rejected for all types of human capital (at the 1% level, and for the goods producing industry at the 10% level). This implies that the aggregate as well as all five industry-specific human capital factors are unlikely to be useless. Hence, I proceed by including them in the cross-sectional regressions.

4.2 Cross-sectional regressions

In the cross-sectional asset pricing tests, I compare the performance of the nontradable assets model with industry human capital to four well-known asset pricing models. Before going to the results, I briefly discuss these four alternative models. First, I estimate the well-known Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner(1965a) and Black (1972). The static CAPM only includes the beta with respect to the tradable market portfolio.

$$E[r_i^{tr}] = c_0 + c_{mkt}\beta_{mkt,i} \tag{10}$$

Second, I consider the so-called human capital CAPM in which the CAPM is extended with one additional factor: the returns on aggregate human capital (Jagannathan and Wang, 1996). The cross-sectional regression model is:

$$E[r_i^{tr}] = c_0 + c_{mkt}\beta_{mkt,i} + c_{US}^{hc}\beta_{US,i}^{hc}, \tag{11}$$

where $\beta_{mkt,i}$ is defined as usual and $\beta_{US,i}^{hc}$ is estimated as the slope coefficient of an OLS regression of the returns on portfolio i on a constant and the growth rate in aggregate labor income. While expression (11) is similar to eq. (6) of the nontradable assets model (when $M = 1$, the cross-sectional regressions are exactly the same), the two models have different backgrounds. In contrast

[14] The reason is that the true betas are zeros and hence, the true risk premium for these useless factors is undefined. Kan and Zhang (1999) show that as the estimated betas go to zero, the estimated risk premium goes to infinity.

to the nontradable assets model, the human capital CAPM assumes human capital is tradable. As such, it should be included in the market portfolio and the CAPM should hold with respect to this total market portfolio. However, the market portfolio returns cannot be calculated as the weight of aggregate human capital is unknown. The human capital CAPM assumes that this weight is constant over time and includes returns on aggregate human capital as an additional factor, next to the returns on the market portfolio of stocks. In the nontradable assets model, additional factors arise due to hedging demand induced by investors' endowments in nontradable human capital.

The third alternative model that I consider is the conditional CAPM. Jagannathan and Wang (1996) show that when betas and expected returns vary over time, the conditional CAPM can be written as an unconditional multi-factor model that includes the market beta and a so-called premium beta, that measures the beta-instability risk.

$$E[r_i^{tr}] = c_0 + c_{mkt}\beta_{mkt,i} + c_{prem}\beta_{prem,i} \tag{12}$$

$\beta_{prem,i}$ is estimated as the slope coefficient of an OLS regression of the excess returns on a constant and on the lagged yieldspread between Moody's BAA and AAA rated corporate bonds, which can be downloaded from the Federal Reserve Bulletin.

Last, I compare the nontradable assets model to the Fama and French (1993) three-factor model (referred to as FF3), based on the following cross-sectional regression model:

$$E[r_i^{tr}] = c_0 + c_{mkt}\beta_{mkt,i} + c_{smb}\beta_{smb,i} + c_{hml}\beta_{hml,i}, \tag{13}$$

where $\beta_{smb,i}$ is estimated as the slope coefficient of a univariate regression of the portfolio returns on a constant and the Fama and French (1993) size factor SMB. $\beta_{hml,i}$ is estimated similarly, using the value factor HML. I download SMB and HML from French's website.

This section evaluates the relative performance of the nontradable assets model with industry human capital with respect to these four asset pricing models. I test all models using the Fama-MacBeth (1973) two-stage approach. The betas used for the cross-sectional regressions are all based on univariate time series regressions. This facilitates the comparison of different model specifications, as the beta estimates do not change when a factor is added. Moreover, the test of this model can be interpreted a test with the null hypothesis that the CAPM holds, i.e. the tradable market portfolio is mean-variance efficient. If this is correct, additional factors should not matter (Chen, Ross and Roll, 1986).

Table 5 reports the results of the estimation of the different models for the monthly excess returns on 25 size - idiosyncratic risk sorted portfolios. It gives the estimated cross-sectional regression coefficients and the corresponding t-values. The t-values have been adjusted for estimation error in the first-stage univariate betas using the Jagannathan and Wang (1996 and 1998a) adjustment. The table also reports the cross-sectional regressions' OLS adjusted R^2s. In addition, I report the GLS R^2 as an alternative measure of model fit. Kandel and Stambaugh (1995) and Lewellen, Nagel and Shanken (2006) argue that it is much more difficult to find a high GLS R^2 than a high OLS R^2. The GLS R^2 is related to a factor's or factor mimicking portfolio's (in case of non-return factors) proximity to the minimum-variance boundary. If a factor or factor mimicking portfolio is nearly mean-variance efficient, the GLS R^2 is close to one, while the OLS R^2 can have almost any value. On the other hand, the OLS R^2 has the straightforward interpretation of the model's ability to explain the expected returns on the test assets. Also, since the GLS R^2 requires an estimation of the returns covariance matrix, the precise finite sample properties are unknown. Hence, I use both the OLS and GLS R^2s as complementary measures of model fit.[15]

Panel A shows that for the static CAPM the estimated market price of risk c_{mkt} is quite large, 0.014, and it is statistically significant. The cross-sectional OLS adjusted R^2 is 19% and the GLS R^2 is much lower, 5%. The estimate of the intercept is significantly negative, while according to economic theory c_0 should be zero in this model that is estimated for excess returns. Next, I consider the human capital CAPM in which aggregate human capital returns are included as a second factor. The estimate of c^{hc}_{US} is 0.0048 and it is significant at the 1% level. Moreover, the estimate of c_{mkt} is 0.0062 and is positive and significant. Also, the intercept is insignificant. The OLS R^2 increases to 27% when aggregate human capital is included in the model and the GLS R^2 increases to 16%. In sum, the human capital CAPM clearly outperforms the static CAPM.

Panel B reports the estimates of the main model of interest: the nontradable assets model with industry-specific human capital. I find that the coefficients for all human capital industries, except for the government, are significant at the 1% level. The coefficients are quite large, ranging from -0.0311 (goods producing) to 0.0287 (service industry). Note that many human capital betas are relatively low, as can be seen in Table 4. The model is able to capture a striking 85% of the cross-sectional variation in expected returns. Also, the GLS R^2 increases to 40% suggesting that the combination of the returns on the tradable market portfolio and industry human capital returns lies closest to the minimum variance boundary. Although the R^2s have been adjusted for the degrees of freedom, to a certain extent one would expect to find a higher R^2 for a model that includes a larger number of factors. The model's intercept is significantly negative, which is further investigated in

[15] For model comparison, I compute R^2s that are adjusted for the different degrees of freedom. Nevertheless, these R^2s might still be affected by the fact that some models include a larger number of factors. Therefore, in future research I plan to simulate the distribution of the OLS R^2 for different numbers of (random) factors. This allows me to formally examine to what extent a higher R^2 for a model with more factors can be attributed to a better ability of the model to capture the cross-section of expected returns.

the robustness check in Section 5. The estimate of c_{mkt} is negative and insignificant. However, expression (5) shows that this coefficient represents the market price of risk minus the covariance between the market portfolio returns and the aggregate nontradable asset returns. Therefore, in theory, c_{mkt} can be negative. In the robustness check I show that when the small size - high IR portfolio is excluded, c_{mkt} become positive.

Panels C and D confirm the well-known results that the conditional CAPM and the FF3 model outperform the static CAPM. The cross-sectional regression coefficients with respect to the premium beta of the conditional CAPM (c_{prem}) and the coefficients with respect to the size and value factors of the FF3 model (c_{smb} and c_{hml}) are all significantly different from zero. Also, the models exhibit higher OLS R^2s (55% and 37%) than the static CAPM and they have higher GLS R^2s as well. However, for both models the intercept is significantly negative and the market price of risk is insignificant in the FF3 model. In terms of R^2s these models outperform the human capital CAPM, but not the nontradable assets model with industry-specific human capital.

Next, I include aggregate and industry-specific human capital in the conditional CAPM and the FF3 model. This is to see whether the yieldspread and size and value factors affect the explanatory power of aggregate and industry-specific human capital. The results are also presented in Panels C and D of Table 5. I find that the coefficient of aggregate human capital loses significance when the yieldspread is included in the model as well[16]. It becomes negative and significant when the size and value factors are included in the model. In this model specification, the value factor c_{hml} becomes statistically insignificant. On the other hand, the coefficients of all five industry human capital factors are highly significant when they are added to the conditional CAPM or FF3 model. Whereas c_{prem} remains significant after the inclusion of industry-specific human capital, the estimates of both c_{smb} and c_{hml} become insignificant. This suggests that industry-specific human capital takes away the explanatory power of the size and value factors. While this confirms the outperformance of the industry human capital CAPM, the results should be interpreted with caution, given the large number of factors in this model specification.

Note that the measure that I use for the returns on human capital, the growth rate in labor income, assumes a constant discount rate. When the yieldspread is added as an additional variable in the regressions, it could also be interpreted as a control variable for changes in the discount rate. Hence, the finding that the industry human capital coefficients remain significant after including the yieldspread suggests that the importance of industry human capital is, at least to a certain extent, robust for changes in the discount rate.

In sum, these cross-sectional regressions show that industry-specific human capital affects the

[16] This contrasts the results of amongst others Jagannathan and Wang (1996) who report significant coefficients. Note that they test the model for a different set of portfolios, namely 100 size-beta sorted portfolios.

cross-section of expected stock returns. The nontradable assets model including industry human capital outperforms the four benchmark models, and in particular, it outperforms the human capital CAPM that includes the growth rate in aggregate labor income.

4.3 Pricing errors

In this section I take a further look at the pricing errors of the models. Figure 1 shows scatterplots of the average realized excess returns versus the fitted expected excess returns for the 25 size-IR sorted portfolios. This figure provides a visual impression of the model fit. If all points would be on the 45 degree line through the origin, the model would correctly price all portfolios. The plots also report the average absolute pricing error (denoted by a.a.p.e.). This is calculated as the average of the absolute differences between the average realized excess return and the fitted expected excess return, which is based on the estimated parameters of the cross-sectional regression models.

First, I evaluate the pricing errors of the four alternative models, then I compare those to the nontradable assets model with industry human capital. The figure confirms the inadequacy of the static CAPM. Many points are quite distant from the 45 degrees line. One portfolio in particular, the S1-IR5 portfolio, has a very large pricing error, more than 3%. The average realized excess return of this portfolio is 4.66%, as can also be seen in Table 2. The dramatic failure of the CAPM to price this portfolio is precisely related to the apparent premium for idiosyncratic risk. I further investigate this in Section 6 of the paper. The a.a.p.e. of the static CAPM is 0.40%. Next, I examine the pricing errors of the human capital CAPM, including aggregate human capital. Whereas in terms of R^2 this model outperforms the static CAPM, it leads to similar or even larger pricing errors. The pricing error for the S1-IR5 portfolio is still very large, namely 2.9%. The a.a.p.e. is even slightly larger than for the static CAPM, it is 0.43%. The average absolute pricing errors for the conditional CAPM and the FF3 model have similar magnitudes, they are 0.35% and 0.42% respectively. These two models also have difficulties in pricing the S1-IR5 portfolio; the pricing errors are 2.2% and 2.5% respectively.

The nontradable assets model with industry human capital clearly outperforms these four models in terms of pricing errors. The scatterplot shows that the points are substantially closer to the 45 degree line than for the other models. Also, this model does a remarkably good job in pricing the S1-IR5 portfolio. The pricing error is only 0.6%. The a.a.p.e. is 0.22% and is almost twice as low as the average absolute pricing errors of the other models. In the robustness check I redo the analysis excluding the S1-IR5 portfolio.

5 Robustness check

5.1 Excluding the small size - high IR portfolio

The first robustness check concerns the small size - high IR portfolio. As discussed in the previous section, this portfolio has the smallest average size, the highest standard deviation of returns and in particular, it has an extreme average excess return of 4.66% per month. Section 4 also showed that, except for the nontradable assets model with industry human capital, all alternative models have severe difficulties with pricing this portfolio. In order to examine to what extent the outperformance of the nontradable assets model is due to its superior ability to price the S1-IR5 portfolio, I exclude this portfolio and perform the Fama-MacBeth regressions and the calculations of the pricing errors for the remaining 24 size-IR portfolios.

The results of the Fama-MacBeth regressions can be found in Table 6, Panel A. The R^2s of the four benchmark models all increase compared to Table 5. On the other hand, for the nontradable asset model with industry-specific human capital R^2s are slightly lower than before. Nevertheless, the model's outperformance is robust. Although the OLS adjusted R^2 of the conditional CAPM is slightly higher (75% versus 74%), the GLS R^2 of the nontradable assets model is higher than those of the alternative models. Whereas the intercept is significantly negative, the estimate of c_{mkt} is significantly positive and the four industry human capital factors remain significant, with the same signs and magnitudes. On the other hand, the aggregate human capital factor of the human capital CAPM is now insignificant, with a t-value of 1.10. The size factor of the FF3 model loses its statistical significance as well and both the conditional CAPM and the FF3 model have significantly negative intercepts. Note that the estimate of c_{mkt} is positive and (at least marginally) significant for all models. This suggests that the negative estimates of c_{mkt} that are reported in Table 5 could be due to the extreme S1-IR5 portfolio. The nontradable assets model again has the lowest average absolute pricing error: 0.12%. The static, human capital and conditional CAPM have average absolute pricing errors of 0.19%, 0.20% and 0.16% respectively. The FF3 model has an a.a.p.e. of 0.18%. In sum, the outperformance of the nontradable assets model with industry-specific human capital is not only due to its ability to price the extreme small size - high IR portfolio.

5.2 Restrictions on the zero beta rate

The nontradable assets model that is derived for excess returns does not include an intercept, since it implicitly assumes that the riskless borrowing and lending rates are the same and equal to the one-month T-Bill rate. In other words, the zero-beta rate should equal the risk free rate. The same holds for the benchmark models that do not include intercepts either.[17] However, as discussed in the previous section, the estimated intercepts of all models, except for the human capital CAPM, are significant and negative. Therefore, in this robustness check I impose restrictions on the intercepts of the cross-sectional regressions of all models, using restricted least squares.

Table 6 Panel B reports the results for the 25 size-IR portfolios. Both the static and human capital CAPM have significant and positive estimates of c_{mkt}. Also, the aggregate human capital factor remains significant. In contrast, the estimates of the c_{mkt} coefficient for the other three models are negative and insignificant. For the nontradable assets model with industry human capital it is only marginally significant, with a t-value of -1.79. Unreported results show that when the extreme small size - high IR portfolio is removed from the regression, the coefficient becomes positive but insignificant. The coefficients of two industry human capital factors are significant and their magnitudes are similar to those of the unrestricted regressions. The cross-sectional OLS adjusted R^2 remains 85% which is higher than for the other models. Note that the R^2 of the human capital CAPM with aggregate human capital is only 26%. In general, these results support the finding that a model with industry-specific labor income growth rates better captures the cross-section of expected stock returns than a model with growth rates in aggregate labor income.

5.3 An alternative measure of human capital returns

So far, I have estimated returns on human capital following Jagannathan and Wang (1996) as the lagged growth rate in per capita labor income (which I will refer to as "JW timing"). The one-month lag is implemented, because labor income data are typically published with a one-month delay. However, the hedging demand of an individual investor is determined by her own human capital. Each investor can observe his or her own labor income for the current month, suggesting that the one-month lag may not be desirable when measuring returns on human capital. This is also noted by Heaton and Lucas (2000), who adjust the timing of the Jagannathan and Wang (1996) measure. With contemporaneous timing, returns on human capital are calculated as:

$$R_t^{hc} = \frac{L_t + L_{t-1}}{L_{t-1} + L_{t-2}} - 1. \qquad (14)$$

Again, I use a two-month moving average to correct for estimation error in the labor income data.

[17] Jagannathan and Wang (1996) derive the conditional CAPM and the human capital CAPM allowing for differences between borrowing and lending rates. If these are different, the zero-beta rate should lie in between the two and the intercept in the regression for excess returns should reflect the difference between the average zero-beta rate and the average T-Bill rate. Hence, in their setup the regressions for the human capital and conditional CAPM can have nonzero intercepts. However, when the borrowing and lending rates are assumed to both equal the T-Bill rate, the intercepts should be zero in these two models as well.

I estimate the human capital CAPM with aggregate human capital and the nontradable assets model with industry-specific human capital using this alternative measure for human capital returns. Table 6 Panel C reports the estimation results for 25 size-IR portfolios. While the estimated coefficient for aggregate human capital is insignificant (the adjusted $t-$value is 1.28), it is statistically significant for three out of the five human capital industries, thereby supporting the nontradable assets model. The magnitudes of the coefficients are lower than with the Jagannathan and Wang (1996) measure of human capital returns. Heaton and Lucas (2000) also find that the returns on aggregate human capital seem to be relatively sensitive to the timing issue. This panel confirms the importance of allowing for industry-specific rather than aggregate human capital. The OLS and GLS R^2s are 16% and 35% for the human capital CAPM. For the nontradable assets model they are remarkably higher: 85% and 52%. In sum, the finding that the industry-specific human capital matters is robust for contemporaneous timing of human capital returns.

5.4 Alternative equity portfolios as test assets

So far, all tests have been performed using monthly returns on 25 size – idiosyncratic risk sorted portfolios. As a robustness check, I test the models for two additional sets of portfolio returns. In particular, I use the well-known 25 size – book to market (size-BM) portfolios, downloaded from Kenneth French's website. The portfolio returns are constructed as in Fama and French (1992, 1993). These portfolios are known to have a strong factor structure, which can lead to a good model fit when using any set of factors that are sufficiently correlated with the size and value factors (Lewellen, Nagel and Shanken, 2006). Therefore, I also use a third set of test assets consisting of both the 25 size-BM portfolios and 30 industry portfolios (from French's website).

Table 7 Panel A reports the results for 25 size-BM portfolios. Similar to the results in Table 5, the static CAPM delivers the worst performance. The OLS and GLS R^2s are lowest and the market price of risk is insignificant. The coefficient for aggregate human capital in the human capital CAPM is marginally significant and the OLS R^2 is slightly higher compared to the static CAPM; 16% versus 10%. The GLS R^2s are similar, 12%. Next, the nontradable assets model with industry-specific human capital outperforms these two models. Three out of the five industry human capital betas are significant and the OLS and GLS R^2s are higher, 46% and 22%. This confirms that allowing for heterogeneity in human capital improves the model performance compared to including only aggregate human capital. However, whereas the nontradable assets model seems to outperform the four benchmark models for 25 size-IR portfolios, for the 25 size-BM portfolios the conditional CAPM shows a similar performance. The FF3 model seems to capture the cross-section of expected returns best, with OLS and GLS R^2s of 73% and 33% respectively. Note that all five models have significant positive intercepts and, except for the static CAPM, have significant negative estimates of c_{mkt}. Unreported results show that when the intercept is restricted to zero, the estimates of c_{mkt} become positive and significant for all models, except for the conditional CAPM for which the coefficient is negative but insignificant.

The results for the combined set of 25 size-BM and 30 industry portfolios are presented in Panel B. The cross-sectional R^2s of all models are substantially lower than in Panel A, suggesting that it is more difficult to capture the cross-sectional variation in expected returns of these 55 portfolios. The static, human capital and conditional CAPM models display very poor performances. The market price of risk is insignificant and the aggregate human capital beta and the premium beta are statistically insignificant as well. The cross-sectional R^2s are very close to zero or even slightly negative. The nontradable assets model shows a better performance. Three out of the five industry betas are significant and the OLS and GLS R^2s are 9% and 8%. Nevertheless, the FF3 model performs best in terms of R^2s (27% and 13%) and whereas the value factor is insignificant, the size factor is significant. Again, when the intercept is set equal to zero, the estimates of c_{mkt} become positive and significant for all model specifications (these results are not reported).

Unreported results show that the FF3 model has the lowest a.a.p.e. for both sets of portfolios. The conditional CAPM and the nontradable assets model with industry human capital have similar pricing errors. The pricing errors of the human capital CAPM and the static CAPM are highest.

In conclusion, the nontradable assets model with industry-specific human capital outperforms the static and human capital CAPM for these alternative portfolio returns. It shows similar performance as the conditional CAPM. The FF3 model best captures the returns on these equity portfolios. These results support the main finding that it is important to consider industry-specific rather than aggregate growth rates in labor income in an asset pricing model.

6 Human capital and the premium for idiosyncratic risk

In the previous two sections I examined the asset pricing implications of industry-specific human capital, corresponding to the first main research question of the paper. The current section deals with the second research question of the paper; I link human capital to the apparent relation between stocks' idiosyncratic volatilities and their expected returns that is documented in the literature.

According to modern portfolio theory, investors should not receive a compensation for stocks' idiosyncratic risk, since this can be diversified away by investing in a portfolio of stocks. The CAPM shows that in perfect and frictionless markets all investors hold the market portfolio. In this setup the market portfolio captures all systematic risk, and idiosyncratic risk with respect to this portfolio does not affect expected returns.

However, various empirical papers report evidence of a cross-sectional relation between idiosyncratic risk (measured as the residual volatility of the market model or FF3 model) and expected returns. Amongst others, King, Sentana and Wadhwani (1994), Malkiel and Xu (1997 and 2004), Spiegel and Wang (2005), and Fu (2007), find a positive relationship. This is in line with theoretical models of Levy (1978), Merton (1987), and Malkiel and Xu (2004) in which investors face certain market frictions (e.g. transaction and information costs).[18] Due to these frictions, investors underdiversify, leading to a positive premium for idiosyncratic risk.

Two recent empirical papers that have received a lot of attention are Ang, Hodrick, Xing and Zhang (2006) and (2008). Their results show that stocks with higher idiosyncratic volatilities earn lower expected returns, suggesting a negative relationship between expected returns and idiosyncratic risk. They measure idiosyncratic volatility as the residual volatility of the FF3 model, using daily data over the past month. Bali and Cakici (2008) report that the sign and magnitude of this effect depend heavily on data frequency, portfolio weighting schemes and portfolio breakpoints. Fu (2007) shows that Ang *et al.*'s measure of lagged idiosyncratic volatility is not a good measure for expected idiosyncratic volatility, because of its time-varying nature. Similar to Spiegel and Wang (2005), he uses an EGARCH model to estimate expected idiosyncratic volatility and reports a positive relationship with expected returns.

Testing whether idiosyncratic risk, measured as the residual volatility of a certain model, is priced can be interpreted as a test of model misspecification. If the model captures all systematic risk, residual volatility should not affect expected returns.[19] However, if the model fails to capture all systematic risk, part of that risk may end up in the error term and the resulting idiosyncratic risk may appear to be priced. The previous sections in this paper show that human capital affects expected returns. Therefore, a natural next question is: what happens if we ignore human capital in the asset pricing model? Could this induce a relation between the model's residual volatility and expected returns? In this section I first use the nontradable assets model to demonstrate this theoretically. Then, I investigate empirically how the apparent premium for idiosyncratic risk is related to nontradable human capital.

[18] Other related models are by Hirshleifer (1988) who considers trading costs and Petajisto (2004) who incorporates active management fees.

[19] This argument can also be made when investors underdiversify, for instance, due to transaction costs. If the model appropriately incorporates these market frictions, idiosyncratic risk with respect to the adjusted measure of systematic risk should not affect expected returns.

6.1 Idiosyncratic risk in the nontradable assets model

The pricing equation of the nontradable assets model, equation (3), can be written as follows:

$$\mu_{tr} = \beta_{mkt}\mu_{mkt} + \bar{\gamma}\left(I_N - \beta_{mkt}\alpha'\right)\Sigma_{tr,nt}q_{nt}, \tag{15}$$

where I_N is an $N \times N$ identity matrix. Without nontradable assets, the second factor would disappear and we end up with the CAPM. If the CAPM would be used to estimate expected excess returns, the resulting idiosyncratic (residual) variance equals:

$$\begin{aligned}\Sigma_\varepsilon &= \Sigma_{tr} - \beta_{mkt}\sigma^2_{mkt}\beta'_{mkt} \\ &= (I_N - \beta_{mkt}\alpha')\Sigma_{tr}.\end{aligned}$$

In the absence of nontradable assets, the market portfolio is an appropriate benchmark for measuring systematic risk and Σ_ε is the true idiosyncratic risk, which does not affect expected returns. However, in the presence of nontradable assets, the CAPM does not capture all systematic risk and Σ_ε contains systematic risk due to nontradable assets. Consequently, Σ_ε affect expected returns. This can be seen by substituting $(I_N - \beta_{mkt}\alpha')$ by $\Sigma_\varepsilon\Sigma_{tr}^{-1}$ in equation (15):

$$\begin{aligned}\mu_{tr} &= \beta_{mkt}\mu_{mkt} + \bar{\gamma}\Sigma_\varepsilon H \qquad (16)\\ \text{where } H &= \Sigma_{tr}^{-1}\Sigma_{tr,nt}q_{nt}\end{aligned}$$

H is the value-weighted average hedge demand of all investors and $\bar{\gamma}$ is the aggregate market risk aversion. This alternative specification of the nontradable asset model shows that expected returns are affected by the CAPM residual risk, depending on the hedging demand induced by nontradable assets.

Note that I only include tradable assets in the market portfolio. Roll (1977) argues that the market portfolio (that is part of the CAPM) should include all risky assets in the economy. However, this is based on the assumption that all assets are tradable. It is straightforward to show that when all tradable and nontradable assets are included in the total market portfolio, expected excess returns are affected only by their covariance with the returns on this total market portfolio and any residual risk is not priced. However, this model cannot be written as a beta relationship with respect to the total market portfolio returns, because the total market portfolio includes nontradable assets.

In order to empirically investigate the link between idiosyncratic risk and nontradable assets, it is convenient to express the model as follows (this can also be seen from eq. (4)):

$$\begin{aligned}E[r_{tr,i}] &= \beta_{mkt,i}E[r_{mkt}] + \bar{\gamma}\sum_{k=1}^{K}\left(Cov[r_{tr,i}, r_{nt,k}] - \beta_{mkt,i}Cov[r_{mkt}, r_{nt,k}]\right)q_{nt,k} \\ &= \beta_{mkt,i}E[r_{mkt}] + \bar{\gamma}\sum_{k=1}^{K}Cov[e_i, r_{nt,k}]q_{nt,k}. \qquad (17)\end{aligned}$$

Equation (17) explicitly shows how the idiosyncratic return with respect to the CAPM (or market model) can enter the pricing equation, depending on its covariance with the returns on the nontradable assets. The apparent premium for idiosyncratic risk increases when the CAPM residual return for asset i is more highly correlated with the return on the nontradable assets.

Equation (17) can be estimated using cross-sectional regressions. In a first stage, I regress excess returns on stock i on a constant and excess returns on the market portfolio. $\beta_{mkt,i}$ is the estimated slope coefficient and e_i is the regression's residual. The second stage cross-sectional regression model is as follows:

$$E[r_{tr,i}] = \psi_0 + \psi_{mkt}\beta_{mkt,i} + \sum_{k=1}^{K} \psi_k Cov(e_i, r_{nt,k}). \tag{18}$$

The cross-sectional regression coefficient ψ_{mkt} is an estimate of the market price of risk μ_{mkt}. The intercept ψ_0 should be zero. If the apparent premium for idiosyncratic risk is indeed related to the presence of nontradable assets, ψ_k should be nonzero.

This cross-sectional regression model can be estimated using the Fama-MacBeth (1973) methodology. Note that equation (18) is a linear transformation of the multi-beta specification of the nontradable asset model (eq. 6) that I estimated in Sections 4 and 5. While the R^2s of the cross-sectional regressions will be exactly the same, the magnitudes of the cross-sectional regression coefficients will be different. Since expression (18) explicitly includes the covariance between the CAPM residual and the nontradable assets returns, it allows me to directly test whether the apparent premium for idiosyncratic risk is related to nontradable human capital. Therefore, I empirically investigate this specification in addition to the multi-beta specification of the model.

6.2 Empirical results

To empirically test the relation between idiosyncratic risk and human capital, I consider the 25 size-IR portfolios from Sections 4 and 5. These portfolios allow me to achieve better estimation accuracy of betas (by avoiding the estimation of stock-level betas), while preserving the relationship between stocks' idiosyncratic volatilities and their expected returns.[20] As described in Section 4, idiosyncratic risk is estimated as the residual volatility of the market model, which is in line with equation (16), using an EGARCH model.

First, I document the empirical relation between idiosyncratic risk and expected returns. Table 8 reports the CAPM alphas (i.e., the intercepts of the market model) for the 25 size-IR portfolios.

[20] A concern for investigating idiosyncratic volatilities for portfolio returns might be that in portfolios, stocks' idiosyncratic risks are diversified away. However, the premium for idiosyncratic risk that is predicted by the nontradable assets model does not concern true idiosyncratic risk (that can indeed be diversified away), but the CAPM residual risk that may in fact be systematic risk which is simply not captured by the CAPM. Hence, for portfolio returns this systematic risk should also be present.

Within the lowest three size quintiles, the alphas of the low IR portfolios are significant and negative or insignificant, while the alphas of the high IR portfolios are positive and highly statistically significant. This suggests a positive relation between idiosyncratic risk and expected returns. Within the highest two size quintiles, the pattern is less clear. Next, I average over all size quintiles within each IR quintile, thereby constructing idiosyncratic risk-sorted portfolios, controlling for size. The estimated alphas for the resulting five IR portfolios are given on the bottom row, denoted by "av.S." I find that whereas the alpha of the low IR portfolio is -0.08% and insignificant, the alpha estimate of the high IR portfolio is 0.92% and is statistically significant at the 1 percent level. The difference between these alphas equals 1% per month and is significant at the 1% level. This confirms the positive relation between expected idiosyncratic volatility and returns that is reported in various existing papers.

The apparent premium for idiosyncratic risk is most prevalent in the small size - high IR (S1, IR5) portfolio, that has a CAPM alpha of 3.91% per month. As can be seen in Figure 1, all benchmark models have very large pricing errors for this portfolio. However, the nontradable assets model with industry-specific human capital can explain the returns of this portfolio with high idiosyncratic risk stocks reasonably well. This is a first indication that the apparent premium for idiosyncratic risk may be related to (industry-specific) human capital.

Next, I take a more detailed look at the time series human capital betas of the 25 size-IR portfolios, reported in Table 4. Whereas in Section 4 I focused on the joint significance of these betas (Panel B), I now consider patterns in individual betas (Panel A). Indeed, there is a remarkable pattern in human capital betas. Within a given size quintile, the human capital betas are higher for portfolios with high IR stocks. This pattern can be seen for all types of human capital, aggregate and industry-specific. This is an important finding, as it shows that stocks with higher CAPM idiosyncratic risk have higher exposures to human capital returns. And, as shown in Table 8, precisely these stocks have higher alphas with respect to the CAPM. This suggests that the mispricing of the CAPM is more severe for high idiosyncratic risk stocks, that also have higher human capital betas. In other words, the apparent premium for idiosyncratic risk is larger for stocks with higher exposures to human capital. These empirical results reveal a link between nontradable human capital and the premium for idiosyncratic risk.

To test this link explicitly, I estimate the cross-sectional regression model from the previous section, eq. (18). I test the model for monthly returns on 25 size-IR sorted portfolios and I specify the nontradable asset returns as growth rates in aggregate and industry-specific labor income. Table 9 reports the results. First, and most importantly, the additional factor(s) of the nontradable assets model are statistically significant at the 1 percent level for both aggregate human capital and industry-specific human capital for all industries, except for the government. This confirms that the covariance between the CAPM idiosyncratic return and the nontradable asset returns is an important determinant of the cross-section of expected stock returns.

Next, I compare the estimates of $\hat{\psi}_0$ and $\hat{\psi}_{mkt}$ with the predictions based on economic theory. First, $\hat{\psi}_{mkt}$ is an estimate of the market price of risk and it should be positive and significant. This holds for both model specifications. Next, the intercept $\hat{\psi}_0$ should equal to zero according to the pricing equation of the nontradable assets model, which is based on excess returns. When the nontradable assets model is estimated using growth rates in aggregate labor income, the intercept is insignificant with a t-value of -0.89. This supports the validity of the model. However, when industry-specific human capital is included the estimated intercept of -0.3% is significant at the 5% level. In order to further investigate this, I redo the cross-sectional regressions imposing the restriction that the intercept equals zero. These regressions are estimated using restricted least squares and the results are presented in Panel B. It shows that the results remain similar, although some coefficients now have lower significance levels. [21]

These findings show that the covariance between the CAPM residual and human capital returns affects the cross-section of expected stock returns. Furthermore, portfolios with high idiosyncratic risk stocks have higher expected returns, and they also have higher exposures to human capital returns. In sum, these results imply that the apparent premium for idiosyncratic risk can (at least partially) be explained by nontradable human capital.

7 Conclusion

In a simple theoretical model, such as the nontradable assets model derived in this paper or in Mayers (1972), it straightforward to see how nontradable human capital affects portfolio choice and expected stock returns. However, an empirical analysis of the relation between stock returns and human capital returns is less straightforward. Returns on human capital are difficult to estimate, since only the cash flow component is observed (labor income), but not the discount rate component that is used to calculate the present value of all future labor income, i.e. the value of human capital.

A typical approach in the literature is based on the growth rate in aggregate (economy-wide) labor income as a measure for human capital returns (e.g. Jagannathan and Wang, 1996). This assumes that labor income in different industries follows the same AR(1) process, with the same growth rate and discount rate. This rather stringent assumption seems to conflict with papers showing that wages and wage structures are, in part, determined by industry affiliation (e.g. Krueger and Summers, 1988). In this paper I estimate returns on industry-specific human capital as the

[21] Note that since this model is a linear transformation of the beta representation of the nontradable assets model, the robustness tests from Section 5 apply to these results as well.

growth rate in labor income of a particular industry. I find that the characteristics of human capital returns indeed vary across industries. Also, I show that the composition of a hedging portfolio for human capital depends on the industry in which the investor works.

Next, I investigate the asset pricing implications of industry-specific human capital. In theory, expected stock returns are affected only by their exposures to the aggregate returns on all nontradable assets. Constructing aggregate human capital returns on the basis of industry-specific human capital returns is problematic, because the weights are unknown. It is very difficult to estimate the relative values of human capital in different industries. Therefore, I include industry-specific rather than aggregate human capital returns in a linear asset pricing model. This way, I avoid the estimation of the value of human capital and I aim to identify those human capital industries that matter most for asset pricing.

The empirical results show that this model, with industry-specific human capital betas, captures the cross-section of expected returns much better than a model that only includes the growth rate in aggregate labor income. When testing the model for 25 size – idiosyncratic risk sorted portfolios, I find that human capital from the goods producing, manufacturing, service and distribution industries have significant coefficients. Only human capital from the government is insignificant. In addition, I consider three other benchmark models: the static CAPM, the conditional CAPM and the Fama and French (1993) three-factor model. I also consider alternative sets of portfolio returns, including 25 size – book to market and 30 industry portfolios.

Last, I relate nontradable human capital to the cross-sectional relation between expected returns and idiosyncratic volatility, that is documented in various empirical papers (e.g. Spiegel and Wang, 2005, and Fu, 2007). Sorting stocks in portfolios based on their residual volatilities with respect to the CAPM shows that portfolios with high idiosyncratic risk stocks have higher CAPM alphas than portfolios with low IR stocks. This confirms a "premium" for idiosyncratic risk. However, precisely the high idiosyncratic risk portfolios also have higher exposures to human capital returns. I show, both theoretically and empirically, that when nontradable (industry-specific) human capital is excluded from the benchmark used to measure systematic risk, the resulting idiosyncratic risk affects the cross-section of expected returns. The size of this effect depends on each stock's covariance with human capital returns.

Appendix: derivation of the nontradable assets model

This appendix contains details on the derivation of the pricing equation of the nontradable assets model from Section 2. The market portfolio is defined as the value-weighted portfolio of all N tradable assets in the economy. Aggregate dollar supply of the tradable assets is denoted by $S = [S_1......S_N]'$. The weights of the market portfolio are $\alpha = \frac{1}{\iota_N' S} S$. The sum of the dollar supply of all tradable assets should equal the dollar amount of wealth invested in tradable assets: $S'\iota_N = \sum_{i=1}^{L}(1 - q_i'\iota_K)W_{0,i}$. Thus, the supply of tradable assets can be expressed as

$$S = \alpha \sum_{i=1}^{L}(1 - q_i'\iota_K)W_{0,i}.$$

Total demand for tradable assets can be found by aggregating the dollar amount of demand over all L investors $(i = 1, .., L)$:

$$D = \sum_{i=1}^{L} W_{0,i}x_i = \sum_{i=1}^{L} W_{0,i}\lambda_i\Sigma_{tr}^{-1}\mu_{tr} - \sum_{i=1}^{L} W_{0,i}\Sigma_{tr}^{-1}\Sigma_{tr,nt}q_i. \tag{19}$$

where $\lambda_i \equiv \gamma_i^{-1}$ is agent i's risk tolerance. Market clearing leads to the following expression for the tradable assets market portfolio weights

$$\alpha = \bar{\lambda}\Sigma_{tr}^{-1}\mu_{tr} - \Sigma_{tr}^{-1}\Sigma_{tr,nt}q_{nt}, \tag{20}$$

where

$$\bar{\lambda} \equiv \frac{\sum_{i=1}^{L} W_{0,i}\lambda_i}{\sum_{i=1}^{L}(1 - q_i'\iota_K)W_{0,i}} \text{ and } q_{nt} \equiv \frac{\sum_{i=1}^{L} W_{0,i}q_i}{\sum_{i=1}^{L}(1 - q_i'\iota_K)W_{0,i}}.$$

$\bar{\lambda}$ is the value-weighted sum of individual risk tolerances divided by total value of all tradable assets and q_{nt} is the $K-$vector of aggregate wealth tied up in the nontradable assets over the total value of the tradable assets. Expression (20) shows that the weights of the market portfolio of tradable assets are affected by the presence of the nontradable assets, as $\Sigma_{tr}^{-1}\Sigma_{tr,nt}q_{nt}$ equals the value-weighted average hedging demand of all investors.

I derive the pricing equation of the model, by expressing eq. (20) as

$$\mu_{tr} = \bar{\gamma}\Sigma_{tr,mkt} + \bar{\gamma}\Sigma_{tr,nt}q_{nt}. \tag{21}$$

$\bar{\gamma} \equiv \frac{1}{\bar{\lambda}}$, which can be interpreted as the market aggregate risk aversion coefficient.

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Table 1: Summary statistics and correlations of returns on (industry-specific) human capital

This table reports summary statistics for the monthly returns on human capital, for aggregate human capital for the US as a whole as well as for industry-specific human capital. Human capital returns are estimated as in Jagannathan and Wang (1996), as the lagged growth rate in per capita labor income. Labor income data are retrieved from the National Income and Product Accounts (NIPA) tables. For the returns on aggregate human capital NIPA table 2.6 is used and labor income is defined as total personal income minus total dividends. For the returns on five industry-specific human capital assets, NIPA table 2.7 is used and labor income is defined as total wages and salary disbursements. The five industries are: goods producing (excluding manufacturing), manufacturing, distributive industries, service industries and government. The sample period runs from April 1959 to December 2005, a total of 561 months. Panel A reports the mean, standard deviation, minimum, maximum and the first-order autocorrelation (denoted by $\rho(1)$) of the monthly growth rates in labor income and the one-month T-Bill rate (denoted by R_f). The $p-$values of the null hypotheses that the mean growth rates in labor income are zero for all five industries, that they are equal and the null hypothesis that the variance in human capital returns is equal for all industries are reported in parentheses. This panel concerns total, not excess, returns, which are denoted by R. Panel B reports the unconditional correlation matrix of the returns on aggregate and industry-specific human capital in excess of the one-month T-Bill rate. Excess returns are denoted by r. ***,** , and * denote significance at the 1, 5 and 10 percent levels respectively.

Panel A: Descriptive statistics

	mean (%)	stdev (%)	min (%)	max (%)	$\rho(1)$	p-value
R^{hc}_{US}	0.49	0.38	-2.05	1.85	0.55	
R^{hc}_{gds}	0.43	0.74	-2.44	5.94	0.53	
R^{hc}_{man}	0.31	0.73	-5.29	3.90	0.55	
R^{hc}_{dist}	0.44	0.46	-3.29	2.56	0.41	
R^{hc}_{serv}	0.64	0.65	-6.42	5.65	0.26	
R^{hc}_{gov}	0.46	0.43	-1.32	3.32	0.44	
R_f	0.45	0.23	0.06	1.35	0.95	
H_o : mean R^{hc} is zero for all 5 industries						(0.00)
H_o : mean R^{hc} is equal for all 5 industries						(0.00)
$H_o : Var(R^{hc})$ is equal for all 5 industries						(0.00)

Panel B: Unconditional correlation matrix for excess returns on HC

	r^{hc}_{US}	r^{hc}_{gds}	r^{hc}_{man}	r^{hc}_{dist}	r^{hc}_{serv}	r^{hc}_{gov}
r^{hc}_{US}	1					
r^{hc}_{gds}	0.44***	1				
r^{hc}_{man}	0.70***	0.37***	1			
r^{hc}_{dist}	0.70***	0.43***	0.72***	1		
r^{hc}_{serv}	0.62***	0.24***	0.59***	0.70***	1	
r^{hc}_{gov}	0.33***	0.06	0.08*	0.13***	0.03	1

Table 2: Hedging demand due to human capital

This table reports the weights of 30 industry equity portfolios in the hedging portfolios due to human capital. The first column gives the 30 weights in the hedging portfolio for aggregate human capital, while the other five columns are based on industry-specific human capital (goods producing, manufacturing, distribution, services and government). The weights are estimated based on an OLS regression of excess returns on human capital on a constant and excess returns on the 30 industry equity portfolios. The estimated weights (w_{hp}) are multiplied by -10^2. The last three rows report the Wald test statistics and p-values (in parentheses) for H_0 : all weights in that column are jointly equal zero, and the sum of the absulte hedging portfolio weights. Monthly returns on human capital are estimated as in Jagannathan and Wang (1996). ***,**, and * denote significance at the 1, 5 and 10 percent levels.

Human capital:	Aggr. US $w_{hp}{\cdot}10^2$	Gds prod. $w_{hp}{\cdot}10^2$	Manuf. $w_{hp}{\cdot}10^2$	Distr. $w_{hp}{\cdot}10^2$	Service $w_{hp}{\cdot}10^2$	Governm. $w_{hp}{\cdot}10^2$
Food products	0.58	0.53	0.96	0.43	0.36	-0.20
Beer and Liquor	0.86*	0.71	1.05	1.02*	1.19	0.00
Tobacco	0.07	1.05	0.13	0.59	0.10	-0.14
Recreation	-0.73	-0.94	-0.14	-0.58	-0.84	-0.31
Printing, publ.	0.05	0.84	0.44	-0.11	-0.26	0.03
Consumer gds	0.14	-0.77	0.71	-1.07	-0.04	-0.05
Apparel	0.83	1.36	1.12	1.64***	1.91**	-0.50
Healthcare	0.10	-1.03	0.07	0.44	0.34	0.36
Chemicals	0.82	2.16	1.88	1.46*	1.70	0.47
Textiles	0.44	1.42	1.35	1.15*	1.81**	-0.27
Contruction	-0.72	-1.61	-0.74	-1.03	-1.37	-0.29
Steel works	-0.96**	-1.13	-2.47**	-1.28**	-2.73***	0.56
Fabricated prod.	-0.71	-5.43***	-0.97	0.18	1.02	-1.51
Electrical eq.	0.07	-0.60	-0.92	-0.07	0.15	0.20
Automobiles	-0.44	0.66	-0.27	-0.68	-1.48**	-0.14
Aircraft, ships	-0.56	-0.73	-0.85	-0.24	-0.49	0.50
Mines	0.49	0.85	1.38**	0.45	1.63***	-0.63
Coal	0.13	0.82*	0.68	-0.02	0.20	-0.23
Petroleum, gas	-1.01**	-0.42	-1.60*	-0.84	-1.25	-1.01*
Utilities	1.59***	0.49	1.84	1.44*	1.26	1.65**
Communication	-0.09	1.13	-0.87	0.04	0.37	0.95
Services	0.61	-0.47	1.33	0.28	0.24	0.44
Bus. equipment	0.37	2.28*	-0.03	-0.10	0.15	-0.03
Bus. supplies	0.79	-0.36	0.31	-0.20	-0.54	1.51
Transportation	0.55	0.06	0.61	-0.12	0.36	0.94
Wholesale	-1.12*	0.28	-1.05	-1.00	-1.30	-0.25
Retail	0.89	1.22	2.30*	1.08	0.51	-0.52
Restaurants	-0.55	-1.10	-0.70	-0.51	-0.78	-0.36
Finance	-0.47	0.71	-1.94	-0.35	-0.89	0.17
Other	-0.55	0.05	-1.78	-0.69	-0.46	-0.31
Wald test stat.	64.05	51.75	54.80	64.64	51.74	36.03
p-value	(0.000)	(0.008)	(0.004)	(0.000)	(0.008)	(0.207)
Sum abs. weights	17.29	31.22	30.47	19.11	25.77	14.54

Table 3: Characteristics of 25 size - IR sorted portfolios

This table reports several characteristics of monthly excess returns on 25 size - idiosyncratic risk sorted equity portfolios. Every month the stocks from all nonfinancial firms that are traded on the NYSE, AMEX and NASDAQ are first sorted into size quintiles, based on their market capitalization at the beginning of the month. Then, within each size quintile, the stocks are sorted into idiosyncratic risk quintiles, based on the estimated idiosyncratic volatility for that month. The idiosyncratic volatility is estimated as the residual volatility of the market model, including a constant and the excess return on the value-weighted CRSP index, estimated using an EGARCH model for all available returns of the asset. S1 (S5) denotes the smallest (largest) size quintile and IR1 (IR5) denotes the lowest (highest) IR quintile. The table reports the time-series averages and standard deviations of the excess returns in percentages, the size of the stocks in each portfolio (in log $ thousands), and the estimated β_{mkt} for each portfolio, which is the slope coefficient of the market model.

Time series average excess returns (%)						Time series standard deviation (%)					
	IR1	2	3	4	IR5		IR1	2	3	4	IR5
S1	-0.12	0.43	0.75	1.48	4.66	S1	4.04	5.99	7.26	8.91	13.54
2	0.16	0.47	0.64	0.84	1.76	2	3.98	5.45	6.68	7.99	11.21
3	0.39	0.64	0.73	0.78	0.95	3	4.03	5.51	6.51	7.64	10.30
4	0.50	0.81	0.76	0.79	0.60	4	3.84	4.99	5.86	6.99	9.36
S5	0.45	0.46	0.50	0.45	0.51	S5	3.65	4.24	4.94	5.80	7.84
Time series average size (log $ thousands)						Estimated β_{mkt}					
	IR1	2	3	4	IR5		IR1	2	3	4	IR5
S1	8.79	8.75	8.69	8.60	8.47	S1	0.67	0.96	1.11	1.27	1.59
2	10.04	10.03	10.01	9.99	9.96	2	0.74	0.99	1.19	1.36	1.66
3	11.03	11.02	11.00	10.98	10.95	3	0.78	1.08	1.27	1.45	1.72
4	12.17	12.13	12.09	12.06	12.02	4	0.78	1.01	1.20	1.42	1.71
S5	14.37	14.18	13.94	13.76	13.53	S5	0.76	0.91	1.08	1.23	1.53

Table 4: Time series betas with respect to returns on (industry-specific) human capital

This table presents the estimated time series betas of 25 size-idiosyncratic risk sorted equity portfolios with respect to excess returns on human capital. Univariate betas are calculated by regressing exccess returns on the equity portfolio on a constant and the excess human capital returns. Returns on aggregate human capital for the US as a whole as well as returns on industry-specific human capital for five industries are considered. The five industries are: goods producing, manufacturing, distribution, services and government. Panel A reports the estimated betas. ***,**, and * denote significance at the 1, 5 and 10 percent levels respectively. Panel B reports results of the Wald tests for the null hypotheses that all $\beta^{hc}_{m,i}$ are equal to zero and that they are all equal, for $i = 1, ..., 25$. The panel reports the Wald test statistics and the p-values in parentheses. The White covariance matrix is used.

Panel A: Time series betas w.r.t. returns on (industry-specific) human capital

	Estimated β^{hc}_{US}						Estimated β^{hc}_{gds}				
	IR1	2	3	4	IR5		IR1	2	3	4	IR5
S1	0.60	1.22*	1.39*	1.72*	2.07	S1	0.19	0.29	0.37	0.28	-0.02
2	0.22	0.63	0.98	1.11	2.06	2	0.10	0.11	0.24	0.11	0.24
3	-0.04	0.00	0.50	0.71	1.43	3	-0.04	-0.02	0.08	-0.01	0.21
4	-0.55	-0.09	-0.03	0.23	1.30	4	-0.22	-0.03	-0.01	0.14	0.31
S5	-0.77**	-0.38	-0.10	0.35	0.65	S5	-0.23	-0.01	0.06	0.17	0.33
	Estimated β^{hc}_{man}						Estimated β^{hc}_{dist}				
	IR1	2	3	4	IR5		IR1	2	3	4	IR5
S1	0.19	0.38	0.43	0.43	0.30	S1	0.18	0.53	0.82	0.73	0.64
2	-0.08	0.12	0.18	0.13	0.35	2	0.00	0.28	0.56	0.63	0.97
3	-0.11	-0.17	0.09	0.01	0.28	3	0.01	-0.08	0.40	0.47	1.18
4	-0.32	-0.19	-0.13	0.02	0.29	4	-0.40	-0.01	0.08	0.50	1.27
S5	-0.21	-0.25	-0.03	0.29	0.38	S5	-0.49	-0.11	0.16	0.84*	1.31**
	Estimated β^{hc}_{serv}						Estimated β^{hc}_{gov}				
	IR1	2	3	4	IR5		IR1	2	3	4	IR5
S1	0.33	0.62**	0.98***	1.02**	1.73**	S1	0.47	0.81	0.82	1.05	1.27
2	0.30	0.66**	0.84**	0.79*	1.53**	2	0.30	0.21	0.45	0.83	1.21
3	0.26	0.33	0.68**	0.61*	1.12*	3	0.24	0.11	0.29	0.49	0.64
4	0.09	0.34	0.44	0.61*	1.11**	4	-0.06	0.09	0.06	-0.06	0.48
S5	0.07	0.25	0.43*	0.65**	0.82*	S5	-0.38	-0.27	-0.22	-0.09	-0.18

Panel B: Tests of joint significance of human capital betas

	β^{hc}_{US}	β^{hc}_{gds}	β^{hc}_{man}	β^{hc}_{dist}	β^{hc}_{serv}	β^{hc}_{gov}
H_o: $\beta^{hc}_{m,i} = 0$ for $i = 1, ..., 25$						
Wald test statistic	43.93	35.45	46.05	65.86	91.47	48.02
p-value	(0.01)	(0.08)	(0.01)	(0.00)	(0.00)	(0.00)
H_o: $\beta^{hc}_{m,1} = ... = \beta^{hc}_{m,25}$						
Wald test statistic	39.60	34.87	44.05	58.40	87.24	47.93
p-value	(0.02)	(0.07)	(0.01)	(0.00)	(0.00)	(0.00)

Table 5: The nontradable assets model with industry human capital and comparison with alternative models

This table evaluates different asset pricing models for monthly excess returns on 25 size - idiosyncratic risk sorted portfolios, from April 1959 to December 2005. Panel A presents tests of the static CAPM and of the human capital CAPM that includes aggregate human capital, based on the cross-sectional regression model:

$$E[r_{tr,i}] = c_0 + c_{mkt}\beta_{mkt,i} + c^{hc}_{US}\beta^{hc}_{US,i},$$

where $r_{tr,i}$ is the excess return on portfolio i, for $i = 1, .., 25$. r_{mkt} is the excess return on the value-weighted CRSP index, r^{hc}_{US} is the excess return on aggregate human capital asset for the US as a whole, estimated as in Jagannathan and Wang (1996) as the lagged growth rate in per capita labor income in excess of the one month T-Bill rate. $\beta_{mkt,i}$ is calculated as the slope of the OLS regression of $r_{tr,i}$ on a constant and r_{mkt} and $\beta^{hc}_{US,i}$ is calculated similarly, as the slope coefficient of an OLS regression on a constant and r^{hc}_{US}. Panel B reports the estimates of the nontradable assets model with industry-specific human capital:

$$E[r_{tr,i}] = c_0 + c_{mkt}\beta_{mkt,i} + \sum_{k=1}^{K} c^{hc}_k \beta^{hc}_{k,i}.$$

r^{hc}_k is the excess return on human capital from industry k, calculated as the lagged growth rate in per capita labor income for that industry. K equals five and the five industries are: goods producing (excluding manufacturing), manufacturing, distributive industries, service industries and government. The betas are calculated as slope coefficients in univariate regressions including a constant and r^{hc}_k. Panel C reports the estimates of the conditional CAPM extended with (industry-specific) human capital:

$$E[r_{tr,i}] = c_0 + c_{mkt}\beta_{mkt,i} + c_{prem}\beta_{prem,i} + c^{hc}_{US}\beta^{hc}_{US,i} + \sum_{k=1}^{K} c^{hc}_k \beta^{hc}_{k,i}.$$

$R_{prem,t-1}$ is the lagged yield difference between Moody's BAA and AAA rated corporate bonds. $\beta_{prem,i}$ is calculated as the slope of the OLS regression of $r_{tr,i}$ on a constant and $R_{prem,t-1}$. Panel D reports the results of the Fama and French (1993) three-factor model, extended with (industry-specific) human capital:

$$E[r_{tr,i}] = c_0 + c_{mkt}\beta_{mkt,i} + c_{smb}\beta_{smb,i} + c_{hml}\beta_{hml,i} + c^{hc}_{US}\beta^{hc}_{US,i} + \sum_{k=1}^{K} c^{hc}_k \beta^{hc}_{k,i},$$

where $\beta_{smb,i}$ and $\beta_{hml,i}$ are estimated similarly, as the slope coefficients with respect to the Fama and French (1993) size and value factors SMB and HML. The cross-sectional regression model is estimated using the Fama MacBeth (1973) procedure. In the first stage, the betas are estimated using multiple time series regressions over the full sample period. In the second stage average returns are regressed on the cross-section of betas. The table gives estimates of the cross-sectional regression coefficients and the corresponding t-values. The t-values have been adjusted for estimation error in the betas using the Jagannathan and Wang (1996 and 1998a) adjustment. The table also reports the cross-sectional regression's OLS adjusted R^2 calculated as in Jagannathan and Wang (1996) and the GLS R^2, both in percentages.

Panel A: Static CAPM and human capital CAPM

Coef.	c_0	c_{mkt}	c_{smb}	c_{hml}	c_{prem}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	R^2_{ols}	R^2_{gls}
$\hat{c}$ $(\cdot 10^2)$	-0.84	1.40										19%	5%
t-value	-3.45	4.14											
$\hat{c}$ $(\cdot 10^2)$	-0.20	0.62				0.48						27%	16%
t-value	-0.89	2.17				3.29							

Panel B: The nontradable assets model with industry human capital

Coef.	c_0	c_{mkt}	c_{smb}	c_{hml}	c_{prem}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	R^2_{ols}	R^2_{gls}
$\hat{c}$ $(\cdot 10^2)$	-0.33	-0.05					-3.11	1.11	-0.95	2.87	-0.22	85%	40%
t-value	-2.10	-0.19					-7.89	3.53	-3.86	10.91	-1.23		

Panel C: Conditional CAPM with (industry-specific) human capital

Coef.	c_0	c_{mkt}	c_{smb}	c_{hml}	c_{prem}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	R^2_{ols}	R^2_{gls}
$\hat{c}$ $(\cdot 10^2)$	-1.32	0.57			0.98							55%	13%
t-value	-4.73	1.90			6.30								
$\hat{c}$ $(\cdot 10^2)$	-1.48	0.67			1.05	-0.10						53%	19%
t-value	-7.63	2.38			9.81	-0.92							
$\hat{c}$ $(\cdot 10^2)$	-0.22	-0.56			0.32		-3.36	0.73	-0.37	2.73	-0.43	85%	41%
t-value	-1.39	-1.87			3.92		-8.90	2.53	-1.92	10.23	-2.57		

Panel D: Fama and French three-factor model with (industry-specific) human capital

Coef.	c_0	c_{mkt}	c_{smb}	c_{hml}	c_{prem}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	R^2_{ols}	R^2_{gls}
$\hat{c}$ $(\cdot 10^2)$	-0.39	0.32	0.87	0.39								37%	13%
t-value	-2.28	0.82	4.09	1.69									
$\hat{c}$ $(\cdot 10^2)$	-0.11	-0.61	1.55	0.06		-0.51						36%	20%
t-value	-0.72	-1.66	7.78	0.26		-5.10							
$\hat{c}$ $(\cdot 10^2)$	-0.27	-0.19	0.16	0.06			-3.16	1.16	-0.92	2.83	-0.38	83%	42%
t-value	-1.65	-0.50	0.87	0.23			-10.15	3.80	-4.34	11.07	-2.47		

Table 6: Robustness tests using size - idiosyncratic risk sorted portfolios

This table presents a number of robustness checks for the static CAPM (eq. 10), the human capital CAPM with aggregate human capital (eq. 11), the nontradable assets model with industry human capital (eq. 6), the conditional CAPM (eq. 12) and the Fama and French (1993) three-factor model (eq. 13). Panel A reports the cross-sectional regressions for 24 size - idiosyncratic risk sorted portfolios, excluding the small size - high IR portfolio. These are unrestricted regressions. Panel B reports the results of restricted regressions for the 25 size-IR portfolios, in which the intercept of the cross-sectional regression is set equal to zero. These regressions are estimated using restricted least squares. Panels A and B the excess returns on human capital r^{hc} are estimated as in Jagannathan and Wang (1996) as the lagged growth rate in per capita labor income in excess of the one month T-Bill rate ("JW timing "). Panel C reports the results for the 25 size - idiosyncratic risk portfolios when returns on human capital are estimated as in Heaton and Lucas (2000) as the contemporaneous growth rate in per capita labor income. This panel reports estimates of the human capital CAPM and the nontradable assets model with industry human capital. The cross-sectional regression model is estimated using the Fama MacBeth (1973) procedure. The table gives estimates of the cross-sectional regression coefficients and the corresponding t-values that are adjusted for estimation error in the betas using the Jagannathan and Wang (1996 and 1998a) adjustment in Panels A and C. The table also reports the cross-sectional regression's OLS adjusted R^2 calculated as in Jagannathan and Wang (1996) and the GLS R^2 in percentages.

Panel A: 24 size-IR portfolios, excl. small size- high IR portf (unrestricted regressions, JW timing)													
Coef.	c_0	c_{mkt}	c_{smb}	c_{hml}	c_{prem}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	R^2_{ols}	R^2_{gls}
$\hat{c}$ $(\cdot 10^2)$	-0.25	0.78										37%	17%
t-value	-1.15	2.51											
$\hat{c}$ $(\cdot 10^2)$	-0.09	0.57				0.14						39%	25%
t-value	-0.37	2.00				1.10							
$\hat{c}$ $(\cdot 10^2)$	-0.76	1.01					-0.62	0.80	-1.10	1.09	0.06	74%	47%
t-value	-4.86	3.55					-1.77	2.67	-4.50	4.72	0.36		
$\hat{c}$ $(\cdot 10^2)$	-0.58	0.48			0.47							75%	40%
t-value	-2.36	1.62			3.41								
$\hat{c}$ $(\cdot 10^2)$	-1.11	2.07	0.06	0.95								56%	38%
t-value	-6.95	5.78	0.29	4.14									

Panel B: Restricted regressions: $\hat{c}_0$= 0 (25 size-IR portfolios, JW timing)												
Coef.	c_0	c_{mkt}	c_{smb}	c_{hml}	c_{prem}	c_{US}^{hc}	c_{gds}^{hc}	c_{man}^{hc}	c_{dist}^{hc}	c_{serv}^{hc}	c_{gov}^{hc}	R_{ols}^2
$\hat{c}$ $(\cdot 10^2)$	0	0.74										13%
t-value	n.a.	5.56										
$\hat{c}$ $(\cdot 10^2)$	0	0.43				0.52						26%
t-value	n.a.	2.41				2.33						
$\hat{c}$ $(\cdot 10^2)$	0	-0.47					-3.44	0.81	-0.61	2.98	-0.21	85%
t-value	n.a.	-1.79					-3.41	0.79	-1.45	5.59	-0.73	
$\hat{c}$ $(\cdot 10^2)$	0	-0.29			0.84							40%
t-value	n.a.	-0.88			3.30							
$\hat{c}$ $(\cdot 10^2)$	0	-0.26	0.95	0.13								36%
t-value	n.a.	-0.58	3.29	0.28								

Panel C: Contemporaneous timing (25 size-IR portfolios, unrestricted regressions)													
Coef.	c_0	c_{mkt}	c_{smb}	c_{hml}	c_{prem}	c_{US}^{hc}	c_{gds}^{hc}	c_{man}^{hc}	c_{dist}^{hc}	c_{serv}^{hc}	c_{gov}^{hc}	R_{ols}^2	R_{gls}^2
$\hat{c}$ $(\cdot 10^2)$	-0.64	1.01				0.17						16%	35%
t-value	-2.92	3.29				1.28							
$\hat{c}$ $(\cdot 10^2)$	-0.96	1.08					0.01	-1.95	-0.72	0.37	0.86	85%	52%
t-value	-5.12	2.86					0.02	-4.23	-2.17	0.94	6.73		

Table 7: Robustness tests using alternative sets of portfolio returns

This table tests the static CAPM (eq. 10), the human capital CAPM with aggregate human capital (eq. 11), the nontradable assets model with industry human capital (eq. 6), the conditional CAPM (eq. 12) and the Fama and French (1993) three-factor model (eq. 13).for two alternative sets of portfolio returns. Panel A reports the estimates of the cross-sectional regressions for 25 size - book to market equity portfolios and Panel B reports the results for the combined set of 25 size- book to market portfolios and 30 industry equity portfolios. The sample period runs from April 1959 to December 2005. Returns on human capital are estimated as the lagged growth rate in per capita labor income. The cross-sectional regression model is estimated using the Fama MacBeth (1973) procedure. The table reports adjusted t-values (Jagannathan and Wang 1996 and 1998a), the cross-sectional OLS adjusted R^2 and the GLS R^2.

Panel A: Results for 25 size-BM portfolios

Coef.	c_0	c_{mkt}	c_{smb}	c_{hml}	c_{prem}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	R^2_{ols}	R^2_{gls}
$\hat{c}$ $(\cdot 10^2)$	1.31	-0.57										10%	12%
t-value	3.71	-1.43											
$\hat{c}$ $(\cdot 10^2)$	1.54	-0.80				0.19						16%	12%
t-value	4.61	-2.17				1.76							
$\hat{c}$ $(\cdot 10^2)$	1.53	-0.73					1.10	-0.23	-0.54	-0.03	0.59	46%	22%
t-value	4.87	-2.01					4.29	-0.90	-2.14	-0.13	3.49		
$\hat{c}$ $(\cdot 10^2)$	1.30	-1.25			0.60							56%	14%
t-value	3.68	-3.32			4.06								
$\hat{c}$ $(\cdot 10^2)$	1.34	-0.81	0.46	0.35								73%	33%
t-value	4.59	-1.91	2.93	2.17									

Panel B: Results for 25 size-BM and 30 industry portfolios

Coef.	c_0	c_{mkt}	c_{smb}	c_{hml}	c_{prem}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	R^2_{ols}	R^2_{gls}
$\hat{c}$ $(\cdot 10^2)$	0.83	-0.18										-1%	2%
t-value	3.13	-0.57											
$\hat{c}$ $(\cdot 10^2)$	0.87	-0.22				0.02						-3%	2%
t-value	3.19	-0.69				0.32							
$\hat{c}$ $(\cdot 10^2)$	0.84	-0.33					0.23	-0.08	-0.31	0.42	0.21	9%	8%
t-value	2.75	-0.92					1.26	-0.38	-1.82	2.14	2.06		
$\hat{c}$ $(\cdot 10^2)$	0.82	-0.27			0.08							-0%	3%
t-value	3.06	-0.82			0.84								
$\hat{c}$ $(\cdot 10^2)$	0.90	-0.33	0.30	0.25								27%	13%
t-value	3.51	-0.87	1.98	1.54									

Table 8: CAPM alphas for 25 size-idiosyncratic risk sorted portfolios

The table reports the estimated alphas (intercepts) with respect to the CAPM for the 25 size - idiosyncratic risk sorted portfolios. The row "av.S" reports the alphas for five idiosyncratic risk sorted portfolios, where each idiosyncratic risk quintile portfolio is averaged across all size quintiles. ***,**, and * denote significance at the 1, 5 and 10 percent levels respectively.

Estimates of CAPM alphas (%)						
	IR1	2	3	4	IR5	IR5 - IR1
S1	-0.44***	-0.02	0.22	0.88***	3.91***	4.35***
2	-0.19*	0.00	0.07	0.19	0.97***	1.16***
3	0.02	0.13	0.12	0.10	0.13***	0.12
4	0.13*	0.33***	0.19*	0.12	-0.21	-0.34
S5	0.09	0.02	-0.02	-0.13	-0.22	-0.31
av.S	-0.08	0.09	0.12	0.23	0.92***	1.00***

Table 9: Nontradable human capital and the apparent premium for idiosyncratic risk

This table reports tests of the nontradable assets model, based on the following cross-sectional regression model:

$$E[r_{tr,i}] = \psi_0 + \psi_{mkt}\beta_{mkt,i} + \sum_{k=1}^{K} \psi_k Cov(e_i, r_k^{hc}),$$

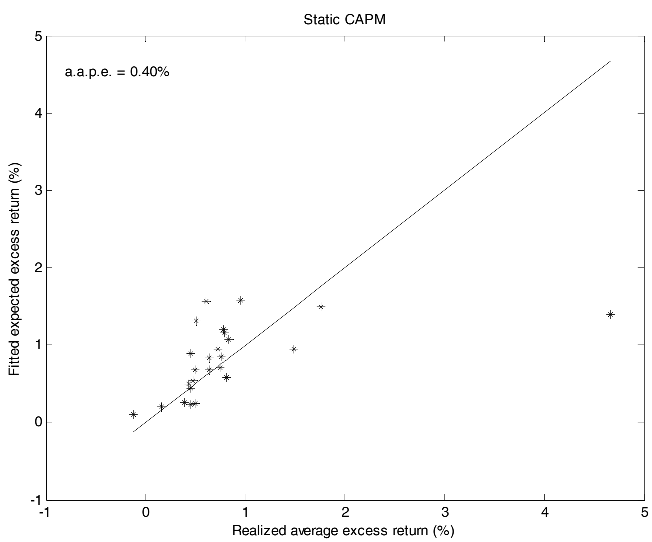
where $r_{tr,i}$ is the excess return on portfolio i. r_{mkt} is the excess return on the value-weighted CRSP index and $\beta_{mkt,i}$ is the slope of an OLS regression of $r_{tr,i}$ on a constant and r_{mkt}. e_i is the residual excess return of portfolio i with respect to the market model and r^{hc} is the excess return on human capital, that is estimated as the lagged growth rate in per capita labor income. I consider the growth rate in aggregate labor income ($K = 1$) and the growth rates in industry-specific labor income, for five US industries ($K = 5$, goods producing, manufacturing, distribution , services and government). The sample period extends from April 1959 to December 2005, a total of 561 months. The model is tested for monthly excess returns on 25 size - idiosyncratic risk sorted equity portfolios, using the Fama MacBeth (1973) procedure. In the first stage, the $\beta_{mkt,i}$ and $Cov(e_i, r_k^{hc})$ are estimated using multiple time series regressions over the full sample period. In the second stage average excess portfolio returns are regressed on the cross-section of betas and covariance estimates. Panel A reports the results of the unrestricted regressions. Panel B reports the results of restricted regressions, in which the intercept of the cross-sectional regression is set equal to zero. These regressions are estimated using restricted least squares. The table provides estimates of the cross-sectional regression coefficients and the corresponding t-values. The table also reports the OLS cross-sectional regression's adjusted R^2 calculated as in Jagannathan and Wang (1996) and the GLS R^2 in percentages.

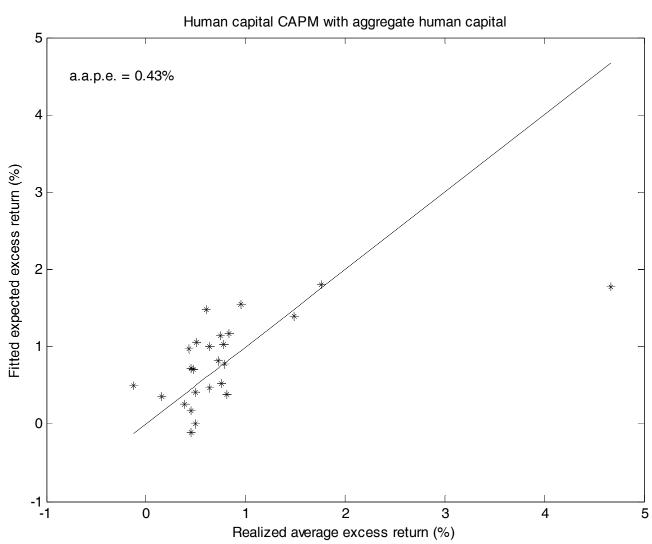
Panel A: Results unrestricted cross-sectional regressions										
Coef.	ψ_0	ψ_{mkt}	ψ_{US}^{hc}	ψ_{gds}^{hc}	ψ_{man}^{hc}	ψ_{dist}^{hc}	ψ_{serv}^{hc}	ψ_{gov}^{hc}	R_{ols}^2	R_{gls}^2
$\hat{\psi}$	-0.002	0.005	346.84						27%	16%
t-value	-0.89	1.79	3.30							
$\hat{\psi}$	-0.003	0.010		-540.91	203.06	-457.08	701.39	-104.68	85%	40%
t-value	-2.15	4.14		-8.05	3.61	-3.93	11.12	-1.26		

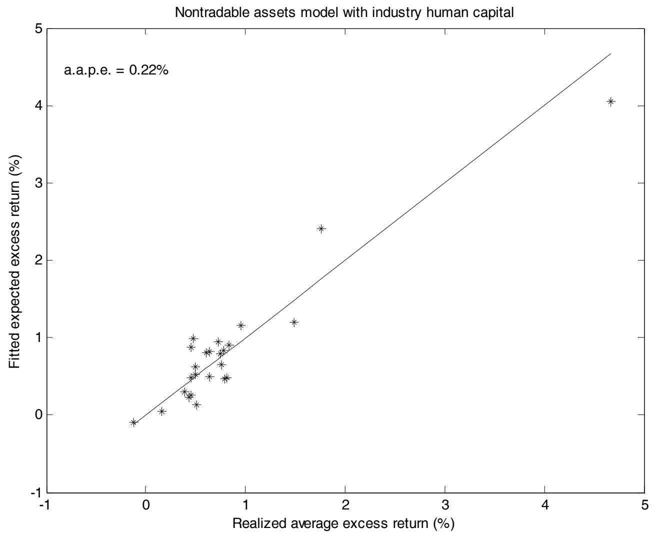
Panel B: Results restricted cross-sectional regressions: $\hat{\psi}_0 = 0$									
Coef.	ψ_0	ψ_{mkt}	ψ_{US}^{hc}	ψ_{gds}^{hc}	ψ_{man}^{hc}	ψ_{dist}^{hc}	ψ_{serv}^{hc}	ψ_{gov}^{hc}	R_{ols}^2
$\hat{\psi}$	0	0.003	376.14						26%
t-value	n.a.	1.52	2.33						
$\hat{\psi}$	0	0.007		-599.37	148.89	-290.27	729.44	-101.79	85%
t-value	n.a.	4.78		-3.41	0.79	-1.45	5.59	-0.73	

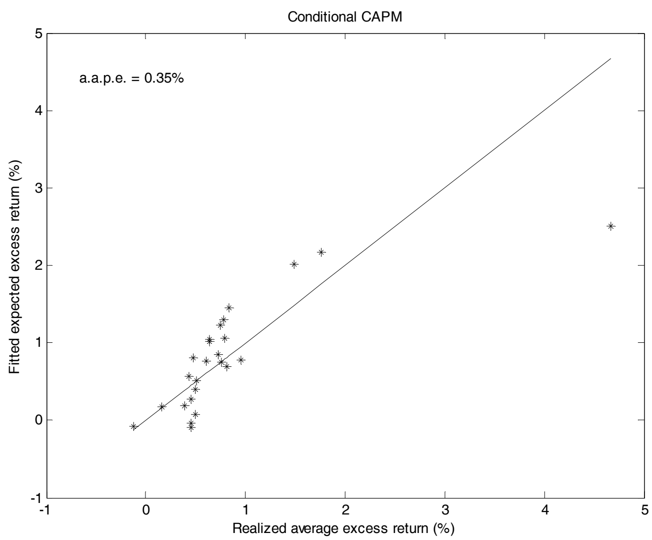
Figure 1: Realized average returns versus fitted expected returns

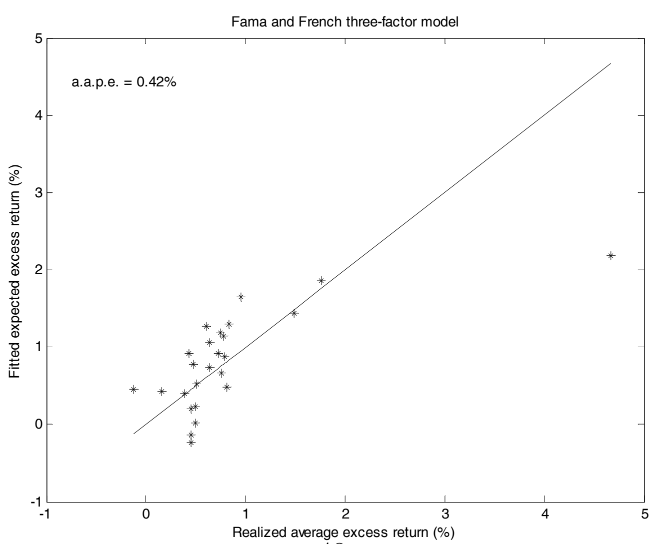
Each scatterplot reports the realized full sample average portfolio excess returns against the fitted expected excess portfolio returns (in percentages) for 25 size - idiosyncratic risk sorted equity portfolios. The fitted value for the expected excess portfolio return $E[r_i^{tr}]$ is based on the estimates of five different models: the static CAPM (eq. 10), the human capital CAPM with aggregate human capital (eq. 11), the nontradable assets model with industry human capital (eq. 6), the conditional CAPM (eq. 12) and the Fama and French (1993) three-factor model (eq. 13). The straight line is the 45 degrees line through the origin. The plots also report the average absolute pricing error (a.a.p.e.), which is calculated as the average of the absolute differences between the average realized excess returns and the fitted expected excess returns.






Nontradable assets model with industry human capital
a.a.p.e. = 0.22%
Fitted expected excess return (%)
Realized average excess return (%)


Conditional CAPM
a.a.p.e. = 0.35%
Fitted expected excess return (%)
Realized average excess return (%)


Fama and French three-factor model
a.a.p.e. = 0.42%
Fitted expected excess return (%)
Realized average excess return (%)