Internet Appendix for

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

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ABSTRACT

This document includes a derivation of the nontradable assets model used in the paper "Industry-Specific Human Capital, Idiosyncratic Risk, and the Cross-Section of Expected Stock Returns" to test the impact of industry-specific human capital on expected stock returns. This document also provides details on the labor income and employment data used, as well as an analysis of lagged versus contemporaneous labor income growth rates. In addition, I present and discuss a number of auxiliary results and robustness tests for the cross-sectional regressions. Finally, this appendix includes summary statistics and human capital betas for monthly returns on 100 size and idiosyncratic risk sorted portfolios.

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I. Derivation of the Nontradable Assets Model

This section derives a simple asset pricing model in which I allow for the presence of multiple nontradable assets. In the empirical analysis of the paper, I specify these assets as human capital from different industries. Consider a standard one-period mean-variance framework with $N+K$ risky assets, where N assets are tradable (tr) and K are nontradable (nt). Their net returns are given in vectors R_{tr} and R_{nt} (sizes $N \times 1$ and $K \times 1$). The vectors x_i and q_i denote investor i's positions in the tradable and nontradable assets, respectively, as fractions of her initial financial wealth $W_{0,i}$. Hence, her total initial wealth including her positions in nontradable assets equals $(1+q_i'\iota)W_{0,i}$, where ι is a vector of ones. The investor's portfolio constraint applies only to her positions in tradable assets. The constraint can be incorporated by using returns on tradable assets in excess of the risk-free rate, that is, $r_{tr} = R_{tr} - R_f\iota$. The investor determines her investments in the tradable assets (x_i) by solving the following portfolio optimization problem:

$$\max_{x_i} E[W_{1,i}] - \frac{1}{2}\gamma_i Var[W_{1,i}] \qquad \text{(IA.1)}$$

$$s.t.\;\; W_{1,i} = W_{0,i}[(1+R_f) + x_i' r_{tr} + q_i' R_{nt}].$$

The coefficient of risk aversion of agent i is denoted by γ_i and $W_{1,i}$ is her financial wealth at the end of the period, that is, her total wealth minus her wealth tied up in nontradable assets. Denote $\mu_{tr} = E[r_{tr}]$, $Var[r_{tr}] = \Sigma_{tr}$, and $Var[R_{nt}] = \Sigma_{nt}$. The $N \times K$ matrix with covariances between returns on tradable and nontradable assets is given by $\Sigma_{tr,nt}$. This utility maximization corresponds to negative exponential utility with normally distributed future wealth. Without the presence of nontradable assets it leads to the CAPM. The investor's optimal portfolio weights are

$$x_i = \gamma_i^{-1}\Sigma_{tr}^{-1}\mu_{tr} - \Sigma_{tr}^{-1}\Sigma_{tr,nt}q_i. \qquad \text{(IA.2)}$$

Equation (IA.2) shows that the investor's demand for tradable assets consists of the usual speculative demand and hedging demand induced by her positions in nontraded assets.[1]

Aggregate dollar supply of the tradable assets is denoted by $S = [S_1 ...... S_N]'$, and the

[1] In this single-period framework, I refer to the portfolio adjustments for an investor's positions in nontradable assets as hedging demand. This should not be confused with hedging demand in an intertemporal setting.

market portfolio weights are $\alpha = \frac{1}{\iota_N' S} S$. The supply of tradable assets can be expressed as

$$S = \alpha \sum_{i=1}^{L} W_{0,i}. \tag{IA.3}$$

Aggregating the dollar amount of demand over all L investors ($i = 1, .., L$) leads to total demand for tradable assets:

$$D = \sum_{i=1}^{L} W_{0,i} x_i = \sum_{i=1}^{L} W_{0,i} \lambda_i \Sigma_{tr}^{-1} \mu_{tr} - \sum_{i=1}^{L} W_{0,i} \Sigma_{tr}^{-1} \Sigma_{tr,nt} q_i, \tag{IA.4}$$

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:

$$\alpha = \bar{\lambda} \Sigma_{tr}^{-1} \mu_{tr} - \Sigma_{tr}^{-1} \Sigma_{tr,nt} q_{nt}, \tag{IA.5}$$

where

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

The value-weighted average of individual risk tolerances is denoted by $\bar{\lambda}$, and q_{nt} is the K-vector of aggregate wealth tied up in the nontradable assets over total financial wealth. Define $\bar{\gamma} \equiv \frac{1}{\bar{\lambda}}$. The pricing equation of the nontradable assets model follows from expression (IA.5):

$$\mu_{tr} = \bar{\gamma} \Sigma_{tr,mkt} + \bar{\gamma} \Sigma_{tr,nt} q_{nt}. \tag{IA.6}$$

This equation must also hold for the market portfolio itself, hence

$$\mu_{mkt} = \bar{\gamma} \sigma_{mkt}^2 + \bar{\gamma} \alpha' \Sigma_{tr,nt} q_{nt}. \tag{IA.7}$$

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

$$\mu_{tr} = \beta_{mkt} \mu_{mkt} + \bar{\gamma} \left(\Sigma_{tr,nt} - \beta_{mkt} \Sigma_{mkt,nt} \right) q_{nt}, \tag{IA.8}$$

where $\Sigma_{mkt,nt} = \alpha' \Sigma_{tr,nt}$ is a $1 \times K$ vector with covariances between the market portfolio and the K human capital industries. This implies that for each tradable asset i the expected excess returns equal

$$E[r_{tr,i}] = \beta_{mkt,i} E[r_{mkt}] + \bar{\gamma} \sum_{k=1}^{K} \left(Cov[r_{tr,i}, R_{nt,k}] - \beta_{mkt,i} Cov[r_{mkt}, R_{nt,k}] \right) q_{nt,k}. \qquad \text{(IA.9)}$$

Defining $\beta_{nt,k,i} \equiv \frac{Cov[r_{tr,i}, R_{nt,k}]}{Var[R_{nt,k}]}$, I can rewrite equation (IA.9) as a multifactor model in which expected stock returns are linear in their exposures to the tradable market portfolio and their exposures to nontradable assets.

II. Labor Income Data

I retrieve monthly labor income data from the National Income and Product Accounts (NIPA) Table 2.7, published by the Bureau of Economic Analysis. This table provides seasonally adjusted labor income data for the following five industries: goods producing (i.e., agriculture, forestry, fishing, hunting, mining, and construction), manufacturing, distributive industries (i.e., trade, transportation, and utilities), service industries (i.e., information, finance, insurance and real estate, and other services), and government. I define labor income as wages and salary disbursements. Jagannathan and Wang (1996) define labor income as personal income minus dividend income. However, this measure of labor income also includes interest income, rental income, and proprietors' income (with inventory valuation and capital consumption adjustments).

I scale labor income by the total number of employees (per industry). For aggregate wages and salaries this is a more appropriate scaling variable than the population, as wages and salaries exclude income that does not directly stem from employment (such as social benefits). For industry-specific labor income this is particularly important, as the relative number of workers in different industries has changed substantially over time.[2] As the NIPA tables do not provide employment data at a monthly frequency, I use data from the Current Employment Statistics (CES) monthly survey, released by the Bureau of Labor Statistics. This survey provides the total number of payroll employees for each industry. Hence, it excludes self-employed and unemployed persons.

Quarterly labor income data for a larger set of more disaggregated industries is reported in the State Quarterly (SQ) Table 7, which is released by the Bureau of Economic Analysis. I use quarterly wages and salary disbursements for nine different industries (at the national, not

[2] Based on the annual number of full-time equivalent employees per industry (NIPA Table 6.5), in 1959 29% of all employees were working in the manufacturing sector and only 18% in the service sector. Over the next 50 years, this changed substantially. In 2009, only 9% of all employees were working in the manufacturing sector, while 49% were employed in the service sector.

regional, level). The industries are: mining (SIC 1000-1499), construction (SIC 1500-1799), manufacturing (SIC 2000-3999), transportation, communication, and utilities (SIC 4100-4999), wholesale trade (SIC 5000-5199), retail trade (SIC 5200-5999), finance, insurance, and real estate (SIC 6000-6799), services (SIC 7000-8999), and government (SIC 9100-9999).[3] I scale quarterly wages and salaries by the average number of workers within the quarter.

Table IA.I Panel A in this appendix reports summary statistics of quarterly returns on industry-specific human capital. The patterns are similar to those based on monthly human capital returns as reported and discussed in the paper. Quarterly labor income growth from the government and retail industry have the lowest means (1.13% and 1.02%) and lowest standard deviations (0.78% and 0.69%, respectively). The financial and mining industries have the highest mean labor income growth rates (both are 1.44%), and the highest standard deviations (2.80% and 2.50%). The null hypotheses that the labor income growth rates have the same means and standard deviations across industries are both rejected at the 1% level. Also, I can reject the null that all mean returns are jointly equal to zero.

Panel B reports the unconditional correlation matrix of monthly orthogonalized industry-specific human capital returns. These returns are included in the model with aggregate and orthogonalized industry-specific human capital returns, as discussed in Section III.C.2 of the paper. Orthogonalized returns are calculated as the residual returns in a regression of industry-level labor income growth rates on a constant and aggregate labor income growth rates. The correlation matrix shows that removing the common component of industry-level labor income growth rates reduces the correlations substantially. Based on orthogonalized human capital returns, the correlations range between -0.44 (service and government) and 0.028 (goods producing and distribution). In comparison, the correlations between industry-level labor income growth rates as reported in Table I of the paper range between 0.038 (service and government) and 0.713 (service and distribution).

III. Hedging Demand in Subsample Periods

Section II.C in the paper discusses portfolio adjustments for industry-specific human capital. The hedging portfolio weights are estimated using the full sample period, from April 1959 to December 2009, which implies that correlations are assumed to remain constant over this period. As a robustness check, Table IA.II in this appendix reports the hedging portfolio

[3] Since 2001, the BEA has used a different industry classification based on NAICS codes. It is relatively straightforward to map the NAICS-code industries into SIC-code industries.

weights estimated for the first half (1959Q3 to 1984Q3) and second half (1984Q4 to 2009Q4) of the sample period separately.

Comparing the two panels suggests that correlations between equity and human capital returns have indeed changed over the full 50-year sample period. Various hedging portfolio weights change sign from the first to the last 25 years of the sample period. The weights that are statistically significant also change from the first to the second period. Note that significance levels are typically higher for the two individual subsamples than for the full sample period. While in Table II in the paper the null that all hedging portfolio weights equal zero could not be rejected for any human capital industry, it can now be rejected for three and four industries, respectively.

IV. Tests for Significance of First-Stage Human Capital Betas

Before performing the cross-sectional regressions, I first test the joint significance of the first-stage betas, as suggested by Kan and Zhang (1999). Table IA.III in this appendix reports the p-values of the Wald tests that the betas with respect to one particular factor (i.e., aggregate human capital returns or human capital returns from one specific industry) are jointly equal to zero. In addition, I test the null hypothesis that all test assets have equal betas. For the 25 size-BM sorted portfolios, I can reject both null hypotheses for aggregate human capital and human capital from the service industry and government. For the 100 size-beta and 100 size-IR sorted portfolios, I can always reject the null hypotheses.

Next, I test whether the matrix with independent variables in the cross-sectional regressions, $[\iota \quad B]$, has full rank. I use the test proposed by Cragg and Donald (1997) and modified by Gospodinov, Kan, and Robotti (2010). Table IA.III shows that the null hypothesis that $[\iota \quad B]$ has less than full rank can always be rejected for the human capital CAPM with aggregate human capital. However, for the nontradable assets model with industry-specific human capital, I can reject the null only when using 100 size-beta or 100 size-IR sorted portfolios as test assets. When using 25 size-BM portfolios as test assets, I cannot reject the null. While this does not necessarily imply that the null hypothesis is true, it suggests that the cross-sectional regressions based on 25 size-BM portfolios should be interpreted with some caution.

V. Contemporaneous Versus Lagged Labor Income Growth

I show that the pricing of aggregate labor income growth in the cross-section of expected stock returns depends crucially on the timing of the labor income growth rates. Table IA.IV Panel A reports the cross-sectional regression results for 25 size and book-to-market sorted portfolios, as in Fama and French (1992, 1993). With a one-month lag, aggregate labor income growth is significantly priced, similar to Jagannathan and Wang (1996). The OLS adjusted-R^2 is 19%. When removing the lag, the ability of aggregate labor income growth to explain stock returns is affected substantially, which is similar to the findings in Heaton and Lucas (2000). The coefficient on aggregate labor income is no longer significant, and the R^2 drops to 9%.[4] As labor income data are relatively smooth, the correlations with stock returns may be more pronounced at a lower frequency. Therefore, as a robustness check, I also report cross-sectional regression results using quarterly returns, for which the impact of timing is even more visible.[5] Again, the coefficient on aggregate labor income growth loses significance when using contemporaneous timing. The OLS adjusted-R^2 decreases from 31% to -6.9%. The GLS R^2 increases, but average pricing errors increase also.

In contrast, a model with industry-specific labor income growth rates captures even more of the cross-sectional variation in returns when using contemporaneous timing rather than lagged growth rates. For example, Panel A of Table IA.IV shows that with a one-month lag, the OLS R^2 is 48% and four out of five industries have significant coefficients. Contemporaneous industry-specific labor income growth leads to an R^2 of 61%, and three industries remain significant. The results based on quarterly returns are similar. For both contemporaneous and lagged timing I find that a model with industry-specific labor income growth outperforms a model with aggregate labor income growth, based on cross-sectional regressions' OLS and GLS R^2s, pricing errors, and significance of coefficients. These results are robust to using monthly or quarterly returns on 100 size-beta sorted portfolios, as can be seen in Panel B.

In sum, the asset pricing implications of aggregate labor income growth are very sensitive to the timing of the data. This suggests that, to some extent, the pricing of lagged aggregate

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[4] These findings are in line with Jagannathan, Kubota, and Takehara (1998), who estimate the human capital CAPM using Japanese data. Jagannathan, Kubota, and Takehara (1998) focus on two-month lagged aggregate labor income growth as the main measure of human capital returns. However, footnote 12 in that paper states that when using contemporaneous aggregate labor income growth for 25 size and book-to-market sorted portfolios, the cross-sectional regression's R^2 is 8% and the coefficient on labor income is not significant.

[5] Quarterly labor income with a one-month lag is calculated as follows: labor income for the second quarter is computed as the sum of monthly labor income in March, April, and May.

labor income growth may be related to announcement effects of aggregate labor income and employment data, rather than the pricing of aggregate human capital risk. The pricing of industry-specific labor income growth is robust to timing issues and the model fit even improves when using contemporaneous timing. This is in line with investors observing their own wages contemporaneously. Therefore, I focus on contemporaneous labor income growth, which from an economic perspective is the most relevant measure of human capital returns.

VI. Cross-Sectional Regressions: Robustness Check

As a first robustness check, I estimate all benchmark models, including the model with aggregate and orthogonalized industry-specific labor income growth rates, using quarterly returns. I leave out the momentum factor as it is based on monthly rebalancing. The results for the 25 size-BM sorted portfolios are presented in Table IA.V Panel A and for the 100 size-beta sorted portfolios in Panel B. The results are very similar to those based on monthly returns and the ranking of the models based on R^2s and average pricing errors is not affected.

Second, to ensure that the outperformance of the model with industry-specific human capital is not simply due to the larger number of factors, I include only one industry at a time. I estimate the resulting three-factor model, which includes the tradable market portfolio, aggregate labor income growth, and orthogonalized industry-specific labor income growth for one industry. The results are presented in Table IA.VI. In Panels A (25 size-BM portfolios) and C (100 size-IR portfolios), the coefficients for all human capital industries are significantly different from zero. In Panel B (100 size-beta portfolios), four out of five industries have significant coefficients. In all cases, the GLS R^2 increases compared to the model with only aggregate labor income growth (see Tables III, IV, and VII of the paper). The OLS adjusted-R^2s are higher in almost all cases as well. The only two exceptions are when human capital from the manufacturing industry is included in Panels A and B. Often, the increase in R^2 is substantial. For example, for the 25 size-BM portfolios the OLS adjusted-R^2 increases from 9% to 55% when including orthogonalized labor income growth from the distribution industry. This confirms that the ability of the model with industry-specific human capital to capture the cross-section of stock returns is not merely driven by a larger number of factors.

Third, I include factors of benchmark models in the models with (industry-specific) labor income growth: the lagged yield spread, the size and value factors, momentum, and the liquidity factor. The results are reported in Table IA.VII. Panel A reports results for the 25 size-BM portfolios. All factors from the benchmark models are significant, except for the momentum factor when added to the model with industry-specific human capital. The significance of the human capital coefficients is not affected substantially. The main difference is that the coefficient on aggregate labor income growth becomes negative and significant when the size and value factors are added to the model. In Panel B (100 size-beta portfolios), the momentum factor is insignificant in both models with human capital. All other benchmark factors are significant. The significance of (industry-specific) human capital returns is similar to that presented in the paper. Finally, Panel C (100 size-IR portfolios) shows that the size, value, and liquidity factors sometimes lose significance. Also, the coefficient on aggregate labor income growth is now negative and marginally significant in half of the specifications. The coefficients on industry-specific human capital are not affected much. Overall, these results show that the nontradable assets model with industry-specific human capital is robust to the inclusion of alternative asset pricing factors.

Fourth, as a test of model misspecification, I include portfolio characteristics in the cross-sectional regressions of the models with aggregate and industry-specific labor income growth. The results can be found in Table IA.VIII. In Panel A, I include the average size and book-to-market ratios of the stocks in each of the 25 size-BM portfolios. Panels B and C include the average size of the 100 size-beta and 100 size-IR portfolios, respectively. Overall, both models fail the test of model misspecification, as the characteristics are significant. The only exception is the model with aggregate labor income growth in Panel C, where the coefficient on size is not significant. However, at the same time, aggregate labor income growth is not significant either. Industry-specific human capital remains significant for two, three, and five industries in Panels A, B, and C.

The fifth robustness check involves estimating monthly human capital returns using three-month average labor income. My main measure of human capital returns is based on a two-month moving average in order to account for measurement errors (following Jagannathan and Wang (1996)). In this robustness check, I estimate human capital returns as follows:

$$R_{k,t}^{hc} = \frac{L_{k,t} + L_{k,t-1} + L_{k,t-2}}{L_{k,t-1} + L_{k,t-2} + L_{k,t-3}} - 1.$$

Table IA.IX in this appendix shows that the cross-sectional regression results are robust to this alternative measure of human capital returns. The performance of the models with aggregate and industry-specific labor income growth in terms of R^2s and pricing errors is very similar for two- and three-month moving averages. Significance levels of the cross-sectional regression coefficients are also similar.

Next, the moving average in the measure of human capital returns may induce additional serial correlation. The summary statistics presented in the paper show that first-order serial correlation coefficients for human capital returns are around 0.4. Therefore, as a robustness check, I adjust the standard errors in the cross-sectional regressions for first- and second-order serial correlation using Newey and West (1987). The results are reported in Table IA.X. This adjustment has a minor effect on the t-statistics and F-statistics, and the results are very similar to those presented in the paper.

In the following robustness check, I estimate cross-sectional regressions when restricting the intercept to zero. Tables III and IV in the paper show that the estimated intercepts of the models with industry-specific or aggregate human capital returns are significantly positive, while the estimated market risk premia are negative (similar to, amongst others, Fama and French (1992), Jagannathan and Wang (1996), and Lettau and Ludvigson (2001)). In theory, the intercept should be zero, since the models are estimated for excess returns. Table IA.XI in this appendix shows the cross-sectional regression results when excluding the intercept. The main difference is that the estimated market risk premium is now always positive and often significant. This suggests that the nonzero estimates of the intercepts in the unrestricted regressions could be related to the similarity in market betas across test assets. The relative performance of the models with aggregate and industry-specific human capital remains unchanged.[6]

Next, I use returns over the previous 60 months to estimate first-stage regression betas. The main results in the paper are based on full sample betas, as the estimated cross-sectional regression coefficients based on rolling window betas are generally not consistent (Kan and Robotti (2012)). Table IA.XII reports the results for this robustness check. Standard errors are adjusted using Newey and West (1987). Overall, the results are robust to using rolling window betas. The coefficient on aggregate human capital is not significant for any of the three sets of test assets (25 size-BM, 100 size-beta, and 100 size-IR sorted portfolios), while the coefficients for respectively two, one, and three industries are significant. For both aggregate and industry-specific human capital, significance levels are lower when estimated for the 100 size-beta portfolios. The nontradable assets model with industry-specific human capital continues to have higher average OLS R^2s than the human capital CAPM with aggregate human capital. Next, I estimate the model with aggregate and orthogonalized industry-specific human capital, where the orthogonalization is performed within the 60-month window used to estimate betas. The results are weaker when this model is estimated

[6] Note that the R^2s are now calculated as one minus the sum of squared errors divided by the sum of squared average returns. Therefore, they are not directly comparable to the R^2s in the unrestricted cross-sectional regressions.

using rolling window instead of full sample betas. Only for the 25 size-BM portfolios do I find that two industries have significant coefficients. The relative performance of the model with industry-specific human capital compared to the alternative asset pricing models is similar to that based on full sample betas. While the model has higher average OLS adjusted-R^2s than the static and conditional CAPM, the Fama and French (1993) model and its extensions with momentum and liquidity factors have higher average R^2s.

Finally, I perform a number of robustness tests for the cross-sectional regressions based on the 100 size-IR sorted portfolios. I exclude the extreme small size high IR portfolio. Table IA.XIII shows that for the remaining 99 size-IR portfolios, the model with aggregate and orthogonalized industry-specific labor income growth still outperforms all benchmark models in terms of R^2s and pricing errors.[7] Next, I construct 100 size-IR sorted portfolios after excluding stocks with IR estimates that are in the top or bottom 0.5%, to reduce the impact of potential outlier idiosyncratic risk estimates from the EGARCH models. Table IA.XIV shows that the results are quantitatively and qualitatively similar. I also measure monthly idiosyncratic risk as the residual volatility of the FF3 model. Table IA.XV Panel A shows that the estimated "premium" for idiosyncratic risk is even higher than when using CAPM residual variance. When sorting stocks into 10 IR-based portfolios (controlling for size), I find that the alpha with respect to the Fama and French (1993) model for the high IR portfolio is 0.91% per month higher than that for the low IR portfolio. This premium is significant at the 1% level. Panel B of Table IA.XV shows that the cross-sectional regression results are similar to those presented in the paper.

VII. 100 Size and Idiosyncratic Risk Sorted Portfolios

The paper reports summary statistics and human capital betas for returns on 10 idiosyncratic risk sorted portfolios. These portfolios are constructed by averaging returns across all size deciles within each IR decile. This appendix reports results for the complete set of monthly returns on 100 size-IR sorted portfolios. Table IA.XVI shows the summary statistics. The table confirms the result that average returns are increasing in IR. The effect is strongest for smaller stocks. Panel E reports time-series alphas with respect to the CAPM.

[7] Note that for the 100 size-IR portfolios, the Jagannathan and Wang (1998) adjusted t-values presented in Table VII of the paper are substantially lower than the Fama-MacBeth (1973) unadjusted t-values. This suggests that estimating human capital betas for 100 size-IR portfolios is subject to greater sampling error. This is related to small stocks with high IR estimates. When excluding the most extreme small size high IR portfolio from the set of test assets, the differences between adjusted and unadjusted t-statistics are considerably smaller.

The difference between the alpha of the high IR portfolio and the low IR portfolio is positive and significant only for the smallest three size deciles. However, the results in the paper confirm that averaging over all size deciles still results in a significant difference, which is referred to as the "premium" for idiosyncratic risk.

Table IA.XVII reports the betas of the 100 size-IR portfolios with respect to aggregate and industry-specific labor income growth. All betas are estimated using simple regressions based on returns from April 1959 to December 2009. For all types of human capital, within at least nine size deciles I find that high IR portfolios have higher human capital betas than low IR portfolios. The difference is statistically significant for almost all size deciles in Panel A (aggregate labor income growth) and Panel C (manufacturing), for about half of the size deciles in Panel E (services), and for a few cases in Panels D (distribution) and F (government). Also, several individual betas are statistically significant, particularly in Panels A and C. Table IA.III Panel C in this document shows that the 100 betas are jointly significant for all types of human capital. This confirms the findings for the 10 IR sorted portfolios that portfolios with higher IR stocks tend to have higher exposures to human capital returns.

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Table IA.I
Additional Summary Statistics of Human Capital Returns

Panel A reports summary statistics of quarterly human capital returns for a set of nine industries: mining, construction, manufacturing, transportation, wholesale trade, retail trade, finance, services, and government. Quarterly labor income data are from the State Quarterly (SQ) personal income tables released by the Bureau of Economic Analysis. Each quarter, industry-specific labor income is scaled by the average number of employees based on CES employment data. Human capital returns are calculated as the quarterly growth rate in per-worker labor income. The sample period runs from 1959Q3 to 2009Q4. The panel reports the mean, standard deviation, minimum, maximum, and first-order autocorrelation (denoted by $\rho(1)$). The panel also reports p-values of the null hypotheses that the mean growth rates in labor income are zero or equal across all nine industries (based on a Newey-West (1987) covariance matrix). The last row reports the p-value of the null hypothesis that the variance of human capital returns is equal across all industries. The asymptotic covariance matrix of the estimated variances is based on Eiling et al. (2012). Panel B reports the unconditional correlation matrix of monthly industry-specific human capital returns, which have been orthogonalized with respect to aggregate human capital returns, for the same five human capital industries that are included in the nontradable assets model. For a given industry, orthogonalized human capital returns are calculated as the residual return of a regression of the industry-specific human capital returns on a constant and aggregate human capital returns. *** denotes significance at the 1% level.

Panel A: Summary statistics of quarterly human capital returns

	mean (%)	median (%)	stdev (%)	min (%)	max (%)	$\rho(1)$	p-value
$R^{hc}_{\min}$	1.44	1.30	2.50	-8.29	17.00	-0.32	
R^{hc}_{cnst}	1.16	1.13	1.03	-2.73	4.88	0.04	
R^{hc}_{man}	1.21	1.21	1.10	-5.82	4.91	-0.13	
R^{hc}_{trnsp}	1.16	1.11	1.18	-4.77	6.88	0.05	
R^{hc}_{whls}	1.24	1.23	1.10	-6.20	4.77	-0.14	
R^{hc}_{ret}	1.02	1.08	0.69	-1.29	3.12	0.10	
R^{hc}_{fina}	1.44	1.51	2.80	-18.77	13.58	-0.51	
R^{hc}_{serv}	1.39	1.46	0.94	-2.38	5.31	0.10	
R^{hc}_{gov}	1.13	0.96	0.78	-0.21	4.74	0.15	
H_0 : mean R^{hc} is zero for all 9 industries							(<0.001)
H_0 : mean R^{hc} is equal for all 9 industries							(<0.001)
$H_0 : Var(R^{hc})$ is equal for all 9 industries							(<0.001)

Panel B: Correlation matrix of monthly orthogonalized human capital returns

	$R^{hc\perp}_{gds}$	$R^{hc\perp}_{man}$	$R^{hc\perp}_{dist}$	$R^{hc\perp}_{serv}$
$R^{hc\perp}_{man}$	-0.040			
$R^{hc\perp}_{dist}$	0.028	0.022		
$R^{hc\perp}_{serv}$	-0.229***	-0.210***	-0.127***	
$R^{hc\perp}_{gov}$	-0.034	-0.299***	-0.273***	-0.440***

Table IA.II
Hedging Portfolio Weights - Subsample Analysis

The table reports hedging portfolio weights for industry-specific human capital for two subsample periods: the first half of the sample period from 1959Q3 to 1984Q3 (Panel A) and the second half of the sample period from 1984Q4 to 2009Q4 (Panel B). The weights (up to q - the value of the investor's human capital over her financial (equity) wealth) are estimated based on an OLS regression of human capital returns on a constant and excess returns on the eight industry equity portfolios. ***,**, and * denote significance at the 1%, 5%, and 10% levels, based on Newey-West (1987) standard errors with six lags. The last rows of both panels report the p-values for the Wald test that all hedging portfolio weights in that column are jointly equal to zero, based on a White covariance matrix.

Panel A: Hedging portfolio weights (in %) from 1959Q3 to 1984Q3

	mining	constr	manuf	transp	wholes	retail	finance	serv	gov
mining	4.84	-4.43***	-1.65	0.23	-0.16	-0.67	0.72	1.46	-0.46
constr	-2.71	1.23	0.36	1.01	0.27	-0.91	0.12	0.32	1.50
manuf	-10.18	7.15**	2.01	-2.32	1.02	1.63	-2.29	-0.83	-1.11
transp	3.93	-0.68	3.09*	4.72	1.92	3.35**	4.06	3.53	9.30***
wholes	14.65*	1.65	0.15	0.68	1.07	-0.60	0.84	1.20	3.88**
retail	-9.09	-1.02	0.59	0.26	1.13	-1.66	1.06	-0.34	1.37
finance	8.36	2.39	-0.55	-2.11	-1.00	-0.17	-1.97	-0.93	-4.88**
serv	-11.86	-4.44**	-1.57	-1.62	-2.30	1.64	-2.03	-2.64	-4.57**
p-value	(0.428)	(0.000)	(0.193)	(0.825)	(0.638)	(0.207)	(0.314)	(0.037)	(0.037)

Panel B: Hedging portfolio weights (in %) from 1984Q4 to 2009Q4

	mining	constr	manuf	transp	wholes	retail	finance	serv	gov
mining	-3.01	-1.41	1.44	0.60	1.16	0.00	5.08	1.35	-0.77**
constr	-1.93	1.52	-0.95	0.69	0.97	0.65	-2.99	-0.18	0.01
manuf	-2.22	-2.37	-6.55*	-2.23	-5.97	-2.05	-11.35	-2.96	1.29
transp	-9.26***	-1.38	0.12	2.75	0.66	-1.19	-2.38	-1.25	1.04
wholes	-7.66*	1.16	-2.17	2.43	0.58	-0.80	-4.70	2.90	-0.55
retail	4.93	-2.22	6.31**	-0.99	2.98	0.16	8.73	4.17*	-2.82***
finance	6.84*	0.85	0.90	-1.78	-2.36	-0.70	-3.80	-2.06	0.52
serv	4.31	2.26	-1.10	-1.20	0.27	1.57	5.33	-1.10	0.98
p-value	(0.004)	(0.508)	(0.014)	(0.215)	(0.257)	(0.695)	(0.187)	(0.066)	(0.000)

Table IA.III
Wald Tests for Joint Significance of Human Capital Betas and Rank Tests

The table reports the results of Wald tests for the joint significance of human capital betas of all test assets. First, the null hypothesis that all betas for one human capital asset (either aggregate human capital returns or human capital returns for one industry) are jointly equal to zero is tested. Next, the table reports results for the test of the null hypothesis that all betas for one type of human capital are equal. The tests are performed for monthly returns on three sets of equity portfolios: 25 size-BM sorted portfolios (Panel A), 100 size-beta sorted portfolios (Panel B), and 100 size-IR sorted portfolios (Panel C). The table reports p-values, which are based on a White covariance matrix. The third row of each panel reports the results of the test of H_0: the matrix $X = [\iota \;\; B]$ has less than full column rank, where B is an $N \times M$ matrix with univariate betas of all N test assets for all M factors. A rejection of the null hypothesis implies that the matrix has full column rank. The factors include the equity market portfolio returns and aggregate labor income growth rates, or labor income growth rates for five different industries. The test is proposed by Cragg and Donald (1997) and modified by Gospodinov, Kan, and Robotti (2010). The test allows for conditional heteroskedasticity. The second column reports the p-values when only aggregate human capital returns are included, and the last column ("All ind") reports the results when human capital returns for five industries are included.

Panel A: Results for 25 size-BM portfolios							
	β^{hc}_{US}	β^{hc}_{gds}	β^{hc}_{man}	β^{hc}_{dist}	β^{hc}_{serv}	β^{hc}_{gov}	All ind
H_0: all betas are zero	(0.006)	(0.910)	(0.338)	(0.386)	(0.003)	(0.064)	
H_0: all betas are equal	(0.007)	(0.924)	(0.345)	(0.444)	(0.003)	(0.072)	
H_0: X less than full rank	(0.036)						(0.943)

Panel B: Results for 100 size-beta portfolios							
	β^{hc}_{US}	β^{hc}_{gds}	β^{hc}_{man}	β^{hc}_{dist}	β^{hc}_{serv}	β^{hc}_{gov}	All ind
H_0: all betas are zero	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	
H_0: all betas are equal	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	
H_0: X less than full rank	(<0.001)						(0.006)

Panel C: Results for 100 size-IR portfolios							
	β^{hc}_{US}	β^{hc}_{gds}	β^{hc}_{man}	β^{hc}_{dist}	β^{hc}_{serv}	β^{hc}_{gov}	All ind
H_0: all betas are zero	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	
H_0: all betas are equal	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	
H_0: X less than full rank	(<0.001)						(0.004)

Table IA.IV
Contemporaneous Versus Lagged Labor Income Growth

This table reports the results of cross-sectional regressions of the nontradable assets model with industry-specific human capital or with aggregate human capital returns. Human capital returns are estimated in two different ways: first, following Jagannathan and Wang (1996) as the one-month lagged labor income growth rate, and second, as the contemporaneous growth rate in labor income, which is the main measure used in the paper. In both cases, monthly labor income is based on a two-month moving average. The table also reports results for quarterly returns, where quarterly labor income is measured either using a one-month lag or based on contemporaneous quarterly labor income. Panel A reports results based on excess returns on 25 size and book-to-market sorted portfolios, constructed as in Fama and French (1992, 1993). Panel B reports results for excess returns on 100 size-beta sorted portfolios, constructed similar to Fama and French (1992) and Jagannathan and Wang (1996). The results are based on the following cross-sectional regression model:

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

where $r_{tr,i}$ is the excess return on portfolio i, $i = 1,..,N$, r_{mkt} is the excess return on the value-weighted CRSP index, and $\beta_{mkt,i}$ is calculated as the slope of the OLS regression of $r_{tr,i}$ on a constant and r_{mkt}. When including aggregate human capital returns, $K = 1$ and $\beta_{US,i}^{hc}$ is calculated as the slope coefficient of an OLS regression on a constant and aggregate labor income growth, R_{US}^{hc}. When including industry-specific human capital returns, $K = 5$. I consider the following five industries: goods producing (excluding manufacturing), manufacturing, distributive industries, service industries, and government. The betas $\beta_{k,i}^{hc}$ are calculated as slope coefficients in simple regressions including a constant and industry-specific labor income growth, R_k^{hc}. The sample period runs from April 1959 to December 2009, a total of 609 monthly observations, or 202 quarterly observations from 1959Q3 to 2009Q4. The cross-sectional regression model is estimated using the Fama-MacBeth (1973) procedure. In the first stage, simple betas are estimated using time-series regressions over the full sample period. In the second stage, average returns are regressed on a constant and the cross-section of betas. The table gives estimates of the cross-sectional regression coefficients, the corresponding Fama-MacBeth t-values (t-value$_{FM}$), and t-values that have been adjusted for estimation error in the betas using the Jagannathan and Wang (1998) adjustment (t-value$_{JW}$). The table also reports the cross-sectional regression's OLS adjusted-R^2 calculated as in Jagannathan and Wang (1996), and below that the GLS R^2, both in percentages. In the last column, the table reports the square root of the mean squared pricing error ("rmspe"), and below that (in square brackets) the F-statistic of the test of H_0 : all pricing errors are equal to zero. This test is robust to estimation error in the first-stage betas as well as conditional heteroskedasticity.

Table IA.IV - *continued*

Panel A: Cross-sectional regressions for 25 size-BM portfolios

Monthly returns

	c_0	c_{mkt}	c_{US}^{hc}	c_{gds}^{hc}	c_{man}^{hc}	c_{dist}^{hc}	c_{serv}^{hc}	c_{gov}^{hc}	$R^2_{ols(gls)}$	rmspe
Human capital returns with a one-month lag										
$\hat{c}$ $(\cdot 10^2)$	1.29	-0.71	0.33						19.18%	0.19%
t-value$_{FM}$	(3.53)	(-1.81)	(2.27)						10.63%	[2.10]
t-value$_{JW}$	(2.42)	(-1.37)	(1.69)							
$\hat{c}$ $(\cdot 10^2)$	1.46	-0.84		0.73	1.04	-0.42	-0.64	0.16	48.46%	0.14%
t-value$_{FM}$	(4.51)	(-2.31)		(4.57)	(3.17)	(-1.92)	(-2.27)	(1.36)	22.33%	[0.65]
t-value$_{JW}$	(2.08)	(-1.05)		(2.07)	(1.35)	(-0.73)	(-0.84)	(0.60)		
Contemporaneous human capital returns										
$\hat{c}$ $(\cdot 10^2)$	1.53	-0.92	0.17						9.35%	0.20%
t-value$_{FM}$	(4.34)	(-2.36)	(1.37)						12.53%	[2.37]
t-value$_{JW}$	(3.38)	(-1.99)	(1.18)							
$\hat{c}$ $(\cdot 10^2)$	1.20	-0.94		0.44	0.61	-0.68	-0.23	-0.04	60.92%	0.12%
t-value$_{FM}$	(4.33)	(-2.50)		(2.66)	(2.79)	(-3.77)	(-0.83)	(-0.42)	24.88%	[0.96]
t-value$_{JW}$	(2.31)	(-1.40)		(1.55)	(1.46)	(-1.86)	(-0.49)	(-0.24)		

Quarterly returns

	c_0	c_{mkt}	c_{US}^{hc}	c_{gds}^{hc}	c_{man}^{hc}	c_{dist}^{hc}	c_{serv}^{hc}	c_{gov}^{hc}	$R^2_{ols(gls)}$	rmspe
Human capital returns with a one-month lag										
$\hat{c}$ $(\cdot 10^2)$	3.39	-1.31	0.68						31.37%	0.54%
t-value$_{FM}$	(3.45)	(-1.19)	(2.86)						5.57%	[1.85]
t-value$_{JW}$	(1.93)	(-0.79)	(1.88)							
$\hat{c}$ $(\cdot 10^2)$	3.53	-2.51		0.66	0.47	-1.21	1.15	0.45	51.17%	0.42%
t-value$_{FM}$	(3.40)	(-1.77)		(2.02)	(1.47)	(-3.12)	(2.89)	(2.13)	21.37%	[1.20]
t-value$_{JW}$	(1.83)	(-1.00)		(1.07)	(0.89)	(-1.81)	(1.68)	(1.14)		
Contemporaneous human capital returns										
$\hat{c}$ $(\cdot 10^2)$	2.31	-0.14	-0.14						-6.87%	0.68%
t-value$_{FM}$	(2.30)	(-0.13)	(-0.51)						23.53%	[2.17]
t-value$_{JW}$	(2.31)	(-0.12)	(-0.51)							
$\hat{c}$ $(\cdot 10^2)$	1.27	2.22		1.36	-0.14	-0.43	-1.85	0.50	58.43%	0.38%
t-value$_{FM}$	(1.22)	(1.64)		(2.50)	(-0.36)	(-1.13)	(-2.92)	(1.67)	29.58%	[0.86]
t-value$_{JW}$	(0.52)	(0.74)		(1.24)	(-0.16)	(-0.54)	(-1.49)	(0.80)		

Table IA.IV - *continued*

Panel B: Cross-sectional regressions for 100 size-beta portfolios

Monthly returns

	c_0	c_{mkt}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	$R^2_{ols(gls)}$	rmspe
Human capital returns with a one-month lag										
$\hat{c}$ $(\cdot 10^2)$	0.87	-0.28	0.44						37.24%	0.18%
t-value$_{FM}$	(5.11)	(-1.17)	(3.37)						0.25%	[1.11]
t-value$_{JW}$	(2.94)	(-0.77)	(2.38)							
$\hat{c}$ $(\cdot 10^2)$	0.80	0.04		0.29	0.12	0.03	0.15	0.39	44.40%	0.16%
t-value$_{FM}$	(5.00)	(0.16)		(4.30)	(0.77)	(0.44)	(1.10)	(3.68)	11.57%	[0.68]
t-value$_{JW}$	(2.71)	(0.09)		(2.40)	(0.41)	(0.24)	(0.60)	(2.31)		
Contemporaneous human capital returns										
$\hat{c}$ $(\cdot 10^2)$	1.01	-0.45	0.37						30.65%	0.18%
t-value$_{FM}$	(5.86)	(-1.87)	(2.95)						1.10%	[1.16]
t-value$_{JW}$	(3.75)	(-1.36)	(2.27)							
$\hat{c}$ $(\cdot 10^2)$	0.73	-0.10		0.32	0.03	0.09	-0.35	0.19	60.99%	0.14%
t-value$_{FM}$	(4.81)	(-0.44)		(4.16)	(0.19)	(0.87)	(-2.55)	(2.63)	11.82%	[0.94]
t-value$_{JW}$	(3.51)	(-0.33)		(2.99)	(0.14)	(0.60)	(-1.49)	(2.09)		

Quarterly returns

	c_0	c_{mkt}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	$R^2_{ols(gls)}$	rmspe
Human capital returns with a one-month lag										
$\hat{c}$ $(\cdot 10^2)$	2.27	0.02	0.77						46.75%	0.56%
t-value$_{FM}$	(3.82)	(0.03)	(3.65)						0.31%	[1.51]
t-value$_{JW}$	(1.70)	(0.01)	(2.48)							
$\hat{c}$ $(\cdot 10^2)$	2.10	0.38		0.25	0.19	-0.27	0.48	0.67	55.37%	0.50%
t-value$_{FM}$	(3.81)	(0.41)		(1.37)	(0.70)	(-1.56)	(2.18)	(3.15)	11.32%	[1.14]
t-value$_{JW}$	(2.27)	(0.27)		(0.88)	(0.45)	(-0.90)	(1.38)	(2.07)		
Contemporaneous human capital returns										
$\hat{c}$ $(\cdot 10^2)$	2.65	-0.52	0.73						19.80%	0.69%
t-value$_{FM}$	(4.38)	(-0.64)	(3.10)						0.76%	[2.08]
t-value$_{JW}$	(2.45)	(-0.45)	(2.48)							
$\hat{c}$ $(\cdot 10^2)$	2.58	0.67		0.77	0.10	-0.27	-0.38	0.89	56.38%	0.50%
t-value$_{FM}$	(4.58)	(0.78)		(3.20)	(0.26)	(-1.01)	(-1.19)	(3.56)	15.79%	[1.01]
t-value$_{JW}$	(3.02)	(0.49)		(2.23)	(0.19)	(-0.65)	(-0.74)	(2.27)		

Table IA.V
Comparison to Alternative Asset Pricing Models using Quarterly Returns

This table evaluates different asset pricing models for quarterly excess returns on 25 size-BM equity portfolios (Panel A) and 100 size-beta sorted portfolios (Panel B), from 1959Q3 to 2009Q4. Five alternative asset pricing models are estimated. First, the nontradable assets model that includes aggregate human capital returns as well as industry-specific human capital returns, which are orthogonalized to the aggregate human capital returns. This is based on the cross-sectional regression model

$$E[r_{tr,i}] = c_0 + c_{mkt}\beta_{mkt,i} + c_{US}^{hc}\beta_{US,i}^{hc} + \sum_{k=1}^{K} c_k^{hc\perp}\beta_{k,i}^{hc\perp},$$

where $r_{tr,i}$ is the excess return on portfolio i, $i = 1, .., N$, r_{mkt} is the excess return on the value-weighted CRSP index, R_{US}^{hc} is the return on aggregate human capital for the U.S. as a whole, estimated as the contemporaneous growth rate in aggregate quarterly per-worker labor income, and $R_k^{hc\perp}$ is the contemporaneous labor income growth rate for industry k, which is orthogonalized to R_{US}^{hc}. I consider the following five industries: goods producing (excluding manufacturing), manufacturing, distributive industries, service industries, and government. The slope of the OLS regression of $r_{tr,i}$ on a constant and r_{mkt} is denoted by $\beta_{mkt,i}$, and $\beta_{US,i}^{hc}$ ($\beta_{k,i}^{hc\perp}$) is calculated as the slope coefficient of an OLS regression on a constant and R_{US}^{hc} ($R_k^{hc\perp}$). The second model is the static CAPM. The third model is the conditional CAPM from Jagannathan and Wang (1996):

$$E[r_{tr,i}] = c_0 + c_{mkt}\beta_{mkt,i} + c_{prem}\beta_{prem,i},$$

where $R_{prem,t-1}$ is the lagged yield difference between Moody's Baa- and Aaa-rated corporate bonds and $\beta_{prem,i}$ is calculated as the slope of the OLS regression of $r_{tr,i,t}$ on a constant and $R_{prem,t-1}$. The last two models are based on the following cross-sectional regression model:

$$E[r_{tr,i}] = c_0 + c_{mkt}\beta_{mkt,i} + c_{smb}\beta_{smb,i} + c_{hml}\beta_{hml,i} + c_{liq}\beta_{liq,i},$$

where $\beta_{smb,i}$ and $\beta_{hml,i}$ are estimated as the slope coefficients with respect to the Fama and French (1993) size and value factors SMB and HML, and $\beta_{liq,i}$ is estimated as the slope coefficient on the Pastor and Stambaugh (2003) liquidity factor. I consider the Fama and French (1993) three-factor model that only includes the first three factors, as well as that model augmented with the Pastor and Stambaugh (2003) liquidity factor. The liquidity factor is available for a shorter sample period, from 1962Q4 to 2008Q4. The cross-sectional regression models are estimated using the Fama-MacBeth (1973) procedure. The table gives estimates of the cross-sectional regression coefficients, the corresponding Fama-MacBeth t-values (t-value$_{FM}$), Jagannathan and Wang (1998) adjusted t-values (t-value$_{JW}$), the cross-sectional regression's OLS adjusted-R^2 calculated as in Jagannathan and Wang (1996), and below that the GLS R^2. In the last column, the table reports the square root of the mean squared pricing error ("rmspe"), and below (in square brackets) the F-statistic of the test of H_0 : all pricing errors are equal to zero. This test is robust to estimation error in the first-stage simple betas as well as conditional heteroskedasticity.

Table IA.V - *continued*

Panel A: Cross-sectional regressions for 25 size-BM portfolios										
Nontradable assets model with aggregate and orthogonalized industry-specific human capital										
	c_0	c_{mkt}	c_{US}^{hc}	$c_{gds}^{hc\perp}$	$c_{man}^{hc\perp}$	$c_{dist}^{hc\perp}$	$c_{serv}^{hc\perp}$	$c_{gov}^{hc\perp}$	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ ($\cdot 10^2$)	-0.80	4.50	-1.37	-0.03	-0.45	-0.45	-0.50	-0.08	60.33%	0.36%
t-value$_{FM}$	(-0.77)	(2.97)	(-4.81)	(-0.10)	(-2.66)	(-3.07)	(-3.06)	(-0.29)	30.30%	[0.58]
t-value$_{JW}$	(-0.31)	(1.14)	(-1.95)	(-0.04)	(-0.78)	(-1.06)	(-0.92)	(-0.12)		
Static CAPM										
	c_0	c_{mkt}							$R^2_{ols(gls)}$	rmspe
$\hat{c}$ ($\cdot 10^2$)	2.60	-0.46							-2.61%	0.68%
t-value$_{FM}$	(2.81)	(-0.42)							0.66%	[2.85]
t-value$_{JW}$	(2.78)	(-0.41)								
Conditional CAPM										
	c_0	c_{mkt}	c_{prem}						$R^2_{ols(gls)}$	rmspe
$\hat{c}$ ($\cdot 10^2$)	3.53	-3.78	0.94						49.98%	0.47%
t-value$_{FM}$	(3.63)	(-2.93)	(4.13)						3.22%	[0.71]
t-value$_{JW}$	(1.39)	(-1.21)	(1.74)							
Fama and French three-factor model										
	c_0	c_{mkt}	c_{smb}	c_{hml}					$R^2_{ols(gls)}$	rmspe
$\hat{c}$ ($\cdot 10^2$)	2.87	-1.84	1.28	1.05					74.51%	0.32%
t-value$_{FM}$	(2.99)	(-1.21)	(2.23)	(2.03)					19.40%	[2.27]
t-value$_{JW}$	(2.88)	(-1.24)	(2.23)	(1.99)						
Fama and French three-factor model + liquidity factor										
	c_0	c_{mkt}	c_{smb}	c_{hml}	c_{liq}				$R^2_{ols(gls)}$	rmspe
$\hat{c}$ ($\cdot 10^2$)	2.92	-3.74	1.14	1.03	4.39				77.03%	0.32%
t-value$_{FM}$	(2.89)	(-1.74)	(1.64)	(1.74)	(1.24)				22.14%	[1.95]
t-value$_{JW}$	(2.41)	(-1.55)	(1.50)	(1.53)	(1.14)					

Table IA.V - *continued*

Panel B: Cross-sectional regressions for 100 size-beta portfolios										
Nontradable assets model with aggregate and orthogonalized industry-specific human capital										
	c_0	c_{mkt}	c_{US}^{hc}	$c_{gds}^{hc\perp}$	$c_{man}^{hc\perp}$	$c_{dist}^{hc\perp}$	$c_{serv}^{hc\perp}$	$c_{gov}^{hc\perp}$	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	2.58	0.79	0.17	0.29	-0.21	-0.12	-0.40	0.29	63.17%	0.45%
t-value$_{FM}$	(4.58)	(0.91)	(1.44)	(1.87)	(-1.71)	(-1.73)	(-2.52)	(1.95)	15.81%	[1.22]
t-value$_{JW}$	(3.14)	(0.66)	(0.98)	(1.51)	(-1.14)	(-1.19)	(-1.44)	(1.25)		
Static CAPM										
	c_0	c_{mkt}							$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	1.39	0.70							6.61%	0.74%
t-value$_{FM}$	(2.22)	(0.79)							0.06%	[1.58]
t-value$_{JW}$	(2.24)	(0.81)								
Conditional CAPM										
	c_0	c_{mkt}	c_{prem}						$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	1.74	-1.30	0.52						46.50%	0.56%
t-value$_{FM}$	(2.86)	(-1.52)	(3.76)						0.37%	[0.97]
t-value$_{JW}$	(1.81)	(-1.00)	(2.83)							
Fama and French three-factor model										
	c_0	c_{mkt}	c_{smb}	c_{hml}					$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	1.79	-0.99	1.39	1.06					69.60%	0.42%
t-value$_{FM}$	(3.23)	(-0.79)	(2.33)	(1.42)					3.73%	[1.83]
t-value$_{JW}$	(3.37)	(-0.82)	(2.39)	(1.48)						
Fama and French three-factor model + liquidity factor										
	c_0	c_{mkt}	c_{smb}	c_{hml}	c_{liq}				$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	1.64	-0.02	1.40	1.20	-1.53				68.00%	0.43%
t-value$_{FM}$	(2.92)	(-0.02)	(2.19)	(1.59)	(-0.92)				3.11%	[1.68]
t-value$_{JW}$	(3.07)	(-0.02)	(2.27)	(1.72)	(-0.95)					

Table IA.VI
Including A Single Human Capital Industry

This table reports the cross-sectional regression results of the nontradable assets model with aggregate human capital and orthogonalized industry-specific human capital, where only one human capital industry k is included per regression:

$$E[r_{tr,i}] = c_0 + c_{mkt}\beta_{mkt,i} + c_{US}^{hc}\beta_{US,i}^{hc} + c_k^{hc\perp}\beta_{k,i}^{hc\perp},$$

where $r_{tr,i}$ is the excess return on portfolio i, $i = 1, .., N$. The excess return on the value-weighted CRSP index is denoted by r_{mkt}. The return on aggregate human capital asset for the U.S. as a whole is denoted by R_{US}^{hc} and estimated as the contemporaneous growth rate in aggregate per-worker labor income (based on a two-month average) while $R_k^{hc\perp}$ is the contemporaneous labor income growth rate for industry k, which is orthogonalized to R_{US}^{hc}. I consider the following five industries: goods producing (excluding manufacturing), manufacturing, distributive industries, service industries, and government. The slope of the OLS regression of $r_{tr,i}$ on a constant and r_{mkt} is denoted by $\beta_{mkt,i}$, and $\beta_{US,i}^{hc}$ ($\beta_{k,i}^{hc\perp}$) is calculated as the slope coefficient of an OLS regression on a constant and R_{US}^{hc} ($R_k^{hc\perp}$). The model is estimated using monthly excess returns on 25 size-BM equity portfolios (Panel A), 100 size-beta portfolios (Panel B), and 100 size-IR portfolios (Panel C) from April 1959 to December 2009. The cross-sectional regression model is estimated using the Fama-MacBeth (1973) procedure. The table gives estimates of the cross-sectional regression coefficients, the corresponding Fama-MacBeth t-values (t-value$_{FM}$), Jagannathan and Wang (1998) adjusted t-values (t-value$_{JW}$), the cross-sectional regression's OLS adjusted-R^2 calculated as in Jagannathan and Wang (1996), and below that the GLS R^2. In the last column, the table reports the square root of the mean squared pricing error ("rmspe"), and below that (in square brackets) the F-statistic of the test of H_0 : all pricing errors are equal to zero. This test is robust to estimation error in the first-stage simple betas as well as conditional heteroskedasticity.

Panel A: Cross-sectional regressions for 25 size-BM portfolios										
	c_0	c_{mkt}	c_{US}^{hc}	$c_{gds}^{hc\perp}$	$c_{man}^{hc\perp}$	$c_{dist}^{hc\perp}$	$c_{serv}^{hc\perp}$	$c_{gov}^{hc\perp}$	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ ($\cdot 10^2$)	0.56	-0.20	0.06	0.75					46.83%	0.15%
t-value$_{FM}$	(1.92)	(-0.57)	(0.51)	(4.11)					19.32%	[0.81]
t-value$_{JW}$	(1.00)	(-0.29)	(0.26)	(1.47)						
$\hat{c}$ ($\cdot 10^2$)	2.03	-1.48	0.21		0.15				8.09%	0.20%
t-value$_{FM}$	(6.24)	(-3.75)	(1.56)		(1.73)				17.18%	[1.70]
t-value$_{JW}$	(4.63)	(-2.86)	(1.02)		(1.22)					
$\hat{c}$ ($\cdot 10^2$)	0.80	-0.42	-0.36			-0.31			55.22%	0.14%
t-value$_{FM}$	(2.51)	(-1.15)	(-3.09)			(-4.32)			16.97%	[0.75]
t-value$_{JW}$	(1.17)	(-0.53)	(-1.50)			(-2.14)				
$\hat{c}$ ($\cdot 10^2$)	0.82	0.08	-0.46				-0.39		44.26%	0.16%
t-value$_{FM}$	(2.42)	(0.19)	(-3.75)				(-4.19)		13.59%	[0.99]
t-value$_{JW}$	(0.94)	(0.08)	(-1.93)				(-2.39)			
$\hat{c}$ ($\cdot 10^2$)	1.15	-0.16	-0.34					0.51	18.93%	0.19%
t-value$_{FM}$	(3.19)	(-0.36)	(-3.06)					(3.37)	12.56%	[0.94]
t-value$_{JW}$	(1.36)	(-0.16)	(-1.58)					(1.99)		

Table IA.VI - *continued*

Panel B: Cross-sectional regressions for 100 size-beta portfolios										
	c_0	c_{mkt}	c_{US}^{hc}	$c_{gds}^{hc\perp}$	$c_{man}^{hc\perp}$	$c_{dist}^{hc\perp}$	$c_{serv}^{hc\perp}$	$c_{gov}^{hc\perp}$	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	0.72	-0.30	0.25	0.38					48.51%	0.16%
t-value$_{FM}$	(4.61)	(-1.26)	(2.41)	(4.00)					8.31%	[0.91]
t-value$_{JW}$	(2.86)	(-0.83)	(1.65)	(1.93)						
$\hat{c}$ $(\cdot 10^2)$	0.99	-0.43	0.37		-0.03				30.13%	0.18%
t-value$_{FM}$	(5.89)	(-1.80)	(2.95)		(-0.65)				1.25%	[1.17]
t-value$_{JW}$	(3.77)	(-1.31)	(2.32)		(-0.47)					
$\hat{c}$ $(\cdot 10^2)$	1.00	-0.57	0.21			-0.11			39.82%	0.17%
t-value$_{FM}$	(5.86)	(-2.22)	(2.69)			(-2.34)			3.84%	[1.12]
t-value$_{JW}$	(4.39)	(-1.79)	(2.14)			(-1.99)				
$\hat{c}$ $(\cdot 10^2)$	0.81	-0.15	0.01				-0.23		59.29%	0.14%
t-value$_{FM}$	(5.22)	(-0.65)	(0.15)				(-3.73)		2.62%	[1.16]
t-value$_{JW}$	(4.22)	(-0.50)	(0.12)				(-2.97)			
$\hat{c}$ $(\cdot 10^2)$	1.00	-0.29	0.14					0.28	50.47%	0.16%
t-value$_{FM}$	(5.85)	(-1.26)	(1.83)					(3.53)	1.20%	[1.02]
t-value$_{JW}$	(4.78)	(-0.98)	(1.43)					(2.84)		

Panel C: Cross-sectional regressions for 100 size-IR portfolios										
	c_0	c_{mkt}	c_{US}^{hc}	$c_{gds}^{hc\perp}$	$c_{man}^{hc\perp}$	$c_{dist}^{hc\perp}$	$c_{serv}^{hc\perp}$	$c_{gov}^{hc\perp}$	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	-0.27	0.58	0.15	0.55					43.15%	0.34%
t-value$_{FM}$	(-1.72)	(2.34)	(1.23)	(4.45)					8.47%	[2.34]
t-value$_{JW}$	(-0.91)	(1.47)	(0.75)	(1.48)						
$\hat{c}$ $(\cdot 10^2)$	-0.42	1.06	0.11		-0.40				49.67%	0.32%
t-value$_{FM}$	(-2.86)	(4.38)	(0.95)		(-5.28)				7.44%	[1.93]
t-value$_{JW}$	(-1.55)	(2.88)	(0.37)		(-2.41)					
$\hat{c}$ $(\cdot 10^2)$	-0.23	0.49	-0.38			-0.30			61.29%	0.28%
t-value$_{FM}$	(-1.45)	(1.95)	(-4.75)			(-6.09)			10.80%	[1.23]
t-value$_{JW}$	(-0.73)	(1.00)	(-2.43)			(-3.44)				
$\hat{c}$ $(\cdot 10^2)$	-0.39	1.07	-0.27				-0.41		55.71%	0.30%
t-value$_{FM}$	(-2.58)	(4.39)	(-3.04)				(-5.32)		11.34%	[1.81]
t-value$_{JW}$	(-1.41)	(2.57)	(-1.67)				(-2.97)			
$\hat{c}$ $(\cdot 10^2)$	-0.10	0.78	-0.04					0.39	41.74%	0.35%
t-value$_{FM}$	(-0.57)	(3.24)	(-0.45)					(3.87)	6.95%	[2.60]
t-value$_{JW}$	(-0.42)	(2.29)	(-0.36)					(3.17)		

Table IA.VII
Including Other Factors in Human Capital Models

This table reports cross-sectional regression results of the human capital CAPM and the nontradable assets model with industry-specific human capital, augmented by the following factors: the yield spread (as in the conditional CAPM of Jagannathan and Wang (1996)), the size and value factors SMB and HML from Fama and French (1993), Carhart's (1997) momentum factor, and the liquidity factor of Pastor and Stambaugh (2003). Human capital returns are estimated as the contemporaneous growth rate in per-worker labor income. The models are estimated for monthly excess returns on 25 size-BM equity portfolios (Panel A), 100 size-beta portfolios (Panel B), and 100 size-IR portfolios (Panel C) from April 1959 to December 2009 using the Fama-MacBeth (1973) approach. The table gives estimates of the cross-sectional regression coefficients, the corresponding Fama-MacBeth t-values (t-value$_{FM}$), Jagannathan and Wang (1998) adjusted t-values (t-value$_{JW}$), the cross-sectional regression's OLS adjusted-R^2 calculated as in Jagannathan and Wang (1996), and below that the GLS R^2. In the last column, the table reports the square root of the mean squared pricing error ("rmspe"), and below that (in square brackets) the F-statistic of the test of H_0 : all pricing errors are equal to zero. This test is robust to estimation error in the first-stage simple betas as well as conditional heteroskedasticity.

Table IA.VII - *continued*

Panel A: Cross-sectional regressions for 25 size-BM portfolios												
	c_0	c_{mkt}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	c_{prem}		$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	2.03	-1.82	0.16						0.60		32.34%	0.17%
t-val$_{FM}$	(5.33)	(-4.05)	(1.29)						(4.14)		12.72%	[1.11]
t-val$_{JW}$	(2.85)	(-2.36)	(0.71)						(2.48)			
$\hat{c}$ $(\cdot 10^2)$	1.44	-1.37		0.49	0.55	-0.55	-0.12	-0.10	0.24		61.74%	0.12%
t-val$_{FM}$	(5.05)	(-3.30)		(2.91)	(2.62)	(-3.16)	(-0.44)	(-0.91)	(2.09)		25.12%	[1.05]
t-val$_{JW}$	(2.85)	(-2.05)		(1.56)	(1.45)	(-1.78)	(-0.25)	(-0.50)	(1.15)			
	c_0	c_{mkt}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	c_{smb}	c_{hml}	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	0.96	-0.49	-0.28						0.58	0.38	78.46%	0.09%
t-val$_{FM}$	(3.34)	(-1.23)	(-2.75)						(3.90)	(2.67)	39.49%	[1.43]
t-val$_{JW}$	(2.80)	(-1.02)	(-2.03)						(2.77)	(1.99)		
$\hat{c}$ $(\cdot 10^2)$	1.18	-0.70		-0.44	0.31	0.08	-0.19	-0.26	0.63	0.69	75.60%	0.09%
t-val$_{FM}$	(3.84)	(-1.53)		(-2.14)	(1.51)	(0.44)	(-0.70)	(-2.30)	(3.47)	(3.24)	40.87%	[0.90]
t-val$_{JW}$	(2.59)	(-0.97)		(-1.35)	(0.96)	(0.26)	(-0.40)	(-1.43)	(1.92)	(1.81)		
	c_0	c_{mkt}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	c_{mom}		$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	0.77	-0.56	0.13						-2.02		26.51%	0.18%
t-val$_{FM}$	(2.91)	(-1.64)	(1.02)						(-3.10)		12.56%	[1.99]
t-val$_{JW}$	(2.24)	(-1.27)	(0.74)						(-2.44)			
$\hat{c}$ $(\cdot 10^2)$	1.19	-0.94		0.44	0.61	-0.69	-0.23	-0.04	0.02		58.62%	0.12%
t-val$_{FM}$	(4.00)	(-2.07)		(2.55)	(2.76)	(-3.76)	(-0.83)	(-0.40)	(0.03)		25.65%	[0.99]
t-val$_{JW}$	(2.09)	(-1.11)		(1.54)	(1.43)	(-1.86)	(-0.50)	(-0.23)	(0.02)			
	c_0	c_{mkt}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	c_{liq}		$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	1.46	-2.92	0.10						7.28		53.03%	0.15%
t-val$_{FM}$	(4.11)	(-4.25)	(0.68)						(4.32)		32.18%	[0.79]
t-val$_{JW}$	(2.09)	(-2.00)	(0.32)						(2.12)			
$\hat{c}$ $(\cdot 10^2)$	0.93	-1.29		-0.11	0.37	-0.86	0.03	0.17	3.09		75.63%	0.10%
t-val$_{FM}$	(3.02)	(-2.49)		(-0.60)	(1.62)	(-4.32)	(0.11)	(1.57)	(2.82)		42.28%	[0.54]
t-val$_{JW}$	(1.44)	(-1.18)		(-0.26)	(0.71)	(-1.68)	(0.05)	(0.77)	(1.24)			

Table IA.VII - *continued*

Panel B: Cross-sectional regressions for 100 size-beta portfolios												
	c_0	c_{mkt}	c_{US}^{hc}	c_{gds}^{hc}	c_{man}^{hc}	c_{dist}^{hc}	c_{serv}^{hc}	c_{gov}^{hc}	c_{prem}		$R^2_{ols(gls)}$	rmspe
$\hat{c}$ ($\cdot 10^2$)	0.91	-0.66	0.24						0.38		48.15%	0.16%
t-val$_{FM}$	(5.64)	(-2.53)	(2.41)						(3.63)		1.32%	[1.01]
t-val$_{JW}$	(4.11)	(-1.88)	(1.79)						(2.94)			
$\hat{c}$ ($\cdot 10^2$)	0.69	-0.24		0.30	-0.10	0.11	-0.22	0.16	0.20		64.07%	0.13%
t-val$_{FM}$	(4.68)	(-0.99)		(4.10)	(-0.73)	(1.16)	(-1.53)	(2.35)	(2.80)		12.03%	[0.89]
t-val$_{JW}$	(3.59)	(-0.78)		(2.67)	(-0.54)	(0.81)	(-1.18)	(1.87)	(2.08)			
	c_0	c_{mkt}	c_{US}^{hc}	c_{gds}^{hc}	c_{man}^{hc}	c_{dist}^{hc}	c_{serv}^{hc}	c_{gov}^{hc}	c_{smb}	c_{hml}	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ ($\cdot 10^2$)	0.64	-0.18	0.10						0.37	0.45	64.12%	0.13%
t-val$_{FM}$	(3.71)	(-0.55)	(1.67)						(2.39)	(2.00)	6.53%	[1.40]
t-val$_{JW}$	(3.61)	(-0.52)	(1.57)						(2.39)	(1.93)		
$\hat{c}$ ($\cdot 10^2$)	0.50	0.12		0.15	-0.08	0.26	-0.32	0.09	0.27	0.42	72.15%	0.11%
t-val$_{FM}$	(3.11)	(0.40)		(2.47)	(-0.76)	(2.98)	(-2.34)	(1.53)	(1.77)	(1.88)	16.80%	[1.05]
t-val$_{JW}$	(2.53)	(0.32)		(2.04)	(-0.61)	(2.13)	(-1.47)	(1.24)	(1.52)	(1.48)		
	c_0	c_{mkt}	c_{US}^{hc}	c_{gds}^{hc}	c_{man}^{hc}	c_{dist}^{hc}	c_{serv}^{hc}	c_{gov}^{hc}	c_{mom}		$R^2_{ols(gls)}$	rmspe
$\hat{c}$ ($\cdot 10^2$)	1.03	-0.57	0.36						-0.36		30.37%	0.18%
t-val$_{FM}$	(5.73)	(-1.93)	(3.08)						(-0.81)		4.25%	[1.18]
t-val$_{JW}$	(3.79)	(-1.44)	(2.42)						(-0.64)			
$\hat{c}$ ($\cdot 10^2$)	0.74	-0.14		0.32	0.02	0.09	-0.36	0.19	-0.13		60.63%	0.14%
t-val$_{FM}$	(4.73)	(-0.54)		(4.19)	(0.18)	(0.97)	(-2.56)	(2.73)	(-0.33)		14.80%	[0.93]
t-val$_{JW}$	(3.43)	(-0.41)		(3.00)	(0.13)	(0.69)	(-1.55)	(2.17)	(-0.23)			
	c_0	c_{mkt}	c_{US}^{hc}	c_{gds}^{hc}	c_{man}^{hc}	c_{dist}^{hc}	c_{serv}^{hc}	c_{gov}^{hc}	c_{liq}		$R^2_{ols(gls)}$	rmspe
$\hat{c}$ ($\cdot 10^2$)	1.04	-1.30	0.35						3.06		41.27%	0.17%
t-val$_{FM}$	(5.85)	(-3.28)	(2.77)						(3.11)		2.34%	[1.09]
t-val$_{JW}$	(3.49)	(-1.98)	(1.89)						(2.09)			
$\hat{c}$ ($\cdot 10^2$)	0.74	-0.61		0.31	0.07	0.14	-0.44	0.14	1.45		64.50%	0.13%
t-val$_{FM}$	(4.73)	(-1.95)		(4.70)	(0.46)	(1.24)	(-2.64)	(2.10)	(2.05)		10.21%	[0.93]
t-val$_{JW}$	(3.36)	(-1.28)		(3.61)	(0.34)	(0.91)	(-1.74)	(1.58)	(1.42)			

Table IA.VII - *continued*

Panel C: Cross-sectional regressions for 100 size-IR portfolios												
	c_0	c_{mkt}	c_{US}^{hc}	c_{gds}^{hc}	c_{man}^{hc}	c_{dist}^{hc}	c_{serv}^{hc}	c_{gov}^{hc}	c_{prem}		$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	-0.27	0.39	-0.16						0.54		65.04%	0.27%
t-val$_{FM}$	(-1.75)	(1.55)	(-1.76)						(6.11)		13.26%	[1.70]
t-val$_{JW}$	(-0.96)	(1.02)	(-0.89)						(3.80)			
$\hat{c}$ $(\cdot 10^2)$	-0.42	0.56		0.06	0.11	-0.22	-0.39	-0.08	0.43		65.59%	0.26%
t-val$_{FM}$	(-2.80)	(2.27)		(0.60)	(0.85)	(-2.24)	(-2.45)	(-1.13)	(6.26)		18.78%	[1.72]
t-val$_{JW}$	(-1.45)	(1.45)		(0.35)	(0.44)	(-1.26)	(-1.32)	(-0.67)	(3.61)			
	c_0	c_{mkt}	c_{US}^{hc}	c_{gds}^{hc}	c_{man}^{hc}	c_{dist}^{hc}	c_{serv}^{hc}	c_{gov}^{hc}	c_{smb}	c_{hml}	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	-0.23	0.54	-0.08						0.44	0.22	43.21%	0.34%
t-val$_{FM}$	(-1.60)	(1.80)	(-1.03)						(2.85)	(1.07)	7.81%	[4.53]
t-val$_{JW}$	(-1.54)	(1.72)	(-1.03)						(2.78)	(1.13)		
$\hat{c}$ $(\cdot 10^2)$	-0.18	0.43		0.66	0.30	-0.86	-0.57	0.21	-0.17	-0.48	61.37%	0.27%
t-val$_{FM}$	(-1.15)	(1.43)		(7.32)	(2.72)	(-8.45)	(-3.72)	(2.62)	(-1.11)	(-2.21)	15.20%	[0.85]
t-val$_{JW}$	(-0.38)	(0.60)		(2.74)	(0.94)	(-3.37)	(-1.58)	(1.06)	(-0.49)	(-0.91)		
	c_0	c_{mkt}	c_{US}^{hc}	c_{gds}^{hc}	c_{man}^{hc}	c_{dist}^{hc}	c_{serv}^{hc}	c_{gov}^{hc}	c_{mom}		$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	-0.29	0.32	-0.15						-2.36		61.59%	0.28%
t-val$_{FM}$	(-1.91)	(1.21)	(-1.70)						(-5.39)		9.14%	[3.17]
t-val$_{JW}$	(-1.36)	(0.89)	(-0.80)						(-4.85)			
$\hat{c}$ $(\cdot 10^2)$	-0.40	0.41		0.09	0.23	-0.41	-0.28	-0.10	-1.73		63.20%	0.27%
t-val$_{FM}$	(-2.70)	(1.56)		(0.89)	(1.66)	(-3.93)	(-1.84)	(-1.68)	(-4.17)		15.65%	[1.86]
t-val$_{JW}$	(-1.62)	(0.96)		(0.61)	(0.84)	(-2.17)	(-1.03)	(-1.11)	(-2.84)			
	c_0	c_{mkt}	c_{US}^{hc}	c_{gds}^{hc}	c_{man}^{hc}	c_{dist}^{hc}	c_{serv}^{hc}	c_{gov}^{hc}	c_{liq}		$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	0.00	1.05	0.18						-1.86		35.10%	0.33%
t-val$_{FM}$	(-0.03)	(2.15)	(1.23)						(-1.37)		14.97%	[3.00]
t-val$_{JW}$	(-0.02)	(2.14)	(1.20)						(-1.37)			
$\hat{c}$ $(\cdot 10^2)$	-0.48	2.64		0.56	-0.02	-0.69	-0.31	0.08	-6.24		65.16%	0.24%
t-val$_{FM}$	(-3.17)	(6.88)		(6.17)	(-0.15)	(-5.43)	(-1.82)	(1.01)	(-5.96)		22.70%	[1.08]
t-val$_{JW}$	(-1.01)	(2.76)		(1.63)	(-0.06)	(-1.83)	(-0.75)	(0.43)	(-2.22)			

Table IA.VIII
Cross-Sectional Regressions Including Characteristics

This table reports cross-sectional regression results of models with aggregate or industry-specific human capital, including times-series averages of portfolio size and book-to-market ratios. The models are estimated for monthly returns on 25 size-BM, 100 size-beta, and 100 size-IR portfolios using the Fama-MacBeth (1973) approach. The table provides coefficient estimates, Fama-MacBeth (1973) t-values (t-val$_{FM}$), Jagannathan and Wang (1998) t-values (t-val$_{JW}$), OLS adjusted-R^2, GLS R^2, and the square root of the mean squared pricing error ("rmspe").

Panel A: Cross-sectional regressions for 25 size-BM portfolios												
	c_0	c_{mkt}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	c_{size}	c_{BM}	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	1.35	0.11	-0.27						-0.10	0.22	85.20%	0.08%
t-val$_{FM}$	(3.88)	(0.32)	(-2.62)						(-3.20)	(3.02)	57.66%	
t-val$_{JW}$	(3.16)	(0.25)	(-1.97)						(-2.49)	(2.24)		
$\hat{c}$ $(\cdot 10^2)$	1.70	-0.18		-0.50	0.26	-0.01	-0.14	-0.21	-0.10	0.37	85.17%	0.07%
t-val$_{FM}$	(4.52)	(-0.44)		(-2.72)	(1.37)	(-0.08)	(-0.50)	(-1.98)	(-2.83)	(4.41)	56.76%	
t-val$_{JW}$	(2.57)	(-0.27)		(-1.56)	(0.82)	(-0.05)	(-0.30)	(-1.23)	(-1.54)	(2.63)		

Panel B: Cross-sectional regressions for 100 size-beta portfolios											
	c_0	c_{mkt}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	c_{size}	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	1.46	-0.21	0.08						-0.10	62.56%	0.14%
t-val$_{FM}$	(5.62)	(-0.88)	(1.00)						(-3.32)	5.52%	
t-val$_{JW}$	(5.61)	(-0.86)	(1.00)						(-3.35)		
$\hat{c}$ $(\cdot 10^2)$	1.16	0.05		0.19	-0.18	0.24	-0.31	0.09	-0.08	71.69%	0.12%
t-val$_{FM}$	(4.86)	(0.20)		(3.22)	(-1.34)	(2.68)	(-2.22)	(1.48)	(-2.73)	16.44%	
t-val$_{JW}$	(3.84)	(0.16)		(2.80)	(-1.01)	(1.86)	(-1.41)	(1.23)	(-2.21)		

Panel C: Cross-sectional regressions for 100 size-IR portfolios											
	c_0	c_{mkt}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	c_{size}	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	0.00	0.72	0.12						-0.02	36.09%	0.36%
t-val$_{FM}$	(0.00)	(2.83)	(1.19)						(-0.66)	19.71%	
t-val$_{JW}$	(0.00)	(2.74)	(1.25)						(-0.67)		
$\hat{c}$ $(\cdot 10^2)$	-1.56	0.35		0.69	0.62	-0.95	-0.65	0.29	0.11	67.26%	0.25%
t-val$_{FM}$	(-5.00)	(1.36)		(7.36)	(4.14)	(-8.13)	(-4.14)	(3.32)	(4.58)	27.33%	
t-val$_{JW}$	(-1.96)	(0.50)		(2.66)	(1.60)	(-3.08)	(-1.55)	(1.35)	(1.70)		

Table IA.IX
Cross-Sectional Regression Results using Growth Rates in Three-Month Average Labor Income

The table reports cross-sectional regression results for the models with aggregate and industry-specific human capital returns. Monthly human capital returns are calculated as the contemporaneous growth rate in labor income, where monthly labor income is based on a three-month moving average instead of a two-month average (i.e., the main measure in the paper). The models are estimated using two-stage cross-sectional regressions. The table gives estimates of the regression coefficients, Fama-MacBeth (1973) t-values, Jagannathan and Wang (1998) adjusted t-values, OLS adjusted-R^2, GLS R^2, the square root of the mean squared pricing error ("rmspe"), and (in square brackets) the F-statistic of the test of H_0 : all pricing errors are equal to zero. The models are tested using 25 size-BM portfolios (Panel A), 100 size-beta portfolios (Panel B), and 100 size-IR portfolios (Panel C).

Panel A: Cross-sectional regressions for 25 size-BM portfolios										
	c_0	c_{mkt}	c_{US}^{hc}	c_{gds}^{hc}	c_{man}^{hc}	c_{dist}^{hc}	c_{serv}^{hc}	c_{gov}^{hc}	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	1.47	-0.88	0.19						13.31%	0.20%
t-val$_{FM}$	(4.11)	(-2.27)	(1.76)						12.66%	[2.21]
t-val$_{JW}$	(3.24)	(-1.98)	(1.46)							
$\hat{c}$ $(\cdot 10^2)$	1.09	-0.09		0.60	0.18	-0.25	-0.69	0.11	60.15%	0.12%
t-val$_{FM}$	(3.51)	(-0.22)		(3.76)	(1.22)	(-2.01)	(-3.30)	(1.45)	25.13%	[0.84]
t-val$_{JW}$	(1.66)	(-0.09)		(1.94)	(0.58)	(-0.97)	(-1.70)	(0.73)		

Panel B: Cross-sectional regressions for 100 size-beta portfolios										
	c_0	c_{mkt}	c_{US}^{hc}	c_{gds}^{hc}	c_{man}^{hc}	c_{dist}^{hc}	c_{serv}^{hc}	c_{gov}^{hc}	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	0.99	-0.42	0.33						33.01%	0.18%
t-val$_{FM}$	(5.75)	(-1.76)	(3.13)						0.90%	[1.07]
t-val$_{JW}$	(3.54)	(-1.23)	(2.37)							
$\hat{c}$ $(\cdot 10^2)$	0.86	0.04		0.22	0.05	0.05	-0.24	0.21	58.52%	0.14%
t-val$_{FM}$	(5.39)	(0.18)		(3.92)	(0.42)	(0.68)	(-2.31)	(2.95)	11.45%	[0.86]
t-val$_{JW}$	(3.90)	(0.13)		(2.86)	(0.32)	(0.47)	(-1.36)	(2.36)		

Panel C: Cross-sectional regressions for 100 size-IR portfolios										
	c_0	c_{mkt}	c_{US}^{hc}	c_{gds}^{hc}	c_{man}^{hc}	c_{dist}^{hc}	c_{serv}^{hc}	c_{gov}^{hc}	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	-0.41	0.93	0.02						35.30%	0.37%
t-val$_{FM}$	(-2.64)	(3.90)	(0.25)						4.88%	[3.93]
t-val$_{JW}$	(-2.46)	(3.90)	(0.26)							
$\hat{c}$ $(\cdot 10^2)$	-0.49	0.81		0.14	0.30	-0.85	0.37	0.12	65.60%	0.26%
t-val$_{FM}$	(-3.19)	(3.37)		(2.21)	(2.26)	(-8.36)	(3.68)	(1.51)	10.34%	[1.14]
t-val$_{JW}$	(-1.56)	(1.66)		(0.99)	(1.00)	(-3.12)	(1.34)	(0.79)		

Table IA.X
Cross-Sectional Regression Results with Newey-West Adjusted Standard Errors

The table reports cross-sectional regression results for the models with aggregate or industry-specific human capital. The models are estimated using two-stage cross-sectional regressions. The table gives estimates of the cross-sectional regression coefficients, Fama-MacBeth (1973) t-values (t-value$_{FM}$), and Jagannathan and Wang (1998) adjusted t-values (t-value$_{JW}$). All standard errors are adjusted for first- and second-order serial correlation using Newey-West (1987). The table also reports the cross-sectional regression's OLS adjusted-R^2 calculated as in Jagannathan and Wang (1996), and below that the GLS R^2. In the last column, the table reports the square root of the mean squared pricing error ("rmspe"), and below that (in square brackets) the F-statistic of the test of H_0 : all pricing errors are equal to zero. The models are tested using three different sets of test assets: 25 size-BM portfolios (Panel A), 100 size-beta sorted portfolios (Panel B), and 100 size-IR portfolios (Panel C).

Panel A: Cross-sectional regressions for 25 size-BM portfolios										
	c_0	c_{mkt}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	1.53	-0.92	0.17						9.35%	0.20%
t-val$_{FM}$	(3.95)	(-2.21)	(1.30)						12.53%	[2.47]
t-val$_{JW}$	(3.03)	(-1.85)	(1.08)							
$\hat{c}$ $(\cdot 10^2)$	1.20	-0.94		0.44	0.61	-0.68	-0.23	-0.04	60.92%	0.12%
t-val$_{FM}$	(4.09)	(-2.40)		(2.41)	(2.73)	(-3.84)	(-0.86)	(-0.43)	24.88%	[1.06]
t-val$_{JW}$	(2.36)	(-1.36)		(1.53)	(1.38)	(-1.79)	(-0.52)	(-0.25)		

Panel B: Cross-sectional regressions for 100 size-beta portfolios										
	c_0	c_{mkt}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	1.01	-0.45	0.37						30.65%	0.18%
t-val$_{FM}$	(5.58)	(-1.90)	(2.85)						1.10%	[1.55]
t-val$_{JW}$	(3.33)	(-1.38)	(1.94)							
$\hat{c}$ $(\cdot 10^2)$	0.73	-0.10		0.32	0.03	0.09	-0.35	0.19	60.99%	0.14%
t-val$_{FM}$	(4.50)	(-0.43)		(4.17)	(0.18)	(0.89)	(-2.59)	(2.56)	11.82%	[1.13]
t-val$_{JW}$	(3.34)	(-0.35)		(2.85)	(0.14)	(0.60)	(-1.39)	(1.98)		

Panel C: Cross-sectional regressions for 100 size-IR portfolios										
	c_0	c_{mkt}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	-0.19	0.67	0.17						36.43%	0.36%
t-val$_{FM}$	(-1.12)	(2.69)	(1.31)						6.93%	[3.84]
t-val$_{JW}$	(-0.92)	(2.53)	(1.30)							
$\hat{c}$ $(\cdot 10^2)$	-0.39	0.72		0.40	0.29	-0.74	-0.41	0.15	59.91%	0.28%
t-val$_{FM}$	(-2.40)	(2.89)		(3.22)	(2.06)	(-5.49)	(-2.48)	(1.56)	14.65%	[1.63]
t-val$_{JW}$	(-1.13)	(1.61)		(1.82)	(0.92)	(-2.57)	(-1.26)	(0.90)		

Table IA.XI
Cross-Sectional Regression Results without Intercept

The table reports cross-sectional regression results for the models with aggregate or industry-specific human capital. The models are estimated using two-stage cross-sectional regressions without intercepts. The table gives estimates of the cross-sectional regression coefficients, Fama-MacBeth (1973) t-values (t-value$_{FM}$), and Jagannathan and Wang (1998) adjusted t-values (t-value$_{JW}$). The table also reports the cross-sectional regression's OLS adjusted-R^2, and below that the GLS R^2, which are based on the (weighted) sum of squared mean returns on the test assets instead of their variance. The models are tested using three different sets of test assets: 25 size-BM portfolios (Panel A), 100 size-beta portfolios (Panel B), and 100 size-IR portfolios (Panel C).

Panel A: Cross-sectional regressions for 25 size-BM portfolios									
	c_0	c_{mkt}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	$R^2_{ols(gls)}$
$\hat{c}$ $(\cdot 10^2)$	0	0.72	-0.23						85.81%
t-val$_{FM}$	n.a.	(3.73)	(-1.68)						17.32%
t-val$_{JW}$	n.a.	(3.29)	(-1.31)						
$\hat{c}$ $(\cdot 10^2)$	0	0.57		0.50	-0.02	-0.49	-0.61	0.14	95.20%
t-val$_{FM}$	n.a.	(2.74)		(3.04)	(-0.07)	(-2.55)	(-2.13)	(1.35)	27.41%
t-val$_{JW}$	n.a.	(1.56)		(1.23)	(-0.03)	(-1.11)	(-1.19)	(0.73)	

Panel B: Cross-sectional regressions for 100 size-beta portfolios									
	c_0	c_{mkt}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	$R^2_{ols(gls)}$
$\hat{c}$ $(\cdot 10^2)$	0	0.57	0.03						84.47%
t-val$_{FM}$	n.a.	(2.95)	(0.29)						3.85%
t-val$_{JW}$	n.a.	(2.96)	(0.30)						
$\hat{c}$ $(\cdot 10^2)$	0	0.58		0.62	-0.31	0.22	-0.68	0.07	93.42%
t-val$_{FM}$	n.a.	(3.01)		(5.90)	(-2.09)	(2.19)	(-4.32)	(1.04)	14.77%
t-val$_{JW}$	n.a.	(1.61)		(2.33)	(-1.12)	(0.99)	(-1.74)	(0.61)	

Panel C: Cross-sectional regressions for 100 size-IR portfolios									
	c_0	c_{mkt}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	$R^2_{ols(gls)}$
$\hat{c}$ $(\cdot 10^2)$	0	0.46	0.25						77.46%
t-val$_{FM}$	n.a.	(2.41)	(1.94)						3.23%
t-val$_{JW}$	n.a.	(2.21)	(1.76)						
$\hat{c}$ $(\cdot 10^2)$	0	0.31		0.40	0.40	-0.77	-0.28	0.22	85.37%
t-val$_{FM}$	n.a.	(1.59)		(3.44)	(2.69)	(-6.25)	(-1.63)	(2.62)	9.68%
t-val$_{JW}$	n.a.	(0.89)		(1.93)	(1.21)	(-2.95)	(-0.83)	(1.50)	

Table IA.XII
Cross-Sectional Regressions with 60-Month Rolling Window Betas

This table reports the results of cross-sectional regressions where first-stage betas are estimated based on returns in the previous 60 months. The table reports results for models with aggregate and (orthogonalized) industry-specific human capital as well as five alternative asset pricing models, estimated for 25 size-BM portfolios (Panel A), 100 size-beta portfolios (Panel B), and 100 size-IR portfolios (Panel C). Orthogonalized industry-specific human capital returns are calculated based on the same 60-month period over which betas are estimated. The table reports regression coefficient estimates, Fama-MacBeth (1973) t-statistics adjusted using Newey-West (1987) with automatic lag selection (as in Newey and West (1994)), as well as the average of the OLS adjusted-R^2s of the monthly cross-sectional regressions.

Panel A: Cross-sectional regressions for 25 size-BM portfolios									
Models including (industry-specific) human capital									
	c_0	c_{mkt}	c_{US}^{hc}	c_{gds}^{hc}	c_{man}^{hc}	c_{dist}^{hc}	c_{serv}^{hc}	c_{gov}^{hc}	$\overline{R}_{ols}^2$
$\hat{c}$ $(\cdot 10^2)$	0.69	-0.13	0.02						29.65%
t-val$_{FM}$	(1.69)	(-0.30)	(0.43)						
$\hat{c}$ $(\cdot 10^2)$	0.74	0.08		0.16	-0.10	-0.10	0.23	-0.09	43.64%
t-val$_{FM}$	(2.12)	(0.19)		(2.22)	(-0.68)	(-0.65)	(0.63)	(-2.08)	
$\hat{c}$ $(\cdot 10^2)$	0.77	-0.01	-0.07	0.03	-0.17	-0.16	-0.21	-0.37	45.53%
t-val$_{FM}$	(2.40)	(-0.02)	(-1.57)	(0.28)	(-0.93)	(-1.88)	(-1.51)	(-2.24)	
Alternative asset pricing models									
	c_0	c_{mkt}	c_{prem}	c_{smb}	c_{hml}	c_{mom}	c_{liq}		$\overline{R}_{ols}^2$
$\hat{c}$ $(\cdot 10^2)$	0.64	-0.02							21.04%
t-val$_{FM}$	(1.50)	(-0.04)							
$\hat{c}$ $(\cdot 10^2)$	0.87	-0.18	-0.04						28.18%
t-val$_{FM}$	(2.14)	(-0.46)	(-0.64)						
$\hat{c}$ $(\cdot 10^2)$	0.96	-0.66		0.50	0.30				45.84%
t-val$_{FM}$	(3.14)	(-1.72)		(1.73)	(1.05)				
$\hat{c}$ $(\cdot 10^2)$	0.86	-0.36		0.29	0.46	0.53			47.72%
t-val$_{FM}$	(2.98)	(-0.90)		(1.05)	(1.43)	(1.33)			
$\hat{c}$ $(\cdot 10^2)$	0.90	-0.78		0.18	0.31	0.53	1.46		49.91%
t-val$_{FM}$	(2.99)	(-1.99)		(0.47)	(1.03)	(1.25)	(1.74)		

Panel B: Cross-sectional regressions for 100 size-beta portfolios									
Models including (industry-specific) human capital									
	c_0	c_{mkt}	c_{US}^{hc}	c_{gds}^{hc}	c_{man}^{hc}	c_{dist}^{hc}	c_{serv}^{hc}	c_{gov}^{hc}	$\overline{R}_{ols}^2$
$\hat{c}$ $(\cdot 10^2)$	0.43	0.16	0.03						24.93%
t-val$_{FM}$	(1.69)	(0.56)	(0.95)						
$\hat{c}$ $(\cdot 10^2)$	0.41	0.13		0.00	-0.14	0.07	0.08	-0.01	31.97%
t-val$_{FM}$	(2.58)	(0.52)		(0.04)	(-1.40)	(1.75)	(0.58)	(-0.34)	
$\hat{c}$ $(\cdot 10^2)$	0.39	0.10	0.01	-0.01	-0.07	-0.02	-0.06	-0.09	32.71%
t-val$_{FM}$	(1.72)	(0.38)	(0.27)	(-0.20)	(-0.93)	(-0.58)	(-1.11)	(-1.26)	

Table IA.XII - *continued*

Panel B: Cross-sectional regressions for 100 size-beta portfolios (continued)									
Alternative asset pricing models									
	c_0	c_{mkt}	c_{prem}	c_{smb}	c_{hml}	c_{mom}	c_{liq}		$\overline{R}^2_{ols}$
$\hat{c}\ (\cdot 10^2)$	0.42	0.21							20.29%
t-val$_{FM}$	(1.57)	(0.74)							
$\hat{c}\ (\cdot 10^2)$	0.64	-0.20	0.03						24.76%
t-val$_{FM}$	(2.68)	(-0.87)	(0.68)						
$\hat{c}\ (\cdot 10^2)$	0.59	-0.25		0.57	0.28				34.21%
t-val$_{FM}$	(3.08)	(-0.96)		(2.51)	(1.12)				
$\hat{c}\ (\cdot 10^2)$	0.61	-0.16		0.63	0.24	0.14			34.72%
t-val$_{FM}$	(3.23)	(-0.64)		(2.51)	(1.03)	(0.74)			
$\hat{c}\ (\cdot 10^2)$	0.66	-0.53		0.44	0.21	0.16	1.04		36.04%
t-val$_{FM}$	(3.53)	(-1.94)		(1.73)	(0.81)	(0.87)	(3.18)		

Panel C: Cross-sectional regressions for 100 size-IR portfolios									
Models including (industry-specific) human capital									
	c_0	c_{mkt}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	$\overline{R}^2_{ols}$
$\hat{c}\ (\cdot 10^2)$	-0.38	0.83	0.04						27.92%
t-val$_{FM}$	(-1.11)	(2.12)	(0.86)						
$\hat{c}\ (\cdot 10^2)$	-0.32	0.75		0.00	-0.23	-0.22	0.69	-0.01	34.86%
t-val$_{FM}$	(-1.20)	(2.37)		(0.08)	(-2.05)	(-2.18)	(1.86)	(-0.25)	
$\hat{c}\ (\cdot 10^2)$	-0.31	0.75	0.02	0.07	0.01	0.00	0.10	-0.01	35.78%
t-val$_{FM}$	(-1.22)	(2.62)	(0.44)	(0.75)	(0.10)	(0.07)	(0.92)	(-0.06)	

Alternative asset pricing models									
	c_0	c_{mkt}	c_{prem}	c_{smb}	c_{hml}	c_{mom}	c_{liq}		$\overline{R}^2_{ols}$
$\hat{c}\ (\cdot 10^2)$	-0.60	1.10							23.73%
t-val$_{FM}$	(-1.57)	(2.79)							
$\hat{c}\ (\cdot 10^2)$	-0.24	0.57	0.06						28.14%
t-val$_{FM}$	(-0.74)	(1.61)	(1.29)						
$\hat{c}\ (\cdot 10^2)$	-0.22	0.59		0.62	0.31				36.36%
t-val$_{FM}$	(-1.05)	(1.78)		(2.40)	(1.01)				
$\hat{c}\ (\cdot 10^2)$	-0.09	0.27		0.39	-0.02	-1.00			37.68%
t-val$_{FM}$	(-0.48)	(0.90)		(1.78)	(-0.08)	(-2.89)			
$\hat{c}\ (\cdot 10^2)$	0.07	0.50		0.35	0.10	-0.71	-0.90		38.41%
t-val$_{FM}$	(0.42)	(1.37)		(1.63)	(0.37)	(-2.61)	(-1.83)		

Table IA.XIII
Cross-Sectional Regressions for 99 Size-IR Sorted Portfolios

The table reports cross-sectional regression results for 99 size-IR sorted portfolios, where the smallest size-highest IR portfolio has been excluded. Panel A reports results for the models with aggregate and (orthogonalized) industry-specific human capital returns, and Panel B reports results for five benchmark models. The table gives estimates of the cross-sectional regression coefficients, Fama-MacBeth (1973) t-values, Jagannathan and Wang (1998) adjusted t-values, OLS adjusted-R^2, GLS R^2, the square root of the mean squared pricing error, and the F-statistic of the test of H_0 : all pricing errors equal zero.

Panel A: Models including (industry-specific) human capital										
	c_0	c_{mkt}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	-0.22	0.75	-0.03						47.91%	0.20%
t-val$_{FM}$	(-1.39)	(3.08)	(-0.29)						9.15%	[2.80]
t-val$_{JW}$	(-1.36)	(3.09)	(-0.30)							
$\hat{c}$ $(\cdot 10^2)$	-0.33	0.64		0.43	-0.06	-0.28	0.06	-0.11	62.92%	0.16%
t-val$_{FM}$	(-2.20)	(2.64)		(3.67)	(-0.46)	(-2.40)	(0.37)	(-1.38)	17.86%	[1.82]
t-val$_{JW}$	(-1.52)	(1.93)		(1.83)	(-0.37)	(-1.64)	(0.23)	(-1.03)		
$\hat{c}$ $(\cdot 10^2)$	-0.38	0.69	-0.11	0.28	-0.07	-0.09	-0.04	-0.22	63.13%	0.16%
t-val$_{FM}$	(-2.73)	(2.90)	(-1.42)	(4.07)	(-1.41)	(-2.39)	(-0.64)	(-3.04)	20.16%	[1.81]
t-val$_{JW}$	(-2.01)	(2.09)	(-1.12)	(2.26)	(-1.13)	(-1.74)	(-0.40)	(-2.16)		

Panel B: Alternative asset pricing models										
	c_0	c_{mkt}	c_{prem}	c_{smb}	c_{hml}	c_{mom}	c_{liq}		$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	-0.17	0.69							48.34%	0.20%
t-val$_{FM}$	(-0.84)	(2.46)							5.91%	[2.83]
t-val$_{JW}$	(-0.86)	(2.51)								
$\hat{c}$ $(\cdot 10^2)$	(0.07)	0.41	0.20						56.81%	0.18%
t-val$_{FM}$	(-0.35)	(1.63)	(2.13)						12.98%	[2.36]
t-val$_{JW}$	(-0.31)	(1.49)	(2.13)							
$\hat{c}$ $(\cdot 10^2)$	(0.38)	0.97		0.03	0.33				51.58%	0.19%
t-val$_{FM}$	(-2.67)	(3.21)		(0.22)	(1.55)				8.00%	[2.82]
t-val$_{JW}$	(-2.53)	(3.12)		(0.22)	(1.49)					
$\hat{c}$ $(\cdot 10^2)$	-0.24	0.65		-0.11	0.08	-0.94			54.25%	0.18%
t-val$_{FM}$	(-1.54)	(1.78)		(-0.75)	(0.33)	(-2.17)			11.03%	[2.54]
t-val$_{JW}$	(-1.37)	(1.57)		(-0.70)	(0.25)	(-2.39)				
$\hat{c}$ $(\cdot 10^2)$	-0.39	1.78		0.08	0.49	-0.06	-2.66		48.46%	0.18%
t-val$_{FM}$	(-2.50)	(4.43)		(0.48)	(1.90)	(-0.14)	(-3.77)		10.24%	[2.24]
t-val$_{JW}$	(-2.20)	(3.92)		(0.45)	(1.74)	(-0.13)	(-3.37)			

Table IA.XIV
Cross-Sectional Regressions for 100 Size-IR Sorted Portfolios, excluding Extreme IR Estimates

Stocks with IR estimates in the top or bottom 0.5% have been removed from the 100 size-IR portfolios. Panel A reports results for the models with aggregate and (orthogonalized) industry-specific human capital returns and Panel B reports results for five benchmark models. The table reports coefficient estimates, Fama-MacBeth (1973) t-values, Jagannathan and Wang (1998) adjusted t-values, OLS adjusted-R^2, GLS R^2, the square root of the mean squared pricing error, and the corresponding F-statistic.

Panel A: Models including (industry-specific) human capital

	c_0	c_{mkt}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	-0.05	0.52	0.18						39.73%	0.30%
t-val$_{FM}$	(-0.31)	(2.10)	(1.54)						5.61%	[3.66]
t-val$_{JW}$	(-0.26)	(1.93)	(1.54)							
$\hat{c}$ $(\cdot 10^2)$	-0.32	0.69		0.44	0.19	-0.46	-0.42	0.09	56.47%	0.25%
t-val$_{FM}$	(-2.14)	(2.86)		(3.97)	(1.40)	(-3.91)	(-2.66)	(1.11)	14.00%	[1.83]
t-val$_{JW}$	(-1.14)	(1.75)		(2.08)	(0.79)	(-2.22)	(-1.41)	(0.71)		
$\hat{c}$ $(\cdot 10^2)$	-0.57	0.93	-0.19	-0.02	-0.23	-0.14	-0.32	-0.54	66.65%	0.22%
t-val$_{FM}$	(-4.01)	(3.91)	(-2.53)	(-0.31)	(-4.93)	(-3.99)	(-5.64)	(-8.44)	23.42%	[2.32]
t-val$_{JW}$	(-2.63)	(2.45)	(-1.09)	(-0.18)	(-2.06)	(-1.77)	(-1.86)	(-3.03)		

Panel B: Alternative asset pricing models

	c_0	c_{mkt}	c_{prem}	c_{smb}	c_{hml}	c_{mom}	c_{liq}	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	-0.33	0.86						38.28%	0.30%
t-val$_{FM}$	(-1.55)	(2.96)						2.81%	[4.25]
t-val$_{JW}$	(-1.59)	(3.04)							
$\hat{c}$ $(\cdot 10^2)$	-0.08	0.26	0.41					59.70%	0.24%
t-val$_{FM}$	(-0.40)	(1.02)	(4.14)					9.46%	[2.46]
t-val$_{JW}$	(-0.28)	(0.74)	(3.18)						
$\hat{c}$ $(\cdot 10^2)$	-0.21	0.61		0.28	0.25			44.28%	0.29%
t-val$_{FM}$	(-1.44)	(1.96)		(1.67)	(1.17)			3.57%	[4.32]
t-val$_{JW}$	(-1.42)	(1.97)		(1.76)	(1.23)				
$\hat{c}$ $(\cdot 10^2)$	0.10	-0.16		-0.22	-0.41	-2.66		61.21%	0.24%
t-val$_{FM}$	(0.62)	(-0.42)		(-1.51)	(-1.58)	(-5.65)		6.50%	[3.22]
t-val$_{JW}$	(0.40)	(-0.26)		(-1.07)	(-0.78)	(-4.21)			
$\hat{c}$ $(\cdot 10^2)$	-0.20	1.80		0.02	0.16	-1.97	-4.84	55.82%	0.24%
t-val$_{FM}$	(-1.25)	(4.27)		(0.14)	(0.60)	(-3.95)	(-6.71)	8.85%	[2.34]
t-val$_{JW}$	(-0.75)	(2.67)		(0.09)	(0.33)	(-2.59)	(-4.60)		

Table IA.XV
Idiosyncratic risk measured as the Residual Variance of the Fama and French (1993) Model

The table reports results for 100 size-IR sorted portfolios, where idiosyncratic risk is estimated as the residual variance of the Fama and French (1993) three-factor model. Monthly idiosyncratic risk is estimated using an EGARCH approach, similar to the main results in the paper. Every month, stocks are sorted into 10 size portfolios, and within each size portfolio they are sorted into 10 IR portfolios. Size and IR breakpoints are based on NYSE stocks only. Panel A reports summary statistics for returns on 10 IR sorted portfolios. Returns on these portfolios are calculated as the average return over all size deciles for a given idiosyncratic risk decile. Panel A reports the mean, median, standard deviation, average log size (in log $ thousands), average conditional idiosyncratic volatility of the stocks in each portfolio, and the CAPM market beta, estimated over the full sample period. The last three columns report the alphas of time-series regressions with respect to the CAPM, the Fama-French three-factor model, and the Carhart four-factor model. The panel also reports the results for the difference between the highest and lowest IR portfolios (H-L). ***,**, and * denote significance at the 1%, 5%, and 10% levels respectively, based on Newey-West (1987) standard errors with four lags. Panels B and C report the cross-sectional regression results for monthly returns on 100 size-IR portfolios. Panel B reports results for the models with aggregate and (orthogonalized) industry-specific human capital returns and Panel C reports results for five benchmark models. The models are estimated using two-stage cross-sectional regressions. Panels B and C give estimates of the regression coefficients, Fama-MacBeth (1973) t-values (t-val$_{FM}$), and Jagannathan and Wang (1998) adjusted t-values (t-val$_{JW}$). The panels also report the cross-sectional regression's OLS adjusted-R^2 calculated as in Jagannathan and Wang (1996), and below that the GLS R^2. In the last column, the table reports the square root of the mean squared pricing error ("rmspe"), and below that (in square brackets) the F-statistic of the test of H_0 : all pricing errors are equal to zero.

Panel A: Summary statistics of 10 idiosyncratic risk sorted portfolios

	mean (%)	median (%)	stdev (%)	avg size	avg IR (%)	β_{mkt}	α_{CAPM} (%)	α_{FF3} (%)	α_{4F} (%)
Low IR	0.25	0.57	3.50	12.73	3.97	0.70	-0.05	-0.28***	-0.27***
2	0.41	0.80	4.01	12.73	5.40	0.82	0.05	-0.18***	-0.17***
3	0.49	0.84	4.38	12.72	6.24	0.90	0.10	-0.12**	-0.09
4	0.52	0.85	4.69	12.70	6.96	0.97	0.10	-0.13**	-0.09*
5	0.50	0.82	4.95	12.69	7.68	1.03	0.06	-0.15***	-0.09*
6	0.61	0.86	5.27	12.68	8.45	1.10	0.13	-0.08	0.00
7	0.61	0.94	5.63	12.67	9.34	1.18	0.10	-0.09*	0.00
8	0.65	1.03	6.00	12.66	10.48	1.26	0.10	-0.06	0.06
9	0.72	0.93	6.67	12.64	12.19	1.38	0.12	-0.01	0.14**
High IR	1.37	1.35	8.57	12.60	18.15	1.65	0.66***	0.63***	0.91***
H-L	1.12	0.78	5.07	-0.13	14.18	0.95	0.71***	0.91***	1.18***

Table IA.XV - *continued*

Panel B: Models including (industry-specific) human capital										
	c_0	c_{mkt}	c^{hc}_{US}	c^{hc}_{gds}	c^{hc}_{man}	c^{hc}_{dist}	c^{hc}_{serv}	c^{hc}_{gov}	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	-0.56	1.05	0.04						38.46%	0.38%
t-val$_{FM}$	(-3.33)	(4.35)	(0.31)						9.42%	[4.42]
t-val$_{JW}$	(-3.14)	(4.41)	(0.33)							
$\hat{c}$ $(\cdot 10^2)$	-0.78	1.23		-0.14	-0.22	-0.94	0.47	0.16	65.82%	0.28%
t-val$_{FM}$	(-5.01)	(5.33)		(-1.22)	(-1.53)	(-7.73)	(2.88)	(1.65)	14.07%	[1.08]
t-val$_{JW}$	(-1.91)	(2.19)		(-0.49)	(-0.70)	(-2.82)	(1.02)	(0.68)		
$\hat{c}$ $(\cdot 10^2)$	-0.86	1.22	-0.42	-0.40	-0.31	-0.26	-0.18	-0.57	74.33%	0.24%
t-val$_{FM}$	(-5.56)	(5.30)	(-7.04)	(-4.25)	(-6.41)	(-7.66)	(-3.29)	(-8.03)	21.25%	[1.25]
t-val$_{JW}$	(-1.98)	(1.99)	(-2.81)	(-1.37)	(-1.98)	(-1.96)	(-0.87)	(-2.54)		

Panel C: Alternative asset pricing models									
	c_0	c_{mkt}	c_{prem}	c_{smb}	c_{hml}	c_{mom}	c_{liq}	$R^2_{ols(gls)}$	rmspe
$\hat{c}$ $(\cdot 10^2)$	-0.60	1.10						39.05%	0.38%
t-val$_{FM}$	(-2.93)	(3.95)						5.84%	[4.60]
t-val$_{JW}$	(-2.98)	(4.10)							
$\hat{c}$ $(\cdot 10^2)$	-0.26	0.32	0.52					67.48%	0.28%
t-val$_{FM}$	(-1.39)	(1.29)	(5.74)					13.55%	[1.99]
t-val$_{JW}$	(-0.83)	(0.84)	(3.43)						
$\hat{c}$ $(\cdot 10^2)$	-1.28	2.02		0.02	0.89			44.33%	0.36%
t-val$_{FM}$	(-7.95)	(6.40)		(0.15)	(3.90)			8.26%	[4.09]
t-val$_{JW}$	(-6.81)	(5.74)		(0.14)	(3.27)				
$\hat{c}$ $(\cdot 10^2)$	-0.34	0.36		-0.50	-0.24	-3.41		68.89%	0.27%
t-val$_{FM}$	(-1.83)	(0.87)		(-3.40)	(-0.84)	(-6.80)		8.46%	[2.89]
t-val$_{JW}$	(-1.09)	(0.46)		(-2.29)	(-0.34)	(-3.57)			
$\hat{c}$ $(\cdot 10^2)$	-0.41	1.98		-0.12	0.10	-2.98	-5.16	57.20%	0.28%
t-val$_{FM}$	(-2.16)	(4.21)		(-0.74)	(0.32)	(-5.23)	(-7.42)	8.86%	[1.89]
t-val$_{JW}$	(-1.14)	(2.15)		(-0.40)	(0.13)	(-2.47)	(-3.81)		

Table IA.XVI
Characteristics of 100 Size-IR Sorted Portfolios

This table reports several characteristics of monthly excess value-weighted returns on 100 size-IR sorted equity portfolios from April 1959 to December 2009. Every month, all stocks that are traded on the NYSE, Amex, and NASDAQ are first sorted into size deciles, based on their market capitalization at the beginning of the month. Then, within each size decile, the stocks are sorted into idiosyncratic risk deciles, based on the estimated conditional idiosyncratic volatility for that month. Size and IR breakpoints are based on NYSE stocks only. Idiosyncratic volatility is estimated as the residual volatility of the market model that includes a constant and the excess return on the value-weighted CRSP index. For each asset, monthly idiosyncratic volatility is estimated using an EGARCH model for all available returns. 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. The last panel reports the estimated alphas (intercepts) with respect to the CAPM. The last column reports the difference between the alphas of the highest and lowest IR portfolios (H-L). ***,**, and * denote significance at the 1%, 5%, and 10% levels, respectively, based on Newey-West (1987) standard errors with four lags.

Panel A: Time-series average excess returns (in %)

	Low IR	2	3	4	5	6	7	8	9	High IR
Small	-0.12	0.13	0.11	0.13	0.29	0.41	0.51	0.93	1.34	4.28
2	0.15	0.32	0.35	0.44	0.59	0.60	0.50	0.76	0.68	2.04
3	0.22	0.57	0.52	0.52	0.65	0.71	0.72	0.88	1.02	1.43
4	0.43	0.46	0.60	0.58	0.66	0.57	0.74	0.76	0.71	1.16
5	0.43	0.53	0.68	0.75	0.61	0.77	0.75	0.50	0.81	0.96
6	0.33	0.46	0.57	0.61	0.76	0.80	0.67	0.69	0.41	0.65
7	0.43	0.47	0.49	0.68	0.60	0.70	0.76	0.76	0.47	0.86
8	0.40	0.51	0.49	0.65	0.60	0.67	0.57	0.72	0.61	0.57
9	0.30	0.43	0.52	0.58	0.57	0.44	0.55	0.67	0.61	0.41
Big	0.41	0.48	0.37	0.37	0.33	0.29	0.30	0.24	0.46	0.44

Panel B: Time-series standard deviation (in %)

	Low IR	2	3	4	5	6	7	8	9	High IR
Small	3.25	4.38	5.02	5.52	5.95	6.74	7.42	8.42	9.51	14.68
2	3.53	4.56	5.05	5.62	5.95	6.49	6.82	7.62	8.53	11.16
3	3.62	4.47	5.13	5.44	6.03	6.27	6.81	7.36	8.32	10.94
4	3.60	4.53	5.03	5.26	5.68	6.02	6.42	7.19	7.83	10.40
5	3.54	4.30	4.64	5.23	5.52	5.80	6.26	6.81	7.35	9.73
6	3.46	4.11	4.61	4.96	5.29	5.67	5.85	6.44	7.16	8.89
7	3.66	4.19	4.50	4.89	5.23	5.42	5.85	6.48	6.77	9.12
8	3.73	4.17	4.46	4.76	5.03	5.37	5.51	6.07	6.65	8.64
9	3.53	4.15	4.18	4.56	4.77	4.99	5.13	5.58	6.02	8.02
Big	3.99	4.11	4.35	4.42	4.51	4.64	5.13	5.16	5.88	7.13

Table IA.XVI - *continued*

	Panel C: Time-series average size (log $ thousands)									
	Low IR	2	3	4	5	6	7	8	9	High IR
S	9.74	9.77	9.74	9.71	9.68	9.62	9.58	9.50	9.41	9.19
2	11.09	11.09	11.09	11.09	11.09	11.09	11.08	11.08	11.08	11.07
3	11.63	11.63	11.63	11.62	11.63	11.63	11.62	11.62	11.62	11.61
4	12.06	12.06	12.06	12.06	12.06	12.05	12.05	12.05	12.05	12.05
5	12.48	12.48	12.47	12.47	12.47	12.47	12.47	12.46	12.46	12.46
6	12.88	12.88	12.88	12.88	12.88	12.88	12.87	12.87	12.87	12.86
7	13.30	13.31	13.31	13.31	13.31	13.31	13.31	13.30	13.30	13.30
8	13.82	13.82	13.82	13.81	13.81	13.81	13.81	13.80	13.80	13.79
9	14.42	14.43	14.43	14.43	14.43	14.43	14.42	14.42	14.41	14.39
B	15.87	15.81	15.69	15.64	15.57	15.55	15.51	15.46	15.42	15.32

	Panel D: Market betas									
	Low IR	2	3	4	5	6	7	8	9	High IR
S	0.61	0.79	0.91	1.00	1.05	1.18	1.27	1.36	1.49	1.81
2	0.68	0.85	0.95	1.05	1.10	1.19	1.27	1.38	1.54	1.77
3	0.70	0.85	0.97	1.04	1.14	1.17	1.28	1.39	1.55	1.82
4	0.70	0.86	0.98	1.00	1.10	1.15	1.21	1.35	1.47	1.78
5	0.67	0.83	0.88	1.01	1.08	1.12	1.21	1.30	1.38	1.73
6	0.66	0.80	0.89	0.97	1.04	1.10	1.14	1.26	1.39	1.61
7	0.69	0.81	0.87	0.97	1.04	1.06	1.16	1.26	1.31	1.63
8	0.70	0.79	0.87	0.95	1.00	1.06	1.11	1.21	1.32	1.62
9	0.66	0.79	0.82	0.90	0.93	1.00	1.03	1.13	1.18	1.51
B	0.77	0.77	0.84	0.83	0.88	0.89	1.00	1.02	1.17	1.33

	Panel E: CAPM alphas (in %)										
	Low IR	2	3	4	5	6	7	8	9	High IR	H-L
S	-0.38***	-0.21*	-0.29**	-0.30**	-0.16	-0.10	-0.04	0.34	0.70**	3.50***	3.88***
2	-0.14	-0.05	-0.06	-0.01	0.12	0.08	-0.05	0.16	0.02	1.28***	1.42***
3	-0.08	0.21*	0.10	0.07	0.16	0.20	0.17	0.28*	0.35*	0.65*	0.73**
4	0.13	0.09	0.18	0.15	0.18	0.07	0.22	0.18	0.07	0.39	0.27
5	0.14	0.18*	0.29***	0.31**	0.14	0.29**	0.22*	-0.06	0.21	0.21	0.07
6	0.05	0.12	0.19*	0.19*	0.31***	0.33***	0.18	0.15	-0.19	-0.04	-0.09
7	0.13	0.12	0.11	0.26**	0.15	0.24**	0.26**	0.22	-0.09	0.15	0.02
8	0.09	0.17*	0.12	0.23***	0.17*	0.21*	0.10	0.19	0.04	-0.13	-0.23
9	0.01	0.09	0.16*	0.19**	0.17	0.01	0.11	0.18**	0.10	-0.24	-0.26
B	0.08	0.14	0.01	0.01	-0.05	-0.09	-0.13	-0.20**	-0.04	-0.14	-0.22

Table IA.XVII
Human Capital Betas of 100 Size-IR Sorted Portfolios

This table presents human capital betas of monthly returns on 100 size-IR portfolios. Simple betas are estimated by regressing excess stock returns on a constant and (aggregate or industry-specific) human capital returns. The column "H-L" reports the difference in betas between the highest and the lowest IR decile portfolios. ***,**, and * denote significance at the 1%, 5%, and 10% levels, based on Newey-West (1987) standard errors with four lags.

Panel A: Estimated β^{hc}_{US}											
	Low IR	2	3	4	5	6	7	8	9	High IR	H-L
Small	0.09	0.56	0.54	0.71	0.79	1.06*	1.12	1.45**	1.41	2.30	2.22*
2	0.08	0.28	0.62	0.72	0.56	0.88	0.80	1.07	1.59*	2.33*	2.25**
3	0.17	-0.11	0.36	0.33	0.28	0.44	0.76	1.18	1.38**	2.07*	1.90**
4	-0.06	0.08	0.36	0.12	0.39	0.41	0.73	0.53	0.75	2.21*	2.27**
5	-0.14	0.26	0.31	0.27	0.31	0.53	0.66	0.49	1.04*	1.65*	1.79**
6	-0.35	0.03	0.00	0.20	0.22	0.26	0.18	0.46	0.45	1.14	1.49*
7	0.08	-0.08	-0.09	-0.10	0.03	0.31	0.45	0.24	0.07	1.49*	1.41
8	-0.47	-0.14	-0.16	0.21	-0.01	0.39	0.24	0.16	0.60	1.27	1.74**
9	-0.15	-0.15	-0.12	-0.33	0.09	-0.03	-0.09	0.19	0.28	1.85**	2.01***
Big	-0.29	-0.12	0.23	-0.06	0.29	0.12	0.54	0.46	0.51	1.09	1.38**

Panel B: Estimated β^{hc}_{gds}											
	Low IR	2	3	4	5	6	7	8	9	High IR	H-L
Small	0.14	0.33	0.30	0.46	0.69	0.56	0.84	0.94	1.15	1.31	1.17
2	0.24	0.32	0.59	0.57	0.53	0.65	0.71	0.64	1.05	1.56	1.32
3	0.16	0.09	0.37	0.13	0.60	0.35	0.56	0.65	0.84	1.34	1.18
4	0.24	0.37	0.21	0.45	0.69	0.14	0.42	0.78	0.53	1.05	0.81
5	0.13	0.13	0.60	0.33	0.32	0.69	0.51	0.50	0.53	0.70	0.57
6	0.07	0.27	0.22	0.36	0.46	0.54	0.43	0.35	0.75	0.34	0.28
7	0.43	0.25	0.32	0.28	0.38	0.62	0.71	0.11	0.27	0.71	0.28
8	0.07	0.32	0.22	0.42	0.07	0.43	0.29	0.63	0.59	0.46	0.39
9	0.23	0.16	0.30	0.19	0.39	0.00	0.14	0.13	0.20	0.60	0.37
Big	0.08	0.25	0.36	-0.20	0.12	0.19	0.23	-0.16	0.10	0.06	-0.02

Table IA.XVII - *continued*

Panel C: Estimated β^{hc}_{man}										
	Low IR	2	3	4	5	6	7	8	9	High IR	H-L
Small	0.07	0.37	0.35	0.44	0.52	0.71*	0.61	0.73	0.71	1.11	1.03
2	0.15	0.16	0.50	0.46	0.42	0.72**	0.60	0.70	1.01*	1.68	1.53*
3	0.19	0.08	0.32	0.32	0.34	0.35	0.50	0.93**	0.98**	1.50*	1.31*
4	0.11	0.16	0.36	0.05	0.39	0.53	0.82**	0.51	0.75*	1.71**	1.59**
5	-0.08	0.29	0.24	0.16	0.37	0.42	0.62*	0.43	0.69*	1.21*	1.29**
6	-0.08	0.16	0.09	0.17	0.28	0.27	0.15	0.39	0.61	1.30**	1.39**
7	0.14	0.01	0.00	0.10	0.19	0.30	0.32	0.19	0.17	1.40**	1.26**
8	-0.08	-0.06	-0.02	0.26	0.12	0.26	0.13	0.09	0.58	1.45**	1.53***
9	-0.02	0.01	0.00	-0.23	0.08	0.01	0.23	0.43	0.09	1.52**	1.54**
Big	-0.04	-0.10	0.10	-0.09	0.28	0.26	0.65**	0.52	0.60	1.05*	1.08**

Panel D: Estimated β^{hc}_{dist}										
	Low IR	2	3	4	5	6	7	8	9	High IR	H-L
Small	-0.16	0.17	-0.03	0.03	-0.04	0.08	-0.01	-0.01	-0.29	-0.80	-0.64
2	-0.25	-0.17	0.01	-0.07	-0.13	-0.03	0.01	-0.23	0.19	0.25	0.51
3	-0.13	-0.48	-0.03	-0.18	-0.43	-0.29	0.02	0.37	-0.08	-0.11	0.02
4	-0.31	-0.13	-0.17	-0.38	-0.03	-0.22	-0.12	-0.30	-0.14	0.67	0.97
5	-0.43	-0.17	-0.10	-0.20	-0.27	0.03	-0.08	-0.04	0.10	0.04	0.47
6	-0.47	-0.17	-0.18	-0.20	0.01	0.09	-0.33	-0.21	0.05	0.43	0.90
7	-0.24	-0.24	-0.40	-0.33	-0.16	0.10	0.27	-0.30	-0.43	0.11	0.36
8	-0.56	-0.15	-0.15	-0.12	-0.11	0.12	-0.16	-0.16	-0.09	0.54	1.10
9	-0.33	-0.40	-0.19	-0.38	-0.12	-0.31	-0.21	-0.02	-0.14	0.95	1.29*
Big	-0.16	-0.08	0.05	-0.05	0.11	0.04	0.43	0.06	0.13	0.70	0.86*

Table IA.XVII - *continued*

Panel E: Estimated β^{hc}_{serv}											
	Low IR	2	3	4	5	6	7	8	9	High IR	H-L
Small	0.02	0.12	0.18	0.24	0.22	0.48	0.37	0.57	0.40	0.44	0.42
2	0.07	0.15	0.26	0.26	0.27	0.31	0.42	0.44	0.90*	0.85	0.78
3	0.14	-0.03	0.15	0.21	0.22	0.20	0.34	0.66	0.73*	1.10*	0.96
4	0.05	0.15	0.31	0.10	0.21	0.30	0.38	0.29	0.33	1.22	1.17**
5	0.03	0.16	0.23	0.16	0.25	0.32	0.44	0.23	0.55	0.99*	0.97**
6	-0.06	0.09	0.07	0.16	0.17	0.20	0.12	0.31	0.31	0.68	0.75
7	0.11	0.07	0.08	0.04	0.13	0.12	0.38	0.24	0.16	0.95*	0.83
8	-0.12	0.06	0.12	0.21	0.03	0.26	0.31	0.20	0.42	0.83*	0.95*
9	0.05	0.07	0.02	-0.03	0.10	0.03	-0.07	0.09	0.21	1.04**	0.99**
Big	0.09	0.05	0.23	0.14	0.34	0.10	0.39	0.38	0.31	0.72	0.64*

Panel F: Estimated β^{hc}_{gov}											
	Low IR	2	3	4	5	6	7	8	9	High IR	H-L
Small	-0.25	0.19	0.12	0.19	0.43	0.41	0.89	0.72	1.06	1.92	2.17*
2	-0.39	-0.21	-0.14	0.37	-0.07	0.45	-0.13	0.59	0.40	1.11	1.50
3	-0.11	-0.56	-0.34	-0.19	-0.28	-0.14	0.25	-0.05	0.24	0.52	0.62
4	-0.57	-0.73	-0.33	-0.28	-0.15	-0.62	-0.10	-0.28	0.05	0.27	0.84
5	-0.48	-0.27	-0.61	-0.35	-0.39	-0.29	-0.26	0.07	0.51	0.79	1.27
6	-0.60	-0.68	-0.52	-0.19	-0.59	-0.47	0.23	-0.04	-0.63	0.04	0.65
7	-0.53	-0.41	-0.56	-0.84	-0.72	-0.23	-0.48	-0.13	-0.14	-0.12	0.41
8	-0.73*	-0.56	-0.75	-0.66	-0.32	-0.04	-0.40	-0.38	-0.07	-0.15	0.58
9	-0.53	-0.55	-0.67	-0.66	-0.58	-0.45	-0.37	-0.37	-0.14	0.28	0.81
Big	-0.81*	-0.39	-0.20	-0.15	-0.53	-0.30	-0.18	-0.42	-0.04	-0.14	0.67