Labor Income, Relative Wealth Concerns, and the Cross-section of Stock Returns*

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Abstract

The finance literature documents the relation between labor income and the cross-section of stock returns. A possible explanation is the hedging of investors with relative wealth concerns who pay a premium for securities that help them to keep up with their peers. At the census division level we find that the risk premium associated with labor income risk is negative and statistically significant. This premium is predominantly local in nature, as opposed to the aggregate, country-wide cross-sectional effect so far documented. Also, it is larger in areas with lower population density, as expected when investors have relative wealth concerns.

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Abstract

The finance literature documents the relation between labor income and the cross-section of stock returns. A possible explanation is the hedging of investors with relative wealth concerns who pay a premium for securities that help them to keep up with their peers. At the census division level we find that the risk premium associated with labor income risk is negative and statistically significant. This premium is predominantly local in nature, as opposed to the aggregate, country-wide cross-sectional effect so far documented. Also, it is larger in areas with lower population density, as expected when investors have relative wealth concerns.

1 Introduction

Over the years, the finance literature has accumulated evidence of a connection between labor income and the cross-section of stock returns. Mayers (1972) is credited as the first to suggest the analysis of labor income as a measure of human capital in an asset pricing setting. In two influential papers, Campbell (1996) and Jagannathan and Wang (1996) use growth in labor income as a measure of the return on human capital. Their intuition is that human capital, a fundamental part of the economy's endowment, has been typically overlooked in the CAPM. The inclusion of the return to human capital in empirical asset pricing models is able to explain a much higher portion of the cross-sectional variation in stock returns relative to the standard CAPM. Lettau and Ludvigson (2001a and 2001b) and Santos and Veronesi (2006) both introduce labor income based variables into conditional asset pricing models and find that the explanatory power of the model increases substantially.

In this paper, we consider an alternative channel for the interaction between returns on human capital and the cross-section of stock returns that is different from the market completeness argument in Campbell (1996) and Jagannathan and Wang (1996) or the time varying risk premium arguments in Lettau and Ludvigson (2001a) and Santos and Veronesi (2006). Specifically, the empirical evidence presented in this paper shows that labor income is related to the cross-section of stock returns through the hedging activity of investors with relative wealth concerns. This idea is based on the *KEEping up Pricing Model* (KEEPM) of relative wealth concerns developed in Gómez, Priestley and Zapatero (2009). In this model investors hedge the risk that their reference group ("peers") will experience an income shock by investing in securities strongly correlated with the income of these peers. Equilibrium prices will reflect the price pressure resulting from the hedging activities of investors with relative wealth concerns.

Relative wealth concerns imply restrictions on the relationship between human capital and stock returns not previously identified in the literature on this topic: i) the risk premium associated with the labor income factor (positive correlation between labor income and security returns) is negative, since investors are willing to pay extra for securities that hedge this risk; ii) this connection must hold at the local level, since the main source of relative wealth concerns pertains to the surroundings of the investor.

We test the KEEPM across the nine US Census divisions to investigate whether relative wealth concerns can be a reason behind the relation behind labor income and the cross-section of stock returns. We already know from the extant literature that aggregate country labor income risk helps to explain the cross-section of stock returns. However, in the presence of relative wealth concerns, local (divisional) non-diversifiable labor income risk, rather than aggregate labor income risk, should be relevant for explaining cross-sectional stock returns, and that is the main research question that motivates our work.

We provide strong empirical evidence that supports this conjecture. In particular, we show that the risk premium associated with orthogonal (with respect to the return on the US stock market portfolio) labor income risk is negative both at the aggregate and divisional level. However, while there is a positive correlation between labor income at the disaggregate and aggregate levels, we find that the additional information of labor income at the disaggregate level has much stronger explanatory power.

Interestingly, the absolute value of the orthogonal risk premium is higher for those divisions with lower population density. The difference in the average premium across divisions with population density less than 100 individuals per square mile (four divisions) and the rest (five divisions) is 2.1% per annum, both economically and statistically significant. This is consistent with the hypothesis that in areas of lower population density there is more peer pressure to keep up with neighbors' wealth because there is a closer interaction, as opposed to a certain degree of anonymity in areas more densely populated.

We use as test assets a set of twenty portfolios for each division formed on the location of a firm's headquarters. We estimate time series regressions that show that a local factor mimicking portfolio of orthogonal local labor income is more important that an aggregate equivalent. This establishes the "local" nature of the labor income. Subsequently, we estimate cross-sectional regressions using both the Fama and MacBeth (1973) and GMM methodologies that reveal estimated prices of risk that are negative and, in an absolute sense, larger for low population density divisions.

Finally, we conduct a range of robustness tests: we include additional test assets, we impose a common market risk premium across divisions, and we reduce the number of test assets. Our results are robust to all these tests. Additionally, we want to check the robustness of our model with respect to a number of existing asset pricing models that successfully employ country-wide labor risk factors to explain the cross-section of stock returns. To this end, we consider if the estimated prices of risk on the orthogonal labor income factors are affected by the inclusion of Lettau and Ludvigson's (2001a) *cay* variable and Santos and Veronesi's (2006) labor to consumption wealth ratio variable. The results are robust to the inclusion of these two variables.

The point of departure of our analysis is the assumption that relative wealth concerns are prevalent in the economy. Evidence of relative wealth concerns is presented in Ravina (2005). Gómez (2007) analyzes the impact of these preferences on portfolio choice. García and Strobl (2011) study the implications of these preferences for information acquisition. Shemesh and Zapatero (2011) document strong evidence of peer pressure in luxury car purchases, and the pressure is stronger in areas of lower population density. A related finding is in Hong, Kubik and Stein (2004), who show that sociable investors (defined as those who interact with their neighbors or attend church) are more likely to invest in stocks, controlling for other factors. They interpret this finding as evidence of market participation as a public good:

wider participation decreases fixed entrance costs for sociable investors. DeMarzo, Kaniel and Kremer (2004) present a model of endogenous, price-driven relative wealth concerns; this principle is then applied to financial bubbles in DeMarzo, Kaniel and Kremer (2008) and technological investment and investment cycles in DeMarzo, Kaniel and Kremer (2008). Brown, Ivković, Smith and Weisbenner (2008) find evidence consistent with keeping up with the Joneses behavior in stock market participation: individual market participation increases with average community market participation.

Gómez, Priestley and Zapatero (2009) examine the asset pricing implications of relative wealth concerns in an open-economy, multi-country model and show that in the presence of local non-diversifiable income or assets, relative wealth concerns result in an approximate multi-beta asset pricing model. According to the KEEPM, stock returns are explained by their covariances with the market portfolio and the local risk factors (one per peer group). The model predicts that the price of risk on each of the local factors (labor income or housing at the aggregate country level) should be negative because investors are willing to pay more (expect lower return) for those stocks that help them to hedge the risk of deviating from their peer's non-diversifiable wealth.[1]

Our paper is related to the literature on portfolio under-diversification. The theory predicts that, in a frictionless model with full market participation and complete financial markets, investors should hold the same well-diversified portfolio. This prediction was first refuted at the international level by the seminal paper of French and Poterba (1991). This is known as the "home bias puzzle" and refers to the finding that investors over-invest in domestic stocks relative to the optimal global risk-diversification level.[2] More recently, several papers have documented that this lack of diversification is also present at the domestic level within the US. This phenomenon has been dubbed the "home bias at home puzzle." Coval and Moskowitz (1999), for instance, study the investment behavior of money managers and observe that they favor (with respect to what would be optimal) local firms. Ivković and Weisbenner (2005) and Massa and Simonov (2006) show that US and Swedish households, respectively, exhibit a strong preference for local investments. Their empirical tests seem to suggest that investors exploit local information to obtain higher returns. The fact that our tests are conducted at the broader division level versus the state or city level limits the potential impact of superior information arguments in our findings.

Although we do not perform any direct test on portfolio holdings in this paper, the KEEPM yields partial equilibrium results that may be consistent with those in the home bias at home literature: investors in a given division are willing to pay a premium for local assets positively correlated with the divisional, non-diversifiable wealth. Our tests show

[1]Galí (1994) shows that in the absence of a market friction, such as the existence of non-diversifiable assets, optimal portfolio holdings are identical across investors and only market risk is priced in equilibrium.

[2]For a literature review of this puzzle and suggested explanations see Lewis (1999).

that after taking into account the hedging properties of local (same division) assets, assets from other divisions can only offer very marginal extra hedging. This would reinforce the assumption of locally biased portfolio holdings. However, we often observe some local assets commanding a negative correlation with the proxy for relative wealth concerns. This has an interesting implication: investors seem willing to short local (same division) stocks that covary negatively with local labor income. Notice that this is consistent with a (Joneses) hedging argument as opposed to a familiarity argument -see, for instance, Huberman (2001)- where investors hold only long position on local stocks.

Our paper contributes to the literature that explores the effects of relative wealth concerns on stock prices. In related work, Korniotis (2008) presents and tests a EHF model where investors at the state level in the US care about broader regional consumption risk (defined at different aggregation levels). As a result, investors are willing to pay for keeping up with regional consumption; hence a negative, statistically significant regional risk-premium arises. The EHF risk factor in Korniotis (2008), however, is averaged across regions whereas our factors are division specific. More importantly, Korniotis's factor is unrelated to labor income, our main object of study. Korniotis and Kumar (2008) find evidence of state-level stock return predictability associated with state unemployment rates and credit constraints. Their paper does not study the cross-section of stock returns. Johnson (2008) finds that financial assets that hedge against inequality risk (changes in the cross-section of income distribution) in the US carry a sizeable and statically significant risk premium. In his model, financial market incompleteness and status considerations drive the hedging demand and the negative risk premium at the aggregate US level.

The paper is organized as follows. We present the theory and derive the KEEPM in section 2. Section 3 describes the data used in the analysis. The time series analysis is performed in section 4 while section 5 presents the cross-sectional tests, using both the Fama-MacBeth and the GMM methods. The robustness tests are reported in section 6. Section 7 offers some final remarks and closes the paper.

2 The KEEPM

We consider the two main specifications discussed in the literature: exogenous and endogenous keeping up with the Joneses preferences. In both specifications, we assume a one-period economy with K divisions denoted by $k \in \{1, 2, ..., K\}$. In each division there is a local firm. At time $t = 0$, each firm issues one share that will yield a random payoff in time $t = 1$. We normalize the initial value of the firm to 1. Let r_k denote the random excess return on a share of firm k. The vector $r = (r_1, ..., r_k, ..., r_K)'$ has a joint distribution function $F(r)$, with mean return vector $E(r)$ and covariance matrix Ω. Firm shares can be freely traded across divisions. There is also a risk-free bond in zero net supply. Let R denote the return on the risk-free bond. Financial markets are assumed to be complete.

In each division there are two types of agents: "investors" and "workers," who are endowed with non-diversifiable stochastic local labor or entrepreneurial income.

The Appendix shows (see equations (A3) and (A5)) that, whether endogenous or exogenous, the existence of keeping up with the Joneses behavior and non-diversifiable income implies the following optimal portfolio for the representative investor in division k:

$$x_k^* = \theta_k b_k X_k^w + \tau_k \, \Omega^{-1} E(r), \tag{1}$$

where X_k^w represents a mimicking portfolio that maps the workers endowment return onto the investment opportunity set; θ_k denotes the the relative wealth at $t = 0$ of the division's workers as a proportion of the total division's wealth. The parameters b and τ represent the portfolio bias and the risk-tolerance coefficient, respectively, with values:

JONESES	b	τ
Exogenous	$\frac{\gamma}{1-\gamma}$	$\frac{1}{\alpha(1-\gamma)}$
Endogenous	$\frac{\alpha-1}{\alpha}$	$\frac{1}{\alpha}$

Notice that, given these definitions, there will exist a bias in portfolio holdings towards the Joneses portfolio (hence, consumption) only if $0 < \gamma < 1$, in the exogenous specification, and $\alpha > 1$, in the endogenous specification.[3]

Market clearing in financial markets at time $t = 0$ requires that $\sum_k \omega_k x_k^* = x_M$, with x_M the market portfolio, with excess return r_M, and $\omega_k = c_k^0 / \sum_k c_k^0$. Spot market clearing at time $t = 1$ implies that workers consume the proceedings of their (non-tradable) endowment, w, and investors the return on their portfolios, c.

We regress the workers non-diversifiable wealth return, $r_k^w = r' X^w$, onto the country market portfolio excess return:

$$r_k^w = \beta_k \, r_M + r_k^F. \tag{2}$$

Portfolio $\beta_k \, x_M$ represents the projection of the workers income onto the security market line spanned by the aggregate market portfolio x_M. Define the portfolio $F_k \equiv X_k^w - \beta_k \, x_M$ as an orthogonal factor portfolio with return $r_k^F = r' F_k$ and mean return μ_k^F. After these definitions, the workers' portfolio can be expressed as a linear combination of the market portfolio and a zero-beta (orthogonal) portfolio: $X_k^w = F_k + \beta_k x_M$. We replace X_k^w in (1):

$$x_k^* = \theta_k \, b_k \, F_k + \theta_k \, b_k \, \beta_k \, x_M + \tau_k \, \Omega^{-1} E(r).$$

This portfolio has three components. Portfolio F_k is division-specific and can be interpreted as a *hedge portfolio*: for each division k, portfolio F_k hedges investors from the risk involved in

[3]The constraint on $\alpha > 1$ is already present in DeMarzo, Kaniel and Kremer (2004).

keeping up with the local non-diversifiable Joneses risk. Given the orthogonality conditions, this portfolio plays the role of a division-specific, zero-beta asset.

The projection component, $\beta_k x_M$, corresponds to that part of the workers wage income perfectly correlated with the country market portfolio. The standard component, $\Omega^{-1}E(r)$, is the highest global Sharpe ratio portfolio and it is common across divisions.

We define the coefficient H as the inverse of the risk-tolerance coefficient $H^{-1} = \sum_k \omega_k \tau_k$. After imposing market clearing, we solve for equilibrium expected returns:

$$E(r) = H\,\Omega \left[\left(1 - \sum_{k=1}^{K} \omega_k \theta_k \, b_k \, \beta_k \right) x_M - \sum_{k=1}^{K} \omega_k \theta_k \, b_k \, F_k \right]. \tag{3}$$

Define the matrix $\boldsymbol{F}$ of dimension $N \times (K+1)$ as the column juxtaposition of the market portfolio and the orthogonal portfolios, $\boldsymbol{F} \equiv (x_M, F_1, ..., F_k, ..., F_K)$. Let $\boldsymbol{r^F} \equiv (r_M, r_1^F, ..., r_k^F, ..., r_K^F)$ denote the vector of factor returns. Additionally, define the wealth vector as

$$\boldsymbol{W} \equiv H \left(1 - \sum_{k=1}^{K} \omega_k \theta_k \, b_k \, \beta_1, -\omega_1 \theta_1 \, b_1, ..., -\omega_k \theta_k \, b_k, ..., -\omega_K \theta_K \, b_K \right)'.$$

Given these definitions, the equilibrium condition (3) can be re-written as $E(r) = \Omega \, \boldsymbol{F} \boldsymbol{W}$.

Pre-multiplying both terms of the previous equation by the transpose of matrix $\boldsymbol{F}$ we obtain the equilibrium condition for the vector of prices of risk, $\boldsymbol{\lambda} \equiv (\lambda^M, \lambda^1, ..., \lambda^k, ..., \lambda^K)$, with the market risk premium, λ^M, as the first component. Thus, $\boldsymbol{\lambda} = \boldsymbol{F}'\Omega \, \boldsymbol{F} \, \boldsymbol{W}$, where $\boldsymbol{F}'\Omega \, \boldsymbol{F}$ is a matrix of dimension $(K+1) \times (K+1)$ whose first column (row) includes the market return volatility and a vector of K zeros and the remaining elements are the covariances between F_k and $F_{k'}$ for all $k, k' \in \{1, 2, ..., K\}$.

The expected risk premia on the market and the zero-beta portfolios will be:

$$\begin{aligned} \lambda^M &= H \left(1 - \sum_{k=1}^{K} \omega_k \theta_k \, b_k \, \beta_k \right) \sigma_M^2, \\ \lambda^k &= -H \left(\omega_k \theta_k \, b_k \, \mathrm{Var}(r_k^F) + \sum_{k' \neq k} \omega_{k'} \theta_{k'} \, b_{k'} \, \mathrm{Cov}(r_k^F, r_{k'}^F) \right), \end{aligned} \tag{4}$$

for all $k \in \{1, 2, ..., K\}$.

The market portfolio, x_M, is partially correlated with each division's non-diversifiable risk. This correlation is captured by the coefficient β_k and offers partial hedging against deviations from the local Joneses (in case $\theta b > 0$). Therefore, the equilibrium price of risk for the country market risk factor, λ^M, varies relative to the symmetric equilibrium. The parenthesis in the first equation in (4), which in the case of a symmetric equilibrium would be 1, captures the net price of risk on the aggregate market risk factor, after discounting the (capitalization weighted) Joneses hedging effect. If the weighted value of the betas is higher than the country market beta (i.e., 1), the model predicts that the market price of risk could turn negative. Intuitively, if the hedging properties of the market portfolio against Joneses deviations outweigh the compensation for systematic risk the *net* expected market price of risk becomes negative.

More importantly, if there is a relative wealth concern ($b > 0$) in the economy (either endogenous or exogenous) and workers income is not diversifiable ($\theta > 0$), there should be K additional risk factors (one per division) together with the market risk factor. Regarding their sign, the model predicts that if $\text{cov}(r^F_k, r^F_{k'}) > 0$ for all $k, k' \in \{1, 2, ..., K\}$, then every λ^k will be negative.[4] To understand this result, suppose for the moment that the zero-beta portfolios were orthogonal ($\text{Cov}(r^F_k, r^F_{k'}) = 0$) for all $k, k' \in \{1, 2, ..., K\}$. Then, the price of risk would be easily isolated and strictly negative. The intuition for the negative sign would be as follows: An asset that has positive covariance with portfolio F_k will hedge the investor in division k from the risk of deviating from the non-diversifiable (local) income of the Joneses. This investor will be willing to pay a higher price for the asset thus yielding a lower return. In equilibrium, the price of risk for F_k would be, in absolute terms, increasing in b_k and the volatility of the hedge portfolio. If the covariance across zero-beta portfolios is positive, this just increases the absolute value of the negative prices of risk for every division's hedge portfolio.

Solving for $\boldsymbol{W}$ we obtain:

$$E(r) = \boldsymbol{\beta}^{\boldsymbol{F}}\, \boldsymbol{\lambda}, \tag{5}$$

where $\boldsymbol{\beta}^{\boldsymbol{F}} = \Omega\, \boldsymbol{F}\, (\boldsymbol{F}'\Omega\, \boldsymbol{F})^{-1}$ denotes the $K \times (K+1)$, in general, for N assets, $N \times (K+1)$, matrix of betas, with the first column as the market betas for all assets.

This pricing model that captures the equilibrium implications of keeping up with the Joneses preferences, both under the exogenous and endogenous specifications, is termed the KEEPM, which stands for "KEEping up Pricing Model". In the following sections, we test the models' restrictions on the prices of risk in (4) and the cross-section performance of the equilibrium condition (5).

3 Data description

Testing the implications of the KEEPM in equations (4) and (5) requires, in the first place, to select the test assets and the risk factors. In this section, we describe the procedures and data used to this end.

[4]Notice that this is a sufficient condition satisfied by our data in Table 1.

In order to construct the risk factors that will proxy relative wealth concerns, it is necessary to make some assumptions regarding the geographical dimension of "the peers". For example, should they be defined at the city, state, division, region or national level? Hong, Kubik and Stein (2008) show that the probability of local bias in an investor's portfolio holdings increases the closer the investor is geographically to the company's headquarters. Even at the Census division level the bias in portfolio holdings is both economic and statistically significant: the probability of holding a stock headquartered in the same division is higher than the unconditional probability of holding any given stock. In defending their choice of Census divisions, the authors conclude that using only the stock demand of those, presumably, more biased investors living closer to the stock (say, at the state level) would leave out most of the local-biased stock demand present at the divisional level.[5]

Our choice regarding the geographical dimension of the peers builds on the same intuition. Arguably, the relevance of keeping up with the Joneses should be higher (larger γ in the model) at the state level. We are, however, measuring the cross-section impact of relative wealth concerns on stock returns through the sign and size of the prices of risk on the orthogonal income factor. As it is clear from equation (4), the size of the prices of risk depends on the local non-diversifiable demand. At the state level, the proportion of local demand relative to the aggregate country demand, $\omega\theta$, is very small. Hence, probably at the expense of underestimating γ, we perform our analysis at the Census division level in order to have a better assessment of the effect of keeping up with the Joneses on stock returns, both in economic and statistical terms. At the same time, defining the Joneses at the broader Census division level, rather than the state level, allows us to differentiate our hedging results from a purely familiarity argument based on geographical proximity -see, for instance, Huberman (2001). As an additional benefit, using the same division sorting as in Hong, Kubik and Stein (2008) allows for a more direct comparison of our findings with theirs.

The second assumption we have to make pertains to the construction of the factor mimicking portfolios used as risk factors in our tests. To proxy local (ie., divisional) wealth, we use personal income data from the Bureau of Economic Analysis (BEA). The BEA provides quarterly personal income data at the state level that we aggregate into divisions. We calculate per capita personal income data at the divisional level using data on annual population in each division from the U.S. Census Bureau. Following Santos and Veronesi (2006), we calculate the return on personal income per capita in quarter t by dividing the difference in personal income between quarter t and quarter $t-1$ by the personal income in quarter $t-1$, all per capita.

[5]Every state belongs to one of the nine Census Bureau divisions which we index with two capital letters: West South Central (WS), Pacific (PA), East South Central (ES), Mountain (MO), East North Central (EN), South Atlantic (SA), West North Central (WN), Middle Atlantic (MA), and New England (NE). These divisions are grouped into four regions: West, Midwest, Northeast and South. We include a map of the nine US Census regions, divisions and the states they comprise in Figure 1.

From CRSP, we obtain stock returns for all NYSE, AMEX and NASDAQ stocks from 1960 to 2006. From COMPUSTAT, we obtain annual information on headquarter location, market capitalization and book value of equity for the period 1963 to 2006. Using the information on headquarters location in COMPUSTAT, each firm is assigned into one of the nine Census divisions.

A question that arises is which stocks to use to form the factor mimicking portfolio. Based on ample evidence of a local home bias in portfolio choice within the US (see references in the Introduction), we use stocks headquartered in the same Census division as the orthogonal labor income we are measuring. That is, to proxy division $k's$ orthogonal labor income we will use stock returns from division k only. Notice that this assumption is not necessary to derive the model's main testable implication: a negative price of risk on the orthogonal component of local non-diversifiable wealth. However, empirical support of the model under this assumption would be consistent with an explanation of the documented home bias at home puzzle based on relative wealth arguments.

The factor mimicking portfolios are constructed as follows: following equation (2) in the model, for each division we regress the return on divisional level personal income per capita on the CRSP aggregate stock market excess return and use the residuals from this regression as the return on orthogonal labor income. Starting in 1960, we use five years of quarterly data and regress the return on every individual stock in the division on a constant and on local orthogonal labor income return.[6] We use the slope coefficient on the orthogonal labor factor, estimated until the fourth quarter of 1964, to rank stocks in 1965. Next, we form three equal weighted portfolios according to the size of the coefficient. We then add one year of quarterly data, re-estimate the coefficient, and then rank stocks, form portfolios and compute their quarterly returns in 1966. We continue adding one year and re-estimating the coefficients until we have thirty-six quarterly observations in the regressions. At this point, we start rolling the data one year at a time: adding on a new year and taking off the first year. We continue this process until the end of the sample.

The above procedure provides three portfolios from the first quarter of 1965 to the final quarter of 2006 which are formed in year t based on the estimated coefficient on orthogonal labor income estimated until year $t-1$. The returns on the factor mimicking portfolio are computed as the returns of the portfolio formed by the stocks with the highest one third of coefficient estimates minus the returns on the portfolio formed by the stocks with the lowest one third of coefficient estimates.

The next step involves the choice of test assets. Daniel and Titman (2005) and Lewellen, Nagel, and Shanken (2010) note that testing asset pricing models using portfolios formed on firm characteristics, such as size and book to market, can lead to spurious conclusions about

[6] We assume that a firm that is headquartered in division k in 1963 is headquartered in that division in 1960, 1961 and 1962.

the usefulness of a proposed factor. The reason for this is that the factor structure of the portfolios is so strong that any proposed factor that is only weakly correlated with size or book-to-market will appear to price the test assets. That is, testing a new proposed factor on test assets sorted by size and book-to-market is likely to have very low power. In order to alleviate this concern we follow the recommendations in Daniel and Titman (2005) and Lewellen, Nagel, and Shanken (2010) and sort stocks by lagged loadings on our proposed factor.

To generate the test assets we repeat the procedure discussed above and calculate twenty equally weighted portfolios for each division (except for ES, for which we only calculate ten portfolios, due to the small number of stocks in this division in the early part of the sample).[7] In addition, in spite of the potential problems in using firm characteristics such as book-to-market to form portfolios, for our robustness exercises, we sort stocks in each division in year t into twenty portfolios according to book to market at the end of year $t-1$. The reason for this is that the book-to-market of a firm might be relevant to test our model because firms with a low book-to-market are growth firms that tend to be younger and might have more human capital specific factors, or unique technology that is specific to a particular geographical area (like Silicon Valley in California). In contrast, firms with a high book-to-market ratio are value firms and are more likely to be diversified geographically with production and sales across divisions and internationally. In addition, firms with a low book-to-market ratio also display high investment in R&D. Typically, the investment in R&D is highly intensive in human capital, which results in the type of non-diversifiable wealth against which investors will want to hedge by holding the security (a growth stock).[8] We calculate excess returns on all the test asset portfolios by subtracting the one month T-bill rate from the actual returns.

In addition to the local risk factors, we also require the excess return on the aggregate stock market portfolio (erm), as proxied by the CRSP aggregate index. We compare the performance of our model to that of the Fama-French three factor model that uses the excess return on aggregate stock market portfolio, the small minus big market capitalization portfolio (smb) and the high minus low book to market portfolio (hml). The quarterly premia on erm, smb and hml are 1.50%, 1.07% and 1.07% respectively, over the sample period.

4 Time Series Regressions

We start our analysis calculating the average premium on the orthogonal labor risk factors. Table 1 reports the mean annualized return of the factor mimicking portfolio returns, μ^F,

[7] All the results presented in the paper are generally robust to the use of market capitalization weighted portfolios.

[8] In unreported results, we also sort stocks by market capitalization since, following the arguments in Hong, Kubik and Stein (2008), smaller stocks are more local and should, other things equal, offer better hedging opportunities. We find a strong role for orthogonal labor income when employing size sorted portfolios.

in each division k, along with their t-statistics. In order to compare our results with Hong, Kubik and Stein (2008), we order the divisions according to population density. Divisions with low population density (less than 100 individuals per square mile) are indicated with a "(L)" following their two-letter symbol.[9] First, we observe that, as predicted by the model, all the risk premia are negative, suggesting that investors are willing to pay a premium in order to hold stocks that are strongly and positively correlated with the orthogonal component of labor income relative to those that have low or negative correlation. The mean premia range from an annual -2.84% in the EN division to -7.39% in MO. Table 1 also reveals a pattern of higher (in absolute value) risk premia in low population density divisions compared to divisions with high population density. For example, the average risk premia across the high population density divisions is -3.3% per annum compared to an average of -5.4% in the low population density divisions. According to the t-statistics, the risk premia are statistically significant in low density divisions, with the exception of ES, and marginally statistically significant in two high population density divisions: SA and EN.[10]

The results in Hong, Kubik, Stein (2008) are in terms of price difference, not returns. Hence, the comparison is not straight forward. The implication, however, is the same: in absolute value, the average risk premium that investors are willing to forgo (analogously, the price they are willing to pay) for holding stocks that hedge them against deviation from the local Joneses is significantly higher in low population density divisions. To understand how our model explains this result, consider the determinants of the prices of risk in equilibrium in equation (4). There are three parameters that may explain the differences across divisions: the variance ($\text{Var}(r^F)$) and covariance of the orthogonal local labor income factor mimicking portfolios, the portfolio bias induced by relative wealth concerns b, and the amount of local non-diversifiable wealth (relative to total country wealth) in the division, $\omega\theta$.

Panel B of Table 1 reports the covariances (lower triangular matrix), variances (diagonal), and correlations (upper triangular matrix) amongst the factor mimicking portfolios. There is not a clear distinction in terms of variance between low and high density divisions, with the exception of MO which has a variance more than double the average for the rest of divisions. The covariances, and in particular the correlations, show that the factor mimicking portfolios are fairly highly correlated (around 0.5). Hence, it is unlikely, that the difference in the prices of risk is induced by the volatility of the residuals.

[9]Population density numbers (Census 2000) are: MA, 399; NE, 222; SA, 194; EN, 185; PA, 136; ES, 95; WS, 74; WN, 38; MO, 21. Like in Harrison, Kubik and Stein (2008), we have excluded Alaska and Hawaii to compute the density of PA.

[10]ES is peculiar in several respects. It has lower population and a substantially lower number of firms than other divisions, as we argued before. More importantly, it is the poorest division on a GDP per capita basis. Out of the four states in this division, in the BEA statistics for 2007, Mississippi ranked dead last among all 50 US states, and Tennessee, Kentucky and Alabama ranked 40, 41 and 44, respectively. From equation (4), wealth is a factor in the determination of the size of the orthogonal risk premia. The low level of wealth of this division can offset the effect of the Keeping up with the Joneses preferences.

The portfolios bias b has different interpretations depending on the nature of the relative wealth concern. In the case of EHF, $b = \frac{\gamma}{1-\gamma}$, and the economic size of the risk premium depends on the "Joneses" parameter γ. Therefore, a possible explanation of our findings is that in divisions with lower population density there is a stronger Joneses concern (higher γ) since, arguably, it is easier for investors to assess the level of wealth of their peers: in smaller communities, for example rural areas, people tend to know each other better and have more information about each other than in densely populated urban communities.

In a purely price driven explanation, $b = \frac{\alpha}{1-\alpha}$, that is, the size of the price of risk increases with the risk aversion of the representative investor α. In other words, if we were to explain the differences in risk premia across divisions only through price hedging induced by relative wealth concerns, we should conclude that the risk aversion of the representative investor is higher for less densely populated divisions.

Finally, divisions with lower population density may contain a higher proportion of the country's non-diversifiable local income wealth. Unlike in Hong, Kubik and Stein (2008), in the case of relative wealth concerns, limited total local wealth is not what drives the negative risk premium (thus, pushing prices up), but rather the proportion of local non-diversifiable wealth.

The premia recorded in Table 1 indicate that, if stocks headquartered in a given division are sorted according to their sensitivity with respect to divisional level orthogonal labor income, there is a reasonable spread in returns. These results are derived after projecting divisional labor income onto purely divisional stocks. This begs two important questions regarding the scope of keeping up with the Joneses behavior. The first concern is to what extent these premia are purely local (divisional) rather than country-wide. A second issue is how much of a given division's cross-section of stock returns can be explained by the orthogonal labor risk in other divisions.

4.1 Country versus divisional Joneses risk hedging

To what extent are the local premia purely local (divisional) rather than country-wide? To answer this question, we calculate first a country-wide measure of orthogonal labor risk premium. Following the same procedure explained in section 3, we take all US stocks, irrespective of their headquarters location, and regress them against the US aggregate orthogonal labor income; we then sort these stocks into three portfolios, depending on the size of the regression beta. Define r^G as the return on the difference between the high and low portfolio (P1-P3). The average premium on this portfolio difference is $\mu^G = -5.15\%$ per annum with a t-statistic of 2.55. This premium is highly correlated with the divisional level premia.

To disentangle local from aggregate (country) effects we perform two kinds of tests. First, we begin by estimating the following regression:[11]

$$r_{i,k,t} = \alpha_{i,k} + \beta^F_{i,k} r^F_{k,t} + \beta^{erm}_{i,k} r_{erm,t} + \beta^{smb}_{i,k} r_{smb,t} + \beta^{hml}_{i,k} r_{hml,t} + u_{i,k,t}, \qquad (6)$$

where $r_{i,k,t}$ is the excess return on portfolio i ($i = 1, ..., 20$) from division k ($k = 1, ..., 9$) at time t; $\alpha_{i,k}$ is the portfolio-specific constant (pricing error); $\beta^F_{i,k}$ is the estimated factor loading on $r^F_{k,t}$, the factor mimicking portfolio of orthogonal local labor income in division k; $\beta^{erm}_{i,k}$ is the estimated factor loading on $r_{erm,t}$ (excess return on the market portfolio); $\beta^{smb}_{i,k}$ is the estimated factor loading on $r_{smb,t}$ (the small-minus-big Fama-French factor); $\beta^{hml}_{i,k}$ is the estimated factor loading on $r_{hml,t}$ (the high-minus-low Fama-French factor); finally, $u_{i,k,t}$ is the error term. We then take the residuals from (6) and regress them against the country factor mimicking portfolio return:

$$u_{i,k,t} = \alpha_{i,k} + \beta^G_{i,k} r^G_t + v_{i,k,t}. \qquad (7)$$

With this test, we want to explore first whether local orthogonal labor risk matters in explaining the return on locally formed portfolios in each division, i.e., whether $\beta^F_{i,k} \neq 0$. Secondly, we would like to know if, on top of what local orthogonal labor explains, country orthogonal labor risk has any relevance, i.e., whether $\beta^G_{i,k} \neq 0$.

Table 2 reports the results. In Panel A, we report the estimates of $\beta^F_{i,k}$. This panel shows that across all the nine divisions there is a large spread in the estimates. For example, in the MA division, the estimates are positive for the first eight portfolios (portfolio 1 is the portfolio with the highest coefficients on the local labor income factor, while portfolio 20 is the portfolio with the lowest coefficients) and in seven cases they are statistically different from zero. Portfolios nine through twenty have negative coefficient estimates on the divisional level factor mimicking portfolio and eleven are statistically significant. The estimates, both negative and positive, are large economically and generally decrease monotonically from portfolio one to portfolio twenty, as we would expect given the sorting procedure. The pattern in the estimated betas, together with the negative premium on the orthogonal labor income factor mimicking portfolios in Table 1, clearly illustrate the following result: stocks positively correlated with the orthogonal component of divisional labor income are stocks that investors are willing to pay a premium to hold; their positive betas indicate that they command a lower expected return, even after controlling for the three Fama and French factors. Investors require an additional premium to hold those stocks that have a negative beta. These results are consistent with the EHF model and the local good in short supply model.

In general, the results of the MA division hold for all the other divisions which are

[11] We also want to explore if the factor mimicking portfolio of orthogonal local labor income is important in the presence of the three Fama-French factors, hence we include these factors in the regression.

listed according to their population density ranking, from highest (first column) to lowest density (last column). In addition, while 60% of the test portfolios in the high population density divisions have a statistically significant coefficient on the factor mimicking portfolio for orthogonal local labor income, 82% of test portfolios in low population density divisions have a statistically significant coefficient. In total 147 out of the 170 coefficient estimates on the orthogonal local labor income factor are statistically significant.

Finally, to have an estimate of the expected return spread due to relative risk hedging across stocks within each division, the last row in Panel A from Table 2 presents the product of the difference between top, P1, and bottom portfolio, P20 (P10 for ES) betas, times the average annualized premium μ_k^F from Table 1. The results show that this return spread can be quite substantial: investors are willing to sacrifice in expected return up to 4.25% in NE and up to 10.42% in MO in order to hedge relative wealth risk. With the exception of ES, the return spread is usually higher in low density divisions than in high density divisions.

In Panel B of Table 2, we record the estimates of β_i^G, the estimate from the regression of the residuals on the global factor in regression (7). In only 15 out of a possible 170 cases do we observe a statistically significant estimate and all but two of these are in high population density divisions. Therefore, there is very little role for global orthogonal labor income once that divisional level orthogonal labor income is accounted for, especially in low density divisions.

To confirm the local nature of our factors premia, we reverse the testing methodology. This means that for each portfolio in each division we estimate first the sensitivity to the aggregate, country-wide Joneses risk:

$$r_{i,k,t} = \alpha_{i,k} + \beta_{i,k}^G r_t^G + \beta_{i,k}^{erm} r_{erm,t} + \beta_{i,k}^{smb} r_{smb,t} + \beta_{i,k}^{hml} r_{hml,t} + u_{i,k,t}, \tag{8}$$

where $r_{i,k,t}$ is the excess return on portfolio i ($i = 1, ..., 20$) from division k ($k = 1, ..., 9$) at time t; $\alpha_{i,k}$ is the portfolio-specific constant (pricing error); $\beta_{i,k}^G$ is the estimated factor loading on r_t^G, the factor mimicking portfolio of orthogonal local labor income at the national level. The remaining factors and loadings are as in regression (6). We then regress for each division the residuals from (8) onto its local orthogonal risk factor mimicking portfolio, $r_{k,t}^F$:

$$u_{i,k,t} = \alpha_{i,k} + \beta_{i,k}^F r_{k,t}^F + v_{i,k,t}. \tag{9}$$

These two regressions allow us to ask first, if national orthogonal labor income is important in determining the returns on the twenty divisional level portfolios, and second, whether after accounting for national level orthogonal labor income, local orthogonal labor income at the division is still important.

Panel A of Table 3 records the estimates of $\beta_{i,k}^G$ from equation (8) where 112 out of 170 coefficients are statistically significant, somewhat less than the 147 statistically significant estimates when employing divisional level orthogonal labour income. More interestingly, Panel B shows that even after accounting for global orthogonal labor income, divisional orthogonal labor income is still important: 73 estimates of $\beta^F_{i,k}$ are statistically significant. We also estimate the residual return spread between portfolio P1 and P20 across divisions, multiplying the difference in betas from Table 3 Panel B times the divisional expected premium in Table 1. The size of the spreads is smaller across divisions, as expected, since we have netted out the country-wide spread component. Interestingly, the residual spread is clearly higher among low density divisions than among high density divisions, ranging from -1.25% for MA (the highest density division) to -5.8% for MO (the lowest density division).

These results jointly suggest that it is local orthogonal labor income that is important in determining the returns on the divisional level portfolios. On the one hand, after controlling for divisional orthogonal labor income, there is no role for global orthogonal labor income. On the other hand, after first controlling for global orthogonal labor income there is still a substantial role for local orthogonal labor income. Moreover, the return spread within divisions between portfolios with high and low correlation with the orthogonal risk factor is higher in low population density divisions, even after netting out the country-wide component. These differences in spread between low and high population density divisions suggest that the ability of the KEEPM in explaining the cross-sectional of stock returns should be stronger in the former divisions (ie., those with lower population density). We will test formally this hypothesis in section 5.

4.2 Orthogonal labor income from other divisions

To a large extent, the previous section showed that divisional level orthogonal labor income is more important than its global equivalent lending support to the notion that either EHF or goods in short supply are relevant at the Census level. We tackle now our second concern: how much of the local cross-section in stock returns in a given division can be explained by the orthogonal labor risk in other divisions. In order to understand this, we will perform two complementary tests. First, we run regression (6) for every portfolio in each division. We then take the residuals, $u_{i,k,t}$, from each portfolio i in division k and regress them against the orthogonal labor risk of divisions $k' \neq k$, one at a time:

$$u_{i,k,t} = \alpha_{i,k} + \beta^F_{i,k,k'} \, r^F_{k',t} + v_{i,k,t},$$

for $i = 1, ..., 20$ and $k, k' = 1, .2, ..., 9$. We are interested in the estimates of $\beta^F_{i,k,k'}$.

Table 4 reports the results. Each row represents the 20 portfolios in each division (10 in the case of ES); each column represents the local (divisional) orthogonal labor risk factor. For a given portfolio i in division (row) k and orthogonal portfolio from divisions (column) $k' \neq k$, the table presents the number of estimated coefficient, $\beta^F_{i,k,k'}$, that are statistically significant (| t-statistic |> 1.96). The diagonal is obviously blank. In most cases the betas are not significant, especially among divisions with low population density. For instance, out of the 160 coefficient estimates for each division (20 portfolios times the other 8 divisions), there are 37 (MA), 28 (NE) and 29 (SA) significant estimates across high population density divisions. In contrast, there are only 7 (WS), 6 (WN) and 16 (MO) statistically significant estimates among low population density divisions. These findings indicate that there is only a minor role for non-local orthogonal labour income.

Even more interesting is the observation that in 75% of the cases the significant coefficients are negative. Thus, reading the table row-wise, once investors in a given division hedge their exposure to local (i.e., same division) orthogonal labor risk with a portfolio of local assets, they are either indifferent (non-significant beta) or they require, in most cases, a price discount (alternatively, a risk premium) to hold local stocks that covary (significant beta) with other division's orthogonal labor risk. We would then expect that those portfolios outside their division would be underweighted by local investors who want to hedge their exposure to local Joneses risk. This evidence would be consistent with home-biased portfolios across divisions.

In a second test, we want to net out the effect of the country orthogonal labor risk and then investigate the role of the purely Joneses risk from other divisions. Recall from the earlier results that when we first included the global orthogonal labor income factor, the residuals from each division could be explained by divisional specific orthogonal labor income factor. We now repeat this exercise but examine the extent to which other divisions orthogonal labor income factors can explain the residuals after considering the global orthogonal labor income factor. The procedure is the following: take division k; for each portfolio i in this division we regress portfolio returns on the country orthogonal labor risk factor, as in equation (8). We then take the time series residuals $u_{i,k,t}$ and regress them against a constant and the orthogonal labor income factor from each of the nine divisions, one at a time:

$$u_{i,k,t} = \alpha_{i,k} + \beta^F_{i,k,k'} r^F_{k',t} + v_{i,k,t}, \tag{10}$$

for $i = 1, ..., 20$ and $k, k' = 1, .2, ..., 9$. We are interested in the estimates of $\beta^F_{i,k,k'}$.

Table 5 reports the number of coefficients $\beta_{i,k,k'}$ in regression (10) corresponding to portfolios from division k (by rows) regressed against orthogonal risk from division k' (by columns) which are statistically significant (t-statistic > 1.96). Reading the table row-wise, the first conclusion is that, with the exception of SA, the highest number of significant coefficients corresponds always to the own division's orthogonal labor income factor (bold numbers in the diagonal). Virtually all the significant betas are positive. Reading the table by columns, we conclude that, maybe with the exception of NE, orthogonal labor income from other divisions is largely uncorrelated with the return on stocks outside the same division. This evidence tells us that own division Joneses risk is more relevant in explaining excess return above and beyond what aggregate country labor risk explains than other division's local Joneses labor risk.

In summary, the results thus far indicate that divisional specific orthogonal labor income is by far the most important factor in explaining stock returns in the time series. The joint evidence leads us to conclude that confining the returns from a given division to be explained by that same divisions local orthogonal labor income factor may not be a too restrictive assumption.

5 Cross-Sectional Regressions

The previous section of the paper identified a clear pattern in the beta estimates with respect to local orthogonal labor income that is important over and above that of the national orthogonal labor income factor and the individual orthogonal labor income from other divisions. Given the risk premia on the factor mimicking portfolios reported in Table 1, this implies that investors are willing to pay for assets that are highly correlated with local orthogonal labor income and need an additional premium to hold stocks with negative correlation with local orthogonal labor income.

In this section of the paper, we test the cross-sectional performance of the model by directly estimating the risk premium associated with the factor mimicking portfolios using two different methodologies: the Fama and MacBeth (1973) two-step approach and GMM estimation based on the Stochastic Discount Factor (SDF) approach. The reason why we employ two different methodologies is that they can help us answer different questions. The Fama and MacBeth methodology allows us to focus not only on whether divisional level orthogonal labor income is priced in the cross-section, but also offers a convenient way to compare the role of global and divisional betas in explaining the cross-section. GMM allows us to perform a different test on the role of betas at the global and divisional level, and furthermore to easily impose a common estimate on the market price of risk on the market portfolio. This allows for pricing kernels across divisions to differ only by the divisional level orthogonal labor income.

Unless otherwise specified, in the cross-sectional tests we use the same portfolios (twenty for all divisions except ES where only ten portfolios are formed) that were used in the time series tests.

5.1 Fama-MacBeth Regressions

The Fama and MacBeth (1973) procedure involves a first step in which time series regressions are used to estimate the betas, and a second step in which cross-sectional regressions are used to estimate the prices of risk. When data are available over a long sample period it is usual to undertake a rolling regression approach by using sixty observations up to time t in the first step to obtain the first beta; then this beta is used in the second step to estimate a cross-sectional regression of average returns at time $t+1$ on the beta estimated until time t. The data are then rolled forward one month and the procedure is repeated. This results in a time-series of cross-section estimates of the market price of risk. However, this rolling procedure is not appropriate with quarterly time series data over a relatively short sample. Instead, we estimate the beta coefficients over the entire sample and we use them in all of the T cross-sectional regressions. This is the method recommended and employed by Lettau and Ludvigson (2001b) for quarterly data over a relatively short time series sample such as ours, and discussed in Cochrane (2005).

In the first instance, we want to know if local orthogonal labor income is important in explaining the cross-section of returns. To this end, we estimate

$$r_{i,k} = \lambda^0 + \lambda_k^F \widehat{\beta}_{i,k}^F + \lambda^{erm} \widehat{\beta}_{i,k}^{erm} + \lambda^{smb} \widehat{\beta}_{i,k}^{smb} + \lambda^{hml} \widehat{\beta}_{i,k}^{hml} + \epsilon_i. \tag{11}$$

where $r_{i,k}$ is the return on the ith portfolio in division k. We use the twenty portfolios formed according to lagged coefficient on orthogonal labor income. Later we repeat the analysis using book-to-market sorted portfolios. We estimate (11) for each division separately.[12] Panel A of Table 6 reports the results and shows that across all nine divisions the estimated price of risk for divisional level orthogonal labor income risk is negative. In six cases the estimated price of risk on the orthogonal local labor income is statistically significant, and there is a clear difference between low and high population density divisions.[13] For example, the low population density divisions have a larger, in absolute terms, estimate, accompanied with a higher level of statistical significance. The average estimated quarterly price of risk across the four low population density divisions is -1.188 compared to -0.796 for the high population density divisions, moreover, if we ignore the very low estimate in the ES division, the estimates in the low population density divisions are almost twice as large as those from the high population density divisions. We also report the cross-sectional $\overline{R}^2$ which range from 0.25 to 0.85 with an average of 0.52, indicating a reasonable explanatory power.[14] The final row of Panel A reports a test that the pricing errors are jointly zero.[15] It is not possible to

[12]This means that we estimate different prices of risk on the market, smb and hml factors for each division, suggesting a separate SDF for each division. In the GMM estimation it is easy to impose a common price of risk on these three factors across all divisions. As we shall see, this has no effect on the inferences that we make regarding the role of orthogonal labor income.

[13]Recall that the estimate sign on λ_k^F should be negative. Therefore, the test is one sided.

[14]Following Jagannathan and Wang (1996) and Lettau and Ludvigson (2001b), we calculate $\overline{R}^2$ as $[Var_c(\overline{r}_i) - Var_c(\overline{e}_i)]/Var_c(\overline{r}_i)$, where Var_c is the cross-sectional variance, $\overline{r}_i$ is the average return and $\overline{e}_i$ is the average residual.

[15]This is a Chi-sq test, $\widehat{\alpha}' cov(\widehat{\alpha})^{-1}\widehat{\alpha}$, where $\widehat{\alpha}$ is the vector of average pricing errors across the twenty five portfolios and cov is the covariance matrix of the pricing errors.

reject the null hypothesis that the pricing errors are jointly zero, except for NE. Therefore, the factors provide a good explanation of the cross-section of returns.

Using the Fama and MacBeth methodology, we can also address the role of divisional and country orthogonal labor income in the cross-section. We will follow a similar structure as in the time series regressions in the previous section. From the time series regression (6) we obtain the estimates for the local betas, $\widehat{\beta}^F_{i,k}$, one per portfolio i in each division k. We also obtain the slope estimates for the market and the *smb* and *hml* Fama and French factors. Then, using the residuals from the first regression, we obtain the country-wide betas, $\widehat{\beta}^G_{i,k}$, from regression (7). With these estimates, we perform a set of T cross-sectional regressions of the form:

$$r_{i,k} = \lambda^0 + \lambda^F_k \widehat{\beta}^F_{i,k} + \lambda^G_k \widehat{\beta}^G_{i,k} + \lambda^{erm} \widehat{\beta}^{erm}_{i,k} + \lambda^{smb} \widehat{\beta}^{smb}_{i,k} + \lambda^{hml} \widehat{\beta}^{hml}_{i,k} + \epsilon_i. \tag{12}$$

In this cross-section regression, we ask whether the beta with respect to the national orthogonal labor income helps price the test assets over and above the local orthogonal labor income factor. Table 6 Panel B reports the results. The price of risk on the local factor is always estimated to be negative and is statistically significant in six cases. The price of risk associated with the country factor, λ^G is only negative on four occasions and is never statistically significant. Note that the correlation ρ between the two betas, local and national, is very low indicating that these betas are not capturing the same thing. We can not reject the null hypothesis that the pricing errors are jointly zero in all cases except division SA.

The findings in Panel B suggest that the global betas are not important in explaining the cross-section of returns. We now reverse the testing procedure of the cross-sectional regressions and take the global factor first from (8) and then regress the residuals from the time series regression on the local factors, as in equation (9). We reestimate (12). Panel C reports the results. In this case, first note that the betas are very highly correlated, suggesting the local factor and national factor betas are capturing the same thing. In the cross-section neither of the prices of risk are statistically significant, which is probably not surprising given their high correlation. Overall, the findings in the three Panels of Table 6 indicate that it is the local factor that is important, over and above the country factor. The country factor seems just a proxy for the local factor.

In the formal derivation of the KEEPM there is no explicit role for the *smb* and *hml* factors. We have included them thus far in order to show that orthogonal labor income is important over and above the information contained in other established risk factors. We repeat the analysis of Table 6 using just the market factor and the orthogonal labor income factor. The results for estimating the prices of risk are reported in Table 7: the estimated prices of risk on the orthogonal labor income factors are very similar to those reported in Table 6. In fact, the model performance as measured by the $\overline{R}^2$ and the pricing error tests is similar to the case when *smb* and *hml* factors are included.[16]

5.2 GMM Estimation of the model

In this section of the paper, we consider an alternative approach to test the existence of relative wealth concerns at the Census division level. There are a number of advantages of using this new methodology. First, we can implement a new, more direct test of whether global risk is important in the presence of local risk. Second, in the Fama-MacBeth regressions, we estimated a separate market price of risk, per division. This amounts to assuming that each division is segmented from the others. Within the GMM methodology that we use in this section, we can easily restrict the parameters in the pricing kernel associated with the aggregate market factor to be the same across divisions. In this case, the only differences in the pricing of the different divisions assets are the parameters associated with each division's specific orthogonal labor income factor.

We first derive an approximate linear expression for the equilibrium stochastic discount factor m where the betas and the prices of risk are a function of the deep parameters of the model. This introduces additional restrictions that will allow us to test the model. The Appendix shows that whether the Joneses are endogenous or exogenous, the following Euler equation must be (approximately) satisfied in equilibrium:

$$E\left(r_{i,t}\left[H^{-1}-(1-\sum_{k=1}^{K}\omega_k\theta_k b_k\beta_k)r_{erm,t}+\sum_{k=1}^{K}\omega_k\theta_k b_k r^F_{k,t}\right]\right)=0, \tag{13}$$

where $b_k=\frac{\gamma_k}{1-\gamma_k}$ in the exogenous Joneses case, and $b_k=\frac{\alpha_k-1}{\alpha_k}$ in the endogenous specification. Therefore, we obtain an approximate linear expression for the stochastic discount factor:

$$m\approx c_0+c_{erm}r_{erm}+\sum_{k=1}^{K}c_k r^F_k,$$

where $c_0=H^{-1}$, $c_{erm}=\sum_{k=1}^{K}\omega_k\theta_k b_k\beta_k-1$ and $c_k=\omega_k\theta_k b_k$.

The time series analysis in section 4 showed that, in most cases, there exists a low covariance between the return on the portfolios in a given division and the orthogonal labor risk of other divisions. Hence, we will employ a truncated version of the linearized stochastic discount factor per division, including only a constant, the stock market return and the corresponding divisional orthogonal risk, as we did in the Fama and MacBeth regressions. As a

[16]We do not report the results that are equivalent to Panels B and C of Table 6 where we aim at understanding whether global or divisional level risk is important in explaining the cross-section. They are available on request and are entirely consistent with the findings in Table 6: once local risk is accounted for there is no role for global risk. When global risk is accounted for, there is a role for local risk. Therefore, whether we use the Fama-French three factor model or not makes no difference in terms of our findings.

robustness check, the country orthogonal risk factor will be added later on.

The stochastic discount factor in division k becomes

$$m_k \approx c_{0,k} + c_{erm,k} r_{erm} + c_k r_k^F. \tag{14}$$

The GMM methodology outlined in Hansen (1982) provides a natural way to estimate our model.[17] For a given division k, define $\boldsymbol{c_k} = (c_{erm,k}, c_k)$. The forecast error at time t for the parameter vector $\boldsymbol{c_k}$ is given by $\mathbf{v}_t(\boldsymbol{c_k}) \equiv r_t(c_{0,k} + \boldsymbol{c_k}'(r_{erm}, r_k^F))$, such that, according to the equilibrium orthogonality condition (13), its unconditional expectation is zero, $E(\mathbf{v}_t(\boldsymbol{c_k})) = 0$. Defining the sample mean of the forecast errors over the T observations as:

$$\mu_T(\boldsymbol{c_k}) \equiv \frac{1}{T}\sum_{t=1}^{T} \mathbf{v}_t(\boldsymbol{c_k}).$$

The GMM methodology estimates the parameter vector $\boldsymbol{c_k}$ that minimizes

$$\widehat{\boldsymbol{c_k}} = \arg\min_{c_k}(\mu_T'(\boldsymbol{c_k})\boldsymbol{\Sigma}\mu_T(\boldsymbol{c_k})),$$

where $\boldsymbol{\Sigma}$ is a positive definite weighting matrix.[18] The ability of the model to price the assets is assessed by testing that the orthogonality conditions, which follow a $\chi^2(N-L)$ distribution, where N is the number of moment conditions, and L the number of parameters, are zero. This is known as Hansen's J-test.

In our model, we are interested in answering the following three questions: first, does the orthogonal labor income factor help to price the assets ($c_k \neq 0$)? Second, does it command a negative price of risk ($\lambda_k^F < 0$), as predicted by the model? Thirdly, we would like to know if country orthogonal labor risk is important in pricing the assets in the presence of divisional orthogonal labor risk, and vice-versa. In order to answer the first two questions simultaneously, we follow Cochrane (2005), who notes that:

$$E\left(m_k\begin{pmatrix} r_{erm} \\ r_k^F \end{pmatrix} - \begin{pmatrix} r_{erm} \\ r_k^F \end{pmatrix} + \begin{pmatrix} \lambda^{erm} \\ \lambda_k^F \end{pmatrix}\right) = \begin{pmatrix} 0 \\ 0 \end{pmatrix},$$

which together with the moment orthogonality conditions in (13) produce efficient estimates of the parameters in the pricing kernel, the vector of prices of risk and their associated

[17]The advantage of this approach in our setting is enhanced by the multicollinearity among the factors. Cochrane (1996) and Jagannathan and Wang (2002) consider the small sample properties of the GMM method of estimating the stochastic discount factor and find that it has about the same performance in finite samples as the Fama-MacBeth methodology.

[18]Under GMM this weighting matrix is the inverse of a consistent estimator of the spectral density matrix of $\mathbf{v}_t$ at frequency zero, defined as $\mathbf{S} = \sum_{j=-\infty}^{\infty} E[\mathbf{v}_t\mathbf{v}_{t-j}'] = T \cdot \text{var}(\mu_T)$. Hansen (1982) shows that it is optimal to use the inverse of a consistent estimator of $\mathbf{S}$ as the weighting matrix, since the estimated parameter vector has the lowest variance asymptotically. When $\boldsymbol{\Sigma}$ is the optimal weighting matrix $\mathbf{S}^{-1}$, the asymptotic standard errors are given by $\text{var}(\widehat{\boldsymbol{c}}) = \frac{1}{T}(\mathbf{D}_T'\mathbf{S}^{-1}\mathbf{D}_T)^{-1}$, where $\mathbf{D}_T = \frac{\partial \mu_T(\boldsymbol{c})}{\partial \boldsymbol{c}'}$.

standard errors (see Li, Vassalou and Xing (2006)).

Table 8 reports cross-sectional tests of the KEEPM using the GMM framework where we consider only divisional level orthogonal labor income.[19] In six cases the local orthogonal labor income factor commands a statistically significant risk premia, all negative, as the theory suggests. Estimates of the risk premia are similar to those of Table 7. Also like in Table 7, there is a clear distinction between estimated risk premia in the high and low population density divisions. In the low population density divisions the average risk premium is estimated at -1.4% per quarter (around -6% per annum). In the high population density divisions the average risk premium is -0.81% per quarter (around -3.3% per annum). Thus, there is substantial evidence that KEEPM preferences are stronger in low population density divisions.

The market factor is not significant in the pricing kernel. These results pertaining to the market portfolio are consistent with other findings that market betas can not explain the cross-section of returns (see, for example, Fama and French (1993)). However, at this stage, we are estimating separate market risk premia across divisions, something which would imply a separate pricing kernel in each division. Later we will impose a common market premium across all divisions.

According to the J-test, the model can only be rejected in SA, and it holds only marginally in MA. In addition to examining the model performance with the J-test, we analyze the size of the pricing errors in each division. This will help us to evaluate whether we are accepting a model that prices the tests assets poorly, but does not reject the J-test because the standard errors are large. The opposite is also true: we might reject statistically a good model because it has economically small pricing errors but very small standard errors (see Cochrane (1996) for a discussion of this point).

Table 8 reports the average absolute pricing errors (*aape*) across each division. In all but one case, NE, the pricing errors are economically small, averaging 0.32% per quarter excluding NE. Interestingly, NE is a division where the J-test accepts the model, and in the two cases where the J-test rejects the model (MA and SA) the pricing errors are economically small, 0.23% and 0.49% per quarter respectively. So, even though we statistically reject the model in the cases of MA and SA, economically the model does perform well given its small pricing errors for these two divisions. Therefore, it is clearly important to check the size of the pricing errors in conjunction with inferences made from the J-test.

The second row from the bottom of Table 8 reports the average absolute pricing errors for the estimation of the pricing kernel when we include the *smb* and *hml* factors ($aapeFF$). In all cases the inclusion of the *smb* and *hml* factors increases the pricing errors. Across all nine divisions the average pricing error is 0.78% per quarter when we include the *smb* and

[19]In Table 8, we use 20 test assets in each division, with the exception of ES where we use 10 test assets, as in Table 6.

hml factors as compared to 0.49% per quarter for the KEEPM. Furthermore, the unreported coefficients in the pricing kernel and the risk premia associated with the *smb* and *hml* factors are rarely statistically significant: regarding *smb*, there are two divisions that have a marginally significant coefficient in the pricing kernel and two that have a significant estimate of this factor's risk premium; with respect to *hml*, there is one division that has a significant coefficient in the pricing kernel, one division with a statistically significant estimate of the risk premium on this factor, and one division with a marginally significant estimate of the factor's risk premium.

The results regarding the lack of a role for the *smb* and *hml* factors is reinforced when we consider the final row of Table 8 which reports the ΔJ statistic that tests the null hypothesis that the *smb* and *hml* factors are not important in pricing the assets. This test involves estimating an unrestricted version of the model that includes all factors, and subsequently estimating a restricted model where the factor is omitted, using the weighting matrix from the unrestricted model. We can then evaluate the restriction using the differences in the two models J-statistics:

$$TJ(restricted) - TJ(unrestricted) \sim \chi^2(\text{\# of restrictions}).$$

In six cases we cannot reject the null hypothesis. Overall, it appears that the *smb* and *hml* factors are not necessary to price the tests assets over and above the KEEPM. This confirms the results reported in Table 7 where the two Fama and French risk factors were removed and the cross-section estimation of the model did not change.

So far, we have estimated the price of risk for the orthogonal labor risk in each particular division, ignoring the effect of the orthogonal labor risk from other divisions and the country overall. We now challenge these results by studying the relative importance of country versus local orthogonal labor income. As noted in the discussion from the Fama-MacBeth cross-sectional regressions, orthogonal country labor income does not seem to be able to price the assets as effectively as orthogonal local labor income. In our case, the SDF approach is particularly useful to evaluate the role of the orthogonal labor income factor and the relative importance of country versus local orthogonal labor income.

With the objective of trying to further distinguish between these two sources of risk in mind, we expand the SDF in (14) to include in each division k both global and local orthogonal labor income. In this test we estimate:

$$m_k \approx c_{0,k} + c_{erm,k} r_{erm} + c_k r_k^F + c_{G,k} r^G,$$

where r^G is the factor mimicking portfolio for country orthogonal labor income.

Table 9 presents the results. Whereas the risk premium associated with the country orthogonal labor income is not significant, in five cases the risk premia associated with the local orthogonal labor income are statistically significant. Only in one case the risk premia on the global factor is statistically significant.

The J-test accepts the model in all but one case (SA). The average absolute pricing error across all nine divisions is 0.58% per quarter. The final row of Table 9 reports the ΔJ statistic, which tests the null hypothesis that the country orthogonal labor income factor is not important in pricing the assets. In all cases, we accept the restriction that this factor is not important.

It is clear from the results of Table 9 that adding country labor income to the KEEPM with local orthogonal labor income does not improve the model, consistent with the results from the Fama-MacBeth cross-sectional regressions. These results indicate that local risk-hedging dominates over country-wide domestic hedging of non-diversifiable wealth which lends indirect support to the local portfolio bias implications of the model.

6 Robustness tests

The time series analysis, and both the Fama-MacBeth and the GMM cross-sectional results so far presented lend empirical support to the main theoretical implication of our model: relative wealth concerns at the US Census division level result in a negative risk premium for those stocks positively correlated with shocks to local, non-diversifiable labor income. This premium is local in its nature and different from a country-wide premium driven by the same relative wealth concerns. Moreover, the results are stronger among divisions with lower population density. The immediate implication is that local labor income at the divisional level is more relevant than aggregate country-wide labor income risk in explaining the cross-section of US stock returns.

We include in this section several robustness checks. In particular, we will study whether including additional portfolios, imposing a single stock market risk premium across divisions, or reducing the number or test portfolios affects our main empirical results. Finally, we investigate the robustness of the KEEPM orthogonal risk factors in the presence of two alternative labor related factors previously studied in the literature: the consumption to wealth, cay, variable in Lettau and Ludvigson (2001a) and the labor income to consumption, s, variable in Santos and Veronesi (2006). We will show that our results remain qualitatively robust.

6.1 Additional Portfolios

We include additional test portfolios that are known to have a large spread in average returns. In particular, we include an additional twenty portfolios formed according to book-to-market ratio. The addition of book-to-market portfolios to the test assets is motivated by the possibility that firms with a low book-to-market are growth firms that tend to be younger, and might have more human capital specific factors, or unique technology that is specific to a particular geographical area (like Silicon Valley in California). In contrast, firms with a high book-to-market ratio are value firms and are more likely to be geographically diversified, with production and sales across divisions and countries. Additionally, firms with a low book-to-market ratio tend to exhibit high investment in R&D. Arguably, the investment in R&D is highly intensive in human capital, which results in the type of non-diversifiable wealth against which investors will want to hedge by holding the security (a growth stock).

Table 10 reports estimates of the coefficients in the pricing kernel. In all cases except the ES division, the estimates of c_k are statistically significant, confirming that local orthogonal labor income helps explain the test assets in all but one division. In comparison to Table 8, where only the twenty portfolios formed on lagged orthogonal local labor income are used as test assets, the estimated coefficients in the pricing kernel are larger and have greater statistical significance. This indicates that the model can help explain the returns on book-to-market portfolios.

In seven (one case marginally) of the nine divisions the local orthogonal labor income factor commands a statistically significant risk premium, in all cases negative. Furthermore, there is still a clear difference between low and high population density divisions (the average quarterly risk premium in the low population density divisions is -1.41 compared to -1.08 in the high population density divisions). Across all divisions, the J-test indicates that the model is accepted. However, in all cases the inclusion of the book to market portfolios increases the pricing errors.

The second row from the bottom of Table 10 reports the average absolute pricing error when we include the *smb* and *hml* factors, $aapeFF$, which might be relevant to price book to market stocks. In five cases, the inclusion of these factors reduces the pricing errors. Moreover, in the final row of Table 10 we report the ΔJ statistic, which tests the null hypothesis that the *smb* and *hml* factors are not important in pricing the assets. In eight cases (one marginally) we reject the null hypothesis in favor of the alternative that the *smb* and *hml* factors are necessary to price these assets. Unlike Table 8, where the test assets do not include book-to-market portfolios, the *smb* and *hml* factors, in conjunction with the local orthogonal labor income factor, are important when we price the original portfolios and the book-to-market portfolios simultaneously.[20]

[20]Results for market capitalization sorted portfolios are very similar to the book-to-market portfolios. These are available on request.

6.2 Common Market Risk Premium across Divisions

The estimations we have considered so far treat each division separately, which amounts to considering a different pricing kernel for each division. However, this would require that each division were segmented from the others. In this part of the paper, we consider a common pricing kernel for the market factor whilst still allowing the divisional risk factors based on the orthogonal labor income to have difference prices of risk.

In order to achieve this, following Cochrane (2005) we employ GMM to estimate the market price of risk from the CAPM using 10 size sorted portfolios from all stocks on CRSP, irrespective of location. This amounts to specifying the SDF as:

$$m \approx c_0 + \hat{c}_{erm} r_{erm},$$

which is estimated jointly with the other moment condition:

$$E\left(m\left(r_{erm}\right) - r_{erm} + \hat{\lambda}^{erm}\right) = 0$$

Using the ten size portfolios as test assets we obtain the following quarterly estimates of the CAPM's parameters: $\hat{c}_{erm} = -3.694(t - \text{value} = 2.27)$; $\lambda^{erm} = 0.0271(t - \text{value} = 2.32)$. We now impose these estimates on each division and estimate the free parameters associated with the divisional level orthogonal labor income. That is, the next step involves imposing these estimates on the SDF that was estimated earlier for each of the k divisions, using the twenty portfolio per division formed on the lagged factor mimicking portfolio coefficients:

$$m_k \approx c_{0,k} + \widehat{c}_{erm,k} r_{erm} + c_k r_k^F, \tag{15}$$

together with the remaining moment conditions

$$E\left(m_k \begin{pmatrix} r_{erm} \\ r_k^F \end{pmatrix} - \begin{pmatrix} r_{erm} \\ r_k^F \end{pmatrix} + \begin{pmatrix} \widehat{\lambda}^{erm} \\ \lambda_k^F \end{pmatrix}\right) = \begin{pmatrix} 0 \\ 0 \end{pmatrix},$$

where the hats indicate the estimates from the first step. Each division now has the same parameters for the market factor, but different estimates for the orthogonal labor prices of risk.[21]

The results are reported in Table 11. In all cases the price of risk associated with the divisional price of risk is statistically significant. Thus, when we impose that the parameters in the market factor are the same across all divisions, we find stronger support for the existence of a negative price of risk associated with relative wealth concerns. We still find that there is a substantial difference between the size of the estimated prices of risk for low

[21] Ideally we would like to estimate one system of equations using ten portfolios from each division, giving ninety tests assets. However, with a small time series and large cross-section, it is not feasible.

and high population density divisions. There is an increase in the size of the pricing errors for some of the divisions. However, the J-test only rejects the null of zero pricing errors in NE. The final row of the Table reports a test of whether we can impose the estimated parameters for the market factor reported above. At conventional levels, we only reject the null hypothesis that the estimated parameters for the market factor reported above are equal to those estimated in Table 8, in the case of MO. Therefore, given that the imposition of the same parameters for the market factor is not often rejected, the fact that the pricing errors remain relatively small in most cases is reassuring.

6.3 Number of portfolios

In the previous GMM tests we have employed twenty test assets, with the exception of ES, and forty tests assets when augmenting the original portfolios with twenty book-to-market portfolios. In this part of the paper, we assess the robustness of the results when we use ten rather than twenty test assets. The motivation for this is the finding in Cochrane (1996) that the results of the iterative GMM procedure are sensitive to the relative size of N (number of moment conditions) with respect to T (number of data points). In our case T is 168 and N is 22. Cochrane (1996) finds that with 37 moment conditions and 186 data points the GMM estimates behave poorly. With twenty portfolios, plus two moment conditions for the risk premium, we have 22 moment conditions and 168 data points. By considering only ten portfolios, we reduce the number of moment conditions to 12.

Table 12 reports the results from the GMM estimation. Three estimates of the local orthogonal labor income factors are statistically significant in the pricing kernel, two of which are in low population density divisions. In three of the four low population density divisions the estimate of the risk premium is statistically significant. It is also statistically significant in three of the high population density divisions. The market portfolio is never statistically significant in the pricing kernel, and never commands a statistically significant risk premium.

According to the J-test, the model is only rejected for one division, NE, and this is the division with relatively large pricing errors (1.43% per quarter). There does seem to be some improvement when using ten, rather than twenty portfolios. First, the average pricing error is 0.23% per quarter for all divisions excluding NE. Recall from Table 8 that when we employ twenty test portfolios the average pricing error is 0.32% per quarter. Moreover, when we use twenty test assets the model is rejected in the cases of MA and SA, even though the pricing errors are small (0.23 and 0.49% per quarter respectively). This is not the case in Table 12 with ten portfolios as test assets.

While there are some improvements in the model when we use ten rather than twenty portfolios as test assets (consistent with the findings in Cochrane (1996)), the overall tenor of the results is unchanged. This is also the case when we include the *smb* and *hml* factors.

There is not much improvement in the model performance and in five cases the pricing errors are actually larger. The final row reports the ΔJ test that examines whether we can accept the null hypothesis that the *smb* and *hml* factors are not important to price the ten assets. In all divisions except ES we can accept the null hypothesis.

6.4 Comparison with alternative models

Labor income has been used in a number of asset pricing applications. Lettau and Ludvigson (2001a) and Santos and Veronesi (2006) both use labor income in time-varying risk premia models. The former conditions consumption growth on their variable *cay*, which measures the long run relationship between consumption, asset wealth and labor income. The latter conditions the market returns on the ratio of labor income to consumption, s. We consider whether the inclusion of the these two conditioning variables is related to the the divisional level orthogonal labor income factor.

Panel A of Table 13 estimates the conditional consumption CAPM of Lettau and Ludvigson (2001a) with the addition of the divisional specific orthogonal labor income. As is evident, the parameters in the pricing kernel are not affected by replacing the market return factor with consumption growth and the conditioning of consumption growth with *cay*. The size of the estimated coefficients and the level of statistical significance is similar to the standard estimates of the KEEPM reported in Table 8.

Very similar results are found in Panel B which estimates the Santos and Veronesi (2006) conditional CAPM that scales the market return with ratio of labor income to consumption, s. Overall, including labor income variables that allow for time varying expected returns does not diminish the role of divisional level orthogonal labor income.

7 Conclusions

Mayers (1972) pointed out the importance of human capital as a component of aggregate wealth. Following up on that hint, the finance literature has used labor income as an indicator of human capital and linked it to the cross-section of stock returns. In this paper, we show that relative wealth concerns can explain the link between labor income and stock returns. Gómez, Priestley and Zapatero (2009) show that relative wealth/income concerns, whether driven by keeping up with the Joneses preferences or local price inflation hedging, can affect equilibrium prices through the hedging strategy of investors. In addition, the risk-premium associated with the risk factor (labor income) is negative. We show that the predictions of their model hold at the US census divisions level. In particular, the risk premium associated with labor income is negative and, even more importantly, the risk factor is strongly local, as consistent with the economic nature of relative wealth concerns. In this respect, we show that the risk premium associated with aggregate (country level) risk is negative and statistically significant. However, our tests support the strong significance of the additional risk -with respect to the aggregate/domestic factor- embedded in the local/divisional risk factor.

Interestingly, we show that the economic size of the effect is stronger the lower the population density of the divisions. This is in line with the results of Hong, Kubik and Stein (2008) and consistent with the local nature of relative wealth concerns: in areas of lower population density (small towns or suburban areas, as opposed to large cities) there is a stronger sense of community and peer pressure is stronger.

In general, local labor income has higher correlation with local stock returns than with stock returns of other divisions, as we show in this paper. However, as we clearly document, the pricing factor is the correlation between stock returns and labor income, and not geographic location. This is clearly different from the notion of familiarity suggested in the literature as a possible factor in portfolio choice.

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Appendix

We summarize here the optimal portfolio choice problem of an agent with either endogenous or exogenous keeping up with the Joneses preferences. For a detailed derivation, we kindly refer the reader to Gómez, Priestley and Zapatero (2009).

Exogenous keeping up with the Joneses preferences

In this subsection we analyze the implications of a version of the keeping up with the Joneses preferences of Abel (1990) and Galí (1994). In particular, in the economy we consider investors are endowed with an utility function[22]

$$u(c, C) = \frac{c^{(1-\alpha)}}{1-\alpha} C^{\gamma\alpha}, \tag{A1}$$

where c denotes the investor's consumption of the single consumption good, the economy's numeraire; C is the division average or per capita consumption; $\alpha > 0$ is the (constant) relative risk-aversion coefficient and $1 > \gamma \geq 0$ is the "Joneses parameter."

Here, workers represent agents endowed with non-tradable income. For instance, their human capital, that will materialize into wage income, or entrepreneurial income. Call w_k^0 the initial aggregate endowment of non-financial wealth for workers in division k; w_k denotes the final ($t = 1$) random value of their non-tradable income. Workers face incomplete markets because they cannot trade their human capital (due to moral hazard issues) and have no access to financial markets; therefore, they cannot hedge their income risk.

Since each investor takes C as exogenous and common, the typical aggregation property of the CRRA utility functions allows us to replace all the investors in a given division by a representative investor with utility function (A1) endowed with the aggregated investors income without affecting the equilibrium prices. At time $t = 0$ each representative investor is endowed with a share of the local firm (unit value by assumption); hence, $c^0 = 1$ in all divisions.

We can write the problem's first order condition as a function of the investor's consumption and the workers relative wealth, w/c:

$$E\left(r\, c^{-\alpha(1-\gamma)}(1 + w/c)^{\alpha\gamma}\right) = 0. \tag{A2}$$

Notice that, in the absence of keeping up with the Joneses behavior ($\gamma = 0$), the previous condition reduces to $E\left(r\, c^{-\alpha}\right) = 0$, the standard CRRA Euler equation.

Condition (A2) allows us to solve for the representative investor's optimal portfolio. Since financial markets are complete, there exists a mimicking portfolio X^w that maps the workers relative income onto the investment opportunity set such that $w/c = w^0(R + r'X^w)$. Following Galí (1994), given w^0 and X^w, for small values of $E(r)$, the optimal portfolio of the representative investor of division k can be approximated as a function of α, γ and the risk adjusted risk premia $\Omega^{-1}E(r)$:

$$x_k^* = \frac{\theta_k \gamma_k}{1-\gamma_k} X_k^w + \frac{1}{\alpha_k(1-\gamma_k)} \Omega^{-1} E(r), \tag{A3}$$

[22] To simplify the notation, we drop the division subindex k for the moment (thus, all variables to be introduced next apply to investors in any division).

with $\theta_k = \frac{w_k^0}{1+w_k^0}$, the workers initial wealth as a proportion of the division's total wealth (investor's plus non-diversifiable wealth).

Notice that even if there is a friction ($\theta_k > 0$) that prevents full risk-diversification for a set of agents (the workers), investors will hold well diversified portfolios unless they exhibit some degree of keeping up with the Joneses behavior ($\gamma_k > 0$). Thus, it is important to emphasize that investors' portfolios will be locally biased if and only if *both* keeping up with the Joneses behavior and a market friction exist.

Endogenous keeping up with the Joneses preferences

In this section, we discuss the endogenous keeping up with the Joneses preferences presented in DeMarzo, Kaniel and Kremer (2004). In this specification agents consume two types of goods: c, which has the interpretation of a global good, and w_k, a local good, like housing services. Utility over consumption for these two goods is given by:

$$u(c, w) = \frac{1}{1-\alpha}(c^{1-\alpha} + \delta w^{1-\alpha}).$$

The parameter $\delta > 0$ specifies the relative importance of the local good. All consumption takes place at the end of the period. At time $t = 0$, investors are endowed with shares of the firm that produces the global good. Call c_k^0 the aggregate value of those shares at the beginning of the period for agents in division k. For simplicity, let $c_k^0 = 1$ in all divisions. Workers in each division will receive a fixed number $\bar{w}_k$ of units of the local good at time $t = 1$. In equilibrium, the relative price of the local good in terms of the global good at $t = 1$ is given by $p_k = \delta \left(\frac{c_k}{\bar{w}_k}\right)^{\alpha}$. As it would be expected, the scarcer the (fixed) local good endowment relative to the (stochastic) global good consumption, the higher the relative price of the former. The investor's hedging demand for this risk will trigger the endogenous keeping up with the Joneses behavior in this model. Financial markets are complete.

If workers can not diversify their endowment risk (due, for instance, to short-selling constraints and moral hazard), Proposition 2 in DeMarzo, Kaniel and Kremer (2004) shows that the representative investor's marginal utility is given by:

$$u_c(c, p) = c^{-\alpha}\left(1 + \delta^{1/\alpha} p^{1-1/\alpha}\right)^{\alpha}. \tag{A4}$$

Let $p^0 = \delta \left(\frac{c^0}{\bar{w}}\right)^{\alpha}$ denote the relative price at $t = 0$ of one unit of the non-diversifiable, local good endowment of workers at time $t = 1$. Recall that we normalized the initial investor's shares endowment $c^0 = 1$. Hence, $p^0 = \delta \bar{w}^{-\alpha}$. The present value of the workers endowment is therefore $\bar{w}^0 = \delta \bar{w}^{1-\alpha}$.

In this model, the relative wealth at $t = 0$ of the workers in division k as a proportion of the total division wealth is given by $\theta_k = \frac{\bar{w}_k^0}{1+\bar{w}_k^0}$. Call $\bar{w}_k p_k / \bar{w}_k^0$ the return on the workers wealth (in units of the global good) over the period. Like in the exogenous preferences specification, under complete (financial) markets, there exists a portfolio X_k^w such that $\frac{\bar{w}_k p_k}{\bar{w}_k^0} = R + r' X_k^w$.

After these definitions, we can write the approximate function for division k investor's optimal portfolio as follows:

$$x_k^* = \frac{\theta_k(\alpha_k - 1)}{\alpha_k} X_k^w + \frac{1}{\alpha_k}\Omega^{-1}E(r). \tag{A5}$$

Notice that, in this model, the optimal portfolio for the logarithmic investor ($\alpha = 1$) coincides with the benchmark, well diversified portfolio $\Omega^{-1}E(r)$. No relative wealth concern arises even in the presence of local, non-diversifiable wealth. Only for $\alpha > 1$ should we observe a local bias in portfolio holdings.

A linear approximation for the Stochastic Discount Factor

We will derive this approximation both for the endogenous and the exogenous case. Like in the derivation of the optimal portfolio, the only difference will lay on the interpretation of the deep parameters.

Let us start with the exogenous Joneses specification. The investor's (first order condition) optimal consumption choice is given in equation (A2). This condition holds for any asset i and any division k. The first-order approximation to the marginal's utility is given by $u_c(c_k, w_k/c_k) \approx u_c(c_k^0, w_k^0/c_k^0) + u_{c,c}(c_k^0, w_k^0/c_k^0)(c_k - c_k^0) + u_{c,w/c}(c_k^0, w_k^0/c_k^0)(w_k/c_k - w_k^0/c_k^0) = u_c(1, w_k^0)\left[1 - \alpha(1-\gamma)(r'x_k^* + R - 1) + \theta_k\, \alpha\gamma(r'X_k^w + R - 1)\right].$

Replacing the later expression in (A2) we obtain the following condition:

$$E\left(r_i\, \left[\tau_k - (r'x_k^* + R - 1) + \theta_k b_k(r'X_k^w + R - 1)\right]\right) = 0, \tag{A6}$$

where $\tau_k = \frac{1}{\alpha_k(1-\gamma_k)}$ and $b_k = \frac{\gamma_k}{1-\gamma_k}$. We multiply (A6) by ω_k, the proportion of country market capitalization in division k and add up across all divisions:

$$E\left(r_i\, \left[H^{-1} - (r_M + R - 1) + \sum_k \omega_k\theta_k b_k(r_k^w + R - 1)\right]\right) = 0, \tag{A7}$$

where $H^{-1} = \sum_k \omega_k\tau_k$ is the aggregate risk aversion coefficient. We have used the market clearing condition $\sum_k \omega_k x_k^* = x_M$ and the definitions $r_M = r'x_M$ and $r_k^w = r'X_k^w$. After regressing the workers non-diversifiable income onto the country market portfolio return - equation (2) - we can write $r_k^w = \beta_k r_M + r_k^F$. We replace the later expression in the Euler equation. Moreover, we assume that $E(r_i)(R-1) \approx 0$ for small values of $E(r_i)$ and the (net) risk-free rate, $R-1$. This results into equation (13).

We turn now to the endogenous Joneses specification. The investor's optimal consumption choice is given in equation (A4). This expression can be linearly approximated as follows: $u_c(c_k, p_k) \approx u_c(c_k^0, p_k^0) + u_{c,c}(c_k^0, p_k^0)(c_k - c_k^0) + u_{c,p}(c_k^0, p_k^0)(p_k - p_k^0) = u_c(1, \delta_k\bar{w}_k^{-\alpha_k})\left[1 - \alpha_k(r'x_k^* + R - 1) + \theta_k\,(\alpha_k - 1)\left(\frac{\bar{w}_k p_k}{\bar{w}_k^0} - 1\right)\right].$

Replacing the later expression in (A4) and given that $\frac{\bar{w}_k p_k}{\bar{w}_k^0} = R + r_k'^w$ we obtain condition (A6) with $\tau_k = \frac{1}{\alpha_k}$ and $b_k = \frac{\alpha_k - 1}{\alpha_k}$. Following the same procedure as in the exogenous case we arrive at equation (A7) and finally equation (13).

Table 1
Factor Risk Premia

Panel A reports the annualized mean percentage return of the factor mimicking portfolios in each division, along with their t-statistics. There are nine Census Bureau Divisions which we index with two capital letters: West South Central (WS), Pacific (PA), East South Central (ES), Mountain (MO), East North Central (EN), South Atlantic (SA), West North Central (WN), Middle Atlantic (MA), NE is New England (NE). Divisions with low population density (less than 100 individuals per square mile) are indicated with a "(L)" following their two-letter symbol. Panel B presents the covariances (lower triangular matrix), variances (diagonal), and correlations (upper triangular matrix) amongst the factor mimicking portfolios.

Panel A: Annualized Mean Returns (%)

	MA	NE	SA	EN	PA	ES(L)	WS(L)	WN(L)	MO(L)
μ_k^F	-2.89	-2.88	-3.98	-2.84	-3.73	-3.03	-6.13	-4.97	-7.39
t-stat	1.45	1.54	1.85	1.96	1.47	1.34	2.22	2.50	2.62

Panel B: Variances, Covariances and Correlations

	MA	NE	SA	EN	PA	ES(L)	WS(L)	WN(L)	MO(L)
MA	0.004	0.512	0.680	0.569	0.726	0.462	0.658	0.566	0.512
NE	0.002	0.004	0.465	0.483	0.594	0.289	0.433	0.496	0.317
SA	0.003	0.003	0.005	0.558	0.669	0.596	0.630	0.546	0.559
EN	0.002	0.003	0.002	0.002	0.514	0.443	0.586	0.600	0.378
PA	0.004	0.003	0.004	0.002	0.003	0.005	0.419	0.465	0.387
ES(L)	0.002	0.001	0.003	0.001	0.003	0.003	0.008	0.623	0.555
WS(L)	0.004	0.002	0.004	0.002	0.004	0.003	0.004	0.579	0.458
WN(L)	0.002	0.002	0.002	0.002	0.003	0.002	0.003	0.004	0.484
MO(L)	0.003	0.002	0.003	0.002	0.003	0.002	0.004	0.003	0.008

Table 2
Regression of Excess Returns on Mimicking Portfolios: Divisions then Country

In Panel A we report, for each portfolio in each division, estimates of the slope $\beta^F_{i,k}$ (t-statistics in parenthesis) from the regression:

$$r_{i,k,t} = \alpha_{i,k} + \beta^F_{i,k}\, r^F_{k,t} + \beta^{erm}_{i,k}\, r_{erm,t} + \beta^{smb}_{i,k}\, r_{smb,t} + \beta^{hml}_{i,k}\, r_{hml,t} + u_{i,k,t},$$

where $r_{i,k,t}$ is the excess return on portfolio i ($i = P1, ..., P20$) from division k at time t; $\alpha_{i,k}$ is the portfolio-specific constant (pricing error); where $\beta^F_{i,k}$ is the estimated factor loading on $r^F_{k,t}$, the factor mimicking portfolio of orthogonal local labor income in division k; $\beta^{erm}_{i,k}$, $\beta^{smb}_{i,k}$ and $\beta^{hml}_{i,k}$ are the estimated factor loading on the corresponding three Fama-French factors; finally, $u_{i,k,t}$ is the error term. The last row reports the expected annualized percentage return spread between portfolios P1 and P20 given their betas and the divisional mean premium μ^F_k in Table 1.

In Panel B we report the slope $\beta^G_{i,k}$ (t-statistics in parenthesis) from the regression:

$$u_{i,k,t} = \alpha_{i,k} + \beta^G_{i,k}\, r^G_t + v_{i,k,t}.$$

where $u_{i,k,t}$ are the residuals from the regression in Panel A and r^G_t the factor mimicking portfolio for the country orthogonal labor risk.

Panel A: $\beta^F_{i,k}$

	MA	NE	SA	EN	PA	ES(L)	WS(L)	WN(L)	MO(L)
P1	0.4199	0.8110	0.6265	0.5806	0.5993	0.6564	0.7980	0.7194	0.7983
	(3.5315)	(5.0066)	(3.4197)	(5.1433)	(5.0613)	(6.2777)	(7.6464)	(6.6815)	(5.8138)
P2	0.3843	0.5364	0.4809	0.6909	0.3801	0.4128	0.9706	0.4438	0.5752
	(4.0363)	(5.7507)	(4.1197)	(6.8514)	(4.0096)	(4.6079)	(9.1537)	(4.6352)	(5.1254)
P3	0.4096	0.5404	0.3582	0.3613	0.2910	0.1857	0.8460	0.5550	0.4797
	(6.1339)	(5.3830)	(3.6599)	(4.2207)	(3.4633)	(2.6958)	(8.9420)	(4.8872)	(4.2396)
P4	0.2714	0.3960	0.3280	0.2333	0.1799	-0.0291	0.7083	0.3359	0.3595
	(2.9226)	(4.1773)	(3.6400)	(2.8249)	(2.1225)	(-0.3095)	(9.8279)	(3.5422)	(3.9425)
P5	0.2760	0.3337	0.1503	0.3046	0.1624	-0.0660	0.5689	0.4709	0.0632
	(3.3598)	(4.1020)	(1.6856)	(3.8253)	(2.0941)	(-0.6442)	(7.6940)	(5.0849)	(0.7438)
P6	0.1748	0.0833	0.1544	0.0789	0.1336	-0.1620	0.4799	0.2325	0.2445
	(2.6342)	(1.0069)	(1.5884)	(1.0193)	(1.6516)	(-1.2582)	(6.8104)	(2.7484)	(2.1187)
P7	0.1680	0.1091	0.0290	-0.0320	0.0612	-0.2393	0.5662	0.2124	-0.0254
	(2.7652)	(1.2359)	(0.3244)	(-0.4003)	(0.8540)	(-2.3422)	(7.5449)	(2.2169)	(-0.2482)
P8	0.1073	0.0734	0.1131	-0.0837	-0.1109	-0.6679	0.3883	-0.2390	-0.0392
	(1.4458)	(0.6775)	(1.3952)	(-1.0896)	(-1.3471)	(-7.1598)	(5.5652)	(-2.9153)	(-0.4266)
P9	-0.1495	0.0750	-0.0017	-0.1793	-0.1450	-0.1831	0.3505	-0.0641	-0.3822
	(-2.0498)	(0.8154)	(-0.0166)	(-2.3029)	(-1.8261)	(-1.6677)	(3.9671)	(-0.8579)	(-3.4986)
P10	-0.2280	0.1088	-0.0775	-0.2872	-0.0935	-0.8523	0.2165	-0.0748	-0.2374
	(-3.1530)	(1.3208)	(-0.7258)	(-3.5285)	(-0.9293)	(-6.4306)	(2.9773)	(-0.8228)	(-2.3983)
P11	-0.2836	-0.1633	-0.1400	-0.3266	-0.1562		0.2290	-0.3521	-0.2571
	(-3.9986)	(-1.8094)	(-1.2643)	(-3.7207)	(-1.3152)		(3.4797)	(-3.7654)	(-2.5618)
P12	-0.0922	-0.0397	-0.2861	-0.2211	-0.4323		0.0881	-0.2928	0.0176
	(-1.3764)	(-0.4484)	(-2.7080)	(-2.6075)	(-5.0392)		(1.0001)	(-2.9195)	(0.1439)
P13	-0.1349	-0.1593	-0.0836	-0.4319	-0.2825		0.0373	-0.3100	-0.2239
	(-1.7884)	(-1.5976)	(-0.7284)	(-5.2839)	(-3.9578)		(0.4696)	(-3.4811)	(-1.9924)
P14	-0.5526	-0.4013	-0.3811	-0.5739	-0.2693		0.0651	-0.2024	-0.4690
	(-7.0888)	(-3.9502)	(-3.5179)	(-6.9635)	(-3.8906)		(0.8632)	(-1.9985)	(-3.8215)
P15	-0.4080	-0.9837	-0.4633	-0.6350	-0.6919		-0.1913	-0.5038	-0.5647
	(-5.6604)	(-7.3034)	(-4.3585)	(-7.3141)	(-7.2489)		(-1.9964)	(-4.7836)	(-4.4522)
P16	-0.7703	-0.4265	-0.6245	-0.3992	-0.7675		-0.2440	-0.6658	-0.4624
	(-8.9604)	(-3.7260)	(-5.7442)	(-4.6085)	(-7.7013)		(-2.4472)	(-4.2580)	(-3.6944)
P17	-0.6982	-0.4057	-0.4460	-0.6196	-0.5687		-0.2260	-0.5612	-0.8700
	(-8.6639)	(-3.8325)	(-4.0843)	(-6.6076)	(-6.1703)		(-2.3927)	(-5.2962)	(-6.2101)
P18	-0.6911	-0.4617	-0.8203	-0.7098	-0.7283		-0.3461	-0.4312	-0.6707
	(-8.0482)	(-4.1567)	(-7.0487)	(-8.2873)	(-7.0151)		(-4.0588)	(-3.9432)	(-4.8162)
P19	-0.5829	-0.4163	-0.7461	-0.7416	-0.8090		-0.4378	-0.5003	-0.7030
	(-6.0548)	(-3.1180)	(-4.3902)	(-7.2128)	(-6.7902)		(-4.1819)	(-4.3553)	(-4.5796)
P20	-1.0761	-0.6633	-1.2161	-0.8616	-1.0538		-0.4392	-0.7439	-0.6110
	(-9.3323)	(-5.0108)	(-7.4083)	(-6.3972)	(-7.7131)		(-4.0234)	(-5.3379)	(-3.8293)
$(P1-P20)\mu^F_k$	-4,3234	-4,2461	-7,3336	-4,0959	-6,1661	-4,5713	-7,5838	-7,2725	-10,4150

Panel B: $\beta^{G}_{i,k}$

	MA	NE	SA	EN	PA	ES	WS	WN	MO
P1	-0,1481	-0.2103	0.0628	-0.0471	0.0200	0.1320	-0.0663	-0.0173	0.1368
	(-1.6745)	(-1.6276)	(0.4994)	(-0.6549)	(0.1775)	(1.3750)	(-0.5632)	(-0.1874)	(0.8469)
P2	-0.0591	0.0232	-0.0082	0.0067	-0.0971	0.0453	-0.0650	0.0114	0.0950
	(-0.8289)	(0.3096)	(-0.1018)	(0.1041)	(-1.0806)	(0.5485)	(-0.5432)	(0.1388)	(0.7190)
P3	-0.0877	-0.2047	-0.0446	0.0058	-0.0675	0.0660	0.0164	-0.0268	0.0816
	(-1.7668)	(-2.5865)	(-0.6647)	(0.1067)	(-0.8462)	(1.0409)	(0.1539)	(-0.2757)	(0.6123)
P4	-0.1278	-0.0363	-0.0489	-0.0199	-0.0871	-0.0420	-0.0079	-0.0656	0.0900
	(-1.8539)	(-0.4766)	(-0.7915)	(-0.3777)	(-1.0838)	(-0.4840)	(-0.0966)	(-0.8085)	(0.8392)
P5	-0.1087	-0.0060	-0.0690	-0.0251	-0.0433	-0.1369	-0.0199	-0.0109	-0.0062
	(-1.7811)	(-0.0910)	(-1.1298)	(-0.4950)	(-0.5876)	(-1.4553)	(-0.2382)	(-0.1373)	(-0.0618)
P6	-0.0932	-0.1313	-0.1968	-0.0074	-0.1307	-0.1785	-0.0318	-0.0492	0.0488
	(-1.8919)	(-1.9982)	(-3.0271)	(-0.1508)	(-1.7135)	(-1.5121)	(-0.3996)	(-0.6790)	(0.3591)
P7	-0.0520	-0.0458	-0.1354	0.0110	-0.0495	-0.0111	-0.0859	-0.1128	0.0231
	(-1.1464)	(-0.6462)	(-2.2378)	(0.2169)	(-0.7266)	(-0.1177)	(-1.0167)	(-1.3800)	(0.1922)
P8	-0.0822	-0.1003	-0.0817	0.0343	-0.0939	0.2201	0.0231	-0.0425	0.0917
	(-1.4864)	(-1.1557)	(-1.4758)	(0.7008)	(-1.2032)	(2.6071)	(0.2930)	(-0.6048)	(0.8480)
P9	-0.1201	-0.1711	-0.0761	0.0336	-0.0856	0.0586	0.0227	-0.0230	0.1312
	(-2.2268)	(-2.3504)	(-1.0643)	(0.6768)	(-1.1370)	(0.5787)	(0.2276)	(-0.3588)	(1.0222)
P10	-0.1277	-0.1576	-0.0914	-0.0149	-0.1655	-0.0634	0.0634	-0.0434	-0.0577
	(-2.3940)	(-2.4206)	(-1.2523)	(-0.2871)	(-1.7457)	(-0.5184)	(0.7738)	(-0.5570)	(-0.4953)
P11	-0.1081	-0.1200	-0.1393	0.0022	-0.1375		0.0035	-0.0183	-0.0750
	(-2.0567)	(-1.6666)	(-1.8478)	(0.0384)	(-1.2222)		(0.0477)	(-0.2282)	(-0.6347)
P12	-0.0653	-0.1250	-0.1796	-0.0076	-0.1302		-0.0280	-0.0160	0.1870
	(-1.3056)	(-1.7718)	(-2.5214)	(-0.1408)	(-1.6079)		(-0.2818)	(-0.1854)	(1.3058)
P13	-0.0438	-0.2393	-0.0801	-0.0336	-0.0668		-0.0491	-0.0259	0.0208
	(-0.7747)	(-3.0677)	(-1.0182)	(-0.6455)	(-0.9873)		(-0.5479)	(-0.3397)	(0.1569)
P14	-0.1243	-0.1378	-0.1746	0.0146	-0.0777		0.0713	-0.0955	0.2476
	(-2.1547)	(-1.7010)	(-2.3853)	(0.2771)	(-1.1846)		(0.8394)	(-1.1031)	(1.7273)
P15	-0.0889	-0.0602	-0.0425	-0.0211	-0.1451		0.0348	-0.0052	0.1583
	(-1.6577)	(-0.5563)	(-0.5818)	(-0.3805)	(-1.6101)		(0.3216)	(-0.0580)	(1.0623)
P16	-0.1129	-0.0900	-0.0523	0.0134	0.0623		-0.0879	0.0998	0.0350
	(-1.7675)	(-0.9801)	(-0.7011)	(0.2423)	(0.6582)		(-0.7821)	(0.7456)	(0.2373)
P17	-0.0822	-0.0824	-0.0233	0.0190	-0.0737		-0.0609	-0.0069	-0.1995
	(-1.3677)	(-0.9706)	(-0.3109)	(0.3177)	(-0.8425)		(-0.5708)	(-0.0758)	(-1.2135)
P18	-0.0641	-0.0670	-0.0852	-0.0108	-0.0752		0.0150	-0.0052	-0.0938
	(-0.9975)	(-0.7510)	(-1.0692)	(-0.1979)	(-0.7631)		(0.1558)	(-0.0558)	(-0.5722)
P19	-0.1037	-0.0641	-0.0373	-0.0293	-0.0957		-0.1488	-0.0666	0.3576
	(-1.4442)	(-0.5981)	(-0.3198)	(-0.4465)	(-0.8461)		(-1.2646)	(-0.6765)	(2.0002)
P20	-0.1434	-0.1471	-0.0382	-0.0689	-0.0513		-0.0594	-0.1106	0.0436
	(-1.6716)	(-1.3904)	(-0.3384)	(-0.8039)	(-0.3950)		(-0.4820)	(-0.9279)	(0.2318)

Table 3
Regression of Excess Returns on Mimicking Portfolios: Country then Divisions

In Panel A we report, for each portfolio in each division, estimates of the slope $\beta^G_{i,k}$ (t-statistics in parenthesis) from the regression:

$$r_{i,k,t} = \alpha_{i,k} + \beta^G_{i,k}\, r^G_t + \beta^{erm}_{i,k}\, r_{erm,t} + \beta^{smb}_{i,k}\, r_{smb,t} + \beta^{hml}_{i,k}\, r_{hml,t} + u_{i,k,t},$$

where $r_{i,k,t}$ is the excess return on portfolio i ($i = P1, ..., P20$) from division k ($k = 1, ..., 9$) at time t; $\alpha_{i,k}$ is the portfolio-specific constant (pricing error); β^G_i is the estimated factor loading on r^G_t, the factor mimicking portfolio of orthogonal local labor income at the national level; $\beta^{erm}_{i,k}$, $\beta^{smb}_{i,k}$ and $\beta^{hml}_{i,k}$ are the estimated factor loading on the corresponding three Fama-French factors; finally, $u_{i,k,t}$ is the error term.

In Panel B we report the slope $\beta^F_{i,k}$ (t-statistics in parenthesis) from the regression:

$$u_{i,k,t} = \alpha_{i,k} + \beta^F_{i,k}\, r^F_{k,t} + v_{i,k,t}.$$

where $u_{i,k,t}$ are the residuals from the regression in Panel A and r^F_t the factor mimicking portfolio for division k labor risk. The last row reports the expected annualized percentage return spread between portfolios P1 and P20 given their betas and the divisional mean premium μ^F_k in Table 1.

Panel A: $\beta^G_{i,k}$

	MA	NE	SA	EN	PA	ES	WS	WN	MO
P1	0.0097	-0.0005	0.5539	0.2705	0.6528	0.6125	0.9144	0.5739	0.9513
	(0.0695)	(-0.0022)	(2.8904)	(2.3500)	(3.7228)	(3.9550)	(4.7046)	(3.8120)	(3.6942)
P2	0.1795	0.3619	0.2994	0.4619	0.1691	0.3011	1.1471	0.4033	0.6774
	(1.6019)	(2.9976)	(2.3970)	(4.4436)	(1.1919)	(2.3093)	(5.6460)	(3.1544)	(3.2535)
P3	0.1362	-0.1443	0.1369	0.2467	0.1447	0.2373	1.1629	0.4126	0.5702
	(1.6387)	(-1.0971)	(1.3050)	(2.9190)	(1.1642)	(2.4659)	(6.6718)	(2.6820)	(2.7540)
P4	-0.0654	0.1479	0.1075	0.1066	-0.0117	-0.1078	0.9254	0.1396	0.4917
	(-0.6074)	(1.2291)	(1.1111)	(1.3167)	(-0.0951)	(-0.8251)	(6.7621)	(1.1010)	(2.9782)
P5	-0.0190	0.1796	-0.0546	0.1410	0.0682	-0.3373	0.7130	0.3766	0.0374
	(-0.1978)	(1.7504)	(-0.5869)	(1.7806)	(0.6058)	(-2.4031)	(5.2436)	(3.0017)	(0.2470)
P6	-0.0663	-0.2448	-0.3372	0.0344	-0.1560	-0.4768	0.5680	0.0882	0.3068
	(-0.8673)	(-2.4803)	(-3.4421)	(0.4613)	(-1.3413)	(-2.7070)	(4.4198)	(0.7897)	(1.4863)
P7	0.0200	-0.0391	-0.2830	0.0040	-0.0482	-0.1407	0.5621	-0.0707	0.0311
	(0.2842)	(-0.3643)	(-3.1470)	(0.0516)	(-0.4686)	(-0.9765)	(3.9655)	(-0.5632)	(0.1714)
P8	-0.0965	-0.1813	-0.1076	0.0224	-0.3220	0.1673	0.5685	-0.2982	0.1728
	(-1.1472)	(-1.3867)	(-1.2795)	(0.3018)	(-2.7747)	(1.1283)	(4.6705)	(-2.8089)	(1.0612)
P9	-0.3890	-0.3384	-0.1709	-0.0411	-0.3380	0.0420	0.5173	-0.1058	-0.0166
	(-5.0008)	(-3.1162)	(-1.5926)	(-0.5406)	(-3.0198)	(0.2726)	(3.3980)	(-1.0974)	(-0.0826)
P10	-0.4695	-0.2887	-0.2551	-0.2191	-0.4642	-0.5544	0.4298	-0.1605	-0.3209
	(-6.1969)	(-2.9518)	(-2.3422)	(-2.7596)	(-3.3160)	(-2.7463)	(3.5054)	(-1.3705)	(-1.8116)
P11	-0.4708	-0.3621	-0.4031	-0.2065	-0.4654		0.3128	-0.3406	-0.3754
	(-6.2343)	(-3.3900)	(-3.6349)	(-2.3891)	(-2.7810)		(2.7550)	(-2.7649)	(-2.0916)
P12	-0.2202	-0.3019	-0.5897	-0.1600	-0.7292		0.0547	-0.2849	0.4315
	(-2.9689)	(-2.8807)	(-5.7877)	(-1.9449)	(-6.1133)		(0.3639)	(-2.1726)	(2.0128)
P13	-0.2069	-0.6258	-0.2339	-0.3545	-0.4358		-0.0599	-0.3217	-0.1349
	(-2.4458)	(-5.6137)	(-1.9872)	(-4.4071)	(-4.2905)		(-0.4430)	(-2.7588)	(-0.6683)
P14	-0.7250	-0.5393	-0.6413	-0.3388	-0.4467		0.2457	-0.3854	0.1729
	(-8.7001)	(-4.4287)	(-6.1064)	(-3.9257)	(-4.5716)		(1.9320)	(-2.9859)	(0.7610)
P15	-0.5289	-0.7029	-0.4006	-0.4578	-1.0259		-0.1770	-0.4406	-0.1040
	(-6.6981)	(-3.9086)	(-3.5759)	(-5.1268)	(-7.5797)		(-1.0758)	(-3.1194)	(-0.4358)
P16	-0.8760	-0.4472	-0.5291	-0.2284	-0.6399		-0.5210	-0.3441	-0.2962
	(-9.0354)	(-3.1893)	(-4.5479)	(-2.6329)	(-4.0194)		(-3.1016)	(-1.6279)	(-1.2858)
P17	-0.7491	-0.4183	-0.3465	-0.3584	-0.7416		-0.4367	-0.4932	-1.1492
	(-8.0364)	(-3.2204)	(-2.9972)	(-3.6731)	(-5.5010)		(-2.7286)	(-3.4440)	(-4.3908)
P18	-0.7028	-0.4163	-0.7318	-0.4833	-0.9070		-0.4273	-0.3788	-0.7522
	(-6.9768)	(-3.0213)	(-5.8445)	(-5.3338)	(-5.8779)		(-2.8747)	(-2.6130)	(-2.9178)
P19	-0.7034	-0.3838	-0.5760	-0.5451	-1.0345		-0.9149	-0.5744	0.2288
	(-6.5648)	(-2.3420)	(-3.1890)	(-5.1793)	(-5.8869)		(-5.2778)	(-3.8213)	(0.7914)
P20	-1.1916	-0.7117	-0.8882	-0.7112	-1.1840		-0.7172	-0.8801	-0.3973
	(-9.0399)	(-4.3635)	(-4.8301)	(-5.3178)	(-5.6575)		(-3.8434)	(-4.8170)	(-1.3498)

Panel B: $\beta^F_{i,k}$

	MA	NE	SA	EN	PA	ES	WS	WN	MO
P1	0.2425	0.6237	0.1213	0.3023	0.1627	0.3563	0.2660	0.3303	0.4095
	(2.6451)	(4.3546)	(1.0188)	(2.9767)	(1.7687)	(4.0214)	(2.8725)	(3.3639)	(3.4332)
P2	0.1586	0.3029	0.1260	0.2841	0.1741	0.2389	0.3122	0.1843	0.2965
	(2.1388)	(3.6377)	(1.6315)	(3.1047)	(2.3568)	(3.1474)	(3.2466)	(2.1693)	(3.0538)
P3	0.1895	0.4591	0.1163	0.1458	0.1289	0.0895	0.2194	0.2666	0.2463
	(3.5243)	(5.2580)	(1.7959)	(1.9256)	(1.9810)	(1.5635)	(2.6326)	(2.6242)	(2.5290)
P4	0.1833	0.2597	0.1112	0.1227	0.1090	-0.0015	0.1993	0.2048	0.1724
	(2.5903)	(3.0964)	(1.8643)	(1.6880)	(1.6851)	(-0.0193)	(3.0673)	(2.4393)	(2.2098)
P5	0.1688	0.2022	0.0781	0.1591	0.0756	0.0130	0.1699	0.2158	0.0396
	(2.6758)	(2.8142)	(1.3536)	(2.2528)	(1.2742)	(0.1548)	(2.6116)	(2.6038)	(0.5470)
P6	0.1271	0.1381	0.1537	0.0423	0.1236	-0.0302	0.1541	0.1450	0.1224
	(2.5246)	(1.9742)	(2.5661)	(0.6272)	(2.0321)	(-0.2864)	(2.5030)	(1.9493)	(1.2434)
P7	0.0910	0.0957	0.0863	-0.0268	0.0499	-0.1445	0.2167	0.1921	-0.0246
	(1.9531)	(1.2485)	(1.5500)	(-0.3859)	(0.9180)	(-1.6876)	(3.2292)	(2.3053)	(-0.2830)
P8	0.0987	0.1113	0.0762	-0.0767	0.0282	-0.5026	0.0895	-0.0673	-0.0617
	(1.7655)	(1.1924)	(1.4624)	(-1.1477)	(0.4585)	(-6.2973)	(1.5174)	(-0.9434)	(-0.7917)
P9	0.0568	0.1601	0.0439	-0.1163	0.0128	-0.1371	0.0795	-0.0079	-0.2791
	(1.0922)	(2.0829)	(0.6576)	(-1.7040)	(0.2162)	(-1.4952)	(1.0731)	(-0.1211)	(-2.9696)
P10	0.0407	0.1710	0.0338	-0.1035	0.0796	-0.5053	0.0135	0.0054	-0.1145
	(0.8023)	(2.4837)	(0.4978)	(-1.4488)	(1.0778)	(-4.4151)	(0.2252)	(0.0681)	(-1.3564)
P11	0.0086	-0.0161	0.0459	-0.1407	0.0431		0.0601	-0.1381	-0.1188
	(0.1695)	(-0.2097)	(0.6644)	(-1.8156)	(0.4868)		(1.0876)	(-1.6775)	(-1.3890)
P12	0.0277	0.0608	0.0326	-0.0843	-0.0425		0.0443	-0.1142	-0.0687
	(0.5581)	(0.8107)	(0.5139)	(-1.1360)	(-0.6740)		(0.6040)	(-1.2989)	(-0.6698)
P13	-0.0022	0.0669	0.0256	-0.1421	-0.0396		0.0456	-0.1129	-0.1398
	(-0.0396)	(0.8383)	(0.3492)	(-1.9744)	(-0.7369)		(0.6915)	(-1.4460)	(-1.4547)
P14	-0.0547	-0.1454	0.0057	-0.2603	-0.0287		-0.0336	-0.0047	-0.3791
	(-0.9821)	(-1.6796)	(0.0874)	(-3.4476)	(-0.5554)		(-0.5418)	(-0.0545)	(-3.6158)
P15	-0.0428	-0.5437	-0.0920	-0.2431	-0.1090		-0.0774	-0.2160	-0.3974
	(-0.8092)	(-4.4630)	(-1.3249)	(-3.0924)	(-1.5313)		(-0.9660)	(-2.3051)	(-3.6096)
P16	-0.1262	-0.1926	-0.1270	-0.1850	-0.2651		-0.0034	-0.3793	-0.2854
	(-1.9636)	(-1.9379)	(-1.7670)	(-2.3950)	(-3.2441)		(-0.0409)	(-2.7209)	(-2.6390)
P17	-0.1311	-0.1854	-0.0988	-0.2849	-0.1190		-0.0179	-0.2397	-0.4249
	(-2.1252)	(-2.0150)	(-1.3793)	(-3.3304)	(-1.6811)		(-0.2298)	(-2.5312)	(-3.5103)
P18	-0.1441	-0.2290	-0.1571	-0.2871	-0.1647		-0.1054	-0.1842	-0.3529
	(-2.1627)	(-2.3576)	(-2.0381)	(-3.6361)	(-2.0420)		(-1.4627)	(-1.9062)	(-2.9289)
P19	-0.0805	-0.2040	-0.1663	-0.2783	-0.1752		-0.0124	-0.1606	-0.5625
	(-1.1236)	(-1.7527)	(-1.4871)	(-2.9987)	(-1.9034)		(-0.1471)	(-1.5973)	(-4.2759)
P20	-0.1882	-0.2947	-0.2844	-0.2813	-0.2756		-0.0773	-0.2286	-0.3760
	(-2.1587)	(-2.5701)	(-2.5280)	(-2.3611)	(-2.5351)		(-0.8503)	(-1.8756)	(-2.7243)
$(P1-P20)\mu^F_k$	-1,2448	-2,6449	-1,6147	-1,6574	-1,6347	-2,6105	-2,1040	-2,7773	-5,8046

Table 4
Orthogonal labor risk from other divisions

We regress each portfolio i in division k against division k orthogonal risk and the Fama and French factors:

$$r_{i,k,t} = \alpha_{i,k} + \beta_{i,k}^{F} r_{k,t}^{F} + \beta_{i,k}^{erm} r_{erm,t} + \beta_{i,k}^{smb} r_{smb,t} + \beta_{i,k}^{hml} r_{hml,t} + u_{i,k,t},$$

where $r_{i,k,t}$ is the excess return on portfolio i ($i = P1, ..., P20$) from division k ($k = 1, ..., 9$) at time t; $\alpha_{i,k}$ is the portfolio-specific constant (pricing error); $\beta_{i,k}^{F}$ is the estimated factor loading on $r_{k,t}^{F}$, the factor mimicking portfolio of orthogonal local labor income in division k; $\beta_{i,k}^{erm}$, $\beta_{i,k}^{smb}$ and $\beta_{i,k}^{hml}$ are the estimated factor loading on the corresponding three Fama-French factors; finally, $u_{i,k,t}$ is the error term.

We then regress the residuals against the local orthogonal risk from each division $k' \neq k$:

$$u_{i,k,t} = \alpha_{i,k} + \beta_{i,k,k'}^{F} r_{k,t}^{F} + v_{i,k,t}.$$

The table reports the number of coefficients $\beta_{i,k,k'}^{F}$ corresponding to portfolios from division k (by rows) regressed against orthogonal risk from division $k' \neq k$ (by columns) which are statistically significant (t-statistic > 1.96). There are 20 portfolios per division except for ES (only 10 portfolios). The last column presents the percentage of significant betas smaller than zero in each division. Overall, among the significant betas, the percentage of those smaller than zero is 75%.

		Orthogonal labor risk from division									
		MA	NE	SA	EN	PA	ES	WS	WN	MO	$\beta_{i,k,k'}^{F} < 0$
Portfolios from division	MA	$\ddots$	1	2	13	0	1	0	9	11	97%
	NE	0	$\ddots$	4	7	1	2	3	4	7	100%
	SA	2	2	$\ddots$	7	0	0	3	6	9	93%
	EN	4	9	0	$\ddots$	0	0	0	1	4	28%
	PA	1	3	2	2	$\ddots$	1	1	2	5	65%
	ES	1	2	0	2	1	$\ddots$	1	2	1	34%
	WS	1	1	2	0	0	0	$\ddots$	0	3	86%
	WN	1	3	0	2	0	0	0	$\ddots$	0	50%
	MO	3	3	0	2	0	1	6	1	$\ddots$	12%

Table 5
Country versus divisional Joneses risk hedging

We regress each portfolio i in division k against the country orthogonal risk and the Fama and French factors:

$$r_{i,k,t} = \alpha_{i,k} + \beta^{G}_{i,k}\, r^{G}_{t} + \beta^{erm}_{i,k}\, r_{erm,t} + \beta^{smb}_{i,k}\, r_{smb,t} + \beta^{hml}_{i,k}\, r_{hml,t} + u_{i,k,t},$$

where $r_{i,k,t}$ is the excess return on portfolio i ($i = P1, ..., P20$) from division k ($k = 1, ..., 9$) at time t; $\alpha_{i,k}$ is the portfolio-specific constant (pricing error); β^{G}_{i} is the estimated factor loading on r^{G}_{t}, the factor mimicking portfolio of orthogonal local labor income at the national level; $\beta^{erm}_{i,k}$, $\beta^{smb}_{i,k}$ and $\beta^{hml}_{i,k}$ are the estimated factor loading on the corresponding three Fama-French factors; finally, $u_{i,k,t}$ is the error term.

We then regress the residuals against the local orthogonal risk from each division $k' = 1, ..., 9$:

$$u_{i,k,t} = \alpha_{i,k} + \beta^{F}_{i,k,k'}\, r^{F}_{k,t} + v_{i,k,t}.$$

The table reports the number of coefficients $\beta_{i,k,k'}$ corresponding to portfolios from division k (by rows) regressed against orthogonal risk from division k' (by columns) which are statistically significant (t-statistic > 1.96). There are 20 portfolios per division except for ES (only 10 portfolios).

		Orthogonal labor risk from division								
		MA	NE	SA	EN	PA	ES	WS	WN	MO
Portfolios from division	MA	**10**	9	0	0	0	0	0	0	1
	NE	0	**12**	0	0	0	2	0	1	3
	SA	0	8	**3**	1	0	0	0	0	0
	EN	3	6	0	**11**	3	0	0	0	3
	PA	0	4	0	0	**6**	0	0	1	1
	ES	2	0	0	0	0	**4**	0	0	0
	WS	0	1	1	0	0	1	**7**	0	3
	WN	0	4	0	0	0	0	0	**9**	1
	MO	0	2	0	1	0	0	1	0	**12**

Table 6
Fama-MacBeth Cross-Sectional Regressions: Including Fama and French factors

The return on each portfolio i in division k, $r_{i,k}$, is regressed on a constant, the same division orthogonal labor risk $r^F_{k,t}$, the market return and the return on the smb and hml Fama and French factors. Slope estimates on the local orthogonal labor risk, the market and the Fama and French factors are obtained. Then, the following cross-sectional regressions are performed:

$$r_{i,k} = \lambda^0 + \lambda^F_k \widehat{\beta}^F_{i,k} + \lambda^{erm} \widehat{\beta}^{erm}_{i,k} + \lambda^{smb} \widehat{\beta}^{smb}_{i,k} + \lambda^{hml} \widehat{\beta}^{hml}_{i,k} + \epsilon_i.$$

Panel A reports the constant and the estimated quarterly prices of risk from the cross-section regression (t-values in parenthesis). $R^2 = [Var_c(\overline{r}_i) - Var_c(\overline{e}_i)] / Var_c(\overline{r}_i)$, where Var_c is the cross-sectional variance, $\overline{r}_i$ is the average return and $\overline{e}_i$ is the average residual. $\bar{R}^2$ is the adjusted R^2. We define the pricing error for a given portfolio i as the difference between the actual return and the expected return according to the cross-sectional test; $p.e.$ represents the square root of the aggregate squared pricing errors across all portfolios in each division (p-value in brackets).

In Panel B, we take the residuals from the time series regression in Panel A and regress them against a constant and the country orthogonal labor risk return, r^G_t. From this regression we obtain the slope $\widehat{\beta}^G_{i,k}$, one per portfolio i in each division k. We then perform a set of T cross-sectional regressions of the form:

$$r_{i,k} = \lambda^0 + \lambda^F_k \widehat{\beta}^F_{i,k} + \lambda^G_k \widehat{\beta}^G_{i,k} + \lambda^{erm} \widehat{\beta}^{erm}_{i,k} + \lambda^{smb} \widehat{\beta}^{smb}_{i,k} + \lambda^{hml} \widehat{\beta}^{hml}_{i,k} + \epsilon_i.$$

Panel B reports the constant and the estimated quarterly prices of risk from the cross-section regression (t-values in parenthesis) both for the local and aggregate country risk factors. ρ is the average correlation between $\widehat{\beta}^F_{i,k}$ and $\widehat{\beta}^G_{i,k}$ across portfolios i within each division k.

In Panel C we revert the order: first, portfolio returns are regressed against the national orthogonal labor risk; then, the residuals are regressed against the local orthogonal labor risk. The panel presents only the estimates for the local, λ^F, and national, λ^G, prices of risk together with the correlation coefficient ρ between local and national betas across portfolios.

Panel A: Cross-Sectional Estimates

	MA	NE	SA	EN	PA	ES(L)	WS(L)	WN(L)	MO(L)
λ^0	3.386	3.119	0.928	0.003	3.572	0.670	1.362	−0.149	0.351
	(2.62)	(2.43)	(0.42)	(0.26)	(2.15)	(0.37)	(1.03)	(0.08)	(0.18)
λ^F	−0.715	−0.794	−0.971	−0.656	−0.847	−0.421	−1.563	−1.019	−1.736
	(1.44)	(1.69)	(1.79)	(1.78)	(1.34)	(0.71)	(2.30)	(2.05)	(2.40)
λ^{erm}	−1.693	−0.528	1.734	0.594	−1.224	0.964	−0.702	1.951	0.720
	(0.97)	(0.34)	(0.88)	(0.31)	(0.73)	(0.33)	(0.44)	(0.86)	(0.38)
λ^{smb}	0.504	0.021	−0.354	1.462	0.283	1.573	1.141	0.961	0.818
	(0.61)	(0.24)	(0.35)	(1.97)	(0.28)	(1.22)	(1.37)	(1.18)	(0.94)
λ^{hml}	−0.752	−1.299	−0.043	0.426	−0.489	−0.653	2.588	0.007	0.938
	(0.60)	(1.29)	(0.03)	(0.24)	(0.51)	(0.31)	(2.83)	(0.00)	(0.97)
$\overline{R}^2$	0.66	0.26	0.40	0.85	0.40	0.30	0.80	0.43	0.57
$p.e.$	14.618	31.686	9.600	9.775	15.368	6.289	6.963	14.789	7.839
	[0.75]	[0.03]	[0.96]	[0.96]	[0.69]	[0.71]	[0.99]	(0.74)	[0.99]

Panel B: First stage local, second stage country orthogonal labor risk

	MA	NE	SA	EN	PA	ES(L)	WS(L)	WN(L)	MO(L)
λ^0	3.350	3.141	0.993	−0.645	3.306	0.830	1.176	−0.054	0.470
	(2.61)	(2.45)	(0.46)	(0.46)	(1.94)	(0.45)	(0.83)	(0.03)	(0.26)
λ^F	−0.724	−0.794	−0.978	−0.681	−0.846	−0.432	−1.588	−1.004	−1.724
	(1.47)	(1.68)	(1.85)	(1.85)	(1.33)	(0.73)	(2.33)	(2.02)	(2.39)
λ^G	0.957	−1.315	0.497	0.557	−1.646	0.893	1.447	1.314	−0.948
	(0.26)	(0.61)	(0.22)	(1.12)	(0.55)	(0.43)	(0.48)	(0.36)	(0.45)
λ^{erm}	−1.429	−0.421	1.672	2.704	−1.107	0.397	−0.438	1.984	0.527
	(0.75)	(0.26)	(0.86)	(1.11)	(0.67)	(0.12)	(0.26)	(0.88)	(0.29)
λ^{smb}	0.425	0.021	−0.378	1.278	0.332	1.768	1.192	0.893	0.922
	(0.47)	(0.02)	(0.38)	(1.70)	(0.33)	(1.33)	(1.41)	(1.15)	(1.02)
λ^{hml}	−0.903	−1.593	0.085	−1.423	−0.677	−0.340	2.422	−0.126	0.976
	(0.63)	(1.49)	(0.05)	(0.62)	(0.71)	(0.15)	(2.16)	(0.12)	(1.00)
$\overline{R}^2$	0.64	0.34	0.42	0.87	0.47	0.22	0.80	0.46	0.56
$p.e.$	20.837	17.09	24.454	6.22	14.627	5.69	9.28	14.94	7.665
	[0.35]	[0.58]	[0.18]	(0.99)	[0.75]	[0.78]	[0.97]	(0.72)	[0.99]
ρ	0.16	-0.08	0.13	0.11	0.014	0.13	0.14	-0.09	0.14

Panel C: First stage country, second stage local orthogonal labor risk

	MA	NE	SA	EN	PA	ES(L)	WS(L)	WN(L)	MO(L)
λ^F	−2.519	−0.262	−2.580	−2.330	−0.275	0.297	−1.372	−1.280	−0.685
	(0.97)	(0.28)	(0.97)	(1.20)	(0.09)	(0.25)	(0.51)	(0.68)	(0.40)
λ^G	−0.373	−0.353	−0.529	0.153	−0.719	−0.693	−0.856	−0.827	−1.393
	(0.36)	(0.44)	(0.68)	(0.11)	(0.79)	(0.72)	(1.28)	(0.71)	(1.24)
ρ	0.93	0.75	0.76	0.94	0.87	0.56	0.86	0.88	0.71

Table 7
Fama-MacBeth Cross-Sectional Regressions: without Fama and French factors

We regress first the return on each portfolio i in division k, $r_{i,k}$, on a constant, the same division orthogonal labor risk $r^F_{k,t}$ and the market return. We estimate the slope on the local orthogonal labor risk, $\widehat{\beta}^F_{i,k}$. We also obtain the slope estimate for the market. We then perform a set of T cross-sectional regressions of the form:

$$r_{i,k} = \lambda^0 + \lambda^F_k \widehat{\beta}^F_{i,k} + \lambda^{erm} \widehat{\beta}^{erm}_{i,k} + \epsilon_i.$$

The table reports the constant and the estimated quarterly prices of risk from the cross-section regression (t-values in parenthesis). $R^2 = [Var_c(\overline{r}_i) - Var_c(\overline{e}_i)] / Var_c(\overline{r}_i)$, where Var_c is the cross-sectional variance, $\overline{r}_i$ is the average return and $\overline{e}_i$ is the average residual. $\bar{R}^2$ is the adjusted R^2. We define the pricing error for a given portfolio i as the difference between the actual return and the expected return according to the cross-sectional test; $p.e.$ represents the square root of the aggregate squared pricing errors across all portfolios in each division (p-value in brackets).

	MA	NE	SA	EN	PA	ES(L)	WS(L)	WN(L)	MO(L)
λ^0	1.425	1.986	2.442	−0.632	2.739	0.170	2.474	0.004	1.590
	(1.23)	(1.66)	(1.34)	(0.54)	(1.65)	(0.11)	(2.24)	(0.32)	(1.05)
λ^F	−0.729	−0.876	−0.887	−0.638	−0.888	−0.442	−1.549	−1.003	−1.737
	(1.47)	(1.84)	(1.64)	(1.73)	(1.41)	(0.73)	(2.27)	(1.99)	(2.41)
λ^{erm}	0.425	0.215	−0.866	2.551	−0.39	2.330	−0.003	1.569	−0.126
	(0.28)	(0.16)	(0.39)	(1.70)	(0.25)	(1.24)	(0.18)	(1.04)	(0.07)
$\overline{R}^2$	0.60	0.25	0.38	0.83	0.36	0.23	0.69	0.48	0.58
$p.e.$	17.164	24.715	28.497	7.753	15.47	9.527	8.233	11.507	8.762
	[0.57]	[0.17]	[0.07]	(0.99)	[0.56]	[0.39]	[0.98]	(0.91)	[0.98]

Table 8
GMM Cross-Sectional Tests of KEEPM

This table presents the GMM estimates of the following pricing equation:

$$E_{t-1}\left(r_{i,k,t}\left[c_{0,k}+c_{erm,k}r_{erm,t}+c_k r^F_{k,t}\right]\right)=0,$$

where $r_{i,k,t}$ is the excess return on portfolio i in division k, $c_{0,k}$ is the intercept, $c_{erm,k}$ is the loading on the market factor, $r_{erm,t}$ is the return on the market portfolio, c_k is the loading corresponding to the orthogonal component of local labor income, and r^F_t is the local labor income return. In the table, λ^F_k is the quarterly risk premium corresponding to the local orthogonal labor income factor, and λ^{erm} is the quarterly risk premium corresponding to the market factor. J represents the J-test of the model, *aape* is the average absolute pricing error of the model, *aape FF* is the average absolute pricing error of a model that also includes the *smb* and *hml* Fama-French factors. ΔJ is the statistic that compares our baseline model and the model augmented with the Fama-French factors. p-values between brackets.

	MA	NE	SA	EN	PA	ES	WS(L)	WN(L)	MO(L)
$c_{0,k}$	0.963	0.996	1.010	1.037	0.951	1.046	0.973	1.041	1.0417
	(23.99)	(30.52)	(22.94)	(25.99)	(24.84)	(20.01)	(28.58)	(23.19)	(22.92)
c_k	1.893	3.598	1.422	1.926	1.937	−0.993	2.391	1.882	2.303
	(1.22)	(2.66)	(0.76)	(1.09)	(1.23)	(0.58)	(2.29)	(1.41)	(2.42)
$c_{erm,k}$	1.005	0.643	−1.157	−2.335	1.569	−4.300	1.485	−2.281	0.084
	(0.48)	(0.36)	(0.42)	(0.06)	(0.63)	(1.72)	(0.81)	(1.15)	(0.04)
λ^F_k	−0.590	−1.179	−1.010	−0.738	−0.820	−0.553	−1.519	−1.165	−1.799
	(1.23)	(2.70)	(1.93)	(2.11)	(1.33)	(0.99)	(2.29)	(2.41)	(2.61)
λ^{erm}	−0.207	0.224	1.248	1.961	−0.442	2.874	−0.517	2.076	0.373
	(0.16)	(0.19)	(0.82)	(1.60)	(4.20)	(1.91)	(0.48)	(1.58)	(0.26)
J	17.562	21.806	28.796	7.774	16.617	8.494	11.436	15.415	7.675
	[0.06]	[0.19]	[0.04]	[0.97]	[0.48]	[0.20]	[0.83]	[0.56]	[0.97]
aape	0.233	1.397	0.495	0.215	0.336	0.390	0.409	0.405	0.485
aape FF	1.077	1.942	0.630	0.260	0.535	0.382	0.660	0.430	0.720
ΔJ	5.189	1.401	7.660	1.348	2.361	0.233	3.791	0.273	0.556
	[0.02]	[0.23]	[0.01]	[0.25]	[0.13]	[0.63]	[0.05]	[0.60]	[0.46]

Table 9
GMM Cross-Sectional Tests of KEEPM: Including Country Labor Income

This table presents the GMM estimates of the following pricing equation:

$$E_{t-1}\left(r_{i,k,t}\ \left[c_{0,k} + c_{erm,k} r_{erm,t} + c_k r^F_{k,t} + c_{G,k} r^G_t\right]\right) = 0,$$

where $r_{i,k,t}$ is the excess return on portfolio i in division k, $c_{0,k}$ is the intercept, $c_{erm,k}$ is the loading on the market factor, $r_{erm,t}$ is the return on the market portfolio, c_k is the loading corresponding to the orthogonal component of local labor income, r^F_t is the local labor income return, $c_{G,k}$ is the loading on the country orthogonal labor risk, r^G_t. In the table, λ^F_k is the quarterly risk premium corresponding to the local orthogonal labor income factor, λ^{erm} is the quarterly risk premium corresponding to the market factor and λ^G is the quarterly risk premium corresponding to the country orthogonal labor risk. J represents the J-test of the model, *aape* is the average absolute pricing error of the model. The last row reports the ΔJ statistic which tests the null hypothesis that the global orthogonal labor income factor is not important in pricing the assets. p-values between brackets.

	MA	NE	SA	EN	PA	ES(L)	WS(L)	WN(L)	MO(L)
$c_{0,k}$	0.990	0.989	1.002	1.033	0.884	1.048	0.972	1.041	1.021
	(18.73)	(26.56)	(19.76)	(13.11)	(14.99)	(20.66)	(18.11)	(23.09)	(23.45)
c_k	−5.714	4.258	2.577	2.083	2.438	−1.434	0.212	2.158	1.387
	(1.15)	(2.15)	(0.64)	(0.31)	(1.25)	(0.78)	(0.05)	(0.63)	(0.76)
$c_{G,k}$	11.078	−1.198	−1.551	0.391	−0.409	1.391	2.275	−0.461	2.201
	(1.53)	(0.40)	(0.36)	(0.07)	(0.11)	(0.48)	(0.45)	(0.09)	(0.57)
$c_{erm,k}$	4.921	0.429	−1.262	−1.227	3.779	−3.556	1.284	−2.439	0.782
	(1.48)	(0.21)	(0.45)	(0.30)	(1.18)	(1.16)	(0.52)	(0.92)	(0.32)
λ^F_k	−0.385	−1.193	−1.001	−0.730	−0.756	−0.532	−0.800	−1.161	−1.800
	(0.84)	(2.73)	(1.91)	(2.12)	(1.22)	(0.95)	(1.31)	(2.40)	(2.65)
λ^G	−1.482	−0.440	−0.663	−1.278	−0.579	−1.128	−0.785	−1.175	−1.245
	(1.81)	(0.58)	(0.97)	(1.44)	(0.77)	(1.59)	(1.05)	(1.38)	(1.47)
λ^{erm}	−1.966	0.198	1.204	1.704	−1.078	2.609	−0.200	2.105	0.313
	(1.19)	(0.16)	(0.78)	(0.82)	(0.69)	(1.57)	(0.14)	(0.63)	(0.22)
J	15.350	21.362	29.593	7.815	15.749	8.494	16.090	15.292	7.128
	[0.49]	[0.16]	[0.02]	[0.95]	[0.39]	[0.20]	[0.44]	[0.50]	[0.97]
aape	0.734	1.763	0.505	0.191	0.314	0.393	0.370	0.406	0.520
ΔJ	2.371	0.503	2.543	0.098	2.361	0.233	0.209	0.008	0.325
	[0.12]	[0.48]	[0.11]	[0.75]	[0.12]	[0.63]	[0.65]	[0.93]	[0.56]

Table 10
GMM Cross-Sectional Tests of KEEPM Augmented with Book-to-Market Portfolios

On top of the twenty portfolio (ten for ES) in each division sorted according to the betas with respect to the local orthogonal labor risk, we include an additional twenty portfolios formed according to book-to-market ratio.

This table presents the GMM estimates of the following pricing equation:

$$E_{t-1}\left(r_{i,k,t}[c_{0,k} + c_{erm,k} r_{erm,t} + c_k r^F_{k,t}]\right) = 1.$$

where $r_{i,k,t}$ is the excess return on portfolio i in division k; $c_{0,k}$ is the intercept, $c_{erm,k}$ is the loading on the market factor, $r_{erm,t}$ is the return on the market portfolio, c_k is the loading corresponding to the orthogonal component of local labor income, and r^F_t is the local labor income return. In the table, λ^F is the quarterly risk premium corresponding to the local orthogonal labor income factor, and λ^{erm} is the quarterly risk premium corresponding to the market factor. J represents the J-test of the model, *aape* is the average absolute pricing error of the model, *aape FF* is the average absolute pricing error of a model that also includes the *smb* and *hml* Fama-French factors. ΔJ is the statistic that compares our baseline model and the model augmented with the Fama-French factors.

	MA	NE	SA	EN	PA	ES(L)	WS(L)	WN(L)	MO(L)
$c_{0,k}$	0.945	0.983	0.933	1.019	0.992	1.005	0.976	0.997	1.017
	(42.21)	(32.74)	(35.35)	(33.19)	(32.37)	(28.56)	(26.50)	(33.04)	(25.67)
c_k	2.548	6.097	4.399	3.908	2.769	0.787	3.712	2.689	3.267
	(2.01)	(4.73)	(3.42)	(2.56)	(2.43)	(0.53)	(3.98)	(2.33)	(3.78)
$c_{erm,k}$	2.555	3.761	3.932	−0.264	0.813	−0.673	3.204	0.429	1.649
	(1.69)	(2.68)	(2.71)	(0.17)	(0.46)	(0.33)	(2.03)	(0.30)	(1.00)
λ^F_k	−0.519	−1.722	−0.913	−0.882	−1.385	−0.568	−1.941	−1.057	−2.026
	(1.06)	(4.41)	(1.76)	(2.57)	(2.41)	(1.01)	(3.09)	(2.19)	(2.97)
λ^{erm}	−1.140	−1.465	−1.598	0.789	0.210	0.705	−1.495	0.185	0.587
	(1.19)	(1.58)	(1.72)	(0.77)	(0.20)	(0.56)	(1.36)	(0.18)	(0.52)
J	37.935	35.390	47.176	29.409	42.823	23.313	34.885	40.342	42.605
	[0.43]	[0.54]	[0.12]	[0.81]	[0.24]	[0.14]	[0.57]	[0.32]	[0.24]
aape	0.729	4.298	0.450	1.045	0.692	0.668	1.657	0.611	1.678
aape FF	1.586	3.906	2.270	0.556	0.640	0.532	0.410	0.800	1.461
ΔJ	13.103	0.198	6.769	11.033	3.117	10.185	21.407	5.080	17.396
	[0.00]	[0.65]	[0.01]	[0.00]	[0.08]	[0.00]	[0.00]	[0.02]	[0.00]

Table 11
GMM Cross-Sectional Tests of KEEPM: Common Market Risk Premium across Divisions

This table presents the GMM estimates of the following pricing equation:

$$E_{t-1}\left(r_{i,k,t}\left[c_{0,k}+c_{erm,k}r_{erm,t}+c_k r^F_{k,t}\right]\right)=0,$$

where $r_{i,k,t}$ is the excess return on portfolio i in division k, $c_{0,k}$ is the intercept, $c_{erm,k}$ is the loading on the market factor, $r_{erm,t}$ is the return on the market portfolio, c_k is the loading corresponding to the orthogonal component of local labor income, and r^F_t is the local labor income return. In the table, λ^F is the quarterly risk premium corresponding to the local orthogonal labor income factor, and λ^{erm} is the quarterly risk premium corresponding to the market factor. We estimate first the market price of risk from the CAPM using 10 size sorted portfolios using GMM. The estimates of the parameters are: $c_{erm} = -3.694(t-\text{value} = 2.27)$; $\lambda^{erm} = 0.0271(t-\text{value} = 2.32)$. We now impose these estimates on each division and estimate the free parameters associated with the divisional level orthogonal labor income. J represents the J-test of the model, *aape* is the average absolute pricing error of the model. The ΔJ-test is a test of whether the restrictions that there is a common market price of risk.

	MA	NE	SA	EN	PA	ES(L)	WS(L)	WN(L)	MO(L)
$c_{0,k}$	1.050	1.073	1.062	1.060	1.056	1.041	1.074	1.064	1.086
	(51.61)	(43.39)	(45.42)	(44.21)	(54.79)	(48.42)	(41.68)	(38.99)	(33.24)
c_k	−0.471	1.362	0.277	0.964	−0.320	−0.349	0.949	1.102	1.294
	(0.56)	(1.32)	(0.35)	(0.74)	(0.46)	(0.38)	(1.33)	(0.99)	(1.56)
λ^F_k	−0.842	−0.963	−1.188	−0.663	−1.189	−0.759	−1.544	−0.953	−1.613
	(2.26)	(2.41)	(3.31)	(2.23)	(3.00)	(1.85)	(2.77)	(2.30)	(2.62)
J	11.836	19.988	8.628	4.150	5.775	9.088	10.781	4.056	6.392
	[0.22]	[0.02]	[0.47]	[0.90]	[0.76]	[0.43]	[0.29]	[0.77]	[0.70]
aape	0.618	1.092	0.973	0.374	1.059	0.393	1.197	0.440	0.893
ΔJ	1.147	3.158	2.994	0.292	3.305	0.245	3.147	0.581	4.166
	[0.28]	[0.08]	[0.08]	[0.59]	[0.07]	[0.62]	[0.08]	[0.46]	[0.04]

Table 12
GMM Cross-Sectional Tests of KEEPM: Ten Portfolios per Division

This table presents the GMM estimates of the following pricing equation:

$$E_{t-1}\left(r_{i,k,t}\ \left[c_{0,k} + c_{erm,k} r_{erm,t} + c_k r^F_{k,t}\right]\right) = 0,$$

where $r_{i,k,t}$ is the excess return on portfolio i in division k, $c_{0,k}$ is the intercept, $c_{erm,k}$ is the loading on the market factor, $r_{erm,t}$ is the return on the market portfolio, c_k is the loading corresponding to the orthogonal component of local labor income, and r^F_t is the local labor income return. In the table, λ^F is the quarterly risk premium corresponding to the local orthogonal labor income factor, and λ^{erm} is the quarterly risk premium corresponding to the market factor. J represents the J-test of the model, *aape* is the average absolute pricing error of the model, *aape* FF is the average absolute pricing error of a model that also includes the *smb* and *hml* Fama-French factors. ΔJ is the statistic that compares our baseline model and the model augmented with the Fama-French factors. p-values between brackets.

	MA	NE	SA	EN	PA	ES(L)	WS(L)	WN(L)	MO(L)
$c_{0,k}$	0.984	1.015	0.966	1.035	0.953	1.046	0.985	1.032	0.990
	(24.26)	(25.86)	(16.47)	(23.50)	(21.31)	(20.01)	(26.13)	(23.08)	(19.45)
c_k	1.010	3.184	3.871	1.815	2.027	−0.993	2.131	1.956	2.396
	(0.57)	(2.24)	(1.48)	(0.98)	(1.17)	(0.58)	(2.06)	(1.39)	(2.25)
$c_{erm,k}$	−0.415	−0.343	2.409	−2.338	1.632	−4.300	0.640	−1.814	1.301
	(0.48)	(0.17)	(0.60)	(1.09)	(0.58)	(1.72)	(0.31)	(0.86)	(0.47)
λ^F_k	−0.578	−1.237	−1.111	−0.704	−0.815	−0.553	−1.578	−1.078	−1.682
	(1.18)	(2.81)	(2.11)	(1.97)	(1.30)	(0.99)	(2.36)	(2.19)	(2.45)
λ^{erm}	0.614	0.876	−0.523	1.815	−0.456	2.874	0.012	1.673	−0.443
	(0.41)	(0.66)	(0.24)	(0.98)	(0.28)	(1.91)	(0.01)	(1.18)	(0.24)
J	10.297	15.835	5.635	3.805	1.846	8.600	7.635	4.056	2.065
	[0.17]	[0.03]	[0.58]	[0.80]	[0.96]	[0.28]	[0.36]	[0.77]	[0.96]
aape	0.188	1.431	0.230	0.117	0.141	0.390	0.311	0.205	0.245
aape FF	2.331	0.561	0.557	0.147	0.121	0.382	0.220	0.204	0.227
ΔJ	2.697	2.074	2.319	1.451	0.174	2.228	2.133	0.451	0.523
	[0.10]	[0.15]	[0.13]	[0.23]	[0.66]	[0.14]	[0.14]	[0.50]	[0.47]

Table 13

Panel A of the Table presents the GMM estimates of the following pricing equation:

$$E_{t-1}\left(r_{i,k,t}\ \left[c_{0,k} + c_{dc,k}dc_t + c_{dc*cay,k}(dc_t * cay_{t-1}) + c_k r^F_{k,t}\right]\right) = 0,$$

where $r_{i,k,t}$ is the excess return on portfolio i in division k, $c_{0,k}$ is the intercept, $c_{dc,k}$ is the loading on the growth rate of aggregate consumption, dc_t, $c_{dc*cay,k}$ is the loading corresponding to consumption growth scaled by cay, and r^F_t is the local labor income return. In the table, λ^F is the quarterly risk premium corresponding to the local orthogonal labor income factor, λ^{dc} is the quarterly risk premium corresponding to consumption growth, and λ^{dc*cay} is the quarterly risk premium corresponding to consumption growth scaled by cay. J represents the J-test of the model p-values between brackets.

Panel B of the Table presents the GMM estimates of the following pricing equation:

$$E_{t-1}\left(r_{i,k,t}\ \left[c_{0,k} + c_{erm,k}r_{erm,t} + c_{erm*s,k}(r_{erm,t} * s_{t-1}) + c_k r^F_{k,t}\right]\right) = 0,$$

where $r_{i,k,t}$ is the excess return on portfolio i in division k, $c_{0,k}$ is the intercept, $c_{erm,k}$ is the loading on the return on the market portfolio, $c_{erm^*\mathrm{s},k}$ is the loading corresponding to the market return scaled by s, the consumption to wealth ratio, and r^F_t is the local labor income return. In the table, λ^F is the quarterly risk premium corresponding to the local orthogonal labor income factor, λ^{erm} is the quarterly risk premium corresponding to return on the market portfolio, and λ^{erm*s} is the quarterly risk premium corresponding to the market return scaled by s. J represents the J-test of the model p-values between brackets.

Panel A: Scaling with cay

	MA	NE	SA	EN	PA	ES(L)	WS(L)	WN(L)	MO(L)
$c_{0,k}$	0.686	1.526	1.123	1.193	1.505	1.601	1.005	1.056	1.127
	(2.82)	(5.26)	(3.70)	(4.46)	(5.78)	(2.93)	(3.24)	(3.44)	(5.28)
c_k	1.337	2.327	1.944	3.304	0.674	0.990	2.072	2.688	2.849
	(1.28)	(1.88)	(1.70)	(2.46)	(0.65)	(0.74)	(2.32)	(2.16)	(2.89)
$c_{dc,k}$	53.390	−109.651	−23.479	−37.951	−106.018	−129.492	3.061	−14.201	−8.855
	(1.10)	(1.88)	(0.36)	(0.71)	(2.07)	(1.15)	(0.05)	(0.22)	(0.21)
$c_{dc*cay,k}$	−4492.589	−3238.957	1137.027	−589.270	−3007.536	−4151.378	2638.364	−3553.456	5569.32
	(1.69)	(1.07)	(0.42)	(0.22)	(1.28)	(0.68)	(0.95)	(0.95)	(1.24)
λ^F_k	−0.601	−1.266	−1.011	−0774	−0.813	−0.532	−1.463	−1.236	−1.936
	(1.26)	(3.11)	(1.93)	(2.16)	(1.33)	(0.92)	(2.22)	(2.52)	(2.92)
λ^{dc}	−0.116	0.208	0.071	0.796	0.166	0.228	0.039	0.023	0.089
	(1.32)	(2.08)	(0.70)	(0.84)	(2.12)	(1.21)	(0.33)	(0.22)	(1.06)
λ^{dc*cay}	−1.004	0.002	−0.001	0.000	0.001	0.002	−0.200	0.003	−0.004
	(1.85)	(0.72)	(0.59)	(0.02)	(0.79)	(0.50)	(0.84)	(1.00)	(1.22)
J	11.643	15.948	26.673	8.832	13.371	6.509	10.244	16.031	8.228
	[0.76]	[0.46]	[0.05]	[0.92]	[0.65]	[0.37]	[0.44]	[0.45]	[0.94]

Panel B: Scaling with s

	MA	NE	SA	EN	PA	ES(L)	WS(L)	WN(L)	MO(L)
$c_{0,k}$	0.962	0.984	1.009	1.038	0.947	1.004	0.961	1.042	1.018
	(31.00)	(22.03)	(21.72)	(24.64)	(23.69)	(18.18)	(25.36)	(23.08)	(21.92)
c_k	1.448	3.114	1.332	1.826	2.077	0.559	2.189	1.833	1.909
	(0.68)	(2.18)	(0.63)	(1.021)	(1.28)	(0.26)	(2.09)	(1.33)	(1.71)
$c_{erm,k}$	32.367	0.338	−1.192	−2.364	1.875	−1.633	1.866	−2.337	−0.307
	(0.37)	(0.20)	(0.39)	(1.22)	(0.75)	(0.49)	(0.98)	(1.17)	(0.14)
$c_{erm*s,k}$	1.448	−217.170	1.332	−27.831	13.872	−169.501	63.131	−22.634	1.909
	(0.68)	(1.98)	(0.63)	(0.31)	(0.16)	(1.44)	(0.55)	(0.22)	(1.71)
λ_k^F	−0.601	−0.925	−0.974	−0.706	−0.845	−0.631	−1.462	−1.141	−1.860
	(1.24)	(2.14)	(1.86)	(2.00)	(1.37)	(1.12)	(2.19)	(2.34)	(2.73)
λ^{erm}	−0.132	0.093	1.254	1.934	−0.578	1.224	−0.681	2.039	0.707
	(0.09)	(0.08)	(0.71)	(1.58)	(0.41)	(0.59)	(0.54)	(1.52)	(0.48)
λ^{erm*s}	−0.020	0.098	−0.007	0.008	−0.005	0.082	−0.029	0.000	−0.047
	(0.54)	(2.09)	(0.15)	(0.18)	(0.15)	(1.41)	(0.55)	(0.01)	(1.03)
J	16.861	14.834	28.055	7.662	16.542	6.277	9.784	15.821	6.791
	[0.40]	[0.54]	[0.03]	[0.96]	[0.42]	[0.39]	[0.87]	[0.47]	[0.98]

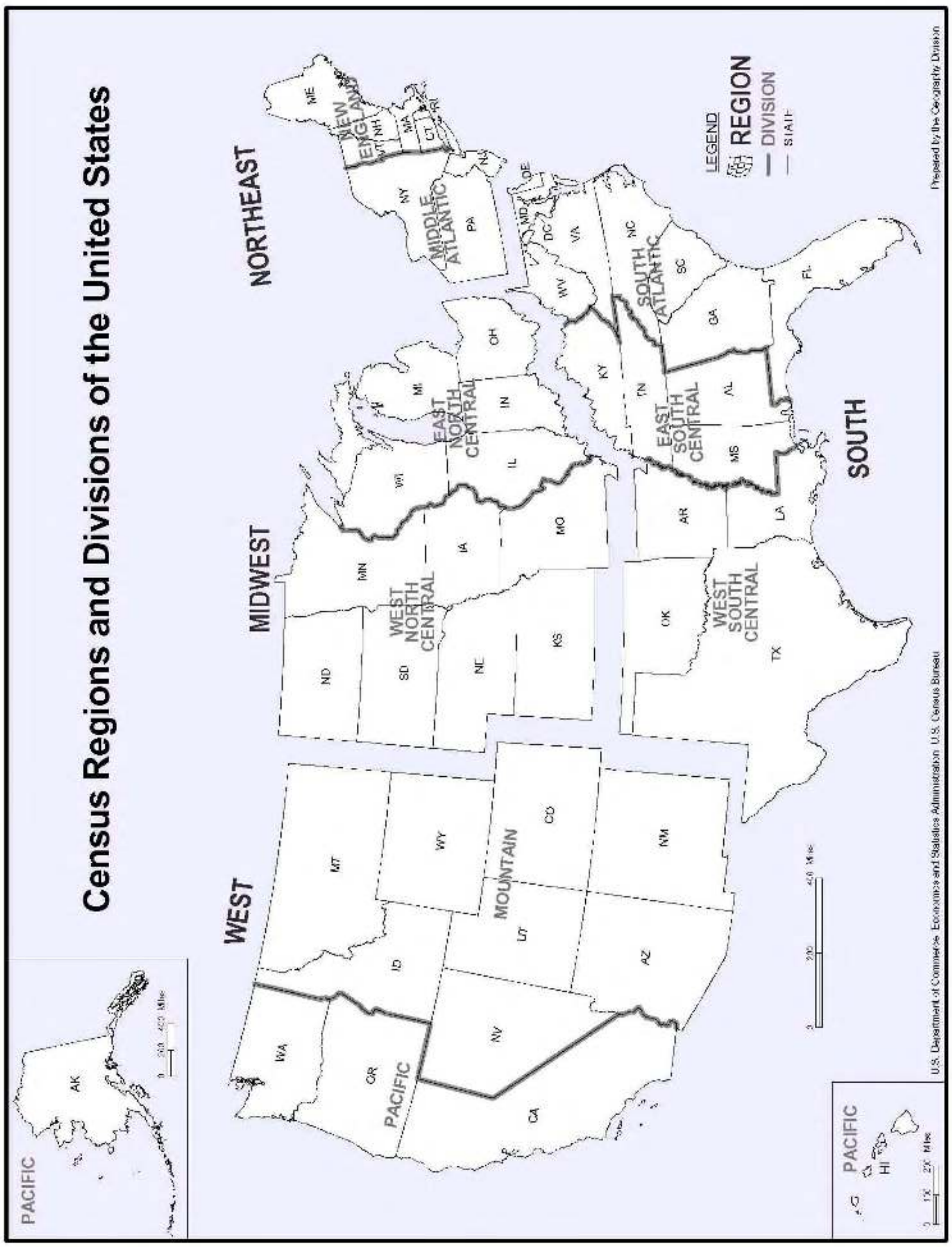

Figure 1: US Census Regions and Divisions.