The Effect of Relative Wealth Concerns on the Cross-section of Stock Returns*

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We test the cross section implications of an asset pricing model where agents have relative wealth concerns with respect to a reference group which we call their peers. The model predicts that a local risk factor -non-diversifiable wealth of the peers- should command a negative premium in equilibrium. We study the empirical implications of this model using as peer groups the nine US Census divisions. As a proxy for the local risk factor we use divisional labor income. We find substantial support for the predictions of the model; moreover the effects are stronger in divisions with lower population density where, arguably, relative wealth concerns are likely to be more important.

1 Introduction

The objective of this paper is to examine empirically if relative wealth concerns are present in the US stock market at some disaggregate level. In particular, we consider the nine US Census divisions and test whether stock returns across the nine divisions are priced by local (divisional) risk factors that proxy for relative wealth concerns.

The literature suggests two, not necessarily exclusive, cases in which investors' relative wealth concerns with respect to some reference group may have an effect on the equilibrium pricing of financial securities. First, agents may display "external habit formation" (EHF) in their preferences. In this case, the utility of investors depends explicitly on the wealth of their peers ("the Joneses") and investors bias their portfolio holdings towards securities which are correlated with the wealth of their peers so as to"keep-up with the Joneses."Second, relative wealth concerns may also arise endogenously, without assuming EHF preferences. DeMarzo, Kaniel and Kremer (2004) show that individuals with standard preferences might care about the wealth of their peers because competition for non-diversifiable assets in limited supply drives their price up; if investors cannot compete in wealth with their peers they might be left out of the market. Hedging this local inflationary risk may, under certain conditions, bias investors' portfolios towards assets positively correlated with the local, non-diversifiable asset. In equilibrium, whatever the cause of the bias in portfolio holdings, investors pay a premium for these assets.

Gómez, Priestley and Zapatero (2008) examine the asset pricing implications of relative wealth concerns and show that in the presence of local non-diversifiable assets (like, for instance, human capital or real estate) relative wealth concerns result in an approximate multi-beta asset pricing model. This result is attained when relative wealth concerns are driven by arguments based on either EHF or non-diversifiable assets which are in short-supply. They call this model the KEEPM, which stands for "KEEping up 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). These factors capture the risk of deviating from the non-diversifiable local wealth. The model predicts that the price of risk on each of the local factors 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]

Gómez, Priestley and Zapatero (2008) find strong support for the KEEPM at the international level. That is, investors consider their country peers as a reference group and are willing to pay extra for securities that are positively correlated with the idiosyncratic, and therefore, the non-diversifiable component of local (national) income. This factor acts as a proxy for the non-diversifiable wealth of the reference group and, in equilibrium, it is shown to command a negative risk premium.

In this paper, we test the KEEPM across the nine US Census divisions. For our analysis, stocks are sorted into the nine divisions depending on the location of their headquarters. As a proxy for the non diversifiable wealth of the peers, we use divisional labor income. More precisely, since our model predicts that the relevant variable is idiosyncratic wealth, we use the residual of labor income with respect to the domestic market portfolio, which we refer to as orthogonal local labor income. In each division, we form a factor mimicking portfolio of orthogonal local labor income and show that there is a substantial negative risk premium associated with stocks that are highly correlated with orthogonal local labor income.

We assess the ability of this factor mimicking portfolio to explain the cross section of divisional stock returns. We undertake the analysis in two ways. First, we perform a time series analysis of returns following Black, Jensen and Scholes (1972) and Fama and French (1993) and test whether the intercepts are jointly zero using the Gibbons, Ross and Shanken (1989), GRS, test statistic. In all but one marginal case, we accept the null hypothesis that the intercepts are jointly zero within a given division. The estimated coefficients on the factor mimicking portfolio exhibit the expected sign: positive and significant for those assets (portfolios) sorted by the highest lagged coefficient estimate, and negative and significant

[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.

for those assets (portfolios) sorted by the lowest lagged coefficient estimate. These results are robust to the presence of the Fama and French (1993) factors and the use of alternative portfolio sorting techniques.

We provide additional insights into the cross-sectional pattern of returns by estimating factor pricing models using the stochastic discount factor methodology of Cochrane (1996) and the cross-sectional methodology of Fama and MacBeth (1973). The orthogonal local labor income factor is an important determinant of the pricing kernel and commands a negative risk premium in all divisions and it is statistically significant in most cases. The pricing errors are economically small, confirming the results from the time series regressions. There is no additional role for risk factors based on size and book-to-market once the orthogonal local labor income factor has been included in the model. In the Fama-MacBeth regressions we also uncover a negative risk premium on the orthogonal local labor income factor in all divisions which is often statistically significant and report reasonable large cross-sectional $\overline{R}^2s$.

We consider the possibility that the local risk factors are not local but instead global. That is, we form a global (national) orthogonal labor income mimicking factor. Although this factor is priced in the cross-section, further analysis suggests that it is the local component of this global factor that investors are concerned with.

The estimated sign and statistical significance of the factor mimicking portfolios and the estimated coefficients in the SDF and Fama-MacBeth regressions, confirm the model predictions: investors demand a lower (higher) return for those assets positively (negatively) correlated with the Joneses risk factor, proxied by the orthogonal labor income return.

Hong, Kubik and Stein (2008) find that prices of stocks in Census divisions with low population density have, controlling for other factors, significantly higher prices than stocks in high population density divisions, although in their framework the effect on lowering expected returns is very small. In their model, some investors (called "local experts") are exogenously restricted to invest in local firms. Low population density is strongly associated with low aggregate book value; the demand for stock of local firms in short supply by locally restricted investors pushes their prices up, driving their returns down. They call this "the only game in town" effect.

Inspired by the insights of Hong, Kubik and Stein (2008), we rank the nine census divisions according to their population density. We find that in divisions with low population density our results are very compelling from an economic point of view (with higher, in absolute value, risk premia) and strongly statistically significant. This finding is attained irrespective of the estimation methodology, the presence of additional risk factors, and the choice of test portfolios.

According to the theoretical model, there may exist two, not mutually exclusive, reasons to explain our finding. First, divisions with lower population density may concentrate 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 it is not the amount of total local wealth which drives the negative risk premium (thus, pushing prices up) but rather the amount of local non-diversifiable wealth. Second, Joneses behavior may be stronger in low density population areas. This can be argued both in the case of EHF or competition for local assets in short supply. In the case of EHF, the economic size of the risk premium depends on the intensity of the "keeping up with the Joneses" behavior. Therefore, a possible explanation of our findings is that in divisions with lower population density there is a stronger Joneses concern since, arguably, it is easier for investors to assess the level of wealth of their peers: in smaller, rural communities, 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, the size of the price of risk increases with the risk aversion of the representative investor. In other words, our findings would be consistent with price hedging induced by relative wealth concerns and higher risk aversion for lower population density divisions.

Our paper is complementary to Gómez, Priestley and Zapatero (2008) who find evidence in favor of the KEEPM at the international level on portfolios of US, UK, German and Japanese stocks. For all countries, prices of domestic stocks that help hedging the country-specific labor risk have a negative risk premium which agents willingly accept. However, focusing on domestic, divisional, rather than international portfolio choices, poses certain advantages and new challenges. First, unlike in an international setting, the purely domestic problem is free of a number of "usual suspects" for portfolio biases. Arguably, barriers, either explicit (like regulation, taxes, financial or human capital controls), or tacit (like language or culture), cannot be invoked to explain domestic portfolio biases. Second, additional risk sources, like exchange risk or country-specific political risk, disappear. Third, as noted above, issues such as population density, and differences in the number of firms and book value across divisions are potential factors that could drive relative wealth concerns at the domestic level.

The paper is organized as follows. The related literature is discussed in section 2. We present the theory and derive the KEEPM in section 3. Section 4 describes the data used in the analysis. In section 5 we provide empirical results using the time-series regressions. Further results using cross-sectional methods are reported in section 6. Section 7 offers some final remarks and closes the paper.

2 Related literature

Keeping up with the Joneses preferences were introduced by Abel (1990) and further studied by Galí (1994) and Abel (1999). Previous papers have studied the theoretical asset pricing implications of relative wealth concerns: Gómez (2007) for the case of EHF and DeMarzo, Kaniel and Kremer (2004, 2006) for the case of price-driven relative wealth concerns. Evidence of the existence of this type of preferences is presented in Ravina (2005). Garcia and Strobl (2009) study the implications of these preferences for information acquisition.

A number of recent papers study the empirical evidence of regional risk diversification within the US in the presence of non-diversifiable wealth. 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, they are willing to pay for keeping up with regional consumption; hence a negative, statistically significant regional risk-premium arises. Our model is different, and complements Korniotis' findings, both theoretically and empirically. Theory wise, our investors are concerned about hedging local non-diversifiable risk. Unlike the regional consumption risk factors in Korniotis' model, our risk factors are defined relative to specific non-diversifiable sources of income, like labor income or house prices. Moreover, these factors may arise endogenously, as shown by DeMarzo, Kaniel and Kremer (2004), without assuming EHF. Empirically, Korniotis's (2008) EHF risk factor is averaged across regions. Our local risk factors are division-specific. We study the sign, magnitude and significance of the negative risk premia across the nine US Census divisions and for a specific source of non-diversifiable risk: labor income. This allows us to understand better the impact of the local risk factors as well and their origin, whether endogenous (hedging local price inflation) or exogenous (EHF).

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. In our model, financial markets at the US level are complete. Local (divisional) labor income or housing wealth risk, along with relative wealth concerns (endogenous and/or exogenous), drive the local bias in portfolio choice and the negative risk premia across divisions. Lustig and Van Nieuwerburgh (2008) study the effect of housing collateral on regional risk-sharing across the largest US metropolitan areas. They find that when housing value (as collateral) decreases relative to human wealth, risk sharing across regions declines.

Our paper is also related to the empirical literature on asset pricing under limited market participation in that we assume the existence of non-diversifiable, non-financial income which may include labor income (see, for example, Campbell (2000) and Haliassos and

Michaelides (2002)) and entrepreneurial income (see, for example, Heaton and Lucas (2000) and Polkovnichencko (2004)). Since our primary objective is to study the implications of keeping up with the Joneses behavior in the cross-section of stock returns, we isolate the Joneses effect by distinguishing between two types of agents in the model: investors, endowed only with financial assets and without non-tradable income, and workers, who only have non-tradable income and do not participate in financial markets.

Arguably, investors with access to financial markets could be also endowed with non-tradable assets. This would result in an additional hedging demand on the side of the investors. Viceira (2001) and Cocco, Gomes and Maenhout (2005) study this problem. We note that the effect we would expect from this *direct* hedging demand for non-financial income would be the opposite to the *indirect* effect resulting from keeping up with the Joneses preferences: assets positively correlated with the investor's non-diversifiable income would be "crowded-out" from the optimal portfolio (whereas, in the case of keeping up with the Joneses preferences, the investor's demand for these assets increases). Hence, investors would demand a higher expected return to hold these assets (contrary to the negative price of risk for the country risk factors resulting from keeping up with the Joneses preferences).

Finally, 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)

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

local firms. Huberman (2001) uses the fact that individuals prefer to invest in their local Bell company to the other divisional Bell companies to argue that "familiarity" drives this bias. Shore and White (2002) propose external habit formation as an explanation for the puzzle. 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. Finally, two recent papers have documented community effects in market participation. Hong, Kubik and Stein (2004) 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. 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.

Although we do not perform any direct test on portfolio holdings in this paper,[3] 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. However, it is important to stress two things. First, that the argument behind the portfolio tilt in our paper is neither familiarity nor information, but hedging. Second, the bias will be local only insofar as local assets offer a better hedge to local investors against the risk of deviating from the non-diversifiable income of their peers.

3 The KEEPM

In this section, we present the main testable implications from the KEEPM. For a more detailed derivation, see Gómez, Priestley and Zapatero (2008). We assume a one-period

[3] Brandt (2004) surveys the literature.

economy. Agents in this economy live in a two-division country: they either live in the north, n, or the south, s. There exists a firm that produces a global good, tradable across divisions. Consumption of the global good is denoted by c and takes place at the end of the period, $t = 1$.

In each division, there are two types of agents: "investors" and "workers." At time $t = 0$, investors are endowed with shares of the firm that produces the global good. For simplicity, we normalize the aggregate value of those shares in each division to one. Workers in each division are endowed with human capital that produces a fixed number, $\bar{w}$, of units of the local good at time $t = 1$.[4] Workers face incomplete markets because they cannot trade their human capital (due, for instance, to moral hazard and short-selling constraints) and have no access to financial markets; therefore, they cannot hedge their income risk. In addition to the firm's shares, there are as many zero net supply stocks as needed for financial markets to be complete. Let r denote the stocks excess return with finite moments $E(r)$ and Ω. The bond (in zero net supply) has gross return R.

As mentioned in the introduction, there are two possible ways in which relative wealth concerns may arise in equilibrium: endogenously, via local inflation risk-hedging, and exogenously, whereby investors derive utility from consumption relative to their peers. In the endogenous case, agents' utility over consumption for the 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; $\alpha > 0$ is the relative risk aversion parameter. DeMarzo, Kaniel and Kremer (2004) show that, in equilibrium, the relative price of the local good in terms of the global good at $t = 1$ is given by $p = \delta \left(\frac{c}{\bar{w}}\right)^{\alpha}$. As expected, the scarcer the (fixed) local good endowment relative to the (stochastic) global good consumption, the higher the relative price of the former. Investor's hedging demand

[4] The term "workers" is widely defined in our model: it includes holders of all kind of human capital that materializes, for instance, in wage income or entrepreneurial income.

against this inflationary risk will result in a local portfolio bias.

Let θ represent the relative wealth at $t = 0$ of the division's workers as a proportion of the total division's wealth. Under complete (financial) markets, there exists a portfolio X^w such that the return on the workers wealth (in units of the global good) over the period can be written as $R + r'X^w$. The approximate function for the investor's optimal portfolio in division $k \in \{n, s\}$ will be:

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

where the parameters $b_k = \frac{\alpha_k - 1}{\alpha_k}$ and $\tau_k = 1/\alpha_k$ represent the portfolio bias and the risk-tolerance coefficient, respectively. Notice that 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.

In the exogenous case, the representative investor is endowed with an utility function

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

where C is the division average or per capita consumption and $1 > \gamma \geq 0$ is the "Joneses parameter." For $\gamma > 0$, the constant average consumption elasticity of marginal utility (around the symmetric equilibrium), $\alpha\gamma$, is positive as well: increasing the average consumption per capita C makes the individual's marginal consumption more valuable since it helps her to "keep up with the Joneses." In short, we assume the division's average consumption to be a positive consumption externality.

Gómez, Priestley and Zapatero (2008) show that the investor's optimal portfolio in the exogenous case coincides with equation (1) with parameters $b_k = \frac{\gamma_k}{1-\gamma_k}$ and $\tau_k = \frac{1}{\alpha_k(1-\gamma_k)}$. Hence, whether endogenously or exogenously driven, both specifications lead to the same testable implications in equilibrium, the only difference being the interpretation of the parameters b and τ.

Let ω_k be the weight of division k in the market clearing portfolio, $x_M = (\omega_n, \omega_s)'$, with variance σ_M^2. We regress the workers non-diversifiable wealth return, $r_k^w = r' X_k^w$, onto the market portfolio return plus a constant:

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

Portfolio $\beta_k \, x_M$ represents the projection of the workers income onto the security market line spanned by the market portfolio x_M. Define the portfolio $F_k \equiv X_k^w - \beta_k \, x_M$ as a "residual" factor portfolio with return $r_k^F = r' F_k$, orthogonal to the market portfolio by construction. Define the matrix $\boldsymbol{F}$ of dimension $N \times 3$ as the column juxtaposition of the market portfolio and the orthogonal portfolios, $\boldsymbol{F} \equiv (x_M, F_n, F_s)$.

Given equations (1) and (2), in equilibrium, after market clearing,

$$E(r) = \boldsymbol{\beta} \, \boldsymbol{\lambda}, \tag{3}$$

where $\boldsymbol{\beta} = \Omega \, \boldsymbol{F} \, (\boldsymbol{F}' \Omega \, \boldsymbol{F})^{-1}$ denotes the 2×3 (in general $N \times (1 + K)$, with N the number of assets and K the number of divisions) matrix of betas, with the first column as the market betas for both assets.

This pricing model is the KEEPM, which stands for "KEEping up Pricing Model." The model has testable implications for the risk premia ($\boldsymbol{\lambda}$). In particular, the model predicts:

$$\begin{aligned} \lambda^M &= H \left(1 - \sum_k \omega_k \theta_k \, b_k \, \beta_k \right) \sigma_M^2, \\ \lambda^n &= -H \left(\omega_n \theta_n \, b_n \, \mathrm{Var}(r_n^F) + \omega_s \theta_s \, b_s \, \mathrm{Cov}(r_n^F, r_s^F) \right), \\ \lambda^s &= -H \left(\omega_n \theta_n \, b_n \, \mathrm{Cov}(r_n^F, r_s^F)) + \omega_s \theta_s \, b_s \, \mathrm{Var}(r_s^F) \right), \end{aligned} \tag{4}$$

with $H^{-1} = \sum_k \omega_k \tau_k$ the market-weighted risk-tolerance coefficient. The country market portfolio, x_M, is partially correlated with each division's non-diversifiable risk. This is captured by the coefficient β_k. That correlation offers partial hedging against deviations from the local, non-tradable risk. Furthermore, if there is a relative wealth concern ($b > 0$) in the economy and workers income is not diversifiable ($\theta > 0$), there are two additional risk factors together with the market risk factor. Regarding their sign, the model predicts that if $\text{cov}(r_n^F, r_s^F) > 0$, then λ^n and λ^s will be negative. The intuition for the negative sign is as follows: An asset that has positive covariance with portfolio F_k will hedge the investor in division k from the local, non-diversifiable income risk. The investor will be willing to pay a higher price for this asset thus yielding a lower expected 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 between both zero-beta portfolios is positive, this just increases the absolute value of the negative prices of risk for every division's hedge portfolio.

In summary, the presence of endogenous or exogenous Joneses imply that, besides the market risk premium, investors require a premium for holding stocks with no, or negative, correlation with the non-hedgeable local labor or entrepreneurial income. In addition, investors are willing to give up expected returns (that is, pay a premium) for the stocks that are correlated with the idiosyncratic component of the local risk and, therefore, help them to hedge against this risk. This result depends in a fundamental way on the market friction that prevents some agents (our workers) from participating in the markets.

4 Data description

The model does not specify the dimension of "the peers." Our choice, the nine Census divisions, is motivated by the following arguments. On the one hand, relative wealth concerns should be easier to observe the smaller the geographical area under consideration. On the other hand, since we are interested in the implications of relative wealth concerns on the cross-section of stock returns, we need a geographical area with a number of firms large enough to perform empirical tests. Additionally, we will measure 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 wealth. For smaller geographical areas, the proportion of local wealth relative to the total country wealth $\omega\theta$ is very small, and therefore it is very difficult to capture any statistically relevant effect. Finally, we use the same division sorting as in Hong, Kubik and Stein (2008) so we can more easily compare our findings to theirs.

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. We calculate per capita personal income data at the divisional level using data on annual population in each division (aggregated from state level population data) from the U.S. Census Bureau. 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), and New England (NE).[5] The model predicts that the component of personal income orthogonal to the aggregate stock market return will be priced with a negative risk premium if investors have keeping up with the Joneses preferences, or if there exist local goods in short supply and agents hedge against their price increases.

The data on stock returns and firm characteristics come from CRSP and COMPUSTAT. We consider all firms in COMPUSTAT/CRSP. From CRSP, we obtain stock returns for 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 divisions.

First, we want to study whether there exists a negative risk premium associated with stocks that are highly correlated with orthogonal labor income. Within each division we form a factor mimicking portfolio of the orthogonal component of divisional labor income

[5]We include a map of the nine US Census divisions in Figure 1.

with respect to the market stock returns. The process is described next.

Following equation (2) in the model, we regress the return on divisional personal income 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 equally 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 (2008) 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 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

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

to alleviate this concern we follow the recommendations in Daniel and Titman (2005) and Lewellen, Nagel, and Shanken (2008) 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). In addition, 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 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. Another reason is the fact that 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). 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.

Table 1 reports the mean annualized return of the factor mimicking portfolio returns in each division, 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.[7] 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.[8]

To understand how our model explains why risk premia are larger (in absolute value) in low population divisions 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 ($\mathrm{Var}(r^F)$) 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) concentrated 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. With the exception of MO, there is not a clear distinction in terms of variance between low and high density divisions. The covariances, and in particular the correlations, show that the

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

[8]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.

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.

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, 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 concentrate 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.

5 Time Series Regressions

We begin the empirical analysis with the standard asset pricing test of Black, Jensen and Scholes (1972). 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. In particular, we estimate the following time series regression:

$$r_{i,k,t} = \alpha_{i,k} + \beta_{i,k}^{F} r_{k,t}^{F} + \beta_{i,k}^{erm} r_{erm,t} + \beta_{i,k}^{smb} r_{smb,t} + \beta_{i,k}^{hml} r_{hml,t} + u_{i,k,t} \tag{5}$$

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); $\beta_{i,k}^{F}$ is the estimated factor loading on $r_{k,t}^{F}$, the factor mimicking portfolio of orthogonal local labor income in division k; $\beta_{i,k}^{erm}$ is the estimated factor loading on $r_{erm,t}$ (excess return on the market portfolio); $\beta_{i,k}^{smb}$ is the estimated factor loading on $r_{smb,t}$ (the small-minus-big Fama-French factor); $\beta_{i,k}^{hml}$ 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.

The cross sectional asset pricing implications of the model are assessed by testing whether the estimated intercepts are jointly significantly different from zero. To this end, we use the Gibbons, Ross and Shanken (1989) GRS test:

$$GRS = \frac{T-N-K}{N} \left[1 + \mu' \Omega^{-1} \mu\right]^{-1} \widehat{\alpha}' \Sigma^{-1} \widehat{\alpha} \rightarrow F(N, T-N-K) \tag{6}$$

where T is the number of observations, N is the number of test portfolios, K is the number of factors, μ and Ω are the sample mean and covariance matrix of the factor returns, $\widehat{\alpha}$ is the vector of estimated intercepts, and Σ is the variance-covariance matrix of the time series regression residuals. The term in brackets adjusts for the sampling error in the estimates of the factor loadings.

Table 2 presents the estimates of equation (5). Panel A reports the estimates for the most densely populated division, MA. The coefficients on the factor mimicking portfolio for the local (orthogonal) component of labor income, β^{F}, 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 factor mimicking portfolio and eleven are statistically significant. The estimates, both negative and positive, are large economically and generally decrease monotonically from portfolio 1 to portfolio 20. The patterns in the estimated betas clearly illustrate that the stocks with a high correlation 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. For those stocks that are not highly correlated, and have a negative beta, investors require an additional premium to hold them. These results are consistent with the EHF model and the local good in short supply model.

Columns four to six report the estimates on the *erm*, *smb*, and *hml* factors respectively. In most cases they are statistically significant. Therefore, it appears that the factor mimicking portfolio for the orthogonal component of local (divisional) labor income captures variations in returns that are independent of the Fama-French three factors. Also note that there is no monotonic pattern in the Fama-French three factors across the twenty portfolios, suggesting that local labor income is independent of the Fama-French sources of risk. The adjusted R^2, $\overline{R}^2$, is large, ranging from 0.76 to 0.89, indicating that most of the time series variation in the portfolio returns is captured by the four factors.

In the second column of panel A, we observe that the estimated intercepts are economically small and only statistically significant in three cases, one of them marginally. The GRS test statistic, reported in the final row of panel A cannot reject the null hypothesis that intercepts are jointly zero.

Panel B of Table 2 reports the coefficients on the factor mimicking portfolios, β^F, for the remaining eight divisions. The divisions are listed according to their population density ranking, from highest (first column) to lowest density (last column). The coefficients on the Fama-French factors and the adjusted R^2 are not reported for brevity but follow similar patterns to those on Panel A. They are available from the authors upon request.

In general, the results of the MA division hold on all the other divisions. 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. As noted before, population density is an important factor in the validation of the KEEPM to explain stock returns.

Panel C presents the intercepts (pricing errors) and the GRS test statistic for the same divisions. Only in the SA division it is possible to marginally reject the null hypothesis that all intercepts are jointly zero. For the low population density divisions the intercepts are even smaller, with strong GRS statistics in favor of the null hypothesis that the intercepts are jointly zero. For example, in only one out of seventy regressions covering the low population density divisions is the intercept statistically significant at the 5% level.

An important observation from Table 1 is that the factor mimicking portfolios across the different divisions are highly correlated. So far we have documented differences between divisions with low and high population density. However, given the relatively high interdivisional correlations, it is not clear whether investors are hedging local or global (domestic) risk. With that question in mind, we form a "global" (at the domestic level) mimicking portfolio that is calculated using the methodology previously described, but with the orthogonal component of aggregate (as opposed to divisional) labor income. In other words, we re-estimate equation (2) but using US global (G), aggregate personal income, r_G^w:

$$r_G^w = a_G + \beta_G r_M + \xi_G.$$

We take the residuals from this regression and create the corresponding global factor mimicking portfolio by regressing all stocks, irrespective of division, on the residuals and sorting them into three equally weighted portfolios. Subtracting the bottom one third from the top one third we obtain the time series of quarterly returns of the global factor mimicking portfolio, r_t^G. The annual mean premium, equivalent to Panel A of Table 1, is -5.15% per annum with a t-statistic of 2.55.

In Panel A from Table 3, we report the estimates of the factor loadings on the global factor mimicking portfolio, β^G, for the portfolios of each division with respect to this global mimicking portfolio. As test portfolios, we keep the 20 portfolios per division (10 in ES) from Table 2. The results are very similar to those of Table 2: we find that most estimated coefficients on the global orthogonal labor income factor, β^G, are statistically significant. There are some differences across the low and high population density divisions; in high population density divisions more portfolios have significant negative betas with respect to the global factor mimicking portfolio, and the size of the coefficients tends to be higher than in low population density divisions. This is not the case when we use the local factor, as in Panel B of Table 2. In this case, the low population density divisions have, on average, as many negative betas as the high population density divisions. The unreported $\overline{R}^2$s indicate that the explanatory power of the model is higher for high population density divisions than for low population density divisions when using the global factor mimicking portfolio. Compared to the results in Table 2, in low population density divisions the explanatory power of the model is higher when we include the local, as opposed to the global, factor mimicking portfolio. With regard to the high population density divisions, the unreported $\overline{R}^2$s indicate that the global and local factor mimicking portfolios explain about the same amount of time series variation in returns.[9]

Panel B of Table 3 reports the intercepts as well as the GRS test statistics. The individual intercepts are economically small and the GRS test statistic indicates that the null hypothesis of jointly zero intercepts in each division can not be rejected in any division, except for SA.

Overall, there is not a substantial difference in the performance between the models that include the global versus local factor mimicking portfolios. Perhaps the only distinction between the two models is that the low population density divisions seem to be affected more by the local than the global factor mimicking portfolio. However, from the previous analysis, we cannot conclude whether the risk factor is of a local or global (domestic) nature.

[9]The coefficients on the Fama-French risk factors (not reported) are generally significant, but appear independent of the orthogonal labor income factors we explore here.

6 Cross-Sectional Regressions

The previous section of the paper identified a clear pattern in the beta estimates with respect to local orthogonal labor income. 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: GMM estimation based on the Stochastic Discount Factor (SDF) approach, and the Fama and MacBeth (1973) two-step approach.

6.1 GMM Estimation

The SDF approach states that under the assumption that the law of one price holds there exists a random variable m_t, termed the stochastic discount factor, or pricing kernel, that prices all assets correctly:

$$E_t[m_{t+1}R_{i,t+1}] = 1, \tag{7}$$

where $R_{i,t+1}$ is the gross return on asset i. An asset pricing model that defines one candidate stochastic discount factor is correct if the stochastic discount factor it defines is part of the set of all stochastic discount factors that price assets correctly. Asset pricing models differ simply by how they specify the stochastic discount factor. The stochastic discount factor can be expressed as

$$m = b_0 + \mathbf{bf}, \tag{8}$$

where b_0 is a constant, $\mathbf{b}$ is a vector of coefficients and $\mathbf{f}$ is a vector of risk factors. In the case of our model, we can specify m_k in every division k most simply as:[10]

[10]Hereafter, for the sake of notation simplicity, we suppress the divisional subindex k.

$$m_k = b_{0,k} + b_{erm,k} r_{erm} + b_{F,k} r_k^F. \tag{9}$$

The GMM methodology outlined in Hansen (1982) provides a natural way to test the asset pricing implications of our model. Given the definition of the stochastic discount factor in (9) and taking the unconditional expectation as in (7) gives, for all assets $i = 1, ..., N$

$$E[R_{i,t+1}(b_0 + b_{erm} r_{erm,t+1} + b_F r_{t+1}^F)] = 1.$$

Let $\mathbf{R}_{t+1}$ be a vector of gross returns; subtracting one, we obtain the moment conditions

$$E[\mathbf{R}_{t+1}(b_0 + b_{erm} r_{erm,t+1} + b_F r_{t+1}^F) - 1_N] = 0.$$

Defining the forecast error for the parameter vector $\mathbf{b}$ as $\mathbf{v}_{t+1}(\mathbf{b})$:

$$\mathbf{v}_{t+1}(\mathbf{b}) \equiv \mathbf{R}_{t+1}(b_0 + b_{erm} r_{erm,t+1} + b_F r_{t+1}^F) - 1_N], \tag{10}$$

and the sample mean of the forecast errors over the T observations as:

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

GMM estimates the parameter vector $\mathbf{b}$ that minimizes

$$\widehat{\mathbf{b}} = \arg \min_{(b)} (\mu_T'(\mathbf{b}) \mathbf{W} \mu_T(\mathbf{b})),$$

where $\mathbf{W}$ is a positive definite weighting matrix. 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 $\mathbf{W}$ is the optimal weighting matrix $\mathbf{S}^{-1}$, the asymptotic standard errors are given by:

$$\text{var}(\widehat{\mathbf{b}}) = \frac{1}{T}(\mathbf{D}_T'\mathbf{S}^{-1}\mathbf{D}_T)^{-1},$$

where $\mathbf{D}_T = \frac{\partial \mu_T(\mathbf{b})}{\partial \mathbf{b}'}$.

The ability of the model to price the assets is assessed by testing that the pricing errors, which follow a $\chi^2(N-k)$ distribution, where N is the number of moment conditions, and k the number of parameters, are zero. This is known as Hansen's J-test,

The advantage of the SDF approach in our setting is based on the multicollinearity among the factors.[11] In our case, the SDF approach is particularly useful to evaluate the role of the orthogonal labor income factor in conjunction with the Fama-French factors, and the relative importance of global versus local orthogonal labor income. Under the assumption that the factors are orthogonal, testing whether a factor i is priced ($\lambda_i = 0$) in the traditional Fama-MacBeth framework is the same as testing whether $b_i = 0$. However, as it is the case with most factor models, the factors are correlated, and testing whether $b_i = 0$ asks the question of whether factor i is marginally important in pricing assets, given the other specified factors. 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-tests:

$$TJ(\textit{restricted}) - TJ(\textit{unrestricted}) \sim \chi^2(\#\text{ of restrictions}). \tag{11}$$

[11] Cochrane (1996) and Jagannathan and Wang (2002) consider the small sample properties of the GMM method of estimating the SDF and find that it has about the same performance in finite samples as the Fama-MacBeth methodology.

In our model, we are interested in answering the following three questions: first, does the orthogonal labor income factor help to price the assets ($b_F = 0$)? Second, is it priced ($\lambda_F = 0$)? In order to answer both these questions simultaneously, we follow Cochrane (2005), who notes that:

$$E(m\mathbf{f} - \mathbf{f} + \lambda) = \mathbf{0}, \tag{12}$$

which we can incorporate into the moment condition given by equation (10) to produce efficient estimates of the parameters in the pricing kernel, the vector of prices of risk λ, and their associated standard errors (see Li, Vassalou and Xing (2006)). Thirdly, we would like to know if factor j is important in pricing the assets in the presence of factor k.

Table 4 reports cross-sectional tests of the KEEPM using the GMM framework.[12] The estimates of the coefficients in the pricing kernel, b_F, are statistically significant in three cases. In addition, in six cases the local orthogonal labor income factor commands statistically significant risk premia, all negative, as the theory suggests. Estimates of the risk premia are similar to those of Table 1. As in Table 1, 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 -1.49% per quarter (around -6% per annum). In the high population density divisions the average risk premium is -0.87% per quarter (around -3.5% 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, and only in one case the estimated market risk premium is statistically significant, although with a negative sign, as in a total of four cases. 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)). In contrast, orthogonal local labor income is an important

[12]As ES has only ten portfolios, we do not report the results related to this division in this Table. In Table 7 we report results using 10 portfolios in all divisions.

determinant of average returns.

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 4 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.

Figure 2 plots the expected average returns predicted by the model against the actual realized returns. Also plotted in each figure is a 45° line along which the assets should lie. With the exception of NE, it appears that the model does a reasonable job in describing the returns on the twenty portfolios of assets in each division. In most cases the plots reveal that the asset returns approximately follow the 45° line.

The second row from the bottom of Table 4 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 hml factors as compared to 0.49% per quarter for the KEEPM. Therefore, while the betas with respect to smb and hml factors are generally important in the time series regressions reported in Table 2, they do not help in the pricing of the assets. 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 the 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, and one division with a marginally significant estimate of the 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 4 which reports the ΔJ statistic that tests the null hypothesis that the *smb* and *hml* factors are not important in pricing the assets. In five 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.

6.1.1 The Role of Local and Global Labor Income

We now assess the relative importance of global and local orthogonal labor income. As noted in the discussion of Table 3, orthogonal global labor income seems to be able to price the assets as effectively as orthogonal local labor income, although there is some difference across low and high population density divisions, since local orthogonal labor income appears more important in the low population density divisions.

With the objective of trying to distinguish between these two sources of risk in mind, we expand the pricing kernel to include in each division k both global and local orthogonal labor income, and estimate:

$$m_k = b_{0,k} + b_{erm,k} r_{erm} + b_{F,k} r_k^F + b_{G,k} r^G, \tag{13}$$

where r^G is the factor mimicking portfolio for global orthogonal labor income. Simultaneously, we estimate the corresponding risk premia on the factors.

Table 5 presents the results, including ten portfolios for the ES division. Neither the global orthogonal labor income factor, nor any of the coefficients on the local orthogonal labor income factors (except NE) are significant in the pricing kernel. However, whereas the risk premium associated with the global orthogonal labor income is not significant, in six cases (one marginally) the risk premia associated with the local orthogonal labor income are statistically significant.

The J-test accepts the model in all but one case (SA). The average absolute pricing error across all nine divisions is 0.59% per quarter, somewhat higher than the model that excludes the global orthogonal labor income factor. The final row of Table 5 reports the ΔJ statistic, which tests the null hypothesis that the global 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 5 that adding global labor income to the KEEPM with local orthogonal labor income does not improve the model. These results indicate that local risk-hedging dominates over global domestic hedging of non-diversifiable wealth which lends indirect support to the local portfolio bias implications of the model.

6.1.2 Additional Portfolios

In our next test, 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 6 reports estimates of the coefficients in the pricing kernel. In all cases except the ES division, the estimates of b_F are statistically significant, confirming that local orthogonal labor income helps explain the test assets in all but one division. In comparison to Table 4, 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 to 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 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 6 reports the average absolute pricing error when we include the *smb* and *hml* factors, 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 6 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 4, 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.

6.1.3 Number of 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 7 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 4 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 7 with 10 portfolios as test assets.

Figure 3 plots the expected average returns predicted by the model against actual returns. Also plotted in each figure is a 45° line along which the assets should lie. Consistent with the use of only twenty portfolios (see Figure 2), it appears that with the exception of NE, the model does an excellent job in describing the returns on the ten portfolios of assets. Relative to the model with twenty portfolios, these plots reveal a closer fit, which is reflected in the smaller pricing errors discussed earlier.

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.

6.2 Fama-MacBeth Regressions

In order to assess the robustness of the results from the estimation of the stochastic discount factor, we also use the traditional cross-sectional methodology of Fama and MacBeth (1973). In particular, we consider the following pricing equation for the expected return of each portfolio in a given division,

$$E(r_{i,k}) = \lambda^0 + \lambda_k^F \beta_{i,k}^F + \lambda^{erm} \beta_{i,k}^{erm}, \tag{14}$$

where, following the notation of equation (5), $E(r_{i,k})$ is the expected return on portfolio i in division k; λ_k^F is the price of risk associated with the orthogonal local (divisional) labor income; $\beta_{i,k}^F$ is the coefficient on $r_{k,t}^F$, the factor mimicking portfolio for division k; λ^{erm} is the market price of risk; $\beta_{i,k}^{erm}$ is the coefficient on r_t^{erm}.

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 is 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 is 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 (2001) for quarterly data over a relatively short time series sample such as ours, and discussed in Cochrane (2005).

As in the previous tests of the cross-sectional performance of the KEEPM, we first consider whether the estimated risk premia on the factor mimicking portfolios for orthogonal local labor income are negative and statistically significant and, in addition, if they can explain the variation in returns across the test assets. In Table 8 we report the percentage average risk premia per quarter for the twenty portfolios of each division. We do not report the results for division ES because we only have ten portfolios.

It is evident from Table 8 that the estimated risk premia on the orthogonal local labor income risk factors are negative in all divisions, and statistically significant in the low density regions. It is also marginally significant in high population density divisions NE, SA and EN, although the estimated risk premia are smaller than in the low population density divisions (the average estimated risk premium is -0.81 in the high population density divisions and -1.43 in the low population density divisions). In terms of the estimated risk premia on the orthogonal local labor income factors, the results from the Fama-MacBeth cross-sectional regressions are consistent with the estimates from the GMM methodology.

We report the adjusted R^2 ($\overline{R}^2$) for the model.[13] These range from 0.16 in NE (the division which consistently had a high pricing error in the GMM tests) to a high of 0.81 in EN. The average is 0.44, reasonable for a two factor model. Unreported pricing errors

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

are similar to those from the time-series regressions in Table 2 and the GMM regressions in Table 3. Overall, the results in Table 8 that use the Fama-MacBeth methodology are entirely consistent with the results of the GMM methodology.

We also assess the role of local and global orthogonal labor income using the Fama-MacBeth methodology. On the right-hand side of equation (14) we include, division by division, both the local orthogonal labor income factor (proxied by the corresponding mimicking portfolio) and the global orthogonal labor income factor, common to all regions (and proxied by the corresponding mimicking portfolio). Table 9 reports our findings. In the three divisions with low population density the risk premium on the local orthogonal labor income factor is statistically significant. The estimated risk premium is marginally significant in three of the divisions with high population density. As in the case of the GMM estimates in Table 5, none of the global orthogonal labor income factors are statistically significant. Thus, the Fama-MacBeth results reported in Table 9 are consistent with the earlier findings that local orthogonal labor income is the major driver of the cross-section variation of stock returns.

As a final robustness test of the Fama-MacBeth methodology, Table 10 includes book-to-market portfolios as additional test assets. In this case, all divisions have a statistically significant risk premium estimate (marginally so in SA). This supports the previous GMM results that the inclusion of the book-to-market factor strengthens the hypothesis of a KEEPM effect.

7 Conclusions

Relative wealth concerns can lead to an equilibrium in which securities that load on a local non-diversifiable risk factor have a negative risk premium. This premium reflects the price investors are willing to pay to keep up with the Joneses. It may arise in equilibrium either endogenously (via local price inflation risk-hedging) or exogenously (preference driven: people directly care about relative consumption). Either way, an approximate multifactor asset pricing model arises: the KEEPM ("KEEping up Pricing Model").

We consider the impact of relative wealth for portfolios of securities for the nine US Census divisions, and use labor income return as a source of non-diversifiable local risk. We test our model using different methodologies and we consistently find strong empirical support: prices of risk for the local non-diversifiable risk are negative and often statistically significant across divisions.

We also report that the size (in absolute terms) of the prices of risk are larger for those divisions with smaller population density. This is related to the finding in Hong, Kubik and Stein (2008), who show that population density is negatively correlated with stock prices. A possible explanation is that relative wealth concerns are stronger in areas with low population density because, for example, it is easier to identify the reference group (the "Joneses") with respect to which each particular investor has relative wealth concerns. Alternatively, lower density may imply higher concentration of assets in short supply (like human capital) and, therefore, a stronger desire to hedge the corresponding inflationary risk.

An important issue that arises in our analysis is whether the non-diversifiable labor income factor is truly local (division-specific) or global (domestic). They are highly correlated, therefore it is not straightforward to sort out if there is an additional local effect over the effect of the global labor income factor. We analyze this problem in our cross-sectional tests, both in the context of a GMM estimation of the coefficient of the stochastic discount factor and in the two-step method of Fama and MacBeth (1973). Both types of tests provide evidence that the local factor is relevant above and beyond the systematic component in the global (domestic factor). This effect is more pronounce for divisions with low population density, consistent with the hypothesis that the keeping up with the Joneses effect is stronger there.

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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)
r_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

There are nine Census Bureau Divisions: 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. In each division, stocks are sorted into twenty equally weighted portfolios (except for the ES division with only ten portfolios) according to their coefficient on the divisional orthogonal labor return; from P1 (highest coefficient) through P20 (lowest coefficient). The following time series regression is estimated:

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

where $r_{i,k,t}$ is the excess return on portfolio i ($i = 1, ..20$) from division k ($k = 1, ..9$) at time t; $\alpha_{i,k}$ is the division-specific constant; $\beta_{i,k}^{F}$ is the estimated factor loading on $r_{k,t}^{F}$, the factor mimicking portfolio for orthogonal local labor income in division k; $\beta_{i,k}^{erm}$ is the estimated factor loading on $r_{erm,t}$ (excess return on the market portfolio); $\beta_{i,k}^{smb}$ is the estimated factor loading on $r_{smb,t}$ (the small-minus-big Fama-French factor); $\beta_{i,k}^{hml}$ 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. Panel A presents the estimated α and βs (t-values in parenthesis) for division MA. ***, ** and * denote statistically significance at, respectively, the 1%, 5% and 10%. $\bar{R}^2$ represents the adjusted R^2. GRS is the Gibbons, Ross and Shanken (1989) joint test on the intercepts (p-value in brackets). Panels B presents the estimated coefficient β^F for the remaining divisions; Panel C reports the estimated intercepts, α, and GRS statistics.

Panel A: MA

	α	β^F	β^{erm}	β^{smb}	β^{hml}	$\bar{R}^2$
P1	-0.009	0.419***	0.999***	1.380***	0.093	0.76
P2	-0.001	0.384***	0.839***	1.141***	0.137	0.76
P3	-0.001	0.409***	0.875***	0.992***	0.170***	0.85
P4	0.001	0.271***	0.879***	0.974***	0.111	0.77
P5	-0.005	0.276***	0.873***	0.885***	0.307***	0.78
P6	-0.002	0.174***	0.828***	0.702***	0.224***	0.82
P7	-0.008***	0.167***	0.815***	0.729***	0.345***	0.85
P8	-0.008**	0.107	0.896***	0.789***	0.389***	0.82
P9	-0.001	-0.149**	0.812***	0.583***	0.298***	0.81
P10	-0.005	-0.227***	0.921***	0.530***	0.429***	0.84
P11	0.001	-0.283***	0.798***	0.718***	0.389***	0.85
P12	-0.006*	-0.092	0.896***	0.765***	0.399***	0.87
P13	-0.004	-0.134*	0.879***	0.878***	0.362***	0.85
P14	-0.002	-0.553***	0.798***	0.705***	0.266***	0.85
P15	-0.005	-0.408***	0.886***	0.821***	0.329	0.88
P16	-0.004	-0.770***	0.818***	0.878***	0.296***	0.87
P17	0.000	-0.698***	0.859***	0.972***	0.066	0.89
P18	0.001	-0.691***	0.843***	0.971***	0.213***	0.87
P19	-0.007	-0.582***	0.992***	1.110***	0.218**	0.86
P20	-0.009	-1.076***	0.956***	1.368***	0.041	0.87
GRS Test	1.316 [0.21]					

Panel B

	NE	**SA**	**EN**	**PA**	**ES(L)**	**WS(L)**	**WN(L)**	**MO(L)**
	β^F	β^F	β^F	β^F	β^F	β^F	β^F	β^F
P1	0.811***	0.626***	0.580***	0.599***	0.656***	0.797***	0.719***	0.798***
P2	0.536***	0.481***	0.691***	0.380***	0.412***	0.971***	0.443***	0.575***
P3	0.540***	0.358***	0.361***	0.291***	0.185***	0.845***	0.554***	0.479***
P4	0.369***	0.328***	0.233***	0.179**	-0.029	0.708***	0.335***	0.359***
P5	0.334***	0.150*	0.304***	0.162**	-0.066	0.568***	0.471***	0.063
P6	0.083	0.154	0.078	0.134*	-0.162	0.479***	0.232***	0.244**
P7	0.109	0.028	-0.031	0.061	-0.239**	0.566***	0.212**	-0.024
P8	0.073	0.113	-0.084	-0.111	-0.667***	0.388***	-0.239***	-0.039
P9	0.075	-0.001	-0.179**	-0.144*	-0.183*	0.350***	-0.060	-0.382***
P10	0.108	-0.077	-0.287***	-0.093	-0.852	0.216***	-0.074	-0.236***
P11	-0.163*	-0.140	-0.327***	-0.156		0.229***	-0.352***	-0.257***
P12	-0.039	-0.286***	-0.221	-0.434***		0.088	-0.292***	0.017
P13	-0.159	-0.083***	-0.432***	-0.282***		0.037	-0.309***	-0.224**
P14	-0.400***	-0.381***	-0.573***	-0.269***		0.065	-0.202**	-0.468
P15	-0.984***	-0.463***	-0.634***	-0.692***		-0.191**	-0.503***	-0.564***
P16	-0.426***	-0.614***	-0.399***	-0.767***		-0.244***	-0.665***	-0.462***
P17	-0.405***	-0.445***	-0.399***	-0.568***		-0.226**	-0.561***	-0.869***
P18	-0.461***	-0.820***	-0.709***	-0.728***		-0.346***	-0.431***	-0.670***
P19	-0.416***	-0.746***	-0.742***	-0.808***		-0.437***	-0.500***	-0.703***
P20	-0.663***	-1.216***	-0.861***	-1.053***		-0.439***	-0.743***	-0.611***

Panel C

	NE	SA	EN	PA	ES(L)	WS(L)	WN(L)	MO(L)
	α	α	α	α	α	α	α	α
P1	-0.010	-0.009	-0.002	-0.005	-0.001	-0.007	-0.003	-0.005
P2	0.000	-0.008	0.001	0.001	0.001	-0.006	-0.001	-0.004
P3	0.008	-0.001	-0.006	0.000	-0.005	-0.001	0.003	-0.015*
P4	0.002	-0.011***	-0.007**	-0.004	-0.002	0.001	0.004	-0.005
P5	-0.005	-0.003	-0.006*	0.004	-0.002	0.000	0.003	-0.005
P6	-0.010**	-0.010**	-0.007**	-0.007	-0.001	-0.004	-0.005	-0.009
P7	-0.002	0.001	-0.002	-0.002	0.005	-0.002	-0.008	-0.007
P8	0.007	-0.011***	-0.005*	-0.004	0.003	-0.002	-0.012***	-0.007
P9	-0.004	-0.001	-0.005*	0.004	-0.007	-0.001	-0.003	-0.005
P10	-0.004	0.004	-0.004	0.002	0.014*	0.005	0.004	-0.005
P11	-0.006	-0.001	-0.006*	0.001		0.005	-0.003	-0.011
P12	-0.008*	-0.007	-0.005	0.005		0.006	-0.009	-0.010
P13	-0.002	-0.005	-0.003	-0.004		0.001	-0.001	-0.003
P14	-0.003	-0.006	-0.002	-0.003		0.002	0.005	-0.012
P15	0.0182**	-0.007	-0.007*	-0.001		-0.005	-0.000	-0.015
P16	0.001	-0.002	-0.004	0.003		-0.001	-0.001	0.001
P17	-0.006	-0.007	-0.003	-0.017***		0.004	-0.001	-0.004
P18	-0.013**	0.004	-0.005	0.001		0.001	-0.001	0.001
P19	0.001	-0.013*	-0.001	-0.010		-0.011	0.007	-0.000
P20	-0.011	-0.014*	-0.005	0.002		-0.001	-0.007	-0.013
GRS	1.477 [0.10]	1.628 [0.06]	0.562 [0.93]	1.133 [0.32]	1.101 [0.36]	0.508 [0.96]	0.961 [0.51]	0.605 [0.90]

Table 3
Regression of Excess Returns on the Global Mimicking Portfolio

There are nine Census Bureau Divisions: 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. In each division, stocks are sorted into twenty equally weighted portfolios (except for the ES division with only ten portfolios) according to their coefficient on the divisional orthogonal labor return; from P1 (highest coefficient) through P20 (lowest coefficient). The following time series regression is estimated:

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

where $r_{i,k,t}$ is the excess return on portfolio i ($i = 1, ..20$) from division k ($k = 1, ..9$) at time t; $\alpha_{i,k}$ is the division-specific constant; $\beta^{G}_{k,i}$ is the estimated factor loading on r^{G}_{t}, the global factor mimicking portfolio for orthogonal local labor income in the US; $\beta^{erm}_{i,k}$ 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. Panel A presents the estimated slope coefficient β^{G} for all divisions. Panel B reports the estimated intercepts, α. ***, ** and * denote statistically significance at, respectively, the 1%, 5% and 10%. GRS is the Gibbons, Ross and Shanken (1989) joint test on the intercepts (p-value in brackets).

Panel A

	MA	NE	SA	EN	PA	ES(L)	WS(L)	WN(L)	MO(L)
	β^G	β^G	β^G	β^G	β^G	β^G	β^G	β^G	β^G
P1	0.528***	0.811***	0.389*	0.271***	0.495***	0.445***	0.817***	0.674***	1.112***
P2	0.471***	0.536***	0.375***	0.461***	0.223*	0.117	1.021***	0.434***	0.811***
P3	0.435***	0.540***	0.284***	0.246***	0.121	0.112	1.045***	0.477***	0.517***
P4	0.381***	0.369***	0.257***	0.106	0.070	-0.205*	0.898***	0.197*	0.520***
P5	0.374***	0.334***	0.068	0.140*	0.175*	-0.435***	0.640***	0.411***	0.067
P6	0.243***	0.083	-0.177*	-0.047	-0.054	-0.737***	0.485***	0.356***	0.222
P7	0.263***	0.109	-0.166***	-0.159**	0.054	-0.305***	0.621***	-0.071	0.019
P8	0.220***	0.073	0.020	-0.053	-0.222**	-0.049	0.520***	-0.422***	0.112
P9	-0.072	0.075	-0.052	-0.202***	-0.270***	-0.132	0.482***	-0.226***	-0.042
P10	-0.136*	0.108	-0.102	-0.343***	-0.416***	-0.471	0.329***	-0.124	-0.430***
P11	-0.216***	-0.163*	-0.243**	-0.418***	-0.421***		0.246**	-0.427***	-0.468***
P12	-0.025	-0.039	-0.428***	-0.316***	-0.656***		-0.011	-0.325***	0.371*
P13	-0.042	-0.159	-0.123	-0.489***	-0.480***		0.033	-0.416***	-0.304
P14	-0.429***	-0.400***	-0.542***	-0.515***	-0.459***		0.186	-0.412***	0.001
P15	-0.295***	-0.984***	-0.316***	-0.616***	-1.036***		-0.120	-0.494***	-0.418*
P16	-0.585***	-0.426***	-0.534***	-0.362***	-0.751***		-0.541***	0.018	-0.239
P17	-0.570***	-0.405***	-0.227**	-0.562***	-0.727***		-0.334**	-0.473***	-1.041***
P18	-0.601***	-0.461***	-0.819***	-0.541***	-0.750***		-0.473***	-0.305**	-0.686***
P19	-0.483***	-0.416***	-0.734***	-0.688***	-1.026***		-0.748***	-0.536***	-0.106
P20	-0.934***	-0.663***	-1.009***	-0.631***	-1.199***		-0.421***	-0.884***	-0.148

Panel B

	MA	NE	SA	EN	PA	ES(L)	WS(L)	WN(L)	MO(L)
	α	α	α	α	α	α	α	α	α
P1	-0.009	-0.010	-0.007	-0.002	-0.005	0.001	-0.008	-0.008	-0.007
P2	-0.001	0.000	-0.007	0.001	0.001	0.002	-0.007	-0.004	-0.006
P3	-0.000	0.008	-0.000	-0.006	0.000	-0.005	-0.002	0.000	-0.017*
P4	0.001	0.002	-0.009**	-0.007**	-0.004	-0.003	0.001	0.002	-0.006
P5	-0.005	-0.005	-0.003	-0.006*	0.004	-0.004	0.000	0.000	-0.005
P6	-0.002	-0.010**	-0.010**	-0.007**	-0.007	-0.005	-0.004	-0.006	-0.009
P7	-0.008***	-0.002	0.000	-0.003	-0.002	0.004	0.001	-0.009	-0.007
P8	-0.008**	0.007	-0.012***	-0.005*	-0.004	0.001	-0.002	-0.011**	-0.007
P9	-0.002	-0.004	-0.001	-0.006*	0.004	-0.008	-0.001	-0.004	-0.002
P10	-0.005	-0.004	0.004	-0.004	0.003	0.017*	0.005	0.005	-0.004
P11	0.000	-0.006	-0.001	-0.007**	0.002		0.005	-0.001	-0.009
P12	-0.007**	-0.008*	-0.009*	-0.006*	0.006		0.006	-0.008	-0.009
P13	-0.004	-0.002	-0.006	-0.004	-0.004		0.001	0.001	-0.002
P14	-0.004	-0.003	-0.008	-0.003	-0.003		0.002	0.006	-0.009
P15	-0.006	0.0182**	-0.008	-0.008**	-0.000		-0.005	0.003	-0.012
P16	-0.005	0.001	-0.000	-0.006	0.003		-0.001	0.002	0.003
P17	-0.001	-0.006	-0.009*	-0.004	-0.017***		0.004	0.002	-0.000
P18	0.000	-0.013**	0.000	-0.006	0.009		0.001	-0.001	0.005
P19	-0.008	0.001	-0.016**	-0.003	-0.010		-0.011	0.010	0.005
P20	-0.009	-0.011	-0.017**	-0.006	0.002		-0.000	-0.003	-0.009
GRS	1.316	1.477	1.720	0.656	1.065	0.420	0.451	1.015	0.519
	[0.18]	[0.10]	[0.04]	[0.85]	[0.39]	[0.99]	[0.98]	[0.44]	[0.96]

Table 4
GMM Cross-Sectional Tests of KEEPM

There are nine Census Bureau Divisions: 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. This table presents the GMM estimates of the following pricing equation:

$$E[R_{i,t+1}(b_0 + b_{erm} r_{erm,t+1} + b_F r^F_{t+1})] = 1.$$

where $R_{i,t+1}$ is the gross return on asset i, b_0 is the intercept, b_{erm} is the loading on the market factor, $r_{erm,t+1}$ is the return on the market portfolio, b_F is the loading corresponding to the orthogonal component of local labor income, and r^F_{t+1} is the local labor income return. In the table, λ_F is the risk premium corresponding to the local orthogonal labor income factor, and λ_{erm} is the 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	WS(L)	WN(L)	MO(L)
b_0	0.963	0.996	1.010	1.037	0.951	0.973	1.041	1.0417
	(23.99)	(30.52)	(22.94)	(25.99)	(24.84)	(28.58)	(23.19)	(22.92)
b_F	1.893	3.598	1.422	1.926	1.937	2.391	1.882	2.303
	(1.22)	(2.66)	(0.76)	(1.09)	(1.23)	(2.29)	(1.41)	(2.42)
b_{erm}	1.005	0.643	−1.157	−2.335	1.569	1.485	−2.281	0.084
	(0.48)	(0.36)	(0.42)	(0.06)	(0.63)	(0.81)	(1.15)	(0.04)
λ_F	−0.590	−1.179	−1.010	−0.738	−0.820	−1.519	−1.165	−1.799
	(1.23)	(2.70)	(1.93)	(2.11)	(1.33)	(2.29)	(2.41)	(2.61)
λ_{erm}	−0.207	0.224	1.248	1.961	−0.442	−0.517	2.076	0.373
	(0.16)	(0.19)	(0.82)	(1.60)	(4.20)	(0.48)	(1.58)	(0.26)
J	17.562	21.806	28.796	7.774	16.617	11.436	15.415	7.675
	[0.06]	[0.19]	[0.04]	[0.97]	[0.48]	[0.83]	[0.56]	[0.97]
aape	0.233	1.397	0.495	0.215	0.336	0.409	0.405	0.485
aape FF	1.077	1.942	0.630	0.260	0.535	0.660	0.430	0.720
ΔJ	5.189	1.401	7.660	1.348	2.361	3.791	0.273	0.556
	[0.02]	[0.23]	[0.01]	[0.25]	[0.13]	[0.05]	[0.60]	[0.46]

Table 5
GMM Cross-Sectional Tests of KEEPM Including Global Labor Income

There are nine Census Bureau Divisions: 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. This table presents the GMM estimates of the following pricing equation:

$$E[R_{i,t+1}(b_0 + b_{erm}r_{erm,t+1} + b_F r^F_{t+1} + b_G r^G_{t+1})] = 1.$$

where where $R_{i,t+1}$ is the gross return on asset i, b_0 is the intercept, b_{erm} is the loading on the market factor, $r_{erm,t+1}$ is the return on the market portfolio, b_F is the loading corresponding to the orthogonal component of local labor income, and r^F_{t+1} is the local labor income return, b_G is the loading corresponding to the orthogonal component of global (domestic) labor income, and r^G_{t+1} is the global labor income return. In the table, λ_F is the risk premium corresponding to the local labor income factor, λ_G is the risk premium corresponding to the global (domestic) labor income factor, and λ_{erm} is the 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. ΔJ is the statistic that compares our baseline model and the model augmented with the global (domestic) labor income factor.

	MA	NE	SA	EN	PA	ES(L)	WS(L)	WN(L)	MO(L)
b_0	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)
b_F	−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)
b_G	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)
b_{erm}	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	−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 6
GMM Cross-Sectional Tests of KEEPM Augmented with Book-to-Market Portfolios

There are nine Census Bureau Divisions: 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. This table presents the GMM estimates of the following pricing equation:

$$E[R_{i,t+1}(b_0 + b_{erm} r_{erm,t+1} + b_F r^F_{t+1})] = 1.$$

where $R_{i,t+1}$ is the gross return on asset i, b_0 is the intercept, b_{erm} is the loading on the market factor, $r_{erm,t+1}$ is the return on the market portfolio, b_F is the loading corresponding to the orthogonal component of local labor income, and r^F_{t+1} is the local labor income return. In the table, λ_F is the risk premium corresponding to the local orthogonal labor income factor, and λ_{erm} is the 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)
b_0	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)
b_F	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)
b_{erm}	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	−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 7
GMM Cross-Sectional Tests of KEEPM with Ten Portfolios

There are nine Census Bureau Divisions: 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. This table presents the GMM estimates of the following pricing equation:

$$E[R_{i,t+1}(b_0 + b_{erm}r_{erm,t+1} + b_F r^F_{t+1})] = 1.$$

where $R_{i,t+1}$ is the gross return on asset i, b_0 is the intercept, b_{erm} is the loading on the market factor, $r_{erm,t+1}$ is the return on the market portfolio, b_F is the loading corresponding to the orthogonal component of local labor income, and r^F_{t+1} is the local labor income return. In the table, λ_F is the risk premium corresponding to the local orthogonal labor income factor, and λ_{erm} is the risk premium corresponding to the market factor. J represents the Jtest 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)
b_0	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)
b_F	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)
b_{erm}	−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	−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 8
Fama-MacBeth Cross-Sectional Tests of KEEPM

There are nine Census Bureau Divisions: 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. This table presents the Fama and MacBeth (1973) estimates for the prices of risk (t-values in parenthesis) in the cross-section model. In particular, we consider the following pricing equation for the expected return of each stock or portfolio in a given division,

$$E(r_{i,k}) = \lambda^0 + \lambda_k^F \beta_{i,k}^F + \lambda^{erm} \beta_{i,k}^{erm},$$

where $E(r_{i,k})$ is the expected return on portfolio i in division k; λ_k^F is the price of risk associated with the orthogonal local (divisional) labor income; $\beta_{i,k}^F$ is the coefficient on $r_{k,t}^F$, the factor mimicking portfolio for division k. λ^{erm} is the market price of risk; $\beta_{i,k}^{erm}$ is the coefficient on r_t^{erm}. t-values in parenthesis. The model predicts that $\lambda_k^F < 0$. $R^2 = [Var_c(\overline{r}_i) - Var_c(\overline{e}_i)]/Var_c(\overline{r}_i)$, 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. ES is not reported because there are not enough securities to form twenty portfolios.

	MA	NE	SA	EN	PA	ES(L)	WS(L)	WN(L)	MO(L)
λ^0	1.425	1.986	2.442	−0.632	2.648		2.473	0.401	1.590
	(1.23)	(1.66)	(1.34)	(0.52)	(1.71)		(2.24)	(0.32)	(1.05)
λ^F	−0.729	−0.876	−0.887	−0.639	−0.890		−1.549	−1.000	−1.738
	(1.47)	(1.84)	(1.64)	(1.73)	(1.42)		(2.27)	(1.99)	(2.41)
λ^{emr}	0.425	0.215	−0.867	2.552	−0.363		−0.247	1.569	−0.126
	(0.29)	(0.16)	(0.39)	(1.70)	(0.23)		(0.18)	(1.04)	(0.07)
$\overline{R}^2$	0.55	0.16	0.30	0.81	0.32		0.42	0.42	0.53

Table 9
Fama-MacBeth Cross-Sectional Tests of KEEPM Using Local and Global Factors

There are nine Census Bureau Divisions: 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. This table presents the Fama and MacBeth (1973) estimates for the prices of risk (t-values in parenthesis) in the cross-section model. In particular, we consider the following pricing equation for the expected return of each stock or portfolio in a given division,

$$E(r_{i,k}) = \lambda^0 + \lambda_k^F \beta_{i,k}^F + \lambda_k^G \beta_{i,k}^G + \lambda^{erm} \beta_{i,k}^{erm},$$

where $E(r_{i,k})$ is the expected return on portfolio i in division k; λ_k^F is the price of risk associated with the orthogonal local (divisional) labor income; $\beta_{i,k}^F$ is the coefficient on $r_{k,t}^F$, the factor mimicking portfolio for division k; λ_k^G is the price of risk associated with the orthogonal global (domestic) labor income; $\beta_{i,k}^G$ is the coefficient on $r_{k,t}^G$, the factor mimicking portfolio for the global (domestic) orthogonal risk factor. λ^{erm} is the market price of risk; $\beta_{i,k}^{erm}$ is the coefficient on r_t^{erm}. t-values in parenthesis. The model predicts that $\lambda_k^F < 0$. $R^2 = [Var_c(\overline{r}_i) - Var_c(\overline{e}_i)] / Var_c(\overline{r}_i)$, 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. ES is not reported because there are not enough securities to get adequate variation in the cross-section of returns.

	MA	NE	SA	EN	PA	ES(L)	WS(L)	WN(L)	MO(L)
λ^0	1.487	2.022	2.549	−0.300	2.739		2.309	0.381	1.568
	(1.32)	(1.64)	(1.35)	(0.22)	(1.65)		(1.88)	(0.31)	(1.06)
λ^F	−0.725	−0.866	−0.891	−0.635	−0.889		−1.571	−1.004	−1.726
	(1.47)	(1.82)	(1.64)	(1.72)	(1.41)		(2.31)	(1.99)	(2.39)
λ^G	−0.718	−0.265	−0.535	−1.280	−0.450		−0.722	−0.811	−1.183
	(0.71)	(0.33)	(0.69)	(1.32)	(0.51)		(1.11)	(0.88)	(1.11)
λ^{erm}	0.241	0.419	−0.947	2.009	−0.390		0.028	1.747	−0.357
	(0.14)	(0.31)	(0.44)	(0.93)	(0.25)		(0.02)	(1.16)	(0.21)
$\overline{R}^2$	0.55	0.16	0.30	0.81	0.32		0.66	0.42	0.56

Table 10
Fama-MacBeth Cross-Sectional Tests of KEEPM augmented with Book-to-Market Portfolios

There are nine Census Bureau Divisions: 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. This table presents the Fama and MacBeth (1973) estimates for the prices of risk (t-values in parenthesis) in the cross-section model. In particular, we consider the following pricing equation for the expected return of each stock or portfolio in a given division,

$$E(r_{i,k}) = \lambda^0 + \lambda_k^F \beta_{i,k}^F + \lambda^{erm} \beta_{i,k}^{erm},$$

where $E(r_{i,k})$ is the expected return on portfolio i in division k; λ_k^F is the price of risk associated with the orthogonal local (divisional) labor income; $\beta_{i,k}^F$ is the coefficient on $r_{k,t}^F$, the factor mimicking portfolio for division k. λ^{erm} is the market price of risk; $\beta_{i,k}^{erm}$ is the coefficient on r_t^{erm}. t-values in parenthesis. The model predicts that $\lambda_k^F < 0$. $R^2 = \left[Var_c(\overline{r}_i) - Var_c(\overline{e}_i)\right] / Var_c(\overline{r}_i)$, 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. ES is not reported because there are not enough securities to get adequate variation in the cross-section of returns.

	MA	NE	SA	EN	PA	ES(L)	WS(L)	WN(L)	MO(L)
λ^0	2.347	3.806	4.337	−0.061	3.267		3.267	2.105	−0.213
	(2.12)	(3.22)	(3.56)	(0.06)	(2.50)		(2.50)	(1.87)	(0.10)
λ^F	−1.429	−1.533	−1.082	−1.111	−1.416		−2.103	−1.166	−1.258
	(2.41)	(2.96)	(1.84)	(2.59)	(2.09)		(2.96)	(2.17)	(1.97)
λ^{erm}	−1.079	−1.781	−3.215	1.530	−1.218		−1.282	−0.361	−2.238
	(0.85)	(1.47)	(2.49)	(1.17)	(0.94)		(0.97)	(0.28)	(1.65)
$\overline{R}^2$	0.54	0.27	0.71	0.46	0.37		0.41	0.19	0.49

Figure 1: US Census Regions and Divisions.

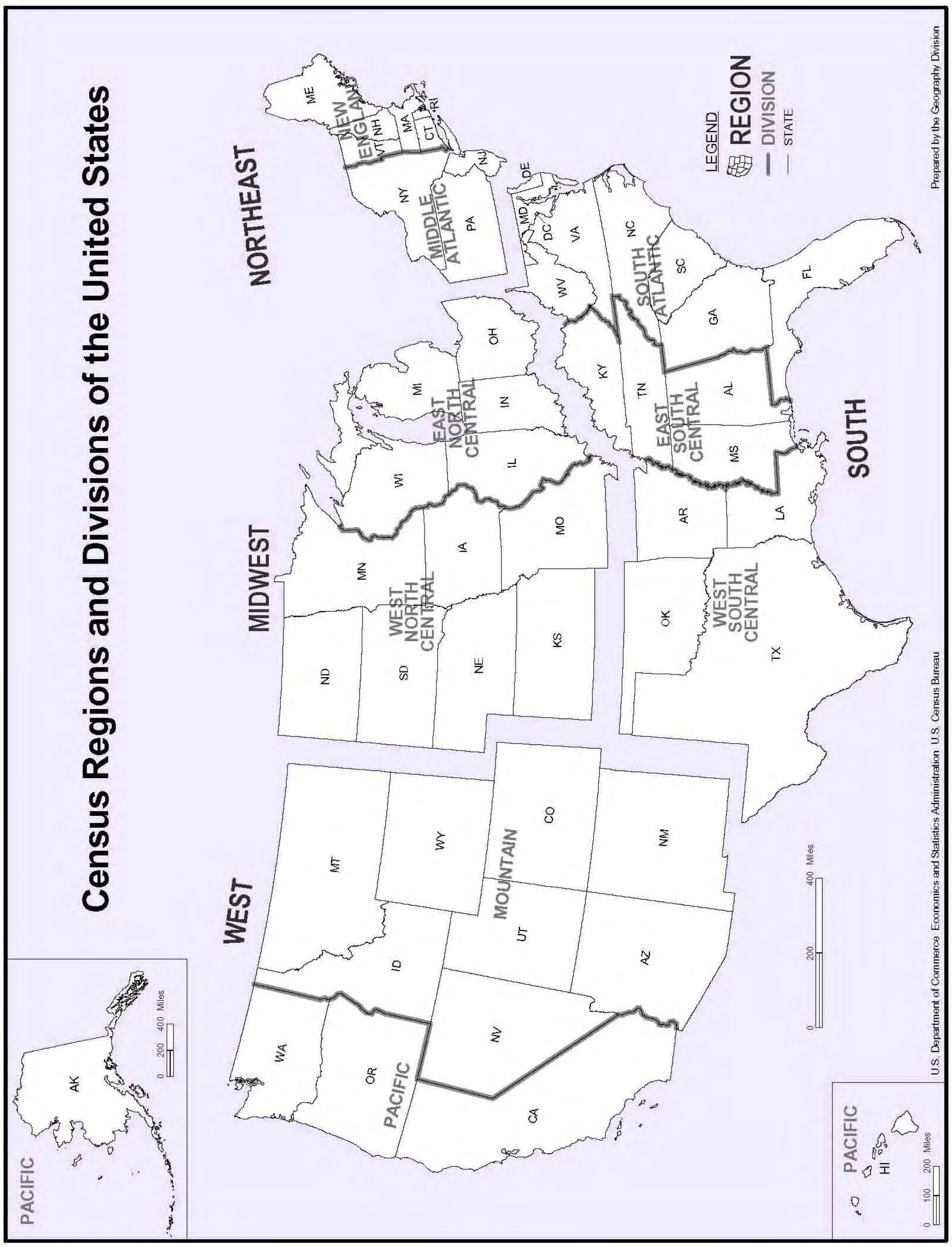

Figure 2: Expected vs. Actual Mean Returns, GMM estimates, 20 portfolios.

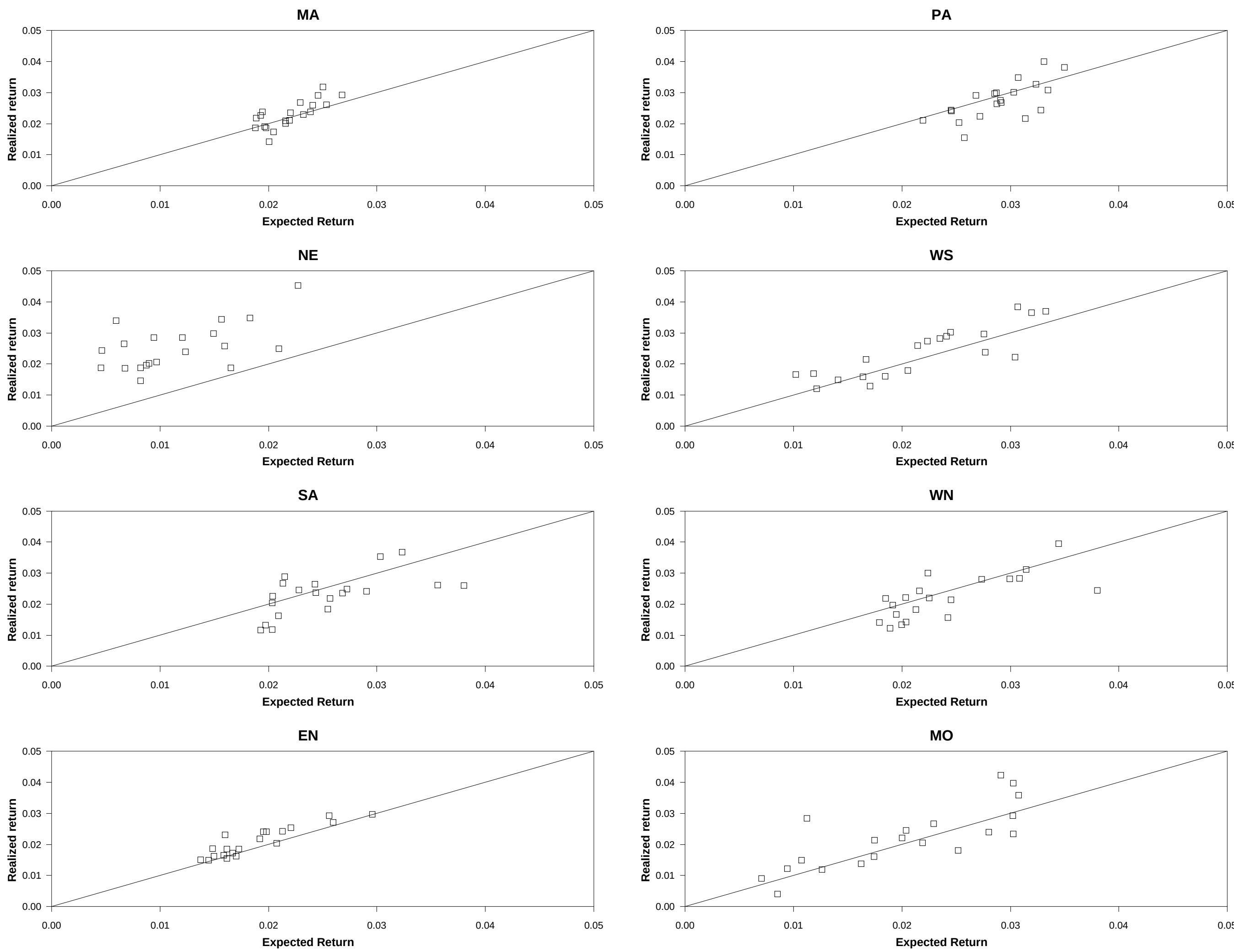

Figure 3: Expected vs. Actual Mean Returns, GMM estimates, 10 portfolios.