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

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Abstract

We examine empirically if relative wealth concerns are present in the US stock market. The literature suggests two reasons (not mutually exclusive) why investors might want to hedge local risk resulting from relative wealth concerns: keeping up with the Joneses preferences and competition for local assets in short supply. In equilibrium, the corresponding hedging results in a negative risk premium for the local risk factors. We use as peer groups the nine US Census divisions. As proxy for the local risk factor we use divisional labor income growth. We find substantial support for the equilibrium implications of relative wealth concerns; moreover, the effects are stronger in divisions with lower population density. A possible explanation is that the effect of relative wealth concerns is stronger in low density regions because it is easier to identify the reference group. Additionally, lower density may imply higher competition for assets in short supply (like human capital) and, therefore, a stronger desire to hedge the corresponding inflationary risk. When we replace labor income return with house price inflation, the cross-section explanatory power of the model remains virtually unchanged. However, negative prices of risk only arise in divisions that record higher house price inflation relative to the other regions.

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1 Introduction

There are two, not necessarily exclusive, cases suggested in the literature in which relative wealth concerns of investors may have an effect in the equilibrium pricing of financial securities. First, agents may display "external habit formation" (EHF) in their preferences. In this case, investors "keep up with the Joneses" and bias their portfolio holdings towards securities which are correlated with the wealth of their peers. In equilibrium, Gómez, Priestley and Zapatero (2008) shows that if some investors face a market friction (like a local, non-diversifiable source of income) they will bias their portfolios towards securities that are correlated with the idiosyncratic component of their peers local wealth (as opposed to the well diversified market portfolio). After market clearing, these securities will carry a negative risk premium with respect to the local factor because investors are willing to give up expected return in order not to distance themselves from their peers' local, non-diversifiable wealth.[1]

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 with prices positively correlated with the local, non-diversifiable asset price. In equilibrium, investors pay a premium for such 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 state) relative wealth concerns result in an approximate multi-beta asset pricing model. This result is attained when relative wealth concerns are driven by either EHF or non-diversifiable assets 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). The latter risk 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 hedge the risk of deviating from their peers' non-diversifiable wealth.

In this paper we examine empirically if relative wealth concerns are present in the US stock market. We consider the nine US Census divisions as peer groups and test whether stock returns across the nine divisions are priced by local risk factors that proxy for relative wealth concerns. Stocks are allocated into one of the nine divisions depending on the location of their headquarters and subsequently sorted into portfolios following several criteria. In equilibrium, the cross section of returns is explained by ten risk factors: the market return and the nine risk factors (one per division) capturing local un-diversifiable risk. As a proxy for undiversified local wealth we use divisional labor income.

Our empirical tests strongly support the equilibrium implications of relative wealth concerns. All the estimated prices of risk across the division specific factors are negative and statistically significant (with the exception of the West North Central division). Sorting stocks by market capitalization into 20

[1] Galí (1994) shows that in the absence of market frictions portfolio holdings are identical across investors and market risk is priced at a discount relative to the case without EHF.

portfolios for each division, the KEEPM (with an $\overline{R}^2$ over 60%) outperforms the CAPM ($\overline{R}^2$ of 4%) and the three-factor Fama and French model ($\overline{R}^2$ of 44%) in explaining the cross section of stock returns. The analysis of the pricing errors for the three models indicates that the KEEPM has smaller pricing errors than the other models across all divisions. Statistically, we reject the null hypothesis that the pricing errors from the KEEPM are the same as the pricing errors from the CAPM and the Fama-French model, in favor of the alternative that they are smaller for the KEEPM.

We study the possible determinants of the level of the risk-premia by focusing on the extent of population density within each division. 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 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.

The model in DeMarzo, Kaniel and Kremer (2004) offers an endogenous risk-hedging explanation of the effect uncovered in Hong, Kubik and Stein (2008). Low population density is not only associated with a shortage of local firms but also with, arguably, more insular labor markets.[2] In other words, stock prices of firms in lower density divisions are more likely to be highly correlated with their respective local, non diversifiable labor risk. Investors, searching to hedge their exposure to this income risk, will pay a higher price for stocks of the local firms. Thus, the negative premium will tend to be higher (in absolute value) in divisions with lower population density. The same result follows if we assume exogenous EHF preferences, as in Gómez, Priestley and Zapatero (2008), and a larger proportion of non-diversifiable labor income in divisions with lower density population density, as the papers just mentioned document. Finally, in low density areas, the keeping up with the Joneses effect is arguably to be stronger. The argument is as follows: the implementation of the optimal strategy of an agent who exhibits EHF preferences depends on, first, the identification of the peer group whose consumption or wealth affects the utility of the agent and, second, on information about the wealth or consumption of that peer group. Both conditions are likely to be easier to obtain in small towns (for example), where most people know and interact with each other, than in heavily populated urban areas.

In the empirical analysis we show that the KEEPM cross sectional tests capture the effect discussed in Hong, Kubik and Stein (2008): the (absolute value) size of the negative premium is higher in lower population density divisions, like Mountain, Pacific and West South Central. The differences in the estimated prices of risk for the low population density divisions and the high population density divisions are substantial, and statistically significant. We also compare the expected returns derived from the model across the divisions relative to the population density of the divisions. For example, if we consider the five divisions that have population densities lower than 100 inhabitants per square mile, the average expected excess return is just over 7.9% per annum, according to the KEEPM. For the remaining four divisions, with a population density greater than 185, the expected excess return is 8.8% per annum. We

[2] Several papers have documented that both population density and population growth are positively related to new firm start-ups. See Armington and Acs (2002) and the references therein.

show that asset pricing models that do not take into consideration relative wealth effects can not capture these differences.

We check the robustness of our results by sorting stocks into portfolios according to a number of alternative criteria. An obvious candidate is the book-to-market ratio, since firms with low book-to-market are growth firms that tend to be younger and might require specialized human capital that may be concentrated in 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 spread both across US divisions and internationally. Firms with a low book-to-market ratio often display high investment in research and development (R&D). By definition, the investment in R&D is highly intensive in human capital, which results in the type of non-diversifiable wealth of "their peers" against which investors would want to hedge by holding the stock (a growth stock). Therefore, we also sort stocks based on R&D. Finally, we sort firms into portfolios based on a measure of leverage (total liabilities relative to total assets) because Coval and Moskowitz (1999) find that fund managers invest in small highly levered stocks that do not trade internationally. Our findings remain robust to the different sorting criteria.

We also use house price inflation as the local non-diversifiable risk factor, as an alternative to labor income. Housing is clearly the largest investment for the average household, it is intrinsically local, and is likely to be in limited supply (hence triggering endogenous inflation-hedging concerns among local investors). Thus, we can test whether inflation hedging can yield the same results as keeping up with the Joneses behavior. The cross-section explanatory power of the KEEPM remains virtually unchanged, both in terms of average fit of the model and pricing errors. However, negative prices of risk only arise for divisions that have recorded substantially higher house price inflation than the average. This lends support to the idea that hedging (housing) price-inflation may result in endogenous relative wealth concerns when the magnitude of inflation risk is large.

The paper is organized as follows. The related literature is discussed in following subsection. We present the theoretical background and derive the KEEPM in section 2. Section 3 describes the data and discusses the empirical results and robustness tests. Section 4 offers some final remarks and closes the paper.

1.1 Related literature

Keeping up with the Joneses preferences were introduced by Abel (1990) and further studied by Galí (1994). 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, 2008) for the case of price-driven relative wealth concerns. Evidence in favor of this type of preferences is presented in Ravina (2005).

Recently, a number of papers have documented the existence of a negative risk premium associated with a local risk factor, on the cross section of stock returns. Gómez, Priestley and Zapatero (2008) find strong support for 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, but maybe most importantly, by making the unit of analysis smaller we can explore factors that would affect the level of the relative wealth concern and its effect on prices: Based on the existing literature, in this paper we focus on population density as a determinant of the level of wealth concerns and differences in the number of firms and firms book values across divisions as determinants of the effect of relative wealth concerns on prices.

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 (2008), both theoretically and empirically. In our model, investors are concerned about hedging local non-diversifiable risk. Unlike the regional consumption risk factors in Korniotis (2008), 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, the EHF risk factor in Korniotis (2008) 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 two sources of non-diversifiable risk, income labor and house prices. This allows us to better understand better the impact of the local risk factors, as well as their origin, whether endogenous (hedging local price inflation) or exogenous (EHF).

Finally, 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 markets 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.

Our paper is closely 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. Counter-evidence of this prediction was first presented 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.[3] More recently, several papers have documented that this lack of diversification is also present at the domestic level within the US. This phenomenon has been dubbed the "home bias at home puzzle." Coval and Moskowitz (1999), for instance, study the investment behavior of money managers and observe that they favor (with respect to what would be optimal) local firms.

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

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 articles 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,[4] the KEEPM yields partial equilibrium results that are consistent with those in the home bias at home literature: investors shun distant assets while favoring close local assets. However, it is important to stress that the argument behind the portfolio tilt in our paper is neither familiarity nor information, but hedging: local assets offer a hedge for the risk to local investors resulting from the non-diversifiable income of their peers.

Finally, our paper is related to the literature on the value premium puzzle (see, for example, Berk et al 1999, Cooper 2006, Zhang 2005, Xing 2008), by which the risk-adjusted expected return of growth firms is smaller than that of value firms. A possible explanation is that firms with low book-to-market ratio also display high investment in R&D; see, for example, Lev (1999) and Hansen, Heaton and Li (2004). By definition, the investment in R&D is highly intensive in human capital, which results in the type of non-diversifiable wealth of "the peers" that investors would want to hedge. Zenger (1994) offers an alternative explanation with a model of diseconomies of scale in R&D: smaller firms are more efficient in overcoming the agency problem of hidden information and hidden behavior in R&D. He finds that small growth firms attract and retain engineers with higher ability (human capital). We argue that this firms should have a high price (negative risk premium) and find strong empirical support.

2 The KEEPM

We present in this section the main testable implications from the KEEPM. For a more detailed derivation, see Gómez, Priestley and Zapatero (2008). We assume a one-period 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 $t = 1$.[5] Workers face incomplete

[4]See, for instance, Michaud (1989). Brandt (2004) surveys the literature.

[5]The term "workers" is widely defined in our model: it includes holders of all kind of human capital that generates income,

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 stock of the firm shares, there are as many zero net supply securities as needed for financial markets to be complete. Let r denote the vector of excess returns 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 $p = \delta \left(\frac{c}{w}\right)^{\alpha}$. As expected, the scarcer the (fixed) local good endowment relative to the (stochastic) global good consumption, the higher the relative price of the former. Hedging demand of the investor due to 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 investor's optimal portfolio in division $k \in \{n, s\}$ is, approximately:

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

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.

The investor's optimal portfolio in the exogenous case is also given by 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

for instance wage income, or entrepreneurial income.

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 $r_k^F = r' F_k$. 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 $\mathrm{cov}(r_n^F, r_s^F) > 0$, then λ^n and λ^s will be negative. The intuition for the negative sign would be as follows: An asset that has positive covariance with portfolio F_k will hedge the investor in division k from the local, non-diversifiable income risk. This investor will be willing to pay a higher price for that 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 either endogenous or exogenous Joneses implies 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 return (that is, pay a premium) for the stocks that are correlated with the idiosyncratic component of the local risk and, therefore, help them hedge that risk. This result depends in a fundamental way on the market friction that prevents some agents (our workers) from participating in the markets.

3 Empirical Results

3.1 Data description

The model does not specify the dimension of "the peers." Our choice, the nine Census divisions, is a compromise between the scale of the relative wealth concern and the existence of a sufficiently large number of firms for the cross sectional test. To proxy local (ie., divisional) wealth, we use personal income which comes from the Bureau of Economic Analysis (BEA). The BEA provides quarterly personal income data at the state level which we use to calculate divisional level personal income. We calculate per capita personal income data at the divisional level using the US Census Bureau data on annual population in each division (aggregated from state level population data). There are nine Census Bureau Divisions which we index with two capital letters: WS is West South Central, PA is Pacific, ES is East South Central, MO is Mountain, EN is East North Central, SA is South Atlantic, WN is West North Central, MA is Middle Atlantic, and NE is New England.[6] The model predicts that the component of personal income which is 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 whose price increase agents wish to hedge against. To this end, we regress the divisional level personal income on the CRSP aggregate stock market excess return and employ the residuals from this regression as the orthogonal personal income data.

The data on stock returns and firm characteristics come from CRSP and COMPUSTAT. We consider all firms in the COMPUSTAT/CRSP data base from 1963 to the end of 2006. From CRSP, we obtain stock returns for NYSE, AMEX and NASDAQ stocks. From COMPUSTAT, we obtain annual information on headquarter location, market capitalization, book value of equity, total liabilities, total assets, and investment in research and development (R&D). Using the information on headquarters location in COMPUSTAT, each firm is assigned into one of the nine Census Bureau divisions.

Within each of these divisions, we sort stocks into twenty portfolios based on a given characteristic that provides a spread of returns. As a first criterion, stocks in each division are sorted into twenty portfolios in year t according to market capitalization at the end of year $t-1$. Table 1 reports the mean excess returns on the twenty portfolios in each division. There is a clear pattern of higher excess returns of small stocks than large stocks. Across the nine divisions the average excess return on the smallest stock portfolio is around 6% per quarter and on the largest stock portfolio it is 0.9% per quarter. We choose market capitalization for two reasons: first, as evidenced in Table 1, size gives a reasonable spread of returns. Second, from an asset pricing point of view, if our model has empirical power it should be able to explain the difference between large and small stock returns.

Table 2 reports the population density in each region, obtained from the Census Bureau's 2000 Census.[7] There is a clear distinction between divisions with low population density (West North Central,

[6]We include a map of the nine US Census divisions in Figure 1 as an appendix.
[7]We include as an appendix (Figure 2) the latest Census map of population density published in 2000.

Pacific, West South Central, Mountains, and East South Central) where there are less than one hundred individuals per square mile (the average is 56 per square mile), and the remaining divisions with high population density which ranges from 194 to 398 individuals per square mile and averages 250. The countrywide average population density is 79.6 individuals per square mile. As we argued in the introduction, we would expect the effect of relative wealth concerns to be greater in low population density divisions.

Table 2 also reports the average number of stocks in each of the twenty portfolios across the nine divisions. They range from a high of 58 stocks in each of the twenty portfolios in the Middle Atlantic division to a low of eight in the East South Central division (note that in this division, because of the low number of stocks, we formed only ten portfolios, so the reported number eight is sixteen divided by two). There is a clear positive relationship, with the exception of the Pacific division, between the number of firms in a division and population density, a pattern identified in Hong, Kubik and Stein (2008).

In order to assess the robustness of the empirical results we also form stocks into portfolios based on alternative characteristics. The second set sorts stocks into twenty portfolios in year t, according to the firm's book to market ratio at the end of year $t-1$. Third, we double-sort stocks into size and book-to-market portfolios because both size and book-to-market are potentially related to local factors. This also provides us with a benchmark against the Fama and French three factor model to compare our model's performance. Fourth, we sort firms into portfolios based on a double sorting of size and a measure of leverage (total liabilities relative to total assets) because Coval and Moskowitz (1999) find that fund managers invest in small highly levered stocks that do not trade internationally.[8] Finally, we form portfolios using a double sorting on size and research and development expenditures (R&D). The reasoning behind this is that local R&D, especially amongst small firms, may reflect local knowledge that is divisional specific, and hence correlated with local labor income

We calculate excess returns on all the portfolio returns by subtracting the one month T-bill rate from the actual returns. In addition to the local risk factors we also include 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 the aggregate stock market portfolio, the small minus big (smb) return, and the high minus low (hml) book to market return. Values of erm, smb and hml are 1.6%, 0.9% and 1.2% per quarter, respectively, over the sample period.

3.2 Main Results

The main asset pricing implication of the model is that local, divisional risk factors that proxy for orthogonal local wealth should be priced in the cross-section of stock returns with a negative risk premium. In order to test this proposition, we estimate the model using the cross-sectional methods of Fama and MacBeth (1973). Since there are nine divisions, the model implies that the expected return on stock i depends on ten risk premia:

[8]We considered forming portfolios based on the amount of exports to total sales based on the notion that firms that export are less likely to be local. However, data on exports is not available until 1980 which would substantially reduce the sample size by around 50%.

$$E(r_i) = \lambda^M \beta_i^M + \sum_{d=1}^{9} \lambda^d \beta_i^d,$$

where $E(r_i)$ is the expected return on asset i, λ^M is the market price of risk, β_i^M is the market beta of stock i, λ^d is the price of risk associated with orthogonal (with respect to the market portfolio) local personal income in division d, and β_i^d is the beta of stock i with respect to the orthogonal local personal income in division d. The model predicts that $\lambda^d < 0$.

To assess the performance of the KEEPM we first consider whether the estimated premia on the divisional risk factors are negative and statistically significant. Furthermore, we report the R^2 of the cross-sectional regression, which measures the amount of cross sectional variation captured by the model. Following Jagannathan and Wang (1996) and Lettau and Ludvigson (2001), we calculate 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. Due to the large number of risk factors, we report the adjusted $R^2, \overline{R}^2$. Although $\overline{R}^2$ gives us an idea of the general fit of the model, it is not a direct test of the model. A direct test of the model is provided by the pricing errors. It is also useful to consider the performance of the model relative to existing models that try to explain the cross section of stock returns. To this end we estimate the CAPM and the Fama-French three factor model and compare their performance to the KEEPM through an examination of the $\overline{R}^2$ and pricing errors of each model.

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, and use sixty observations up to time t in the first step to obtain the first beta. Then, in the second step we estimate a cross-sectional regression of average returns at time $t+1$ on the betas estimated up 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 when using quarterly time series data over a relatively short sample. Instead, the betas are estimated over the entire sample and used in all of the T cross-sectional regressions. Estimating a single beta over the sample period when employing quarterly data is the method followed in Lettau and Ludvigson (2001), and discussed in Cochrane (2001).

Table 3, panel A, reports estimates of the model using twenty equally weighted size sorted portfolios from each of the nine divisions (ten in the case of East North Central). All of the prices of risk associated with the nine divisions are estimated to be negative and all are statistically significant, with the exception of the West North Central division where the estimated price of risk is marginally significant. The sign and significance of the estimated prices of risk offer strong support for the theory that local risk is important, whether this is driven by keeping up with the Joneses preferences or by local goods being in short supply. Economically, the magnitudes of the prices of risk are substantial, ranging from -0.011 per quarter for the Mountain division to -0.003 per quarter for the West North Central division, which is the division that recorded a marginally significant price of risk. The $\overline{R}^2$ is 63% which is impressive for size sorted portfolios and indicates that the model can explain a good proportion of the cross-sectional variation.[9]

Interestingly, the divisions that have the highest (absolute) prices of risk include West South Central, Pacific, East South Central and Mountain. According to Table 2 these divisions and the states within them are characterized by having the lowest population density (less that 100 inhabitants per square mile) and a lower number of firms.[10] On the other hand, the divisions with the lowest (absolute) prices of risk, East North Central, Middle Atlantic and New England are among the divisions with the highest population density. The lower part of panel A reports F-tests of the restriction that the prices of risk on the high population density divisions are the same as the average price of risk in the division with the lowest population density (Mountain (MO); λ_{MO} = -0.011). In every case, it is possible to reject the null hypothesis that the prices of risk in the high population density divisions are the same as in the Mountain division. We also provide F-tests of the restriction that the prices of risk in the high population density divisions are equal to the average price of risk across all five divisions with low population density (-0.008). In all but one case we reject the null hypothesis of equal prices of risk in favor of the alternative that the prices of risk in the low population density divisions are larger (absolutely). Thus, not only does the model find general support in the sense that the prices of risk are estimated to be negative and statistically significant, but, in addition, the size of the estimated prices of risk are largest (in an absolute sense) in the divisions where we would expect them to be: divisions with low population density and a low number of stocks.

The next two rows of panel A of Table 3 report estimates from the CAPM and the Fama-French three factor model. The market price of risk in the CAPM is positive but not statistically significant. Not surprisingly, according to the $\overline{R}^2$ it can only explain 4% of the cross-sectional variation in the average excess returns of the test assets. This inability of the CAPM to explain the cross section of stock returns is, of course, a well known result. The Fama-French three factor model does considerably better than the CAPM in terms of explaining the cross section of stock returns. The *smb* and *hml* risk factors both have positive and statistically significant estimates, marginally so in the later case. It is evident from their respective $\overline{R}^2$ that the model that incorporates local non-diversifiable divisional risk does somewhat better than the Fama-French model in terms of explaining the cross-section of returns.

An alternative way to assess the relative performance of the KEEPM and the Fama-French model is to examine the expected returns they produce across the divisions relative to the population density. If we consider the five divisions that have population densities less than 100 inhabitants per square mile, the average expect return is just over 7.9% per annum according to the KEEPM model. For the remaining four divisions with a population density greater than 185 the expected return is 8.84% per annum. Therefore, the KEEPM indicates that the expected returns in the low population density divisions are lower. In contrast, expected returns from the Fama-French model are 8.72% per annum and 8.6% per annum in the high and low population density divisions, respectively. Thus, irrespective of the extent of the population

[9]We also estimated the model using a sixty observation rolling window, as is often employed when using monthly data. We found that the prices of risk are all negative and statistically significant except West North Central. However, this rolling procedure leaves us this just over one hundred time series observations which is quite small compared to the size of the cross-section.

[10]West North Central is the division with second lowest overall population density, although a large proportion of the population of this division lives in dense urban areas: Minneapolis-St. Paul, St. Louis and Kansas City.

density, the Fama-French model provides essentially the same expected returns, whilst the KEEPM model can distinguish between the differences in actual returns across low and high population density divisions that are driven by the hedging of local personal income risk factors.

Panel B of Table 3 repeats the previous analysis, but uses value weighted portfolios instead. The results are entirely consistent with those reported in Panel A for equally weighted returns.

The discussion thus far has focussed on the sign and statistical significance of the prices of risk and the value of $\overline{R}^2$ to assess the performance of the models. In table 4, we report the square root of the average squared pricing errors of the model along with standard errors in parentheses and tests of differences in pricing errors across models. The left hand side of the table reports results for the equally weighted portfolio and the right hand side reports results for the value weighted portfolios. Dealing first with the equally weighted portfolios, the first three columns report the square root of the squared pricing errors for the KEEPM, CAPM and Fama-French models. A starred value indicates that we cannot reject the null hypothesis that the pricing errors are jointly zero. The first row of pricing errors considers all 170 portfolios and the remaining rows each of the nine divisions. The first point to note is that it is possible to reject the null hypothesis that the pricing errors are jointly zero across all 170 portfolios and within each division. However, the pricing errors are small in an economic sense.

Columns four and five of the table provide tests that the pricing errors from the KEEPM model are the same as those from the CAPM and Fama-French model. Looking at the first row (including all 170 portfolios), it is possible to reject the null hypothesis of equal pricing errors in favor of the pricing errors from the KEEPM model being smaller than the other two models, consistent with the difference in the $\overline{R}^2$'s. The remaining rows of the left hand side of the table report the average pricing errors for the twenty portfolios in each division and the tests of equal pricing errors in each division across the three models. Whilst some caution needs to be used when interpreting these tests given the small sample (see, for example, Burnside and Eichenbaum (1996) and Hansen, Heaton and Yaron (1996)), the tests indicate that across all divisions it is possible to reject the null hypothesis of zero pricing errors. The small sample problems are probably illustrated in the tests that consider whether the pricing errors are the same across models. It is difficult to reject the null hypothesis of equal pricing errors across the models, even though the economic magnitudes between them are similar to the case of all 170 portfolios, where we rejected the null hypothesis. Thus, it is worth bearing in mind that the pricing errors are smaller in the KEEPM model than the other two models in all but one case. The results on the right hand side of the table consider value weighted portfolios and report very similar findings, with the difference that the pricing errors are generally smaller for the value weighted portfolios than the equally weighted portfolios.

Overall, the analysis of the pricing errors indicates that the KEEPM model has smaller pricing errors than the other models across all 170 portfolios and across the 20 portfolios in each division. In the case of the 170 portfolios it is possible to reject the null hypothesis that the pricing errors from the KEEPM are the same as those from the CAPM and the Fama-French model. We always reject the null hypothesis that the pricing errors are zero, but in economic terms they are small and lower for the KEEPM than the other two models.

In order to give a visual impression of the relative performance of the three models, Figure 3 plots the expected returns from the three estimated models (fitted returns) against the realized returns for the size portfolios in each of the low population density divisions. Each row in the figure plots the series for a given division. The final column of Figure 3 reports the plots for the CAPM and shows that only a small fraction of the average realized returns is explained by the model. In particular, the small stock portfolios, which have the highest realized return (see table 1) are hopelessly mispriced by the CAPM as they lie furthest away from the 45-degree line. The CAPM predicts roughly the same expected returns across all divisions for all size portfolios, reflecting inability to capture the size effect in divisional realized returns.

In contrast, simple visual inspection of the performance of the KEEPM and the Fama-French model (columns one and two of Figure 3), shows that they both perform better than the CAPM. The result reported earlier regarding the smaller pricing errors of the KEEPM relative to the Fama-French model is also evident in the plots: the small stock portfolios lie closer to the 45-degree line for the KEEPM.

Figure 4 plots the same relationship between average realized returns and expected returns for the high population density divisions. The final column indicates that in high population density divisions the CAPM is no more successful in explaining realized returns than in low population density divisions. Similar to the case of low population density divisions, the KEEPM explains the cross sectional patterns in realized returns as well as the Fama-French model, and sometimes better.

3.3 Alternative Portfolios

In this section, we check the robustness of our empirical findings to other sorting criteria than size. First, we consider book to market. 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 high book-to-market ratio are value firms, and are more likely to diversified geographically with production and sales across divisions and internationally. Hence, we expect that book to market will generate a sizeable spread of stock returns related to the fundamentals of our model. Another justification is the fact that firms with a low book-to-market ratio typically exhibit high investment in R&D. By definition, the investment in R&D is highly intensive in human capital, which results in the type of non-diversifiable wealth which investors will want to hedge by holding growth stocks. Thus, we also sort firms according to R&D investment and market capitalization. Finally, we sort firms into portfolios based on a double sorting of size and a measure of leverage (total liabilities relative to total assets) because Coval and Moskowitz (1999) find that the local bias tends to be more prominent for small, highly leveraged firms (although their argument is superior information and ours is risk-hedging)

Panel A of Table 5 reports the parameter estimates from the three models using twenty equally weighted portfolios (ten in the case of East North Central) formed on the basis of the book-to-market ratio. Because of the lack of data on book value in the early years of the sample, the sample starts in 1966:Q1. Similar to the case of size sorted portfolios, each of the local risk factors commands a negative price of risk and each one is statistically significant except in the West North Central and Middle Atlantic divisions. The $\overline{R}^2$ is 68%, slightly higher than when using the size sorted portfolios. The KEEPM performs substantially better than the CAPM, that has $\overline{R}^2$ of 11%, and slightly better than the Fama-French model with $\overline{R}^2$ of 60%. Again, as in the case of the size sorted portfolios, the local orthogonal wealth factors are able to price book-to-market portfolios moderately better than the Fama-French model.

Panel A of Table 5 also reports values of the F-tests of the restrictions that the prices of risk in the high population density divisions are equal to the price of risk in the Mountain division. We reject the null hypothesis in two of the four cases. When we test whether the prices of risk in the high population density divisions are equal to the average price of risk in the low density divisions we reject the null in one case.

Unreported analysis of the pricing errors for each division are similar to those of size portfolios reported in Table 4. Across all 170 portfolios the average pricing errors are 0.58% per quarter from the KEEPM, 0.62% for the Fama-French model, and 0.92% for the CAPM. The final column of Panel A of Table 5 reports values of the F-test that the average pricing errors from the CAPM and the Fama-French models are equal to those from the KEEPM model. We reject the null hypothesis that the pricing errors are equal between the CAPM and KEEPM in favor of them being smaller for the KEEPM, but we cannot reject the null of equal pricing errors between the KEEPM and the Fama-French model. Thus, as far as the book-to-market portfolios are concerned, there is only a slight difference between the performance of the KEEPM and the Fama-French model.

The small difference in performance between the two models also shows in the average expected returns across low and high population density divisions. For example, the expected excess returns in low density divisions according the KEEPM and the Fama-French model are 7.65% per annum and 8.03% per annum respectively. Across the high population density divisions they are 8.96% and 8.79%, respectively. Both the KEEPM and Fama-French model provide lower expected returns in the low population density divisions relative to the high population density division.

The findings thus far have shown that the KEEPM can explain cross-sectional differences in realized returns for size and book-to-market sorted portfolios separately. Perhaps the most challenging data to explain is double-sorted size and book-to-market portfolios, given that theoretical asset pricing models such as the CAPM and Consumption CAPM have failed in tests with portfolios based on this criterion. In addition, examining double-sorted size and book to market portfolios permits comparison with the existing literature.

Results using 15 double-sorted size and book-to-market portfolios are reported in Panel B of Table 5. In this case the KEEPM model records statistically significant prices of risk in all cases (marginally so in the Middle Atlantic and West North Central divisions). In terms of testing restrictions on the prices of risk, we reject in all four cases that the prices of risk in the high population density divisions are the same as those in the Mountain division. In one case, we also reject the null hypothesis that the average price of risk in the low population density divisions is equal to the price of risk in the high density divisions. $\overline{R}^2$ is 59%, which compares favorably relative to the CAPM 4%, and the Fama-French model 41%. The superior performance of the KEEPM relative to the Fama-French model also shows in unreported pricing errors across the respective divisions. Across all 130 portfolios, the average pricing error from the KEEPM is 0.56% per quarter and 0.67% per quarter from the Fama-French model.

The final column of Panel B of Table 5 shows that the difference between pricing errors of the two models is statistically significant, as it is the case between the average pricing errors from the CAPM and the KEEPM. In summary, the KEEPM, a based on an equilibrium model, performs better than the

Fama-French model using portfolios formed on the basis of the risk factors in the Fama-French model.

The superior performance of the KEEPM is also reflected in the expected returns provided by the model across the low and high population density divisions. In the low population density divisions the KEEPM provides an average expected excess return of 8.03% per annum compared to 8.88% for high density divisions. In contrast, the difference in expected returns across low and high population density divisions according to the Fama-French model is only 0.4% per annum.

In Table 6, we examine portfolios based on double-sorting according to size and R&D (Panel A), and size and leverage (Panel B). With respect to the R&D and size sorted portfolios, all of the orthogonal local wealth prices of risk are negative and statistically significant, and $\overline{R}^2$ is 64%. The CAPM records a positive but insignificant price of risk and $\overline{R}^2$ is only 4%. The Fama-French model records significant positive prices of risk (although only marginally significant for the excess return on the market portfolio), with $\overline{R}^2$ 39%, substantially smaller than that of the KEEPM. The tests of the restrictions that the prices of risk in the high population density divisions are equal to the price of risk in the Mountain division are rejected in two cases; when we test that they are equal to the average across all the divisions with low population density, we reject in one case.

The difference in performance between the KEEPM and the Fama-French model is reflected in the pricing errors, with an average across all 130 portfolio for the KEEPM of 0.59% per quarter, compared to 0.74% per quarter for the Fama-French model. The final column of Panel A reports the values of the F-test that average pricing errors are equal for the models and rejects this null hypothesis in both the case of the Fama-French model and the CAPM, in favor of the pricing errors from the KEEPM being smaller. Regarding differences in expected excess returns across divisions with low and high population density, we find that in the former divisions the KEEPM generates an expected excess return of 7.90% per annum while in the latter division it is 8.71% per annum. The Fama-French model generates an expected excess return of 8.33% per annum and 8.23% per annum in the low and high population density divisions respectively.

Panel B of Table 6 presents the results using the leverage and size sorted portfolios. The overall tenor of the results is similar to Panel A, both with respect to the parameter estimates, size of pricing errors and differences in expected returns across divisions with different population densities.

In summary, when we sort stocks into portfolios based on characteristics other than just size that are possibly related to local orthogonal wealth, we find that local risk factors are priced and that their importance is related to the extent of population density of the division. Overall, we find extensive evidence that local, divisional, risk factors that proxy for orthogonal local wealth are important determinants in the cross section of returns, and are likely to contribute to the well known home bias at home empirical regularity, that investors bias their portfolio holdings to stocks that are closer to their home.

3.4 House Price Inflation

In the introduction we discussed two possible economic reasons that would result on relative wealth concerns. On one hand, keeping up with the Joneses preferences, or external habit formation (EHF), as studied in Gómez, Priestley and Zapatero (2008). On the other hand, relative wealth concerns may also arise endogenously, as the result of competition for non-diversifiable assets in limited supply, as studied in DeMarzo, Kaniel and Kremer (2004). One possible way to separate out the resons for relative wealth concerns between EHF and hedging price inflation of goods in short supply is to examine if risk factors associated with a particular good in short supply are priced in the cross-section of stock returns. Housing is an obvious choice, since it is in short supply, is clearly local, and represents a major purchase that household undertake and whose risk would like to hedge. We collect divisional level house price indices from the Office of Federal Housing Enterprise Oversight over the period 1977:Q1 to 2006:Q4.

Panel A of Table 7 reports estimates of the prices of risk associated with the orthogonal (with respect to the market portfolio) component of house price inflation. Four of the prices of risk are estimated with a negative and statistically significant coefficient: Pacific, South Atlantic, Middle Atlantic and New England. Of the remaining five divisions, three have positive but insignificant estimates and the remaining two have negative but statistically insignificant prices of risk. $\overline{R}^2$ is 59%, and is therefore comparable to that of earlier models estimated using orthogonal labor income.

At first glance, there is mixed evidence of hedging demand for housing inflation. However, if we consider the extent of house price inflation and the estimated prices of risk, an interesting pattern emerges. For example, the average house price inflation in the four divisions with a statistically significant negative price of risk is 1.7% per quarter. In the remaining five divisions it averages only 1.1% per quarter, 50% lower than the average among the four divisions with statistically significant prices of risk. This result is very intuitive and provides powerful evidence that in divisions where house price inflation is high, investors wish to hedge this risk by buying divisional level stocks, and willingly accept a lower premium. This is not the case when house price inflation is low.

As a robustness check, Panel B of Table 7 reports estimates of the model using orthogonal labor income over this shorter sample period. In all divisions, with the exception of WN, we find that prices of risk are estimated to be negative and statistically significant. $\overline{R}^2$ is 58%, and thus, the two models in Table 7 perform about the same when considering the same sample period. Indeed, analysis of the pricing errors reveals that in the case of orthogonal labor income the square root of the squared pricing errors is 0.0064 and in the case of orthogonal house price inflation 0.0067. The final column of Table 7 reports a F-test of the null hypothesis that the pricing errors are equal and this cannot be rejected.

The findings in this section seem to suggest that hedging local price inflation may result, per se, in relative wealth concerns being priced in equilibrium. Of course, there is no reason, in theory, why these two effects cannot coexist.

3.5 Robustness Tests

In this section of the paper we consider two robustness checks of our results. First, we assess the sensitivity of the ordinary least squares (OLS) t-statistics to the errors in variables (EIV) problem that occurs from using estimated betas in the second step of the Fama-MacBeth estimation procedure. In order to do this, Panel A in Table 8 presents Shanken (1992) standard errors that correct for the EIV, for both our tests with orthogonal labor income and housing, respectively. As we have explained, the former is estimated over the whole sample period, and the latter over the shorter period for which housing data is available. In both cases we use the equally weighted size sorted portfolios. In the labor income results, all the estimated coefficients are statistically significant with the exception of the West North Central Division.

The OLS t-statistic for this division is 1.64 (see Table 3). In general, relative to the OLS t-statistics, the EIV-corrected standard errors produce lower t-statistics, but eight out of the nine divisions retain their statistical significance. Therefore, whilst correcting for EIV does have an impact on the estimated standard errors, it does not render the estimated coefficients insignificant.

The findings are very similar when we correct the standard errors from the regressions that use orthogonal house price growth. Four of the five divisions still have a statistically significant estimated coefficient after correcting for EIV. One division, East South Central, which has a marginally significant estimated coefficient using OLS (t-statistic of 1.81, see Table 7) has an EIV corrected standard error that is no longer statistically significant.

Second, we consider that possible multicollinearity among the factors would affect the statistical significance of any one particular factor. One way around this problem is to estimate the cross-sectional model separately for each division, assuming that the only risk factors that are important in each division are the market return and the labor income factor for that division. Because the labor income factor is orthogonalized with respect to the market return, the estimates of the market beta, the local labor income beta and t-statistics can be interpreted in a straightforward manner. However, this only a robustness test that enables us to confirm earlier findings from estimating the full model. In equilibrium, a given stock return from one division may well be affected by the labor income of another division. For example, if a stock in division X is correlated with labor income of investors in division Y, then investors in division Y will want to buy the stock in division X, since it will help them hedge their division's non-diversifiable risk.

Panel B of Table 8 reports the results from estimating the following model:

$$E(r_{i,j}) = \lambda^M \beta_i^M + \lambda^j \beta_i^j,$$

where $E(r_{i,j})$ is the expected return on asset i from division j, λ^M is the market price of risk, β_i^M is the market beta of stock i, λ^j is the price of risk associated with orthogonal local personal income in division j, and β_i^j is the beta of stock i to the measure of orthogonal local personal income in division j. This model is estimated nine times, once for each division, using twenty equally weighted size sorted portfolios from each division (ten portfolios in the case of the East South Central Division). The estimates of the divisional specific risk premia, λ^j, are all negative, and all statistically significant, with the exception of the West North Central division (the same division that scored a statistically insignificant estimated coefficient in the full model estimates in Table 3). Therefore, it is apparent that the full model estimates provided in Table 3 are reliable and there is substantial support for the KEEPM, stemming either from keeping-up-with-the-Joneses preferences or local goods being in short supply.

4 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, a multifactor asset pricing model arises called the KEEPM: KEEping up Pricing Model.

We consider the impact of relative wealth for portfolios of securities for the nine US Census divisions, using labor income return as a source of non-diversifiable local risk. We find strong empirical support for our conjecture: prices of risk for the local non-diversifiable risk are negative and mostly significant across divisions. In addition, the cross section performance of our model, both in terms of average fit and pricing errors, is equivalent, and sometimes superior, to the performance of the Fama and French three-factor model.

We also report that sizes (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 competition for assets in short supply (like human capital) and, therefore, a stronger desire to hedge the corresponding inflationary risk.

We perform a number of robustness tests. Our findings are robust to different portfolio sorting criteria: size, book-to-market, size and book-to-market, size and R&D, and size and leverage. In all cases, the KEEPM model performs at least as well as, and some times better than, the three-factor Fama and French model. Unlike the factors in Fama and French, our model offers an economic argument for the sign and size of these premia: investors hedging demand against deviation from their peers non-diversifiable risk.

Finally, we replace labor income return with house price inflation as a source of non-diversifiable risk. This allows us to test whether inflation hedging *per se* might yield the same results as keeping up with the Joneses behavior (or a combination of both), as shown in the tests with labor income return as the non-diversifiable asset. The cross-section explanatory power of the model remains virtually unchanged, both in terms of average fit of the model and pricing errors. However, the negative price of risk only arises for divisions that register noticeably higher house price inflation. This lends support to the idea that hedging (housing) price-inflation may result *per se* in endogenous relative wealth concerns when the size of the inflation risk is high enough.

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Table 1

Mean Excess Returns for Size Sorted Portfolios

	NE	MA	EN	WN	SA	PA	WS	MO	ES
P1	0.062	0.067	0.050	0.050	0.069	0.074	0.077	0.071	0.041
P2	0.037	0.046	0.032	0.031	0.033	0.046	0.047	0.056	0.020
P3	0.027	0.032	0.028	0.016	0.026	0.030	0.022	0.047	0.027
P4	0.036	0.024	0.022	0.014	0.030	0.026	0.031	0.027	0.034
P5	0.022	0.018	0.019	0.023	0.015	0.023	0.022	0.004	0.021
P6	0.020	0.020	0.019	0.026	0.017	0.017	0.017	0.017	0.021
P7	0.019	0.023	0.012	0.018	0.018	0.030	0.015	0.012	0.018
P8	0.025	0.013	0.018	0.028	0.015	0.025	0.009	0.008	0.019
P9	0.018	0.019	0.020	0.024	0.021	0.022	0.013	0.011	0.017
P10	0.023	0.016	0.016	0.023	0.014	0.019	0.016	0.000	0.007
P11	0.020	0.014	0.018	0.012	0.018	0.010	0.014	0.003	-
P12	0.014	0.014	0.023	0.010	0.018	0.013	0.017	0.010	-
P13	0.011	0.016	0.014	0.026	0.016	0.020	0.014	0.013	-
P14	0.018	0.014	0.018	0.020	0.017	0.017	0.011	0.005	-
P15	0.014	0.014	0.017	0.015	0.013	0.015	0.013	0.007	-
P16	0.010	0.014	0.019	0.014	0.015	0.020	0.020	0.008	-
P17	0.021	0.011	0.012	0.017	0.011	0.016	0.009	0.004	-
P18	0.013	0.015	0.012	0.012	0.011	0.013	0.011	0.007	-
P19	0.016	0.012	0.011	0.014	0.011	0.018	0.010	0.005	-
P20	0.008	0.011	0.009	0.014	0.009	0.013	0.007	0.008	-

This table reports the mean excess returns in each division on equally weighted portfolios sorted by market capitalization. P1 is the portfolio of stocks with the smallest market capitalization, P20 is the portfolio of stocks with the largest market capitalization. For the East South Central (ES) division we form ten portfolios only, due to the small number of stocks in this division. The divisions are indexed with two capital letters: WS is West South Central, PA is Pacific, ES is East South Central, MO is Mountain, EN is East North Central, SA is South Atlantic, WN is West North Central, MA is Middle Atlantic, and NE is New England. The data are sampled 1963:Q1 to 2006Q4.

Table 2

Population Density and Number of Firms Across Divisions

Division	Population Density	Number of Firms
MOUNTAIN	21.2	14
WEST NORTH CENTRAL	37.9	15
PACIFIC	50.2	51
WEST SOUTH CENTRAL	73.8	25
EAST SOUTH CENTRAL	95.3	8
EAST NORTH CENTRAL	185.4	38
SOUTH ATLANTIC	194.5	41
NEW ENGLAND	221.7	29
MIDDLE ATLANTIC	398.9	58
USA	79.6	31*

Population density is measured as the number of individuals per square mile of land area. The data is from the Census 2000, U.S. Census Bureau. The number of firms is the number of stocks in each of the twenty portfolios at the end of the sample. Note that there are only ten portfolios in the East South Central division and the value recorded in the table is the number of stocks in each of the ten portfolios divided by two. *Average number of stocks in each portfolio across divisions.

Table 3
Cross-Sectional Estimates
Size Sorted Portfolios

Panel A: Size, Equally Weighted

λ_{WS}	λ_{PA}	λ_{ES}	λ_{MO}	λ_{EN}	λ_{SA}	λ_{WN}	λ_{MA}	λ_{NE}	λ_m	λ_{smb}	λ_{hml}	$\overline{R}^2$
−0.010	−0.007	−0.007	−0.011	−0.004	−0.007	−0.003	−0.004	−0.005	−0.006			0.63
(4.24)	(4.53)	(4.18)	(5.47)	(3.17)	(4.77)	(1.64)	(2.87)	(3.85)	(0.67)			
									0.017			0.04
									(1.48)			
									−0.015	0.014	0.012	0.44
									(1.49)	(2.46)	(1.84)	

Testing Restrictions

	$\lambda_{EN} = \lambda_{MO}$	$\lambda_{SA} = \lambda_{MO}$	$\lambda_{NE} = \lambda_{MO}$	$\lambda_{MA} = \lambda_{MO}$
F-Test	27.447	4.965	26.307	20.406
	[0.00]	[0.03]	[0.00]	[0.00]
	$\lambda_{EN} = -0.008$	$\lambda_{SA} = -0.008$	$\lambda_{NE} = -0.008$	$\lambda_{MA} = -0.008$
F-Test	8.671	0.101	4.991	8.676
	[0.00]	[0.75]	[0.00]	[0.00]

Panel B: Value Weighted

λ_{WS}	λ_{PA}	λ_{ES}	λ_{MO}	λ_{EN}	λ_{SA}	λ_{WN}	λ_{MA}	λ_{NE}	λ_m	λ_{smb}	λ_{hml}	$\overline{R}^2$
−0.008	−0.006	−0.005	−0.010	−0.004	−0.006	−0.002	−0.003	−0.004	−0.006			0.59
(3.48)	(4.01)	(3.49)	(4.67)	(2.69)	(3.91)	(1.05)	(2.32)	(3.08)	(0.67)			
									0.016			0.05
									(1.49)			
									−0.012	0.012	0.011	0.41
									(1.23)	(2.23)	(1.77)	

Testing Restrictions

	$\lambda_{EN} = \lambda_{MO}$	$\lambda_{SA} = \lambda_{MO}$	$\lambda_{NE} = \lambda_{MO}$	$\lambda_{MA} = \lambda_{MO}$
F-Test	25.619	5.956	27.691	22.667
	[0.00]	[0.02]	[0.00]	[0.00]
	$\lambda_{EN} = -0.006$	$\lambda_{SA} = -0.006$	$\lambda_{NE} = -0.006$	$\lambda_{MA} = -0.006$
F-Test	3.835	0.010	2.631	4.964
	[0.05]	[0.92]	[0.10]	[0.03]

This table reports results from estimating cross-sectional regressions of average excess returns on the nine divisional betas and market beta. We use returns on twenty size portfolios for each of the nine divisions (ten in the case of EN). λ_i is the estimated price of risk for division i. The table also presents F-Tests of the restriction that the prices of risk in the high population density divisions are equal to the price of risk in the division with the lowest density (Mountain) and to the average price of risk across all five divisions with low population density. The divisions are indexed with two capital letters: WS is West South Central, PA is Pacific, ES is East South Central, MO is Mountain, EN is East North Central, SA is South Atlantic, WN is West North Central, MA is Middle Atlantic, and NE is New England. λ_m is the market price of risk, λ_{smb} is the price of risk associated with the small minus big factor, λ_{hml} is the price of risk associated with the high minus low book to market factor. Data are sampled 1963Q1 to 2006Q4. Numbers in parentheses are t–statistics. $\overline{R}^2$ is the adjusted R^2.

Table 4
Pricing Errors
Size Sorted Portfolios

	Size EW					Size VW				
	KEEPM	CAPM	FF	F_C	F_{FF}	KEEPM	CAPM	FF	F_C	F_{FF}
All	0.006 (0.005)	0.009 (0.010)	0.007 (0.007)	12.468 [0.00]	4.303 [0.04]	0.005 (0.005)	0.008 (0.008)	0.006 (0.006)	22.563 [0.00]	9.829 [0.00]
WS	0.006 (0.006)	0.009 (0.011)	0.008 (0.009)	1.092 [0.31]	0.728 [0.40]	0.005 (0.004)	0.008 (0.009)	0.007 (0.006)	1.784 [0.19]	1.813 [0.19]
PA	0.006 (0.005)	0.010 (0.010)	0.008 (0.009)	2.614 [0.12]	0.778 [0.38]	0.005 (0.004)	0.009 (0.008)	0.007 (0.007)	5.029 [0.04]	1.061 [0.31]
ES	0.006 (0.006)	0.007 (0.008)	0.005 (0.005)	0.196 [0.66]	0.947 [0.35]	0.006 (0.006)	0.007 (0.008)	0.005 (0.005)	0.369 [0.55]	0.851 [0.38]
MO	0.011 (0.007)	0.016 (0.012)	0.013 (0.008)	3.457 [0.07]	0.980 [0.33]	0.011 (0.006)	0.015 (0.011)	0.013 (0.008)	4.645 [0.04]	1.763 [0.19]
EN	0.004 (0.003)	0.005 (0.007)	0.005 (0.007)	0.471 [0.50]	1.258 [0.27]	0.003 (0.003)	0.005 (0.006)	0.004* (0.003)	2.000 [0.17]	2.893 [0.10]
SA	0.005 (0.005)	0.008 (0.010)	0.006 (0.006)	2.394 [0.14]	0.609 [0.44]	0.005 (0.004)	0.008 (0.008)	0.006 (0.005)	2.187 [0.16]	0.185 [0.67]
WN	0.006 (0.004)	0.006 (0.007)	0.006 (0.005)	0.014 [0.90]	0.010 [0.91]	0.005 (0.004)	0.006 (0.005)	0.005 (0.004)	0.234 [0.63]	0.120 [0.73]
MA	0.005 (0.005)	0.008 (0.009)	0.008 (0.007)	2.061 [0.17]	3.121 [0.09]	0.005 (0.005)	0.007 (0.008)	0.007 (0.005)	1.727 [0.20]	1.634 [0.21]
NE	0.005 (0.005)	0.008 (0.009)	0.006 (0.006)	3.909 [0.06]	1.541 [0.22]	0.004 (0.004)	0.007 (0.008)	0.005 (0.005)	3.426 [0.08]	1.083 [0.311]

This table reports analysis of pricing errors. KEEPM is the Keeping-up-with-the-Joneses model, CAPM is the CAPM, FF is the Fama and French model. All includes size sorted portfolios from all 9 divisions. We report the square root of the average squared pricing error for all divisions aggregated together and for the 20 portfolios in each division (10 portfolios for EN). We report F-tests that the square root of the average pricing error from the CAPM and Fama-French models are equal to the square root of the average pricing error from the KEEPM (F_C and F_{FF}). The divisions are indexed with two capital letters: WS is West South Central, PA is Pacific, ES is East South Central, MO is Mountain, EN is East North Central, SA is South Atlantic, WN is West North Central, MA is Middle Atlantic, and NE is New England. Data are sampled 1963Q1 to 2006Q4. Standard errors are reported in parenthesis. Probability values are in brackets. * indicates that the null hypothesis that the pricing errors are jointly zero cannot be rejected.

Table 5
Book-to-Market and Size Portfolio Formation Criteria
Panel A: Book-to-Market Portfolios

λ_{WS}	λ_{PA}	λ_{ES}	λ_{MO}	λ_{EN}	λ_{SA}	λ_{WN}	λ_{MA}	λ_{NE}	λ_m	λ_{smb}	λ_{hml}	$\overline{R}^2$	$F(p.e)$
−0.006	−0.007	−0.005	−0.007	−0.005	−0.006	−0.002	−0.002	−0.003	−0.017			0.68	
(2.61)	(3.54)	(3.02)	(3.07)	(3.61)	(3.21)	(1.06)	(1.49)	(1.75)	(1.62)				
									−0.025			0.11	30.648
									(2.26)				[0.00]
									0.007	0.012	0.031	0.60	0.835
									(0.67)	(1.73)	(4.70)		[0.00]

Testing Restrictions

	$\lambda_{EN} = \lambda_{MO}$	$\lambda_{SA} = -\lambda_{MO}$	$\lambda_{NE} = \lambda_{MO}$	$\lambda_{MA} = \lambda_{MO}$
F-Test	1.042	0.053	9.863	5.342
	[0.30]	[0.81]	[0.00]	[0.02]
	$\lambda_{EN} = -0.0054$	$\lambda_{SA} = -0.0054$	$\lambda_{NE} = -0.0054$	$\lambda_{MA} = -0.0054$
F-Test	0.014	0.522	4.199	1.390
	[0.90]	[0.47]	[0.04]	[0.23]

Panel B: Size and Book-to-Market Portfolios

λ_{WS}	λ_{PA}	λ_{ES}	λ_{MO}	λ_{EN}	λ_{SA}	λ_{WN}	λ_{MA}	λ_{NE}	λ_m	λ_{smb}	λ_{hml}	$\overline{R}^2$	$F(p.e)$
−0.005	−0.006	−0.004	−0.009	−0.005	−0.006	−0.004	−0.003	−0.004	−0.002			0.59	
(2.13)	(3.32)	(2.55)	(3.85)	(3.32)	(3.23)	(1.91)	(1.90)	(2.77)	(0.23)				
									0.015			0.04	16.574
									(1.21)				[0.00]
									−0.012	0.012	0.011	0.41	3.760
									(1.12)	(2.06)	(1.36)		[0.05]

Testing Restrictions

	$\lambda_{EN} = \lambda_{MO}$	$\lambda_{SA} = -\lambda_{MO}$	$\lambda_{NE} = \lambda_{MO}$	$\lambda_{MA} = \lambda_{MO}$
F-Test	5.753	3.296	15.969	8.823
	[0.02]	[0.07]	[0.00]	[0.00]
	$\lambda_{EN} = -0.0056$	$\lambda_{SA} = -0.0056$	$\lambda_{NE} = -0.0056$	$\lambda_{MA} = -0.0056$
F-Test	0.241	0.171	4.116	1.113
	[0.62]	[0.89]	[0.04]	[0.29]

This table reports results from estimating cross-sectional regressions of average excess returns on the nine divisional betas and market beta. We use returns on twenty book-to-market equally weighted portfolios for each of the nine divisions and fifteen size and book to market portfolios for each division. λ_i is the estimated price of risk for division i. We report F-tests that the square root of the average pricing error from the CAPM and Fama-French models are equal to the square root of the average pricing error from the Joneses model ($F(p.e)$) over all divisions. The table also presents F-Tests of the restriction that the prices of risk in the high population density divisions are equal to the price of risk in the division with the lowest density (Mountain) and to the average price of risk across all five divisions with low population density. The divisions are indexed with two capital letters: WS is West South Central, PA is Pacific, ES is East South Central, MO is Mountain, EN is East North Central, SA is South Atlantic, WN is West North Central, MA is Middle Atlantic, and NE is New England. λ_m is the market price of risk, λ_{smb} is the price of risk associated with the small minus big factor, λ_{hml} is the price of risk associated with the high minus low book to market factor. Data are sampled 1966Q1 to 2006Q4. Numbers in parentheses are t–statistics. Probability values are in brackets. $\overline{R}^2$ is the adjusted $R^{2.}$

Table 6
R&D and Total Leverage Formation Criteria

Panel A: R&D and Size

λ_{WS}	λ_{PA}	λ_{ES}	λ_{MO}	λ_{EN}	λ_{SA}	λ_{WN}	λ_{MA}	λ_{NE}	λ_m	λ_{smb}	λ_{hml}	$\overline{R}^2$	$F(p.e)$
−0.008	−0.008	−0.006	−0.011	−0.006	−0.008	−0.005	−0.005	−0.007	0.010			0.64	
(3.10)	(4.16)	(3.30)	(4.81)	(3.71)	(4.36)	(2.42)	(3.06)	(4.09)	(1.02)				
									0.013			0.04	15.086
									(1.08)				[0.00]
									−0.019	0.013	0.025	0.39	4.761
									(1.69)	(2.15)	(2.76)		[0.03]

Testing Restrictions

	$\lambda_{EN} = \lambda_{MO}$	$\lambda_{SA} = -\lambda_{MO}$	$\lambda_{NE} = \lambda_{MO}$	$\lambda_{MA} = \lambda_{MO}$
F-Test	9.704 [0.00]	3.267 [0.07]	15.200 [0.00]	7.197 [0.01]
	$\lambda_{EN} = -0.0076$	$\lambda_{SA} = -0.0076$	$\lambda_{NE} = -0.0076$	$\lambda_{MA} = -0.0076$
F-Test	1.571 [0.21]	0.015 [0.90]	4.000 [0.05]	0.694 [0.40]

Panel B: Total Leverage and Size

λ_{WS}	λ_{PA}	λ_{ES}	λ_{MO}	λ_{EN}	λ_{SA}	λ_{WN}	λ_{MA}	λ_{NE}	λ_m	λ_{smb}	λ_{hml}	$\overline{R}^2$	$F(p.e)$
−0.008	−0.007	−0.006	−0.012	−0.006	−0.008	−0.005	−0.005	−0.006	−0.005			0.63	
(3.21)	(4.04)	(3.50)	(4.96)	(3.79)	(4.41)	(2.67)	(2.82)	(3.83)	(0.53)				
									0.012			0.02	14.137
									(1.08)				[0.00]
									−0.016	0.013	0.011	0.40	5.516
									(1.48)	(2.23)	(1.49)		[0.02]

Testing Restrictions

	$\lambda_{EN} = \lambda_{MO}$	$\lambda_{SA} = -\lambda_{MO}$	$\lambda_{NE} = \lambda_{MO}$	$\lambda_{MA} = \lambda_{MO}$
F-Test	13.656 [0.00]	6.192 [0.01]	21.329 [0.00]	13.065 [0.00]
	$\lambda_{EN} = -0.0076$	$\lambda_{SA} = -0.0076$	$\lambda_{NE} = -0.0076$	$\lambda_{MA} = -0.0076$
F-Test	1.462 [0.22]	0.035 [0.85]	4.573 [0.03]	1.280 [0.25]

This table reports results from estimating cross-sectional regressions of average excess returns on the nine divisional betas and market beta. We use returns on fifteen equally weighted portfolios for each of the nine divisions based on size and the amount of R&D and fifteen equally weighted portfolios for each of the nine divisions based on size and total leverage. λ_i is the estimated price of risk for division i. We report F-tests that the square root of the average pricing error from the CAPM and Fama-French models are equal to the square root of the average pricing error from the Joneses model ($F(p.e)$) over all divisions. The table also presents F-Tests of the restriction that the prices of risk in the high population density divisions are equal to the price of risk in the division with the lowest density (Mountain) and to the average price of risk across all five divisions with low population density. The divisions are indexed with two capital letters: WS is West South Central, PA is Pacific, ES is East South Central, MO is Mountain, EN is East North Central, SA is South Atlantic, WN is West North Central, MA is Middle

Atlantic, and NE is New England. λ_m is the market price of risk, λ_{smb} is the price of risk associated with the small minus big factor, λ_{hml} is the price of risk associated with the high minus low book to market factor. Data are sampled 1966Q1 to 2006Q4. Numbers in parentheses are t–statistics. Probability values are in brackets. $\overline{R}^2$ is the adjusted R^2.

Table 7
Cross-Sectional Estimates Using Housing
Size Sorted Portfolios

Panel A: Orthogonal House Price Inflation

λ_{WS}	λ_{PA}	λ_{ES}	λ_{MO}	λ_{EN}	λ_{SA}	λ_{WN}	λ_{MA}	λ_{NE}	λ_m	$\overline{R}^2$
−0.003	−0.013	0.004	0.002	0.001	−0.006	−0.002	−0.013	−0.010	−0.003	0.59
(1.23)	(4.59)	(1.81)	(0.64)	(0.79)	(3.18)	(1.27)	(4.42)	(3.42)	(0.29)	

Panel B: Orthogonal Labor Income

λ_{WS}	λ_{PA}	λ_{ES}	λ_{MO}	λ_{EN}	λ_{SA}	λ_{WN}	λ_{MA}	λ_{NE}	λ_m	$\overline{R}^2$
−0.009	−0.007	−0.005	0.010	−0.004	−0.007	−0.002	−0.006	−0.006	−0.012	0.58
(3.60)	(3.88)	(3.07)	(4.63)	(2.89)	(3.98)	(1.19)	(3.64)	(3.55)	(1.20)	

This table reports results from estimating cross-sectional regressions of average excess returns on the nine divisional betas and market beta. We use returns on twenty size portfolios for each of the nine divisions. λ_i is the estimated price of risk for division i. The divisions are indexed with two capital letters: WS is West South Central, PA is Pacific, ES is East South Central, MO is Mountain, EN is East North Central, SA is South Atlantic, WN is West North Central, MA is Middle Atlantic, and NE is New England. λ_m is the market price of risk Data are sampled 1977Q1 to 2006Q4. Numbers in parentheses are t–statistics. $\overline{R}^2$ is the adjusted $R^{2.}$

Table 8

Robustness Tests

Panel A: Shanken Correction

Orthogonal Labor Income										
λ_{WS}	λ_{PA}	λ_{ES}	λ_{MO}	λ_{EN}	λ_{SA}	λ_{WN}	λ_{MA}	λ_{NE}	λ_m	$\overline{R}^2$
−0.010	−0.007	−0.007	−0.011	−0.004	−0.007	−0.003	−0.004	−0.005	−0.006	0.63
(3.10)	(3.37)	(3.00)	(4.11)	(2.39)	(3.57)	(1.23)	(2.13)	(2.89)	(0.53)	
Orthogonal Housing										
λ_{WS}	λ_{PA}	λ_{ES}	λ_{MO}	λ_{EN}	λ_{SA}	λ_{WN}	λ_{MA}	λ_{NE}	λ_m	$\overline{R}^2$
−0.003	−0.013	0.004	0.002	0.001	−0.006	−0.002	−0.013	−0.010	−0.003	0.59
(0.81)	(3.08)	(1.16)	(0.38)	(0.53)	(2.18)	(0.89)	(3.02)	(2.34)	(0.19)	

Panel B: Estimates Using Division-by-Division

	Orthogonal Labor Income								
	WS	PA	ES	MO	EN	SA	WN	MA	NE
λ	−0.019	−0.010	−0.010	−0.013	−0.009	−0.008	−0.004	−0.019	−0.013
	(4.52)	(3.54)	(2.34)	(4.23)	(2.65)	(3.41)	(1.34)	(4.39)	(3.10)
λ_m	0.015	−0.030	0.017	−0.009	0.064	−0.019	−0.002	0.029	0.005
	(0.88)	(1.93)	(0.66)	(0.60)	(2.68)	(1.39)	(0.11)	(1.31)	(0.26)

This table reports two sets of robustness tests. Panel A reports t-statistics for the estimates of the parameters of the full model using the Shanken (1992) correction for errors-in-variables. Panel B reports estimates of the parameters when we estimate the model separately for each division. In this case we use twenty equally weighted size portfolios from each division except East South Central where we use ten portfolios. The risk factors are the market excess return and orthogonal labor income of the division. Data are sampled 1963Q1 to 2006Q4 for the models that use labor income and 1977Q1 to 2006Q4 for the models that use house price growth.

Figure 1: US Census Regions and Divisions

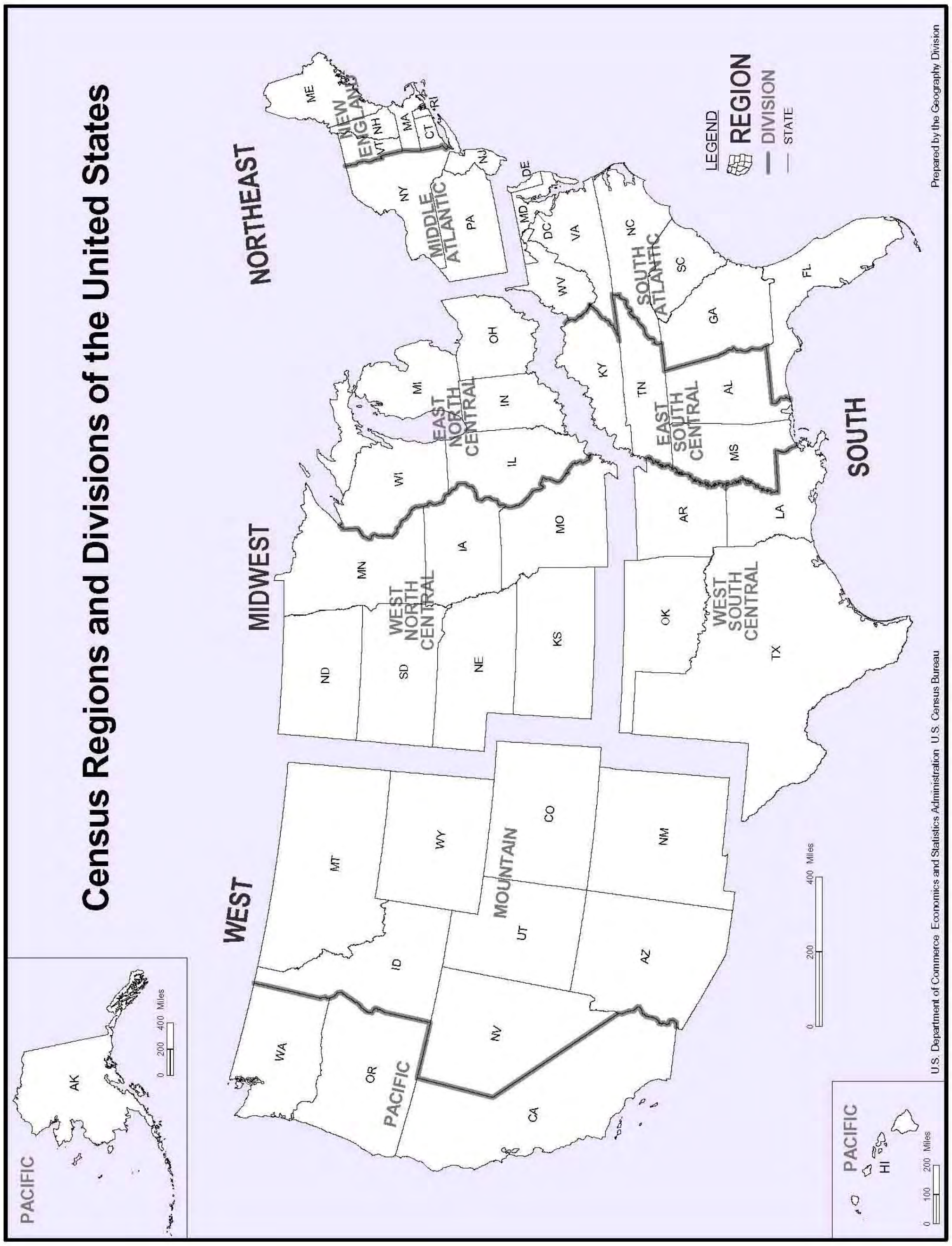
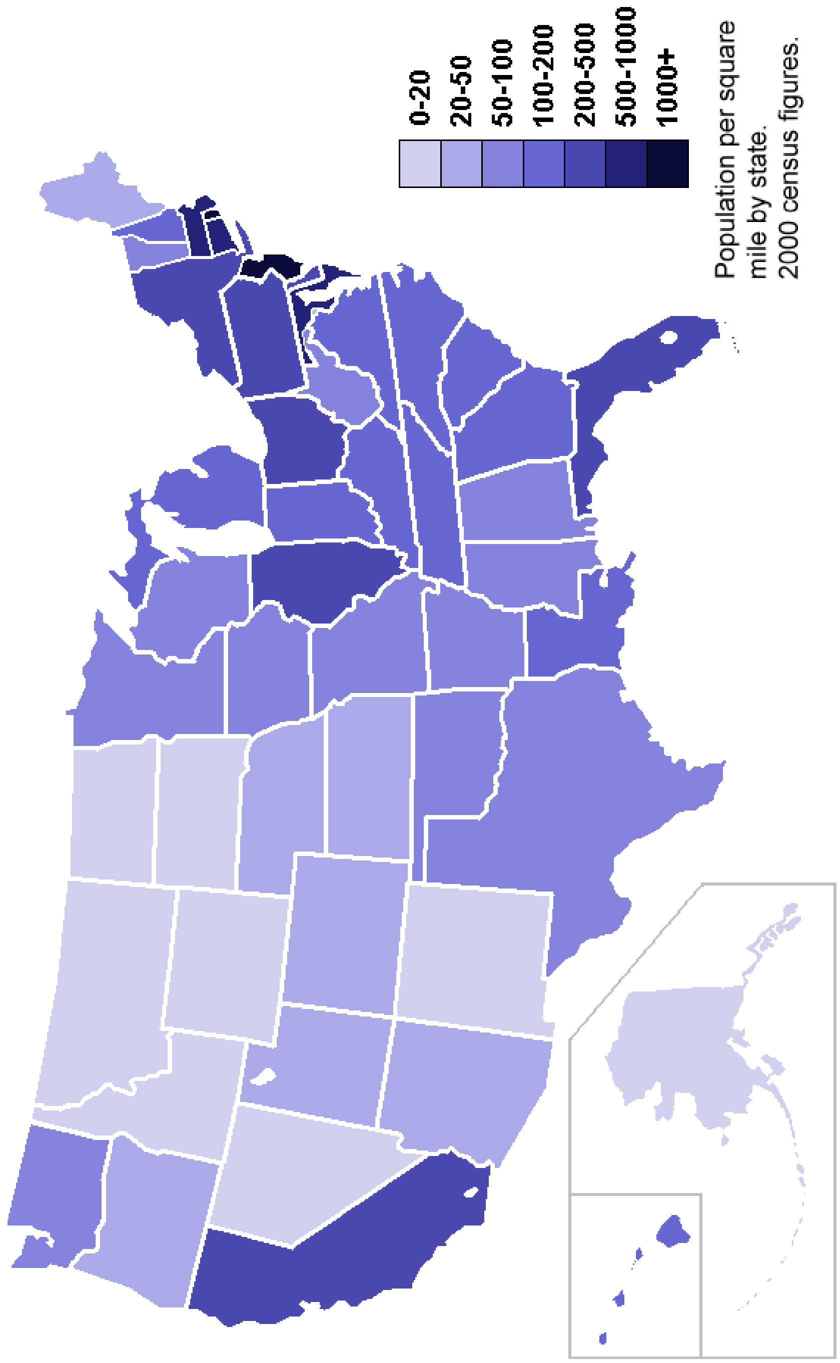
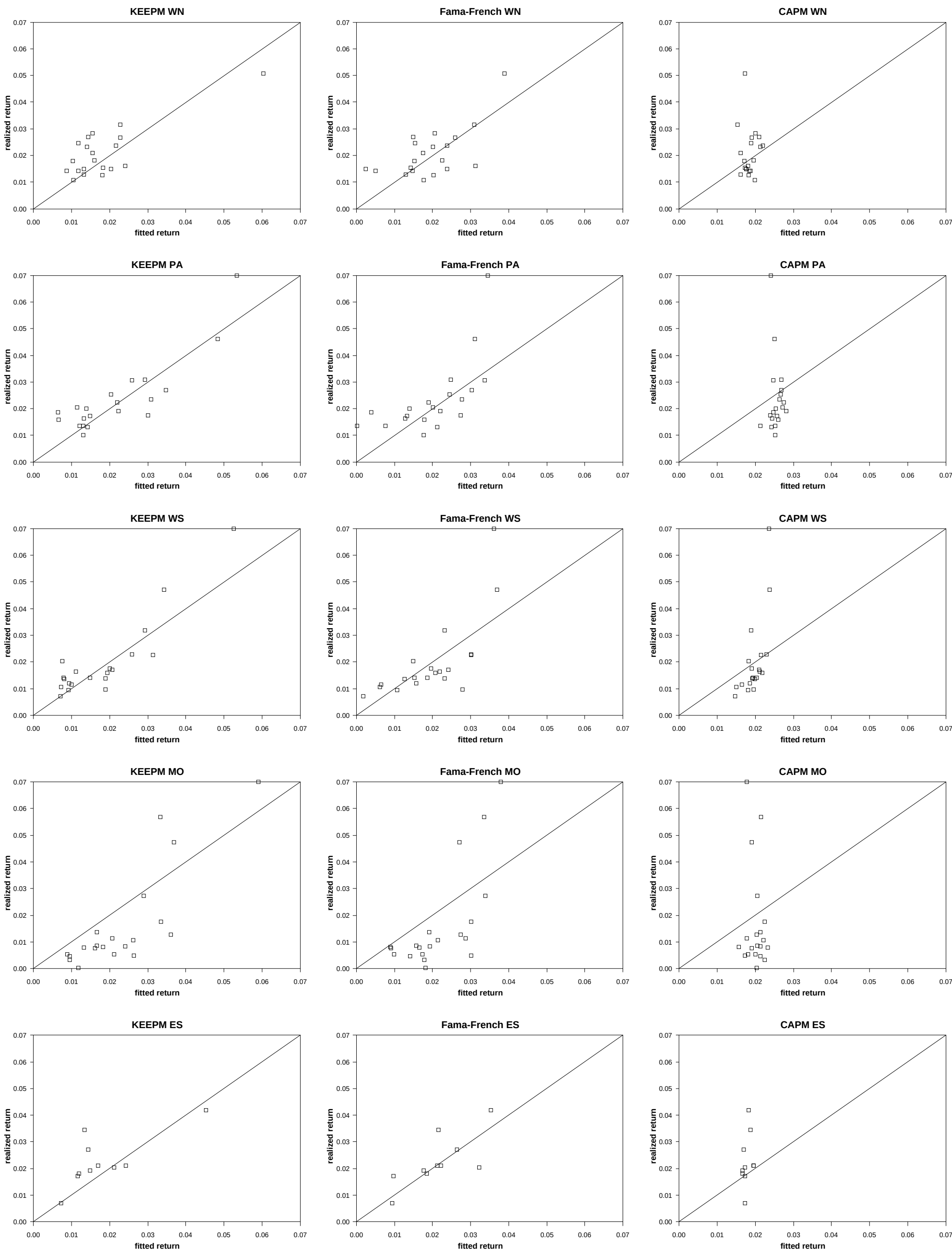


Figure 2: Population Density in the US



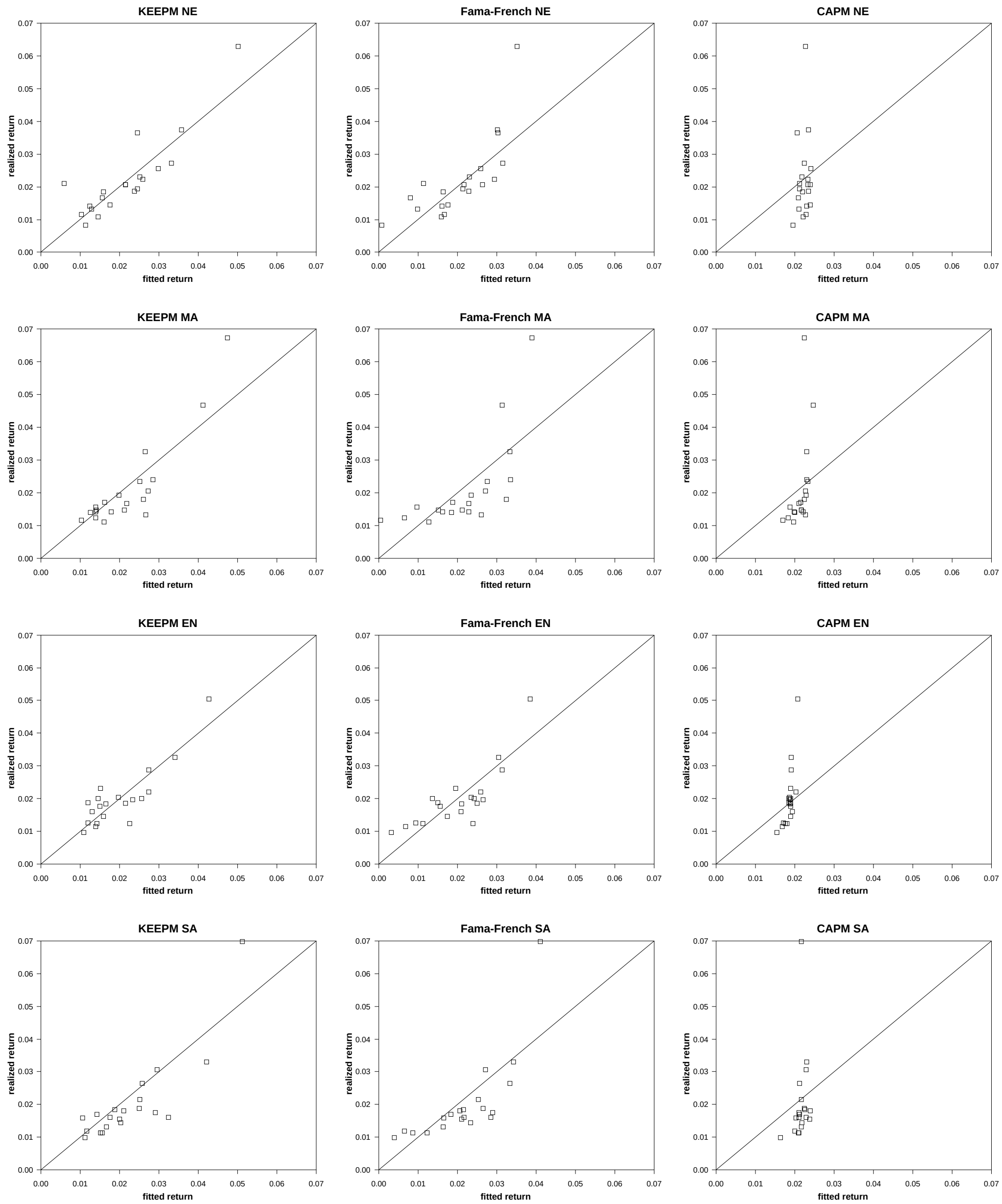
Population per square mile by state. 2000 Census figures.

Figure 3: Realized Returns and Fitted Returns: Low Population Density Divisions



This figure plots the expected returns from the three estimated models (fitted returns) in the horizontal axis against the realized returns for the size portfolios (vertical axis) in each of the low population density divisions (below 100 inhabitants per square mile of land area). Each row in the figure plots the series for a given division. The divisions are indexed with two capital letters: PA is Pacific, ES is East South Central, MO is Mountain, WN is West North Central and WS is West South Central.

Figure 4: Realized Returns and Fitted Returns: High Population Density Divisions



This figure plots the expected returns from the three estimated models (fitted returns) in the horizontal axis against the realized returns for the size portfolios (vertical axis) in each of the high population density divisions (above 100 inhabitants per square mile of land area). Each row in the figure plots the series for a given division. The divisions are indexed with two capital letters: EN is East North Central, SA is South Atlantic, MA is Middle Atlantic, and NE is New England.