Resurrecting the (C)CAPM: A Cross-Sectional Test When Risk Premia Are Time-Varying *

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Abstract

This paper explores the ability of theoretically-based asset pricing models such as the CAPM and the consumption CAPM–referred to jointly as the (C)CAPM–to explain the cross-section of average stock returns. Unlike many previous empirical tests of the (C)CAPM, we specify the pricing kernel as a conditional linear factor model, as would be expected if risk premia vary over time. Central to our approach is the use of a conditioning variable which proxies for fluctuations in the log consumption-aggregate wealth ratio and is likely to be important for summarizing conditional expectations of excess returns. We demonstrate that such conditional factor models are able to explain a substantial fraction of the cross-sectional variation in portfolio returns. These models perform much better than unconditional (C)CAPM specifications, and about as well as the three-factor Fama-French model on portfolios sorted by size and book-to-market ratios. This specification of the linear conditional consumption CAPM, using aggregate consumption data, is able to account for the difference in returns between low book-to-market and high book-to-market firms and exhibits little evidence of residual size or book-to-market effects. (JEL G10, E21)

1 Introduction

Asset pricing theory has fallen on hard times. The capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) has long been a pillar of academic finance and early evidence seemed to reflect favorably on the theory's central tenet that the market portfolio should be mean-variance efficient.[1] But recent evidence has mounted that the CAPM is simply inconsistent with numerous empirical regularities of cross-sectional asset pricing data.[2] Perhaps most damning, the CAPM has displayed virtually no power to explain the cross-section of average returns on assets that vary according book-to-market equity ratios (Fama and French 1992, 1993).

One critique of the CAPM is that its static specification fails to take into account the effects of time-varying investment opportunities in the calculation of an asset's risk. Intertemporal asset pricing models, the most prominent of which is the consumption CAPM (CCAPM), initially held out hope of remedying this defect. Unfortunately, these models have also proven disappointing empirically. The consumption-based model has been rejected on U.S. data in its representative agent formulation with time-separable power utility (Hansen and Singleton 1982, 1983); it has performed no better and often worse than the simple static-CAPM in explaining the cross-section of average asset returns (Mankiw and Shapiro 1986; Breeden, Gibbons, and Litzenberger 1989; Campbell 1996; Cochrane 1996; Hodrick, Ng and Sengmueller 1998); and it has been generally replaced as an explanation for systematic risk by a variety of portfolio-based models (for example, Fama and French 1993, Elton, Gruber and Blake 1995).

Despite the empirical shortcomings of the consumption-based model, the reputation of the theoretical paradigm itself remains well preserved.[3] And for good reason. As a measure of systematic risk, an asset's covariance with the marginal utility of consumption achieves a degree of theoretical purity that is unmatched by other asset pricing models. These other models, including the static-CAPM, can almost always be expressed as either special cases of, or proxies for, the consumption-based model.[4] Moreover, the consumption-based framework is a simple but powerful tool for addressing the criticisms of Merton (1973), that the static-CAPM fails to account for the intertemporal hedging component of asset demand, and Roll (1977), that the market return cannot be adequately proxied by an index of common stocks. According to these rationales, the puzzle is not which model should replace the consumption-based paradigm, but

[1]See Black, Jensen, and Scholes (1972), Fama and MacBeth (1973), Blume and Friend (1973).

[2]For example, see Banz (1981), Basu (1977), Shanken (1985), Fama and French (1992, 1993).

[3]This theory was developed by Rubinstein (1976), Breeden and Litzenberger (1978), and Breeden (1979).

[4]Cochrane (1999), chapter 8, emphasizes this point.

rather why there has been no confirmation of it empirically.

One possible reason for the poor empirical performance of both the CAPM and the CCAPM–referred to jointly as the (C)CAPM–is that previous tests may have made inadequate allowances for time-variation in the conditional moments of returns. For example, time-variation in expected excess returns has been documented in a large and growing body of empirical work.[5] If risk premia are time-varying, parameters in the stochastic discount factor will, in general, vary according to changing investor expectations of future excess returns. In this case, the CAPM will be a linear function of the market return with time-varying weights. Similarly, the consumption CAPM states that the stochastic discount factor for expected future returns should be a function of consumption growth. However, this does not in general preclude the possibility that the discount factor is a state-dependent function of consumption growth, as it would be in models with habit-formation where risk-aversion is not constant over time (e.g., Sundaresan 1989; Constantinides 1990; Campbell and Cochrane 1999a.)

In this paper, we assume that the true unobservable stochastic discount factor in the CAPM or consumption CAPM may be expressed as a linear function of the appropriate fundamental factors, but we allow the parameters of this function to be state dependent.[6] Note that precisely the same fundamental factors that price assets in traditional derivations of the static-CAPM and the unconditional consumption-CAPM are assumed to price assets in this approach. The difference is that factors in the stochastic discount factor are expected only to conditionally price assets, leading to conditional rather than fixed linear factor models. As we discuss further below, habit-formation models provide a particularly good motivation for the form of conditional linear factor model we investigate. Conditional linear factor models in turn imply conditional "beta" models, where the expected return on an asset is a function of its conditional covariance with the factor, normalized by the conditional variance of the factor.

[5]See for example, Shiller (1984), Campbell and Shiller (1988), Campbell (1991), Fama and French (1988), Hodrick (1992), Lamont (1998) and Lettau and Ludvigson (1999).

[6]In tests of the CCAPM, empirical studies carried out to date have concentrated on investigating the model's unconditional implications using specific functional forms for the investor's utility function. Consequently, there are at least two possible reasons why these tests have failed to find support for the consumption-based model. First, an approximate linear factor model may hold conditionally even if it does not hold unconditionally; second, specification of either the functional form of the investor's utility function or its temporal separabilities may have been wrong. As we discuss below, we address these difficulties in a less structured way, by assuming that the true unobservable discount factor may be approximated as a linear, state-dependent function of consumption growth rather than specifying and testing an explicit model of consumer behavior.

Before such a conditional asset pricing framework can be tested, an important question must be answered. How should these conditional moments be modeled? One approach would be to estimate an explicit model of the joint conditional distribution of asset returns and the discount factor. The drawback of this approach is that it assumes knowledge of the true conditional model, and the number of parameters in the conditional distribution that must be estimated in any reasonably flexible specification is typically infeasible given the samples sizes commonly encountered.

As an alternative approach, one could explicitly model the dependence of parameters in the discount factor on current period information. This dependence can be specified by simply interacting, or "scaling," factors with instruments that are likely to be important for summarizing variation in conditional moments. We adopt this approach here. In doing so, we may express a conditional linear factor model as an unconditional, multifactor asset pricing model where the additional factors are simply scaled versions of the original factors. We refer to this version of the (C)CAPM as the *scaled multifactor* model.

The methodology of scaling factors by instruments that are likely to capture variation in conditional moments was first advocated by Cochrane (1996) and later employed by Ferson and Harvey (1999).[7] These authors use lagged economy-wide indicators as scaling variables in cross-sectional asset pricing tests. The methodology is also closely related to the approach of Jagannathan and Wang (1996) who show that the performance of the CAPM is dramatically improved by conditioning the market factor on financial indicators such as the default premium. This literature has demonstrated the usefulness of conditioning variables in a variety of asset pricing applications. Scaling factors is one way to incorporate conditioning information; here we use the terms scaling and conditioning interchangeably.

The choice of conditioning variable in this study is central to our approach. The linear factor model we consider is a function of investors' conditioning information which is unobservable. This unobservability constitutes the most important practical obstacle to testing conditional factor models: the econometrician's information set is, at best, a subset of the investors' information set. We argue here that we may circumvent this difficulty by using a conditioning variable which *summarizes* investor expectations of excess returns.

To find such a summary measure of investor expectations, we appeal to a defining feature of

[7]This methodology builds off of the work of Ferson, Kandel, and Stambaugh (1987); Harvey (1989); and Shanken (1990) who suggest scaling the conditional betas themselves (rather than the factors directly) in a cross sectional linear regression model where market betas are expected to vary over time.

any forward looking model: agents' own behavior reveals much of their expectations about the future. Theories of consumption behavior provide an excellent example of this. In a wide class of dynamic, optimizing models, log consumption and log aggregate (human and nonhuman) wealth share a common stochastic trend (they are cointegrated), but they may deviate from one another in the short term based on changing expectations of future returns. Accordingly, the log consumption-aggregate wealth ratio summarizes investor expectations of discounted future returns to the market portfolio.

The difficulty with this observation is that the consumption-aggregate wealth ratio, specifically the human capital component of it, is not observable. In a recent paper, Lettau and Ludvigson (1999) demonstrate, however, that movements in the log consumption-aggregate wealth ratio may be well captured by movements in three observable variables, namely consumption, nonhuman wealth and labor income. This observable quantity is the difference between log consumption (c) and the appropriate weighted average of log asset (nonhuman) wealth (a) and log labor income (y), referred to subsequently as *cay* for short. Lettau and Ludvigson (1999) argue that movements in *cay* are better characterized as transitory movements in wealth, rather than as transitory movements in consumption or labor income, because fluctuations in *cay* forecast asset growth, while consumption and labor income follow relatively persistent processes. For this reason, we will refer to *cay* interchangeably as the *trend deviation in wealth.* Lettau and Ludvigson (1999) provide a more detailed explanation of this characterization.

If the trend deviation in wealth is a good proxy for movements in the consumption-aggregate wealth ratio (and therefore a good summary of investor expectations), it should forecast future movements in the return to aggregate wealth. Consistent with this proposition, Lettau and Ludvigson find that *cay* has striking forecasting power for excess returns on common stock market indexes. As a consequence, we argue that movements in *cay* are a good proxy for movements in the consumption-aggregate wealth ratio. This methodology of measuring investor expectations is founded on the recognition that investors' own behavior–as captured by movements in *cay*–reveals to us what we need to know to control for the fact that investors know more than we do.

According to the theoretical framework sketched above, the consumption-aggregate wealth ratio provides a uniquely comprehensive summary of conditional expectations. Other variables, such as an aggregate dividend-price ratio, may also summarize investor expectations about future returns (Campbell and Shiller 1988). Unlike the consumption-aggregate wealth ratio, however, the dividend-price ratio only summarizes expectations about those assets that pay dividends (i.e., stocks). By contrast, consumption can be thought of as the dividend paid from aggregate wealth, or the market portfolio, implying that movements in the consumption-aggregate wealth ratio summarize expectations about the entire market portfolio, not just the stock market component of it. Since Campbell (1996), Jagannathan and Wang (1996) and others have emphasized that stocks are a relatively small part of aggregate wealth, the scaling variable *cay* is likely to have an important advantage over more traditional forecasting variables in condensing information.

To investigate the empirical performance of the scaled multifactor version of the (C)CAPM, we must also choose a set of portfolios upon which to carry out the cross-sectional tests. This choice is likely to be an important one. The small firm effect of Banz (1981) notwithstanding, it is well known that the static-CAPM is relatively better at explaining the average returns on stock portfolios formed according to size (market value) or industry. In addition, Jagannathan and Wang (1996) show that a conditional CAPM model does a good job of explaining the cross-section of returns on portfolios sorted according to size and market betas (covariance with the CRSP value-weighted index). By contrast, on portfolios sorted according to size and book-to-market equity ratios, the CAPM performs very poorly (Fama and French 1992). Instead, Fama and French (1993) show that a three-factor model with factors related to firm size and book-to-market equity, along with an overall stock market factor, do a good job of explaining the cross-section of returns on these portfolios. Fama and French (1993, 1995) argue that these related factors proxy for unobserved common risk in portfolio returns, but this interpretation is somewhat controversial since it is not yet entirely clear how they relate to the underlying macroeconomic, nondiversifiable risk so proxied.[8]

Nevertheless, it is clear that explaining the cross-section of returns on portfolios sorted according to both size and book-to-market equity has presented the greatest challenge so far for theoretically-based asset pricing models such as the CAPM and the consumption CAPM. At issue is whether the strong variation in returns across portfolios that differ according to book-to-market equity ratios can be attributed to variation in the riskiness of those portfolios. If the Fama–French factors truly are mimicking portfolios for underlying sources of macroeconomic risk, there should be some set of macroeconomic factors that performs well in explaining the cross-section of average returns on those portfolios. As yet, however, there is little empirical

[8]Liew and Vassalou (forthcoming) provide a first step in establishing an empirical link between the size and book-to-market factors and future macroeconomic variables: they find that for some countries, these variables have forecasting power for GDP growth.

evidence that macroeconomic variables can explain even a small fraction of the variation in these returns.

We take on this challenge by investigating the performance of the scaled multifactor (C)CAPM using the size/book-to-market sorted portfolios as constructed in Fama and French (1992, 1993). To the best of our knowledge, this paper is the first to study the performance of conditional linear factor models of the (C)CAPM using portfolios formed according to the criteria in Fama and French (1992).

Our main findings can be summarized as follows. We find that the scaled multifactor version of the (C)CAPM performs very well in explaining the cross section of average returns. Perhaps most strikingly, the scaled consumption CAPM, using aggregate consumption data, can explain nearly 70 percent of the cross-sectional variation in average returns on the 25 Fama–French portfolios described above, about as well as the Fama-French three-factor model. This result contrasts sharply with the 1 percent explained by the unconditional static-CAPM. The unconditional consumption CAPM performs a bit better than this, explaining about 16% of the cross-sectional variation, but still falls far short of the scaled multifactor consumption CAPM. These results, in particular, seem to support a habit-formation version of the consumption CAPM, where the multiplicative, or scaled, consumption factors are important. The scaled multifactor CAPM performs quite well once we include the proxy for the return to human capital advocated by Jagannathan and Wang (1996), in addition to a broad stock market factor. This model explains about 75 percent of the cross-sectional variation in average returns. But the consumption-based model performs better than even this version of the scaled multifactor CAPM along other dimensions. In particular, firm specific characteristics such as size and book-to-market equity are no longer significant explanatory variables for the cross-section of average returns once the scaled consumption factors are included. These findings suggest that an asset's risk is determined not by its unconditional correlation with the model's underlying factor, but rather by its correlation conditional on the state of the economy. (We discuss this further below.) Finally, we find that the choice of conditioning variable is important: in general, when factors are scaled with variables such as the dividend-price ratio or the default spread, the conditional factor models we investigate can explain only a small fraction of the cross-sectional variation in average returns that they can when they are scaled by *cay*.

An important aspect of our results is that the conditional consumption model, scaled by *cay*, goes a long way toward explaining the celebrated "value premium," that is the well documented pattern found in average returns that firms with high book-to-market equity ratios have higher average returns than do firms with low book-to-market ratios. This finding is important because there exists considerable controversy over whether the observed value premium is due to phenomena captured by firm characteristics (implying a mispricing of value stocks) or to genuine covariance with common risk factors (implying that value stocks are rationally priced).[9] The results presented here demonstrate that an asset's covariance with scaled consumption growth can go a long way toward accounting for the value premium, thereby lending support to the view that the reward for holding high book-to-market stocks arises, at least in part, as a consequence of true nondiversifiable risk rather than as a simple reflection of the mispricing of value stocks.

The rest of this paper is organized as follows. In section 2 we present the general conditional factor model that forms the basis of our empirical work and show how it can be specialized to accommodate particular asset pricing theories. Next we review the theory in Lettau and Ludvigson (1999) motivating the use of *cay* as a scaling variable. Section 3 describes the data and our empirical procedure for testing the (C)CAPM, and presents empirical results on the cross-section of average returns on the Fama-French portfolios. We compare the performance of conditional factor models in which the return on a broad stock market index or consumption growth are the fundamental factors, with the performance of the simple static-CAPM, a conditional scaled multifactor CAPM that includes both a value-weighted stock market index and the labor income growth measure advocated by Jagannathan and Wang (1996) as factors, and with the three factor model advocated by Fama and French (1993, 1995). Finally, we present tests of the conditional factor models using forecasting variables other than *cay* to scale factors. Section 4 concludes.

2 Linear Factor Models with Time-Varying Coefficients

We begin by imposing virtually no theoretical structure, appealing instead to a well known existence theorem to motivate our empirical approach.[10] This theorem states that, in the absence arbitrage, there exists a stochastic discount factor (SDF), or pricing kernel, M_{t+1}, such that for any traded asset with a net return at time t of $R_{i,t+1}$, the following equation holds

$$1 = E_t[M_{t+1}(1 + R_{i,t+1})], \tag{1}$$

[9]This debate is borne out in several recent papers; for example, see Daniel and Titman (1997, 1998) and Davis, Fama and French (forthcoming).

[10]See Harrison and Kreps (1979).

where E_t denotes the mathematical expectation operator conditional on information available at time t, $M_{t+1} = a_t + b_t R_{e,t+1}$, and $R_{e,t+1}$ is a return on the unobservable mean-variance efficient frontier. We refer to models of the form $M_{t+1} = a_t + b_t R_{e,t+1}$ as *conditional linear factor models*. Models with constant coefficients, e.g. $M_{t+1} = a + bR_{e,t+1}$, will be referred to hereafter as *unconditional linear factor models*.

It is straightforward to show that the conditional linear factor model given above implies a conditional beta representation given by $E_t R_{i,t+1} = R_{0,t} - b_t R_{0,t} \text{Var}_t[R_{e,t+1}]\beta_{it}$, where $R_{0,t}$ is the return on a "zero-beta" portfolio correlated with M_{t+1}, $b_t = -\frac{E_t R_{e,t+1} - R_{0,t}}{R_{0,t}\text{Var}_t[R_{e,t+1}]}$ and $\beta_{it} = \frac{\text{Cov}_t[R_{e,t+1}, R_{i,t+1}]}{\text{Var}_t[R_{e,t+1}]}$. If conditional moments are varying over time, the parameter b_t in the stochastic discount factor will in general not be constant. Although predictable movements in volatility may be source of variation in b_t, they appear to be more concentrated in high frequency data (e.g., Christoffersen and Diebold, 1998). Since risk-free interest rates are also not very variable, the denominator of b_t is not likely to vary much in monthly or quarterly data. On the other hand, a large empirical literature (cited in the introduction) documents that excess returns are forecastable. Therefore, asset pricing tests that are implemented using monthly or, as in this paper, quarterly data should allow for the possibility of time-variation in b_t. In this paper we focus on time-variation in equity premia as a source of variation in b_t.

By plugging M_{t+1} into (1) and taking unconditional expectations, it is also straightforward to demonstrate that the conditional model in (1) does not necessarily imply an unconditional version where a_t and b_t are constants. It follows that the model specified above does not necessarily imply a beta representation with constant unconditional betas. The difficulty of course is that the parameters of the stochastic discount factor may co-vary with both $R_{e,t+1}$, as well as with the product $R_{e,t+1}R_{i,t+1}$. One approach to addressing this difficulty would be to specify a flexible model for changes in conditional moments. As we argue above, however, this approach has important disadvantages because the true conditional distribution is unobservable and any reasonable specification would likely depend on a large number of parameters that would have to be estimated.

Instead, we adopt an approach advocated in Cochrane (1996). We test conditional factor pricing models of the form given above by explicitly modeling the dependence of the parameters a_t and b_t on a time t information variable, z_t, where z_t is a forecasting variable for excess returns.[11] (We discuss our choice of conditioning variable further in the next section.) In particular, we may *scale* the factors with instruments containing time t information by modeling

[11] The specification can be easily extended to allow for multiple conditioning variables.

the parameters as linear functions of z_t, $a_t = a_0 + a_1 z_t$, $b_t = b_0 + b_1 z_t$. Plugging these equations into M_{t+1} above allows us to rewrite a conditional linear factor model as a *scaled multifactor model* with constant coefficients taking the form

$$\begin{aligned} M_{t+1} &= (a_0 + a_1 z_t) + (b_0 + b_1 z_t) R_{e,t+1} \\ &= a_0 + a_1 z_t + b_0 R_{e,t+1} + b_1 (z_t R_{e,t+1}). \end{aligned} \tag{2}$$

It follows that the scaled multifactor model can be tested using unconditional moments by rewriting (1) as an unconditional three factor model with constant coefficients a_0, a_1, b_0, and b_1 in the form

$$1 = E[(a_0 + a_1 z_t + b_0 R_{e,t+1} + b_1 (z_t R_{e,t+1}))(1 + R_{i,t+1})]. \tag{3}$$

2.1 Application of Conditional Factor Pricing to the (C)CAPM

The derivation above shows how a scaled multifactor model can be obtained from a linear factor model where a return on the true mean-variance efficient portfolio serves as the reference return. This derivation is useful for demonstrating how one can test models in which factors price assets conditionally, but the framework itself contains little theoretical content. In order to test particular theories, we need to place more structure on the discount factor M_{t+1}, and in particular on the choice of reference return, $R_{e,t}$. In the (C)CAPM theories, the true mean-variance efficient reference return may be written as a conditional linear combination of various fundamental factors, where the jth factor is denoted f_{jt}. In the CAPM the single factor is the return on all invested wealth, including both human and nonhuman wealth, and the pricing kernel is a conditional linear function of this return. In the CCAPM a single factor, f_t, is proportional to consumption growth and the pricing kernel may be expressed as a conditional linear function of consumption growth. In the Fama and French (1993) specification, a vector of factors, $\mathbf{f}_t$, is comprised of three portfolio returns. We discuss these models, each a special case of the broader class of scaled multifactor models, in more detail below.

To describe the class of scaled multifactor models more comprehensively, we use vector notation.[12] Denote the vector $\mathbf{F}_{t+1} = (1, z_t, \mathbf{f}_{t+1}, \mathbf{f}_{t+1} z_t)'$, or separating out the variable factors z_t, $\mathbf{f}_{t+1}$ and $\mathbf{f}_{t+1} z_t$ and denoting these together as $\bar{\mathbf{f}}_{t+1}$, write $\mathbf{F}_{t+1} = (1, \bar{\mathbf{f}}_{t+1})'$. We will refer to $\mathbf{f}_{t+1}$ as *fundamental factors* (e.g., the market return, consumption growth). The SDF of the scaled multifactor representation for each model can be expressed as $M_{t+1} = \mathbf{c}'\mathbf{F}_{t+1}$ where the

[12]This discussion follows the derivation in Cochrane (1996).

constant vector $\mathbf{c}' = (a, \mathbf{b})$, a is a scaler, and $\mathbf{b}$ is the vector of constant coefficients on the variable factors, $\bar{\mathbf{f}}_{t+1}$. This representation for M_{t+1} implies an unconditional multifactor beta representation for asset i with constant betas given by

$$E[R_{i,t+1}] = E[R_{0,t}] + \boldsymbol{\beta}'\boldsymbol{\lambda}, \tag{4}$$

where $E[R_{0,t}]$ is the average return on a "zero-beta" portfolio which is uncorrelated with the stochastic discount factor (Black 1972) and $\boldsymbol{\beta} \equiv \mathrm{Cov}(\bar{\mathbf{f}}, \bar{\mathbf{f}}')^{-1}\mathrm{Cov}(\bar{\mathbf{f}}, R_{i,t+1})$ is a vector of regression coefficients from a multiple regression of returns on the variable factors. In the empirical analysis that follows, we focus on this Black version of the (C)CAPM (which assumes that borrowing and lending rates differ) and freely estimate the constant $E[R_{0,t}]$ as part of the cross-sectional model.

Given (4), it is straightforward to show that

$$\boldsymbol{\lambda} = -E[R_{0,t}]\mathrm{Cov}(\bar{\mathbf{f}}, \bar{\mathbf{f}}')\mathbf{b}. \tag{5}$$

It is important to note that the individual λ_j coefficients in (5) from the scaled multifactor versions of the (C)CAPM do not have the straightforward interpretation that the risk price does in a conditional linear factor model. To see this, notice that for each scaled multifactor model, there is an associated conditional factor model from which the scaled multifactor model is derived. For example, the conditional CAPM factor model would be specified $M_{t+1} = a_t + b_t R_{vw,t+1}$ (where $R_{vw,t+1}$ is a proxy for the market return) from which we derive the scaled multifactor model $M_{t+1} = a_0 + a_1 z_t + b_0 R_{vw,t+1} + b_1(z_t R_{vw,t+1})$, using the conditioning information, z_t. More generally, given a conditional linear factor model of the form $M_{t+1} = \mathbf{c}_t'\mathbf{f}_{t+1}$, the conditional beta representation for this model is given by analogy to (4) as $E_t[R_{i,t+1}] = R_{0,t} + \widetilde{\boldsymbol{\beta}}_t'\widetilde{\boldsymbol{\lambda}}_t$, where $\widetilde{\boldsymbol{\lambda}}_t$ is the vector of period-t risk prices of the fundamental factors, $R_{0,t}$ is again the return on a "zero-beta" portfolio, $\widetilde{\boldsymbol{\beta}}_{t+1} \equiv \mathrm{Cov}_t(\mathbf{f}_{t+1}, \mathbf{f}_{t+1}')^{-1}\mathrm{Cov}_t(\mathbf{f}_{t+1}, R_{i,t+1})$ and

$$\widetilde{\boldsymbol{\lambda}}_t = -R_{0,t}\mathrm{Cov}_t(\mathbf{f}_{t+1}, \mathbf{f}_{t+1}')\mathbf{b}_t. \tag{6}$$

The methodology employed here (and discussed in more detail later) does not produce direct estimates of $\widetilde{\boldsymbol{\lambda}}_t$. Instead, we estimate cross-sectional regressions of the form (4), which delivers estimates of $\boldsymbol{\lambda}$. But note that (5) and (6) are related by $\mathbf{b}$. Estimates of $\boldsymbol{\lambda}$ can be used to uncover $\mathbf{b}' = -\boldsymbol{\lambda}'[E[R_{0,t}]\mathrm{Cov}(\bar{\mathbf{f}}, \bar{\mathbf{f}}')]^{-1}$ which we may combine with the definition of $\mathbf{b}_t = \mathbf{b}'z_t$ to obtain an estimate of $\mathbf{b}_t$. Without additional assumptions, we cannot compute the risk prices for the fundamental factors, $\widetilde{\boldsymbol{\lambda}}_t$, because we do not estimate the conditional covariance, $\text{Cov}_t(\mathbf{f}_{t+1}, \mathbf{f}'_{t+1})$, in (6).

Equation (6) shows that the value of $\widetilde{\boldsymbol{\lambda}}_t$, the vector of risk prices for each fundamental factor in $\mathbf{f}_t$, depends on $\mathbf{b}_t$. Our linear specification $\mathbf{b}_t = \mathbf{b}' z_t$ presumes that fluctuations in $\mathbf{b}_t$ are primarily driven by fluctuations in risk premia, and implies a linear forecasting equation for excess returns. While these forecasting equations do a good job of picking up fluctuations in future excess returns, as with any linear forecasting model, there are periods in which the model predicts a negative excess return. Since $\mathbf{b}_t$ inherits the properties of these linear forecasting models, the value of $\mathbf{b}_t$ may change sign from time to time. This aspect of the prediction equation is purely a result of the linear regression specification and is not unique to the use of any particular forecasting variable, z_t. The linear forecasting equations we use below do predict a positive risk premium on average, however, so that it is reasonable to expect the *average* risk price on each fundamental factor in the conditional model to be nonnegative, i.e., $E[\widetilde{\boldsymbol{\lambda}}_t] \geq 0$.

Note that this condition does *not* imply that the individual λ_j coefficients from the scaled multifactor representation in (5) should be nonnegative. In the case of a single factor model such as the static-CAPM, the average risk price for the market beta will have the opposite sign (see [6]) as the average value of $\mathbf{b}_t$, and will be positive as long as the average risk premium is positive. This follows from the fact that the conditional covariance term in (6) will simply be a conditional variance for the value-weighted return. For models with multiple factors, the conditional covariance is not simply a conditional variance, and the average price of risk need not have the opposite sign as the average value of $\mathbf{b}_t$ if the factors are not orthogonal. If we assume that the conditional covariances and the average zero-beta rate are approximately constant,[13] however, and using the specification $\mathbf{b}_t = \mathbf{b}' z_t$, we may compute a value for the average risk price, $E[\widetilde{\boldsymbol{\lambda}}_t]$, of each fundamental factor in the associated conditional factor model using (6).

We now move on to discuss the special cases of (4) that correspond to the particular scaled multifactor asset pricing models of the CAPM and the CCAPM.

2.1.1 The Consumption CAPM

Consider a representative agent economy in which all wealth, including human wealth, is tradable. Let W_t be aggregate wealth (human and nonhuman) in period t. C_t is consumption and $R_{m,t+1}$ is the net return on aggregate wealth, or the market portfolio. Subject to an accumulation

[13] For the factors we use in our empirical investigation, a value-weighted return, labor income growth, and consumption growth, this is probably not a bad approximation in quarterly data.

equation for aggregate wealth, investors maximize the present discounted value of instantaneous utility functions, $u(C_t, X_t)$ where C_t is consumption and X_t captures other factors (for example, a habit level) that may influence an investor's utility. The first order conditions for optimal consumption choice are simply special cases of (1) where the equation holds for every asset in the market portfolio and the discount factor, $M_{t+1} \equiv \delta \frac{u_c(C_{t+1}, X_{t+1})}{u_c(C_t, X_t)}$, is the intertemporal marginal rate of substitution, with δ the subjective rate of time preference.

Instead of specifying a particular functional form for marginal utility, we assume that M may be approximated as a linear function of consumption growth, but, as discussed above, we allow the parameters of this function to depend on the current period state:

$$M_{t+1} \approx a_t + b_t \Delta c_{t+1}, \tag{7}$$

where a_t and b_t are (potentially time-varying) parameters and Δc_{t+1} is consumption growth, the single fundamental factor in the asset pricing model. Throughout this paper, we use lowercase letters denote logarithms of variables written in uppercase, e.g., $c_t = \ln C_t$. In the notation above, this specification of the CCAPM has a single factor, $f_t = \Delta c_t$ and a scaled multifactor model is obtained by interacting consumption growth with an instrument z_t so that $\mathbf{F}_{t+1} = (1, z_t, \Delta c_{t+1}, \Delta c_{t+1} z_t)'$.

Regardless of the particular functional form of the investor's utility function, the discount factor can always be expressed as an approximate linear function of consumption growth by taking a first-order Taylor expansion of M. Examples include time-separable power utility with constant relative risk aversion, $u(C_t) = \frac{C_t^{1-\gamma}}{1-\gamma}$, in which case $M_{t+1} \approx \delta(1 - \gamma \Delta c_{t+1})$; or the habit-persistence framework of Campbell and Cochrane (1999a), $u(C_t, X_t) = \frac{(C_t - X_t)^{1-\gamma}}{1-\gamma}$, in which case M_{t+1} takes the form

$$M_{t+1} \approx \delta\Big(1 - \gamma g \lambda(s_t) - \gamma(\phi - 1)(s_t - \overline{s}) - \gamma(1 + \lambda(s_t))\Delta c_{t+1}\Big), \tag{8}$$

where X_t is the external consumption habit, s_t is the log of the surplus consumption ratio, defined as $S_t \equiv \frac{C_t - X_t}{C_t}$, γ is a parameter of utility curvature, g is the mean rate of consumption growth, ϕ is the persistence of the habit stock, and $\lambda(s_t)$ is the sensitivity function specified in Campbell and Cochrane. Similar, but more complicated, expressions can be derived for internal habit-formation models (e.g., Constantinides 1990, Sundaresan 1989) by taking a local linear approximation of the respective stochastic discount factors.

Note that (8) provides a particularly good motivation for the scaled multifactor model in (3) which contains three factors, z_t, Δc_{t+1}, and $.z_t \Delta c_{t+1}$. The coefficient that multiplies consumption growth in the stochastic discount factor of habit models such as (8) varies over time. Although this coefficient may be a function of unobservable variables, such as $\lambda(s_t)$ in (8), its fluctuations should be well captured by suitable proxies for time-varying risk premia. We argue below that the lagged value of *cay* is such a proxy and we assume the coefficients in the stochastic discount factor may be well approximated as linear functions of *cay*. Thus, whereas traditional, discrete time derivations of the conditional CAPM (e.g., Jagannathan and Wang 1996) produce unconditional beta representations with just two betas (one for the fundamental factor and one for the risk premium) habit models may imply the existence of at least one beta for the multiplicative "cross-term" of the factor (consumption growth) and the risk premium. We discuss this further below.

2.1.2 The CAPM

A standard derivation of the static-CAPM would require simply replacing Δc_{t+1} in (7) with the return to the market portfolio as the relevant factor, $f_{t+1} = R_{m,t+1}$. The market portfolio is typically proxied by the return on an index of common stocks, but this practice has been challenged by Roll (1977) who argues that such proxies ignore the human capital component of aggregate wealth. Following Mayers (1972) and Fama and Schwert (1977), Jagannathan and Wang (1996) and Campbell (1996) argue that labor income growth may proxy for the return to human capital, and find that it has a statistically significant risk price in cross-sectional tests of the CAPM. This specification of the CAPM, explicitly accommodating human capital, would have two factors, for example the return on a value-weighted stock index, $R_{vw,t}$ and labor income growth, Δy_t, implying that $M_{t+1} = a_t + b_{vwt} R_{vw,t+1} + b_{\Delta yt} \Delta y_{t+1}$. To model the time-variation of the parameters in M_{t+1}, a scaled multifactor model given by $\mathbf{F}_{t+1} = (1,\, z_t,\, R_{vw,t+1},\, \Delta y_{t+1},\, R_{vw,t+1} z_t,\, \Delta y_{t+1} z_t)'$ can be specified in analogy to the consumption model outlined above.

A critical consideration in using the scaled multifactor approach to test the (C)CAPM, or any conditional asset pricing model, is the choice of conditioning variable, z_t. Because the investor's information set is not observable, it is crucial that the conditioning variable be an indicator that summarizes the relevant information in investor information sets. But what are investors forming conditional expectations over? The answer to this question is revealed by referring back to (1). This equation shows that the conditional expectation is formed about the discounted return on each asset held. This can be expressed more succinctly noting that (1) must also hold for the market portfolio and replacing $R_{i,t+1}$ with $R_{m,t+1}$ in (1). Moreover, by the law of iterated expectations, the expectation conditional on time t information in (1) must hold for discounted returns in all future time periods, $t+1, t+2, t+3, \ldots$ etc. Thus, in an infinite-horizon specification, investors form expectations of the sum of future returns to the market portfolio, discounted by a function of consumption growth, from now until an arbitrarily large future time period T, i.e., as $T \rightarrow \infty$.

The information set upon which these expectations are based is large and unobservable. We argue here that it is not necessary to observe these information sets directly because investors' own behavior is likely to reveal to us much of what we need to know to control for the fact that investors know more than we do. To exploit the implication of this assertion, however, we require an observable variable that summarizes investor expectations about all discounted future returns to the market portfolio. We now describe our choice of conditioning variable and discuss how it furnishes such a summary by providing a brief overview of the results in Lettau and Ludvigson (1999).

2.2 The Conditioning Variable

In a recent paper, Lettau and Ludvigson (1999) argue that the difference between consumption and the appropriate weighted average of log asset wealth and log labor income (*cay* for short) does a good job of picking up fluctuations in the consumption-aggregate wealth ratio. This is important because, in a wide class of forwarding looking consumption models, the consumption-aggregate wealth ratio summarizes agents' expectations of future returns to the market portfolio. Furthermore, as Cochrane (1999) emphasizes, the CAPM can be derived from several special cases of the CCAPM.[14] These special cases also often imply that the parameters in the stochastic discount factor of the CAPM (i.e., a_t and b_t in $M_{t+1} = a_t + b_t R_{vw,t+1}$) will be a function of the consumption-aggregate wealth ratio. For these reasons, fluctuations in the consumption-aggregate wealth ratio may play a special role in both the CAPM and the CCAPM when they are specified as linear factor models with time-varying coefficients. We now summarize the framework which is explained in more detail in Lettau and Ludvigson (1999).

By making a loglinear approximation to the investor's intertemporal budget constraint, $W_{t+1} = (1 + R_{m,t+1})(W_t - C_t)$, the log consumption-wealth ratio may be expressed in terms of future returns to the market portfolio and future consumption growth. A full derivation is of this approximation is given in Appendix A. Because this approximate equation holds simply as a consequence of the agent's intertemporal budget constraint, it holds *ex-post*, but it also

[14] See Cochrane (1999), chapter 8.

holds *ex-ante*. Accordingly, we may express the log consumption-wealth ratio as a function of expected future returns and expected consumption growth:[15]

$$c_t - w_t \approx E_t \sum_{i=1}^{\infty} \rho_w^i (r_{m,t+i} - \Delta c_{t+i}). \tag{9}$$

The important implication of (9) is that the log consumption-wealth ratio summarizes, to a first approximation, the same investor expectations that are formed in (1). This can be verified by noting that (9) is a function of the conditional expectation of consumption growth through the last term on the right-hand-side. The appropriate value for expected consumption growth must be obtained from the stochastic discount factor, $1 = E_t[(1 + R_{m,t+1})M_{t+1}]$ since this is just the first order condition for optimal consumption choice.

Note that the specification in (9) is directly analogous to the linearized formula for the log dividend-price ratio. If the consumption-wealth ratio is high, then the agent must be expecting either high returns on wealth in the future or low consumption growth rates. The key difference between the consumption-wealth ratio and the dividend price ratio is that what's on the right-hand-side is the return to the *entire* market portfolio, not just the stock market component of it. Thus the consumption-wealth ratio is a superior summary measure of investor expectations. Equation (9) also implies that it is not necessary to observe the nature of investor preferences, the sources of aggregate risk, or the particular information set upon which investors base conditional expectations: agents' own behavior, as revealed by movements in $c_t - w_t$, summarizes conditional expectations of future returns to the market portfolio.

Of course, the log consumption-aggregate wealth ratio is not observable. The primary difficulty is that human capital is not observable. Rather than proposing an explicit proxy for human capital, Lettau and Ludvigson (1999) pursue a strategy which allows us to express the important predictive components of $c_t - w_t$ for future market returns in terms of observable variables. This approach begins with the assumption that aggregate labor income, Y_t, may be well described by the product of a stationary simple net return to human capital, $R_{h,t+1}$, times the stock of human wealth, H_t: $Y_t = R_{h,t+1} H_t$. Ignoring a linearization constant, $r_{h,t+1} \equiv \log(1 + R_{h,t+1}) \approx 1/\rho_y (y_t - h_t)$, where $\rho_y \equiv \frac{1+Y/H}{Y/H}$.[16]

With these assumptions, we are now in a position to express the log consumption-aggregate

[15] We omit unimportant linearization constants in linearized equations.

[16] This definition uses the timing convention that the stock of human capital, H_t, is measured beginning-of-period, dividends and labor earnings are paid at the end of the period, and the return, $R_{h,t+1}$, denotes the return on the stock of human capital held from (the beginning of) time t to time $t + 1$.

wealth ratio in terms of observable variables. Let A_t be nonhuman, or asset, wealth, and let $1 + R_{a,t+1}$ be its gross return. Aggregate wealth is therefore $W_t = A_t + H_t$ and log aggregate wealth may be approximated as $w_t \approx \omega a_t + (1 - \omega)h_t$, where ω equals the average share of nonhuman wealth in total wealth, A/W. Using this approximation allows us to express the left-hand-side of (9) as the difference in log consumption and a weighted average of log asset wealth and log labor income, plus an approximation term. This equation takes the form

$$cay_t \equiv c_t - \omega a_t - (1 - \omega)y_t \approx E_t \sum_{i=1}^{\infty} \rho_w^i (r_{m,t+i} - \Delta c_{t+i}) - (1 - \omega)\rho_y r_{h,t+1}. \qquad (10)$$

Because all the variables on the right-hand-side of (10) are stationary, the model implies that consumption, asset wealth and labor income share a common stochastic trend, where ω and $(1 - \omega)$ are parameters of this shared trend. As long as the last term on the right-hand-side is not too variable, this equation implies that the observable quantity on the left-hand-side should be a good proxy for the log consumption-aggregate wealth ratio.

This implication can be tested directly assuming that expected returns to human capital and expected consumption growth are not too volatile relative to asset wealth, by assessing the forecasting power of cay_t for returns to nonhuman wealth. Lettau and Ludvigson (1999) present evidence that cay_t is a strong univariate predictor of both raw stock returns and excess stock returns over a Treasury bill rate, and can account for a substantial fraction of the variation in future returns. Moreover, this variable provides information about future stock returns that is not captured by lagged values of other popular forecasting variables. This evidence suggests that cay_t is likely to summarize a large amount of information about investor expectations and, as a consequence, is an excellent candidate conditioning variable.

The consumption CAPM (7) allows the discount factor to depend flexibly on consumption growth, conditional on information available at time t. Although we do not specify and test an explicit functional form for the intertemporal marginal rate of substitution, M_{t+1}, it should be noted that this scaled multifactor specification can be well motivated by the framework in Campbell and Cochrane (1999a) discussed above. Because their model has time-varying risk aversion, the parameters in a linearized specification for M_{t+1} are not constant. As (8) shows, consumption growth should be scaled by a function of the *surplus consumption ratio*. Because the surplus consumption ratio is not observable, however, the appropriate conditioning variable in their model must be an observable indicator that captures movements in time-varying expected excess returns. Lettau and Ludvigson (1999) show that the estimated value of cay_t, denoted $\widehat{cay}_t$, is such a variable because it has strong forecasting power for aggregate stock returns: when $\widehat{cay}_t$ is low, excess returns are forecast to fall; when $\widehat{cay}_t$ is high, excess returns are forecast to rise.[17] Campbell and Cochrane (1999b) argue similarly that a scaled consumption CAPM specification for $M_{t+1}$with the dividend-price ratio as the conditioning variable can also be motivated by the habit persistence framework in Campbell and Cochrane (1999a).

An important task in using the left-hand-side of (10) as a scaling variable is the estimation of the parameters in cay_t. Lettau and Ludvigson (1999) show how these parameters can be estimated consistently and why measurement considerations suggest that the coefficients on asset wealth and labor income may sum to less than one. The reader is referred to Appendix B for details on data construction and data definition, and for a description of the procedure used to estimate ω and $(1-\omega)$. We simply note here that we obtain an estimated value for cay_t equal to $\widehat{cay}_t = c_t^* - 0.31a_t^* - 0.59y_t^* - 0.60$, where starred variables indicate measured quantities.[18] We use this estimated value, plotted in Figure 1, as a scaling variable in our empirical investigation.

3 Econometric Specification and Tests

3.1 Empirical Models

We use the beta representation (4) as the basis of our empirical work, specialized to the particular asset pricing model under consideration. In this section, we examine whether these specifications can explain the cross-section of expected returns given that the conditioning variable, z_t, is set equal to $\widehat{cay}_t$. We test the usefulness of $\widehat{cay}_t$ as a scaling variable for beta representations of the CAPM and CCAPM. In each case, the scaled multifactor beta representation (4) nests an associated unconditional model where the β's on the scaling variable and on the scaled factors are zero. We compare the ability of all these models to explain the cross-section of average returns with that of the three factor model in Fama and French (1993). In addition, we follow the suggestion in Jagannathan and Wang (1998) to include firm size (market equity) and book-

[17] This pattern in the data may also be plausibly interpreted using the time-varying risk aversion framework of Campbell and Cochrane (1999a). In that model, consumption booms are periods during which consumption increases above habit, leading to a decline in risk aversion. The decline in risk aversion leads, in turn, to a greater demand for risky assets and a decrease in expected excess returns, or risk premia. Thus booms are times of rising consumption but declining *ratios* of consumption to aggregate wealth, consistent with what is found in Lettau and Ludvigson (1999).

[18] The estimation of the parameters in $\widehat{cay}_t$ is done in a first-stage time-series analysis using only consumption, asset wealth and labor income and is completely unrelated to the cross-sectional data on portfolio returns.

to-market characteristics as additional explanatory variables as a test for model misspecification. Finally, we test the (C)CAPM using two alternative scaling factors: the log dividend-price ratio on the CRSP value-weighted (CRSP-VW) Index and the default yield spread between BAA and AAA bonds.

3.2 Econometric Tests and Portfolio Data

The unconditional model in (4) can be consistently estimated by the cross-sectional regression methodology proposed in Fama and MacBeth (1973), an approach we use here. In principle, there are other empirical procedures for testing the model in (4). In practice, the size of our sample limits our choices. Because our conditioning variable, $\widehat{cay}_t$, is available only on a quarterly basis, we have fewer than 150 time series observations for each portfolio, considerably less than most asset pricing studies which use monthly data. As one example, researchers have used Generalized Method of Moments (GMM) to test asset pricing models such as (4), a technique we also experimented with. However, we found that this technique did not deliver stable results. We have reason to believe that this is a result of the small size of our time series.[19] It is well known that GMM estimation can be especially problematic in studies that have a small time-series for a fixed cross-section sample size (for example, Ferson and Foerster 1994; Altonji and Segal 1996). In addition, the need to estimate the covariances among many asset returns makes it unsuitable for studying a reasonably large cross-section of returns using quarterly time series. Thus, the Fama-MacBeth procedure has important advantages for our application, in which we have only a moderate number of time series observations but in which we require a reasonably large number of asset returns to test the model's cross-sectional implications.[20]

[19] For example, we replicated the GMM results in Jagannathan and Wang (1996) using their monthly data. When the data were converted to a quarterly frequency, however, the models considered by Jagannathan and Wang were consistently rejected and the standard errors on the model's coefficients, as well as the estimates of the Hansen-Jagannathan distance, displayed considerable instability. These differences between the monthly and quarterly models did not appear to be a feature of the time-aggregation needed to convert from monthly to quarterly data: the difficulties with the results using quarterly data lessened when we used a small number of portfolios relative to the time-series sample size.

[20] Other researchers have recommended the use of Generalized Least Squares (GLS) on the grounds that asset returns may display conditional heteroskedasticity. When conditional heteroskedasticity is present, the GLS approach should improve efficiency. However, there are several reasons we believe that the potential advantages of GLS for our application are highly uncertain. First, as in any application of GLS, the improvement in efficiency depends on knowing the true covariance matrix of returns. Since this knowledge is rare, GLS is often

For comparing the relative performance of the different empirical specifications we consider, we use the R^2 of the cross-sectional regression showing the fraction of the cross-sectional variation in average returns that is explained by each model.[21] In addition, we test whether the coefficients $\boldsymbol{\lambda}$ in (4) are statistically different from zero. Following Shanken (1992), we report the standard errors of these coefficients corrected for sampling error that arises because the regressors $\boldsymbol{\beta}$ are estimated in a first stage time-series regression for each $R_{i,t+1}$.[22] Jagannathan and Wang (1998) show, however, that the Fama-MacBeth procedure does not necessarily overstate the precision of the standard errors if conditional heteroskedasticity is present, so we also report the conventional t-statistics. Since the Shanken correction assumes that returns are homoskedastic, if there were any heteroskedasticity in our data, the corrected standard errors would be overcorrected, in the sense that they could *understate*–but would never overstate–the true degree of precision of our estimates.

It is important to note that standard errors do not need to be adjusted to account for the use of the generated regressor $\widehat{cay}_t$. This follows from the fact that estimates of the parameters in $\widehat{cay}_t$ are "superconsistent," converging to the true parameter values a rate proportional to the sample size T rather than proportional to $\sqrt{T}$ as in ordinary applications (Stock 1987). Appendix B provides details.

Our data on returns consists of 25 portfolios formed according to the same criteria as those used in Fama and French (1992, 1993). These data are value-weighted returns for the intersections of five size portfolios and five book-to-market equity (BE/ME) portfolios on NYSE, AMEX, and NASDAQ stocks in COMPUSTAT. The portfolios are constructed at the end of June and market equity is market capitalization at the end of June. BE/ME is book equity at

less robust than the Fama-MacBeth procedure based on Ordinary Least Squares (OLS). Second, conditional heteroskedasticity in quarterly data is less evident than in the monthly data commonly used, so the improvement in efficiency from GLS is likely to be marginal, at best. Third, in small samples, the relative advantages of GLS over OLS are even more uncertain than they are in large samples, especially when the form of heteroskedasticity involves unknown parameters. In particular, the GLS transformation can place too much weight on what appear to be nearly riskless portfolios so measured due to luck in a short sample. Cochrane (1999) emphasizes that this is especially true in samples where the cross section is more than one tenth of the time series.

[21]This goodness of fit measure follows Jagannathan and Wang (1996) and is given by $(\mathrm{Var}_c(\overline{R}_i) - \mathrm{Var}_c(\overline{\varepsilon}_i))/\mathrm{Var}_c(\overline{R}_i)$, where $\overline{\varepsilon}_i$ is the average residual for portfolio i, Var_c denotes a cross sectional variance, and variables with bars over them denote time series averages.

[22]The beta coefficients are estimated from a multiple time-series regression for each asset. We use the entire sample to estimate the $\boldsymbol{\beta}'$s; a rolling regression approach is not applicable in quarterly data which limits us to less than 150 time series observations.

the last fiscal year end of the prior calendar year divided by ME at the end of December of the prior year. This procedure is repeated for every calendar year starting in July 1963 to June 1998. We refer the reader to the Fama-French articles cited above for details and data characteristics. We convert the returns to quarterly data producing a time series spanning the third quarter of 1963 to the third quarter of 1998, i.e., 141 observations for each of the 25 portfolios.

3.3 Empirical Results

3.3.1 Forecasting Pre-test

This section assesses the power of various scaled multifactor models given in (4) for explaining the cross-section of average returns. In advance of presenting these findings, we briefly display some evidence on the power of $\widehat{cay}$ and other variables for forecasting asset returns and key macroeconomic variables. This serves as a pre-test for our scaling variables, since–in principle–these indicators should reveal investor expectations about future returns to either financial wealth or future labor earnings or both.[23] In short, they should forecast some indicator that is plausibly correlated with future returns to human and nonhuman wealth.

Table 1 shows a typical set of results using the lagged value of $\widehat{cay}_t$, the lagged log dividend-price ratio on the CRSP-VW Index ($d-p$), the lagged spread between BAA and AAA bond yields (SPR), and the "small-minus-big" (SMB) and "high-minus-low" (HML) portfolios constructed in Fama and French (1993)[24] as a predictive variables for the excess return on the CRSP value-weighted stock index, for growth in real Gross Domestic Product (GDP), and real consumption growth using the consumption measure discussed in Appendix B. We include the two Fama-French mimicking portfolio variables in this assessment on the grounds that these variables may forecast some indicator that is plausibly related to future returns on the market portfolio if they proxy for rationally priced risk. In each case, we ask whether the explanatory variable "Granger causes" the future values of the predicted variables and we report the adjusted R^2 as a measure of overall forecasting power. Lettau and Ludvigson (1999) present a much more extensive analysis of the forecasting power of $\widehat{cay}$ for excess stock returns, including both in-sample and out-of-sample tests.

[23] We demean the scaling variables in all of the empirical investigations of this paper.

[24] The definitions of these variables are by now well known and can be found in Fama and French (1993). In essence, SMB is the difference between the returns on small and big stock portfolios with about the same weight-average book-to-market equity. HML is the difference between returns on high and low BE/ME portfolios with about the same weighted-average size.

The first row of Table 1 shows that the estimated trend deviation in wealth, $\widehat{cay}$, explains a substantial fraction of the variation in future CRSP-VW excess returns. The table reports that, at a horizon of four quarters, this variable alone explains about 18% of the variation in excess returns; results not reported in the table show that this forecasting power peaks at a horizon of about 5 quarters, explaining about 21% of the variation in excess returns. Lettau and Ludvigson (1999) consider a number of popular forecasting variables and show that $\widehat{cay}$ is the best univariate predictor of excess returns one to five quarters ahead; other forecasting variables display, at best, only weak forecasting power at quarterly horizons. As one example, Table 1 shows that the dividend-price ratio is a comparatively poor forecaster of future returns one to eight quarters ahead. Thus a forecasting equation using $\widehat{cay}$ as a predictive variable is likely to do a good job of picking up fluctuations in equity premia at a quarterly horizons.

The other variables, SPR, SMB, and HML have only weak forecasting power for excess stock returns. Nevertheless, Table 1 demonstrates that HML has some forecasting power for GDP growth at a one-quarter horizon, while SPR is valuable for predicting GDP growth from one to four quarters out. The final row of Table 1 shows that, although SMB has only weak univariate predictive power for any of the three variables forecast, in a bivariate regression which includes $\widehat{cay}$ as a predictive variable for the return on the CRSP-VW index, SMB is individually significant, and the forecasting equation predicts a larger fraction of the variation in future returns using both variables than it does using either variable in isolation. None of the predictive variables have forecasting power for consumption growth, however.

3.3.2 Cross-Sectional Results

The CAPM

Unconditional Models

Using returns on the 25 Fama-French portfolios described earlier, we now examine the power of various beta-representations to explain the cross-section of average returns. To form a familiar a basis for comparison, we begin by presenting results from a series of unconditional models, that is for models where the factors in (4) are not scaled by a conditioning variable. Of these, the most familiar is the static CAPM, with the CRSP-VW return, R_{vw}, used as a proxy for the unobservable market return. This implies a cross-sectional specification taking the form

$$E[R_{i,t+1}] = E[R_{0,t}] + \beta_{vwi}\lambda_{vw}. \tag{11}$$

The results are presented in the first row of Table 2. The $t-$statistic for λ_{vw} shows that the beta on the value-weighted return is not a statistically significant determinant of the cross-section of average returns. Both the corrected and uncorrected standard errors signal that the beta on the value-weighted index is not statistically different from zero. Moreover, it has the wrong sign. The R^2 of the regression is only 0.01; in other words, only 1 percent of the cross-sectional variation in average returns can be explained by the static CAPM. Note that the R^2 adjusted for degrees of freedom, denoted $\bar{R}^2$, is negative. These results are now familiar (see Fama and French 1992). By contrast, a specification which includes–in addition to the value-weighted return beta–the beta for labor income growth, Δy,[25] advocated by Jagannathan and Wang (1996) performs much better, explaining about 58 percent of the cross sectional variation in returns (row 2). These results are consistent with those of Campbell (1996) and Jagannathan and Wang (1996) which find that including the return to human capital is important for assessing the performance of the (C)CAPM.[26]

Noting the failures of the static CAPM using the return on a value-weighted index as the single factor, Fama and French (1993) propose a three-factor model as an alternative, where the factors are the return to a value-weighted common stock index along with the return to the HML and SMB portfolios described above. We confirm that these variables do indeed explain a large fraction of the variation in average returns in our quarterly data set. These results are presented in row 3 of Table 2 from an estimation of the three-factor cross-sectional model

$$E[R_{i,t+1}] = E[R_{0,t}] + \beta_{vwi}\lambda_{vw} + \beta_{\mathrm{SMB}i}\lambda_{\mathrm{SMB}} + \beta_{\mathrm{HML}i}\lambda_{\mathrm{HML}}. \tag{12}$$

This model explains about 80 percent of the cross-sectional variation in these returns, and the

[25]Here we use the measure of labor income growth advocated by Jagannathan and Wang (1996): the growth in total personal, per capita income less dividend payments from the National Income and Product Accounts published by the Bureau of Economic Analysis. In addition, we followed the timing convention of Jagannathan and Wang (1996), in which labor income is lagged one month to capture lags in the official reports of aggregate income.

[26]Following Heaton and Lucas (forthcoming), we also split the Jagannathan and Wang (1996) measure of labor income into wages and salaries, and proprietor's income. Consistent with the results of Heaton and Lucas, we find that most of the explanatory power of the CAPM specification including human capital income growth derives from the proprietor's income component of Jagannathan and Wang's measure of labor income. If labor income is split into proprietor's income and wage and salary income, the beta for proprietor's income is highly significant, while the beta for wage and salary income is not. A full investigation of why the proprietor's income component is relatively more important is beyond the scope of this paper, and the interested reader is referred to Heaton and Lucas for more in-depth discussion.

$t-$statistic on the HML factor is highly statistically significant even after correcting for sampling error in the β's. These results are consistent with what has been reported in the literature using monthly data.

Scaled Factor Models

We now present the results from estimating scaled multifactor versions of the CAPM models. For comparison with the static CAPM, Table 2 shows results for the scaled, conditional CAPM with one factor, $f_{t+1} = R_{vw,t+1}$, and a single scaling variable $z_t = \widehat{cay}_t$. This cross-sectional regression takes the form

$$E[R_{i,t+1}] = E[R_{0,t}] + \beta_{zi}\lambda_z + \beta_{vwi}\lambda_{vw} + \beta_{vwzi}\lambda_{vwz}. \tag{13}$$

The results are reported in row 4 of Table 2. The estimated value of λ_z is not statistically different from zero, implying that the time-varying component of the intercept is not an important determinant of average returns. Moreover, the fifth row of Table 2 shows that eliminating β_{zi} as an explanatory variable does not have an important effect on the marginal predictive power of the remaining betas, or on the overall fit of the regression. We found this to be generally true in a variety of cross-sectional regressions we report in Tables 2 and 3.

By contrast, the coefficient on β_{vwi} is strongly significant. Nevertheless, we think that, throughout these tests, it makes more sense to ask whether the betas of the fundamental factor and its scaled counterpart (e.g., $R_{vw,t}$ and $R_{vw,t}z_{t-1}$), are *jointly* significant. Recall that the conditional factor model underlying a scaled multifactor representation such as (13) has a single fundamental factor, and the additional scaled factor simply follows from our specification of the time-varying coefficient on that factor. Thus, there is no implication following from the conditional model that the betas for the scaled and unscaled fundamental factor be individually significant. Moreover, results (not reported) indicated that if the unscaled market beta, β_{vwi}, is eliminated from (13), the R^2 falls considerably, reflecting the fact that, even though λ_{vw} is not by itself marginally significant, λ_{vw} and λ_{vwz} are jointly significant. This can be verified by a Wald test for joint significance of λ_{vw} and λ_{vwz}, the results of which are displayed in panel B of Table 2.[27] Note also that the R^2 in row 4 for the scaled, conditional CAPM is considerably higher than for the simple static CAPM; it jumps to 31 percent from 1 percent by simply including β_{vwz} as an additional regressor.

[27]These tests are carried out by forming a Wald statistic using the either the uncorrected or the Shanken-corrected coefficient covariance matrix provided by the Fama-MacBeth procedure. Results for both covariances matrices are presented in Panel B of Table 2.

The scaled CAPM specification including human capital takes the form

$$E[R_{i,t+1}] = E[R_{0,t}] + \beta_{zi}\lambda_z + \beta_{vwi}\lambda_{vw} + \beta_{vwzi}\lambda_{vwz}\beta_{\Delta yi}\lambda_{\Delta y} + \beta_{\Delta yzi}\lambda_{\Delta yz}. \tag{14}$$

The estimation results are presented in rows 6 and 7 (with and without β_{zi}) of Table 2. This model performs much better than the unscaled version, explaining about 75 percent of the cross-sectional variation in average returns, about as well as the Fama-French three factor model in row 3. In particular, the coefficients on the scaled factors, λ_{vwz} and $\lambda_{\Delta yz}$ are statistically different from zero according to the uncorrected $t-$statistics. Note that the Shanken correction to the $t-$statistics for models that include macroeconomic factors, and particularly for models that include scaled macroeconomic variables, is substantially larger than for models that include only returns as factors. For example, in the static-CAPM where the single factor is $R_{vw,t}$, the Shanken correction (which in this case is just one plus the square of the Sharp ratio) is negligible, as exhibited in row 1 of Table 1. The reason for this difference in the magnitude of the correction is that the sampling error that arises from replacing the true betas by their first stage estimates (and therefore the Shanken correction itself) is directly related to residual variance in the second stage estimation, but is *inversely* related to factor variability. The macroeconomic variables are far less variable than stock returns, so there is a much larger correction for sampling error in the estimated betas of macro factors in the (C)CAPM than in the betas of portfolio return data, such as the static, unconditional CAPM or the Fama-French three factor model.[28] We find that these differences in the magnitude of the Shanken correction across models with and without macro variables arises in all of our tests, consistent with what has been found in other studies that include macroeconomic variables as factors (for example, see Shanken's [1992] example using macro data and Jagannathan and Wang 1996).

Several other features of the cross-sectional results bear noting. First, in the case of the CAPM (13), the average risk price for the value-weighted return from the associated conditional linear factor model will be a weighted average of λ_{vw} and λ_{vwz}, the latter multiplied by z_t see (6). Given these estimates, and under the assumption that $\mathrm{Var}_t(R_{vw,t+1})$ is approximately constant, the average risk price for the value-weighted return is found to be positive (recall the discussion in section 2.1). For the CAPM model which includes labor income growth, (14), this same

[28] More precisely, the Shanken correction is directly related to the magnitude of each λ coefficient estimate and inversely related to factor variability. Thus, although the models with macro factors have smaller λ estimates than models with financial indicators as factors, the estimates of λ are not proportionally smaller relative to their smaller factor variance.

calculation yields a positive average risk price on the human capital beta but a negative average risk price on the value-weighted beta.[29]

A second notable feature of the scaled multifactor CAPM (with or without labor income) estimated above that is also shared by the scaled multifactor consumption CAPM (results presented in the next section) is that the estimated value of the average zero-beta rate is large. The average zero-beta rate should be between the average "riskless" borrowing and lending rates. While it is not entirely inconceivable that this spread could be 16 percent at an annual rate for some borrowers, this value is implausibly high for the average investor. Although the (C)CAPM can explain a substantial fraction of the cross-sectional variation in these 25 portfolio returns, this aspect of the model appears inconsistent with the data. Still, this finding is not uncommon in the literature (the estimated values for the zero-beta rate we find here are of the same order of magnitude found in other studies, e.g., Jagannathan and Wang 1996) and is plausibly explained by the large amount of sampling error in the estimated betas of the (C)CAPM models. The early literature on cross-sectional asset pricing tests recognized that this sampling error will bias up the constant in cross-sectional regressions (e.g., Black, Jensen, and Scholes 1972; Miller and Scholes 1972), and it is not surprising that this error is greater for betas of macroeconomic variables estimated from quarterly data than that for betas estimated for mimicking portfolios using financial return data. The latter is of higher quality and is typically available at a higher frequency. But, more importantly as discussed above, the data itself indicate that the sampling error is in fact much larger for the scaled (C)CAPM models using macroeconomic data than it is for the Fama-French three factor model: because the sampling error from replacing the true betas by their first stage estimates is inversely related to the variance of the factors, this error is much greater for models that include the less variable macro factors than it is for the Fama-French three factor model which uses the more variable portfolio return data. This explains why the Shanken correction reduces the t-statistics for the coefficients on betas of macroeconomic factors in the scaled CAPM and also, as shown in the next section, in the scaled consumption CAPM by a far greater degree than it reduces those for the betas of factor mimicking portfolios in the Fama-French model.

The Consumption CAPM

Next we present the results of estimating specifications of the consumption CAPM, using

[29] Jagannathan and Wang (1996) report a similar finding for the signs of the risk prices on the market and human capital betas.

consumption growth as the fundamental factor. We write the scaled multifactor consumption CAPM using $z_t = \widehat{cay}_t$ as the single conditioning variable, a special case of (4), in the form

$$E[R_{i,t+1}] = E[R_{0,t}] + \beta_{zi}\lambda_z + \beta_{\Delta ci}\lambda_{\Delta c} + \beta_{\Delta czi}\lambda_{\Delta cz}. \tag{15}$$

Δc denotes the log difference is consumption, where the data sources for both this variable and for $\widehat{cay}$ are documented in Appendix B.[30] The factors in this model are $\widehat{cay}$, current period consumption growth, and consumption growth scaled by $\widehat{cay}$. Row 1 of Table 3 shows that the unconditional consumption CAPM (with consumption growth the single factor) performs only slightly better than the unscaled CAPM without labor income (11), explaining just 16 percent of the variation in average returns. The results of estimating the scaled specification (15) are presented in row 2.

Like the case for the scaled CAPM, the time-varying component of the intercept term in (15) does not appear to be important: λ_z is not statistically significantly different from zero and eliminating β_{zi} from the cross-sectional regression does not have an important effect on either the other coefficients in the regression, or on the overall fit of the regression. This is revealed in row 3 which eliminates β_{zi} as a regressor in (15). In the interest of maintaining more parsimonious specifications, from here on we present the results from estimating the beta specification under consideration omitting the time-varying component of the constant from the regressions (i.e., λ_z is restricted to be zero). The β for the scaling variable itself may capture the effects of time-variation in the risk-free rate, but do not capture the effects of time-varying risk premia. None of the results presented in Table 2 or 3 are qualitatively influenced by imposing this restriction.[31]

Row 2 shows that the estimated values of $\lambda_{\Delta c}$ and $\lambda_{\Delta cz}$ are strongly jointly significant (panel B) and the estimated value of $\lambda_{\Delta cz}$ is individually statistically different from zero; the $t-$statistic

[30] Breeden, Gibbons and Litzenberger (1989) investigate the effects of several data issues that arise when testing the consumption CAPM with measured consumption. They emphasize, in particular, that measured quarterly consumption is the time-average of instantaneous consumption rates during the quarter. They show that one can compensate for this bias by multiplying quarterly consumption growth rates by 3/4. Such an adjustment would scale the point estimates of the risk prices by 3/4, but would obviously not effect the $t-$statistics or the R^2 statistics we report.

[31] Note that the parameter b_j for a factor j may be nonzero in the pricing kernel even if the its beta is not priced ($\lambda_j = 0$) in the cross-sectional regression (bs and βs are not the same). We found that including the scaling variable $\widehat{cay}$ as a factor in the pricing kernel was important despite the fact that the β for this factor was not typically priced. Thus we always include the scaling variable as a factor in our specification of M_{t+1} regardless of whether we include its β in the cross-sectional regression.

equals 3.2 in the regression reported in row 4; the corrected $t-$statistic is 2.41. More strikingly, the R^2 statistic indicates that the specification in (15) explains 70 percent of the cross-sectional variation in average returns on the 25 Fama-French portfolios. This stands in sharp contrast to the 1 percent explained by the static CAPM (row 1, Table 2) or the 16 percent explained by the unconditional consumption CAPM (row 1, Table 3). Furthermore, it is quite close to the 80 percent R^2 produced from the Fama-French three factor model (row 3, Table 2).[32]

The fact that the beta for the cross-term factor $z_t \Delta c_{t+1}$ is important suggests that the data are better modeled by the habit models discussed above than they are by a traditional conditional consumption CAPM where no cross-term beta would arise. Note also that the improvement in R^2 derived from scaling the unconditional CCAPM is quite dramatic and is larger than that derived from scaling the version of the CAPM which includes labor income growth. This feature of the data provides some support for the argument presented in Campbell and Cochrane (1999b) that, when excess returns are time-varying, the unconditional CAPM is likely to perform better in pricing assets than an unconditional CCAPM even if the consumption-based model is true by construction. Campbell and Cochrane show, by contrast, that the conditional versions of these two models should perform equally well, consistent with what we find.[33] Finally, we also note that, even though the coefficient $\lambda_{\Delta c}$ in (15) is negative, the implied average risk price for the consumption beta in the conditional consumption CAPM, $E[\widetilde{\lambda}_{\Delta c,t}]$, computed as described above, is positive, consistent with the theory.

Average Pricing Errors

Although the R^2 statistics give a summary measure of the overall fit of each cross-section

[32]Note that it is not surprising that the Fama-French three-factor model explains a slightly larger fraction of the variation in average returns on these portfolios. If there is any measurement error in a set of theoretically-derived aggregate indicators determining the discount factor, M, the factor-mimicking portfolios for those variables will always price assets better than the underlying economic indicators. This phenomenon is likely to occur because the mimicking portfolios are typically better measured and often available on a more timely basis than are macroeconomic data. On the other hand, if the Fama-French factors are not mimicking portfolios for consumption risk but are simply *ex-post* mean-variance efficient portfolios, they will again always beat the theoretically-derived factors in-sample.

[33]Campbell and Cochrane (1999b) show this by constructing artificial data from the habit-persistence framework in Campbell and Cochrane (1999a). Because the CAPM is better able to capture some of the time-variation in expected returns than is the unconditional consumption-factor model, the CAPM is a better approximate unconditional model even though it has no advantage over the CCAPM when both models are specified as conditional factor models.

regression, it is also helpful to have a visual impression of the relative empirical performance of each specification we investigate. This is furnished in Figure 2, panels A through F. For a given empirical specification, each figure plots the fitted expected return for each portfolio, using the coefficient estimates for that specification, against the realized average return. If the model fit perfectly, all the fitted returns would lie along the 45 degree line also plotted. For reference, the data for these plots (the pricing errors for each portfolio for the various empirical specifications we consider) are given in Table 4.

Figure 2 shows the pricing errors for each of the 25 Fama-French portfolios in six different models. Each two-digit number represents one portfolio. The first digit refers to the size quintiles (1 indicating the smallest firms, 5 the largest), the second digit refers to book-to-market quintiles (1 indicating the portfolio with the lowest book-to-market ratio, 5 with the highest). Figure 2A confirms that the simple, static-CAPM explains virtually none of the variation in average returns on these portfolios. We can spot the main source of difficulty immediately: the mispricing of portfolios that have different book-to-market equity ratios for a given size value. For example, portfolios 11 and 15–those that are in the smallest size category but in the lowest and highest book-to-market categories–lie farthest from the 45 degree line. This illustrates a familiar result: the value effect destroys the static CAPM when confronted with these portfolios. Figure 2B shows that scaling the CAPM with $\widehat{cay}$ improves the fit substantially. Figure 2C illustrates that the unscaled consumption CAPM also has difficulty explaining the difference in return between high and low book-to-market portfolios. Again we see that the return on portfolio 15 is substantially higher than that of portfolio 11, yet the fitted expected returns from the unconditional consumption CAPM for these two portfolios are roughly the same. By contrast, Figure 2D shows that the scaled multifactor consumption CAPM does a much better job of explaining the value effect: the fitted expected returns on value portfolios are high while the fitted expected returns on growth portfolios are low, consistent with the data. A similar result holds for the scaled CAPM with labor income in Figure 2E. Comparing these results to Figure 2F, which plots the fitted values from the Fama-French three-factor model, it is evident that the scaled consumption CAPM and the scaled CAPM with labor income do about as well as the Fama-French model in explaining this value effect, and the portfolios that are most mispriced in the scaled (C)CAPM models 2D and 2E are the same portfolios that are most mispriced in the Fama-French three factor model 2F.

How do the pricing errors vary across more aggregated portfolios? Table 4, panel B reports the square root of the average squared pricing errors across ten aggregated portfolios formed on the basis of the size and book-to-market quintiles. It is clear that the pricing errors for the scaled consumption CAPM are lower for large size portfolios and high book-to-market portfolios, and vice versa. A similar pattern can be found for the Fama-French model. The last row of Table 4 gives the average pricing errors across all portfolios. The conditional consumption-CAPM we consider has average errors a little more than one-half the size of those for the simple static-CAPM, whereas the Fama-French three-factor model has average errors about 42 percent as large as the static-CAPM.[34]

The last row in Table 4 reports the results of an asymptotic χ^2 test of the null hypothesis that the pricing errors are zero.[35] The table shows that the only models for which the null of zero pricing errors may not be rejected are the scaled multifactor models. We are reluctant to place emphasis on this result. The test, at least on these data, does not appear to have much power to distinguish among various models. It is clear that the Fama-French three factor model, the scaled CAPM with labor income growth, and the scaled consumption CAPM all have average pricing errors of roughly the same magnitude, and the economic size of these errors is not large. The difference in statistical significance again appears to be due to the fact that the there is more sampling error in the first-stage estimates of the betas in the scaled multifactor (C)CAPM models than there is in any of the unscaled models, translating into a larger upward correction to the asymptotic variance-covariance matrix of the pricing errors in the scaled multifactor models. This finding is consistent with the results reported above. Just as the greater sampling error in

[34]These results are consistent with Avramov (1999) who finds that *cay* has important predictive power for returns on large and medium size, as well as on high book-to-market portfolios in a Bayesian study of return forecasting models.

[35]The test statistic requires the assumption that the errors in the Fama-MacBeth regressions are i.i.d. over time, and is given by

$$(1+\boldsymbol{\lambda}'\Sigma_f^{-1}\boldsymbol{\lambda})^{-1}\widehat{\boldsymbol{\alpha}}'_{FM}\mathrm{Cov}(\widehat{\boldsymbol{\alpha}}_{FM})^{-1}\widehat{\boldsymbol{\alpha}}_{FM} \sim \chi^2_{N-K},$$

where Σ_f is the variance-covariance matrix of the factors, $\widehat{\boldsymbol{\alpha}}_{FM}$ is the estimated vector of pricing errors given by the Fama-MacBeth estimates, N is the number of portfolios, and K is the number of factors. The first multiplicative term in parentheses is a correction for sampling error in $\boldsymbol{\beta}$, and is due to Shanken (1992). Note that this formula is numerically equivalent to the analogous test statistic for OLS estimates from cross-sectional regressions, where the OLS standard errors are corrected for cross-sectional correlation:

$$T(1+\boldsymbol{\lambda}'\Sigma_f^{-1}\boldsymbol{\lambda})^{-1}\widehat{\boldsymbol{\alpha}}'_{OLS}[(I_N-\boldsymbol{\beta}(\boldsymbol{\beta}'\boldsymbol{\beta})^{-1}\boldsymbol{\beta}')\Sigma(I_N-\boldsymbol{\beta}(\boldsymbol{\beta}'\boldsymbol{\beta})^{-1}\boldsymbol{\beta}')]^{-1}\widehat{\boldsymbol{\alpha}}_{OLS} \sim \chi^2_{N-K},$$

where Σ is the $N \times N$ covariance matrix of pricing errors from the OLS cross-sectional regression. See Cochrane (1999), chapter 12.

the betas of the scaled (C)CAPM models reduces the precision of the Fama-MacBeth estimates of $\boldsymbol{\lambda}$ by much more than it does in the unscaled models using portfolio return data, it also reduces the precision of the estimated pricing errors in the scaled multifactor models by more than in the unscaled models.

Intuition

The results in Tables 2 and 3 and in Figure 2 demonstrate that the scaled (C)CAPM goes a long way toward explaining why value stocks earn higher returns than growth stocks. What is the intuition for this finding? Recall that the scaled (C)CAPM, unlike its unconditional counterpart, allows for time-variation in risk premia, the source of which may be time-variation in risk aversion (as in models with habit persistence, e.g., Campbell and Cochrane 1999a), or time-variation in risk itself (as in models with time-varying labor earnings or default risk, e.g., Constantinides and Duffie 1996; and Sundaresan 1999). Accordingly, bad times are periods of relatively high risk aversion or high earnings/default risk, and the rise in this risk or risk aversion upon entering a recession reduces the demand for risky assets driving down their price and with it the value of wealth. In these models, recessions are therefore times of falling consumption but increasing *ratios* of consumption to aggregate wealth, while the opposite holds true for booms. Figure 1, reproduced from Lettau and Ludvigson (1999), shows that these implications are consistent with the data: $\widehat{cay}_t$ tends to decline during expansions (forecasting a decline in future excess returns) and rise in recessions (forecasting an increase in future excess returns). Thus, value portfolios are not riskier than growth stocks because their returns are more highly unconditionally correlated with consumption growth, as, for example, the unconditional CCAPM would predict. Rather, value portfolios are riskier because their returns are more highly correlated with consumption growth in recessions, when $\widehat{cay}_t$ is high, than they are in booms, when $\widehat{cay}_t$ is low. Put another way, value portfolios are riskier because their returns are more highly correlated with consumption growth in recessions, when risk/risk-aversion is high, than they are in booms, when risk/risk-aversion is low. The empirical results presented above suggest that it is this *conditional* correlation of factors with returns, far more than the unconditional correlation frequently tested, that is important for pricing assets.

Scaling the Fama-French Model

Table 5 considers a scaled version of the Fama-French three factor model in (12), now a six factor specification which includes loadings for the scaled Fama-French factors as well as for the original factors as explanatory variables. For comparison, the results for the standard, unscaled Fama-French three-factor model are reproduced in row 1.

The scaled, Fama-French model, like its unscaled three-factor counterpart (12), explains a substantial fraction of the cross-sectional variation in average returns: the R^2 of the cross sectional regression is 83 percent. But, more significantly, the explanatory power of the scaled Fama-French specification is no greater than the unscaled specification: the adjusted R^2 is precisely the same in scaled version reported in Table 5 as it is in the unscaled version reported in Table 2. This finding is in sharp contrast to that for the CAPM and even more in contrast to the CCAPM where, in each case, the scaled factor models do substantially better than their unscaled counterparts. The result suggests that the success of the Fama-French three factor model in explaining the variation in average returns on these portfolios may be, in large part, a function of its ability to proxy for the role of conditioning information in the (C)CAPM. Moreover, given that the conditioning information is important because it captures time-varying risk premia, the finding implies that the Fama-French model performs better than the unconditional factor models because it picks up this time-variation. This explains why the Fama-French model outperforms the unconditional versions of the (C)CAPM which ignore time-variation in expected returns, but conveys a far lesser advantage over these models when they are scaled to account for time-varying risk premia.

Including Characteristics

We now investigate whether there are any residual effects of firm characteristics in the scaled (C)CAPM models investigated above. This examination is done by first including firm size–the time-series average of the log of market equity for each firm–as an additional explanatory variable in the cross-sectional regressions. Berk (1995) and Jagannathan and Wang (1998) argue that including this firm-specific characteristic provides a natural specification test for any cross-sectional asset pricing model. These results are presented in Table 6. For reference, the table presents results for models which include various factors; we summarize only the main findings from a few specifications here.

Again, to form a basis of comparison, we begin by presenting the results of including firm size in the static CAPM model (11). The results of this estimation are shown in row 1 of Table 6. These results confirm the well-documented difficulty posed by the inclusion of firm-specific characteristics for the static-CAPM: the coefficient on the size variable is statistically significant, the R^2 statistic jumps from 1 to 70 percent from including firm size, and the risk price for the value-weighted return is now negative and statistically significant. A similar result is obtained by including size in the scaled CAPM (13) as demonstrated in row 2. By including labor income growth in the scaled CAPM (row 4) these size effects are attenuated, but not completely eliminated; the coefficient on size is not statistically different from zero according to the corrected $t-$statistic, but remains statistically significant according to the uncorrected $t-$statistic.

By contrast, the effects of size are completely eliminated in the CCAPM and are much weaker than in even the scaled CAPM specification with labor income growth. Size is not a significant determinant of the cross-section of average returns in either the consumption CAPM (equation (15) with $\beta_{\Delta cz} = \beta_z = 0$) or in the scaled consumption CAPM (15); the coefficient on this variable is not statistically significant and the overall fit of the regression is roughly the same regardless of whether size is included in the regression.

In the bottom panel, we include the log of the book-to-market (BM) equity ratio for each firm as an additional explanatory variable in the cross-sectional regressions. As with firm size, the BM variable is significant for both the unscaled and scaled version of the CAPM. Moreover, the R^2 increases substantially once BM is included. Both the scaled and unscaled versions of the CAPM which include labor income growth also have difficulty eliminating residual BM effects (rows 3 and 4). For these models, BM remains statistically significant even according to the corrected standard errors. A similar result holds for the unscaled consumption CAPM

In the scaled consumption CAPM specification, residual book-to-market effects are, on the contrary, eliminated. The coefficient on BM is not statistically different from zero at conventional levels using either the uncorrected or Shanken-corrected standard errors. More importantly, a comparison with the results in Table 3 shows that, compared to that for the CAPM, their is no substantial increase in adjusted R^2 from including BM in the scaled consumption CAPM specifications. These results provide further support for the earlier finding that the consumption CAPM goes a long way toward explaining the size and value anomalies documented in this set of portfolio returns.

Alternative Scaling Variables

So far we have considered scaled multifactor models using $\widehat{cay}$ as a conditioning variable. We argued above that $\widehat{cay}$ is an excellent candidate for a scaling variable because both theory and empirical evidence suggest that it should do a good job of summarizing investor expectations about future returns on the market portfolio. Nevertheless, others have suggested that the dividend-price ratio (Campbell and Shiller 1988) or the spread between yields on a BAA rated bond and a AAA rated bond (Jagannathan and Wang 1996) may do a good job of summarizing investor expectations. Table 7 presents results for scaled multifactor versions of the (C)CAPM using either the log dividend-price ratio on the CRSP-VW Index ($z_t = d_t - p_t$) or the yield spread between the BAA and AAA rated bonds ($z_t = \mathrm{SPR}_t$) as conditioning variables, in place of $\widehat{cay}_t$.

The performance of the conditional consumption CAPM (15) is quite sensitive to the choice of scaling variable. In contrast to the results presented in Table 2, the results in Table 7 shows that the scaled consumption CAPM performs poorly in explaining the cross-section of average returns when the scaling variable z_t is either the dividend-price ratio or, to a lesser extent, the default spread. Neither $\lambda_{\Delta c}$ or $\lambda_{\Delta cz}$ are statistically significant when either of these measures are employed as scaling variables. Furthermore, the R^2 of the cross-sectional regression is considerably lower than the 70 percent reported in Table 3 obtained using $\widehat{cay}$. For the model with $z_t = d_t - p_t$, the R^2 statistic for the scaled consumption-CAPM is just 14 percent; for the model with $z_t = \mathrm{SPR}_t$ it is 37 percent. This finding supports the hypothesis that $\widehat{cay}$ has an important advantage over other conditioning information in summarizing expectations. It also suggests that the log consumption-aggregate wealth ratio, as proxied by $\widehat{cay}$, plays a meaningful role in explaining the cross-section of average asset returns. These results are similar for the scaled CAPM. An exception is the scaled CAPM with labor income growth, which does almost as well using the dividend-price ratio as a scaling variable as it does using $\widehat{cay}$.

In summary, the results presented above show that a conditional (C)CAPM, using $\widehat{cay}$ as conditioning information, does the best job of explaining the cross-section of average returns. We also investigated the empirical performance of this consumption-based model using the 27 portfolios employed by Davis, Fama and French (forthcoming), formed by triple sorting stocks on size, book-to-market equity ratios and risk loadings on a the HML mimicking portfolio. We repeated the tests presented in Table 2 for these 27 portfolios. The results (not reported) are qualitatively very similar to those presented using the size/book-to-market sorted portfolios presented here.

4 Conclusion

Empirical asset pricing has presented an abundance of formidable challenges for both the CAPM and the consumption-based CAPM in recent years. One of the most compelling of these was presented by Fama and French (1992, 1993) who showed that a broad stock-market beta could not explain the difference in return between portfolios with high and low book-to-market equity ratios. Consumption-based asset pricing models fared little better in this regard.

The failures of the CAPM and the consumption CAPM documented over the last 15 years have prompted researchers to seek alternative empirical models for explaining the pattern of returns on portfolios formed according to size and book-to-market equity ratios. Fama and French (1993) demonstrate that a three factor model consisting of a broad stock market beta and betas on two mimicking portfolios formed to proxy for risk related to size and book-to-market equity ratios can capture strong common variation in returns. Yet these results have been a source of controversy as some researchers question whether the two mimicking portfolios capture true nondiversifiable, and therefore macroeconomic, risk. Since models that specify actual macroeconomic variables as risk factors have, as yet, failed to explain a significant fraction of the variation in these returns, this contention persists.

We argue that the results presented in this paper go a long way toward resolving this controversy. We provide an empirical test of the (C)CAPM by positing that the true unobservable discount factor may be approximated as a linear function of the model's fundamental factors. Instead of assuming that the parameters of this function are fixed over time, as in many previous studies, we model the parameters as time-varying by scaling them with conditioning information. Unlike the simple static CAPM or unconditional consumption CAPM, we find that these scaled multifactor versions of the (C)CAPM can explain a substantial fraction of the cross-sectional variation in average returns on stock portfolios sorted according to size and book-to-market equity ratios. These results seem to be especially supportive of a habit-formation version of the consumption CAPM, where the multiplicative, or scaled, consumption factor is important. This scaled consumption CAPM does a good job of explaining the celebrated value-premium: portfolios with high book-to-market equity ratios also tend to have returns that are more highly correlated with the scaled consumption factors we consider, and vice versa. Furthermore, the scaled consumption model eliminates residual size and book-to-market effects that remain in the CAPM. Thus, these findings lend support to the view that the value-premium can, at least in part, be attributed to the greater nondiversifiable risk of high book-to-market portfolios, and not simply to elements bearing no relation to risk such as firm characteristics or sample selection biases.

Our results also help to shed light on *why* the Fama-French three factor model performs so well relative to the unscaled (C)CAPM: the data suggest that the Fama-French factors are mimicking portfolios for risk factors associated with time-variation in risk premia. Once the (C)CAPM is modified to account for such time-variation, it performs about as well as the Fama-French model in explaining the cross-sectional variation in average returns. Of course, as with any model, the one investigated here is only an approximation of reality; as such, some features of the cross-sectional variation in returns remain unexplained even after accounting for these consumption covariances. The success of the (C)CAPM model tested here rests with its relative accuracy, rather than with its ability to furnish a flawless description of reality.

A key component of this success is our choice of conditioning information. We argue here that the difference between log consumption and a weighted average of log asset wealth and log labor income is likely to provide a superior summary measure of conditional expectations. The use of such a variable as conditioning information allows us to deliver a powerful test of the (C)CAPM because it circumvents the need to observe information sets directly. Consistent with this proposition, we find that the scaled consumption CAPM using $\widehat{cay}$ as an instrument performs far better than it does using other possible instruments, such as the dividend-price ratio or the default spread.

The conditional linear factor models we explore here are quite different from unconditional models. If conditional expected returns to the market portfolio are time-varying, the investor's discount factor will not simply depend unconditionally on consumption growth or the market return, but instead will be a function of these factors conditional on information about future returns. Assets are riskier if their returns are more highly *conditionally* correlated with factors, rather than unconditionally correlated as in unconditional versions of the (C)CAPM. The approach taken here, of scaling factors with information available in the current period, leads to a multifactor, unconditional model in place of a single-factor, conditional model. This approach therefore provides a justification for requiring more than one factor to explain the behavior of expected returns, even if one believes that the true model is, for example, a consumption-based intertemporal asset pricing model with a single fundamental factor. By deriving this multifactor structure from an equilibrium framework, we can mitigate a common criticism of multifactor models, namely that multiple factors are chosen without regard to economic theory.[36] The empirical results we obtain from doing so suggest that a multifactor version of the (C)CAPM can explain a meaningful portion of the cross-section of expected asset returns.

[36]For example, these criticisms can be found in Lo and MacKinlay (1990); Breen and Korajczyk (1993) and Kothari, Shanken, and Sloan (1995).

Appendix A: Derivation of Approximate Log Consumption-Wealth Ratio

The approximation of the log consumption-aggregate wealth ratio presented here was first derived in Campbell and Mankiw (1989).They show that the investor's intertemporal budget constraint, $W_{t+1} = (1 + R_{m,t+1})(W_t - C_t)$, may be expressed

$$\Delta w_{t+1} \approx k + r_{m,t+1} + (1 - 1/\rho_w)(c_t - w_t) \tag{16}$$

where W_{t+1} is aggregate (human plus nonhuman) wealth in period $t+1$, ρ_w is the steady-state ratio of invested to total wealth, $(W - C)/W$, and k is a linearization constant that plays no role in our analysis. Solving this difference equation forward and imposing that $\lim_{i\to\infty} \rho_w^i (c_{t+i} - w_{t+i}) = 0$, the log consumption-wealth ratio may be written

$$c_t - w_t = \sum_{i=1}^{\infty} \rho_w^i (r_{m,t+i} - \Delta c_{t+i}). \tag{17}$$

After taking expectations of (17) we obtain the equation given in (9).

Appendix B: Empirical procedure for estimating parameters in *cay*

This appendix provides a brief summary of the empirical procedure used in Lettau and Ludvigson (1999) to estimate the parameters of the expression on the right-hand-side of (17).

We begin by noting that these coefficients are simply parameters in a cointegrating relationship among consumption, labor income and asset wealth. Lettau and Ludvigson present evidence that these three variables share a single, common stochastic trend; the reader is referred to the article for details. Before estimating the parameters of the shared trend, we deal with a measurement issue that arises from the nature of the data on consumption.

Parameter estimation requires first deciding on the data and previous empirical work which has investigated consumption-based models like that which we explore has used expenditures on nondurables and services as a measure of consumption. The use of these expenditure categories is justified on the grounds that the theory applies to the *flow* of consumption; expenditures on durable goods are not part of this flow since they represent replacements and additions to a stock, rather than a service flow from the existing stock. Accordingly, we use expenditures on nondurables and services (less shoes and clothing) as our measure of consumption, denoted c^*. But since nondurables and services expenditure is only a component of consumption, the standard solution to this problem requires the researcher to assume that total consumption is unobservable and a constant multiple of nondurable and services consumption (Campbell 1987; Blinder and Deaton 1985; Galí 1990).

We follow in this tradition and use nondurables and services as our consumption measure, and assume a constant scale factor governing the relationship between the log of total consumption and the log of nondurables consumption, denoted c_t^*. Thus we write log total consumption, $c_t = \lambda c_t^*$, where $\lambda > 1$, implying that the estimated cointegrating vector for c_t^*, a_t^*, and y_t^* will be given by $[1, -\frac{1}{\lambda}\omega, -\frac{1}{\lambda}(1-\omega)]$.[37] We define $\beta_a = \frac{1}{\lambda}\omega$, and $\beta_y = \frac{1}{\lambda}(1-\omega)$, the parameters of the cointegrating relation to be estimated. Note that $\beta_a + \beta_y$ identifies $1/\lambda$.

The data used for this estimation are quarterly, seasonally adjusted, per capita variables, measured in 1992 dollars.[38] To estimate β_a and β_y, we employ a method that generates optimal estimates of the cointegrating parameters in a multivariate setting by following the dynamic least squares (*DLS*) technique of Stock and Watson (1993). This technique specifies an equation taking the form

$$c_t^* = \alpha + \beta_a a_t^* + \beta_y y_t^* + \sum_{i=-k}^{k} b_{a,i} \Delta a_{t-i}^* + \sum_{i=-k}^{k} b_{y,i} \Delta y_{t-i}^* + \epsilon_t, \tag{18}$$

where the symbol Δ is the first difference operator.

Equation (18) is estimated by *OLS* using data from the fourth quarter of 1952 to the third quarter of 1998. This methodology provides a consistent estimate of the cointegrating parameters through its estimates of β_a and β_y. We also make a Newey-West correction to the t-statistics for generalized serial correlation of the residuals. It is important to recognize that estimates of β_a and β_y will be consistent despite the fact that ϵ_t will typically be correlated with the

[37] Previous research has worked with formulations in levels, rather than in logs as we do here. Because Blinder and Deaton (1985) report that the share of nondurables and services in measured expenditures has displayed a secular decline over the sample period, the assumption that total consumption is a constant multiple of nondurable consumption may be questionable. By contrast, we postulate that the *log* of total consumption is a constant multiple of the log of nondurable and services consumption. Unlike the ratio of levels, the ratio of logs appears to have exhibited little secular movement during our sample period.

[38] The consumption data are for nondurables and services excluding shoes and clothing in 1992 chain weighted dollars. The nonhuman wealth data is the household net worth series provided by the Board of Governors of the Federal Reserve. Labor income is defined as wages and salaries plus transfer payments plus other labor income minus personal contributions for social insurance minus taxes. Taxes is defined as (wages and salaries/ (wages and salaries + proprietors income with IVA and Ccadj + rental income + personal dividends + personal interest income))*(personal tax and non tax payments). Both the net worth variable and the labor income variable are deflated by the PCE chain-type price deflator.

regressors a_t and y_t. Moreover, standard errors do not need to be adjusted to account for the use of the generated regressor in our subsequent empirical tests. Both of these follow from the fact that *OLS* estimates of cointegrating parameters are "superconsistent", converging to the true parameter values a rate proportional to the sample size T rather than proportional to $\sqrt{T}$ as in ordinary applications (Stock 1987). Implementing the regression in (18) using data from the fourth quarter of 1952 to the third quarter of 1998 generates the point estimates given in the text. The results are not sensitive to our choice of lead/lag lengths in the *DLS* specification.

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Table 1: Long-Horizon Forecasting Regressions

	R^e_{vw}				GDP				Δc			
H	1	4	8	20	1	4	8	20	1	4	8	20
$\widehat{cay}$	$0.09^{\dagger}$	$0.18^{\dagger}$	$0.16^{\dagger}$	$0.13^{\dagger}$	$0.15^{\dagger}$	$0.13^{\dagger}$	$0.09^{\dagger}$	0.01	0.01	0.03	0.01	−0.00
$d-p$	0.01	0.04	0.06	$0.16^{\dagger}$	0.14	0.03	0.00	0.03	0.01	0.00	0.00	0.00
SPR	0.01	0.00	0.01	−0.01	$0.20^{\dagger}$	$0.14^{\dagger}$	0.03	0.02	0.11	0.09	0.01	0.00
SMB	$0.01^{\dagger}$	0.01	0.01	−0.00	0.14	$0.04^{\dagger}$	0.00	0.00	0.00	0.01	0.00	−0.01
HML	$0.01^{\dagger}$	0.01	0.00	−0.01	$0.15^{\dagger}$	0.04	0.00	0.00	0.00	0.00	0.00	0.00
$\widehat{cay}$ & SMB	$0.13^{\dagger\ddagger}$	$0.22^{\dagger\ddagger}$	$0.20^{\dagger\ddagger}$	$0.14^{\dagger}$	$0.15^{\dagger}$	$0.13^{\dagger}$	$0.08^{\dagger}$	0.00	0.00	0.03	0.01	−0.02

Notes for Table 1: This table reports adjusted R^2's from long-horizon regressions. The regressions of the form $x_{t+1} + ... + x_{t+H} = \gamma_1 y_t + \gamma_2 x_t + \epsilon_t$ are estimated using OLS. Three different horizons H are considered: one, four and eight quarters. The dependent variables x are the value-weighted CRSP excess return (R^e_{vw}), per-capita GDP growth (GDP) and per-capita consumption growth (Δc), respectively. The explanatory variable y is one of the following variables: the deviations from trend $\widehat{cay}$, the log dividend-price ratio of the CRSP value-weighted index, the yield spread SPR of BAA and AAA bonds, and the Fama-French factors SMB and HML. A '†' indicates that the estimated coefficient $\hat{\gamma_1}$ is significant at the 5% level (where the t-statistics are computed using Newey-West corrected standard errors). The last row reports a regression including $\widehat{cay}$ and SMB. In this case a '†' indicates that $\widehat{cay}$ is significant at the 5% level while a '‡' indicates that SMB is significant. Data from 1952Q4-1998Q3 is used to estimate the model.

Table 2: CAPM Fama-MacBeth Regressions using 25 FF Portfolios

Panel A: Coefficient Estimates

#	CONST	$\widehat{cay}_t$	factors$_{t+1}$ R_{vw}	Δy	SMB	HML	$\widehat{cay}_t \cdot$ factors$_{t+1}$ R_{vw}	Δy	SMB	HML	R^2 / $\bar{R}^2$
1	4.18		-0.32								0.01
	(4.47)		(-0.27)								-0.03
	(4.45)		(-0.27)								
2	3.21		-1.41	1.26							0.58
	(3.37)		(-1.20)	(3.42)							0.54
	(1.87)		(-0.67)	(1.90)							
3	1.87		1.33		0.47	1.46					0.80
	(1.31)		(0.83)		(0.94)	(3.24)					0.77
	(1.21)		(0.76)		(0.86)	(2.98)					
4	3.70	-0.52	-0.06				1.14				0.31
	(3.88)	(-0.22)	(-0.05)				(3.59)				0.21
	(2.61)	(-0.15)	(-0.03)				(2.41)				
5	3.70		-0.08				1.16				0.31
	(3.86)		(-0.07)				(3.58)				0.25
	(2.60)		(-0.44)				(2.41)				
6	5.18	-0.44	-1.99	0.56			0.34	-0.17			0.77
	(5.59)	(-1.60)	(-1.73)	(2.12)			(1.67)	(-2.40)			0.71
	(3.32)	(-0.95)	(-1.02)	(1.26)			(0.99)	(-1.42)			
7	3.81		-2.22	0.59			0.63	-0.08			0.75
	(4.02)		(-1.88)	(2.20)			(2.79)	(-2.52)			0.70
	(2.80)		(-1.31)	(1.53)			(1.94)	(-1.75)			

Panel B: Tests for Joint Significance

#	all	factors$_{t+1}$	$\widehat{cay}_t \cdot$ factors$_{t+1}$	f_{t+1} and $\widehat{cay}_t \cdot f_{t+1}$ for each factor f: R_{vw}	Δy	SMB	HML
1	0.798						
	0.798						
2	0.000						
	0.022						
3	0.000						
	0.002						
4	0.000	0.963	0.000				
	0.000	0.975	0.016				
5	0.000	0.948	0.000				
	0.003	0.965	0.016				
6	0.000	0.001	0.000	0.008	0.000		
	0.000	0.092	0.021	0.079	0.040		
7	0.000	0.001	0.000	0.001	0.000		
	0.001	0.032	0.002	0.012	0.004		

Notes for Table 2: This table presents estimates of cross-sectional Fama-MacBeth regressions using returns of 25 Fama-French portfolios:

$$E[R_{i,t+1}] = E[R_{0,t}] + \boldsymbol{\beta}'\boldsymbol{\lambda}.$$

The time-series betas $\boldsymbol{\beta}$ are computed in one multiple regression. The factors for each model are indicated in the figure heading. The set of factors include the return of the value-weighted CRSP index (R_{vw}), labor income growth (Δy_{t+1}) and the Fama-French factors SMB and HML. The scaling variable is $\widehat{cay}$. Panel A of the table reports the Fama-MacBeth cross sectional regression coefficient and two t-statistics in brackets for a variety of factors. The top statistic uses uncorrected Fama-MacBeth standard errors while to bottom statistic uses the Shanken (1992) correction. R^2 denotes the unadjusted cross-sectional R-square while $\bar{R}^2$ adjusts for the degrees of freedom. Panel B reports p-values of χ^2-tests of joint significance of all right-hand-side variables, the factors themselves, the scaled factors, and the factor joint with the scaled factor of each individual factor. The top number is computed using the uncorrected variance-covariance matrix while the bottom number uses the Shanken (1992) correction. The model is estimated using data from 1963Q3 to 1998Q3. The coefficient estimates of the factors are multiplied by 100 while the estimates of the scaled terms are multiplied by 1000.

Table 3: Consumption CAPM Fama-MacBeth Regressions using 25 FF Portfolios

Panel A: Coefficient Estimates

#	CONST	$\widehat{cay}_t$	Δc_{t+1}	$\widehat{cay}_t \cdot \Delta c_{t+1}$	$R^2(\bar{R}^2)$
1	3.24		0.22		0.16
	(4.93)		(1.27)		0.13
	(4.46)		(1.15)		
2	4.28	-0.13	0.02	0.06	0.70
	(6.10)	(-0.43)	(0.20)	(3.12)	0.66
	(4.24)	(-0.30)	(0.14)	(2.17)	
3	4.10		-0.02	0.07	0.69
	(6.82)		(-0.14)	(3.20)	0.66
	(5.14)		(-0.10)	(2.41)	

Panel B: Tests for Joint Significance

#	all	factors_{t+1}	$\widehat{cay}_t \cdot \text{factors}_{t+1}$	Δc_{t+1} and $\widehat{cay}_t \cdot \Delta c_{t+1}$
1	0.205			
	0.249			
2	0.000	0.840	0.002	0.000
	0.001	0.888	0.030	0.009
3	0.000	0.893	0.001	0.000
	0.001	0.919	0.016	0.001

Notes for Table 3: This table presents estimates of cross-sectional Fama-MacBeth regressions using returns of 25 Fama-French portfolios:

$$E[R_{i,t+1}] = E[R_{0,t}] + \boldsymbol{\beta}'\boldsymbol{\lambda}.$$

The time-series betas $\boldsymbol{\beta}$ are computed in one multiple regression. The factors is per capita consumption growth (Δc). The scaling variable is $\widehat{cay}$. Panel A of the table reports the Fama-MacBeth cross sectional regression coefficient and two t-statistics in brackets for a variety of factors. The top statistic uses uncorrected Fama-MacBeth standard errors while to bottom statistic uses the Shanken (1992) correction. R^2 denotes the unadjusted cross-sectional R-square while $\bar{R}^2$ adjusts for the degrees of freedom. Panel B reports p-values of χ^2-tests of joint significance of all right-hand-side variables, the factors themselves, the scaled factors, and the factor joint with the scaled factor of each individual factor. The top number is computed using the uncorrected variance-covariance matrix while the bottom number uses the Shanken (1992) correction. The model is estimated using data from 1963Q3 to 1998Q3. The coefficient estimates of the factors are multiplied by 100 while the estimates of the scaled terms are multiplied by 1000.

Table 4: Pricing Errors

Panel A: Individual Portfolios

Portfolio	R_{vw}	R_{vw} scaled	Δc	Δc scaled	R_{vw}, Δy scaled	R_{vw}, SMB, HML
S1B1	-1.0378	-1.1857	-1.7303	-1.0083	-0.6451	-0.8611
S1B2	0.2601	0.0859	-0.3686	-0.1109	-0.0435	0.0055
S1B3	0.3494	0.1532	-0.0105	-0.0809	-0.1852	-0.0276
S1B4	0.9048	1.0021	0.4774	0.3803	0.5386	0.3722
S1B5	1.3108	0.7976	0.8278	0.3704	0.3504	0.1555
S2B1	-0.7860	-0.7558	-1.0749	-0.0362	-0.1149	-0.1416
S2B2	-0.0189	0.3796	-0.0847	-0.2823	-0.2661	0.0478
S2B3	0.6786	0.8639	0.5696	0.5310	0.7516	0.5134
S2B4	0.7561	0.6316	0.7800	0.0964	0.0753	0.3244
S2B5	1.0436	0.4944	0.7576	0.3070	-0.0309	0.0757
S3B1	-0.8062	-0.2985	-0.7324	0.3645	-0.0300	-0.0310
S3B2	-0.0659	0.1049	0.1019	-0.0868	0.1712	0.2053
S3B3	0.0486	0.2463	0.1996	-0.4457	-0.0357	-0.0291
S3B4	0.4098	0.0956	0.6398	0.2218	-0.1837	0.1066
S3B5	0.9036	1.1403	0.8631	0.4109	0.7183	0.0225
S4B1	-0.6513	-0.1532	-0.3754	0.4252	0.1218	0.4184
S4B2	-0.8487	-0.2545	-0.6870	-0.3924	-0.4210	-0.5041
S4B3	-0.1903	-0.2714	0.1383	-0.0626	-0.2180	-0.1749
S4B4	0.2339	-0.3943	0.4651	0.0130	-0.3444	-0.0347
S4B5	0.7553	-0.2413	0.6952	0.3610	0.0678	-0.0073
S5B1	-0.7959	-0.9014	-0.4572	0.4159	0.6455	0.5342
S5B2	-0.8186	-0.7850	-0.2918	-0.7343	-0.2759	0.0035
S5B3	-0.9287	-0.3369	-0.6240	-0.4895	-0.1888	-0.1980
S5B4	-0.4252	-0.2523	0.0760	0.1226	-0.2116	-0.2715
S5B5	-0.2811	-0.1650	-0.1547	-0.2901	-0.2457	-0.5043

Table 4, Panel B: Pricing Errors of Aggregated Portfolios

Portfolio	R_{vw}	R_{vw} scaled	Δc	Δc scaled	R_{vw}, Δy scaled	R_{vw}, SMB, HML
S1	0.872	0.784	0.899	0.513	0.416	0.421
S2	0.740	0.649	0.731	0.305	0.362	0.257
S3	0.573	0.542	0.590	0.334	0.341	0.094
S4	0.601	0.274	0.516	0.306	0.269	0.333
S5	0.697	0.572	0.378	0.458	0.356	0.336
B1	0.825	0.762	1.004	0.549	0.415	0.484
B2	0.541	0.411	0.377	0.398	0.267	0.253
B3	0.545	0.451	0.393	0.382	0.370	0.239
B4	0.599	0.571	0.542	0.209	0.314	0.276
B5	0.924	0.673	0.709	0.351	0.375	0.211
Avg.	0.705	0.589	0.648	0.393	0.352	0.308
χ^2	63.67*	27.24	53.03*	33.88	27.54	45.33*

Notes for Table 4: This tables reports the pricing errors (in %) from the Fama-MacBeth regression presented in Tables 2-3. The top panel lists the average errors for each Fama-French portfolio for a variety of factors. S1 refers to the portfolios with the smallest firms, while S5 includes the largest firms. Similarly, B1 includes firms with the lowest book-to-market-ratio and B5 the highest. Panel A reports pricing errors for the 25 size and book-to-market sorted portfolios, panel B computes the square root of the average squared pricing errors for aggregated portfolios. The last two rows report the square root of the average squared pricing errors across all portfolios a well as the χ^2 statistic for a test that the pricing error is zero. A '$*$' indicates that the average pricing error is statistically different from zero at the 5% level. The model is estimated using data from 1963:Q3 to 1998:Q3.

Table 5: Fama-French Model: Unscaled and Scaled

Coefficient Estimates

		factors$_{t+1}$			$\widehat{cay}_t \cdot$ factors$_{t+1}$			R^2
#	CONST	R_{vw}	SMB	HML	R_{vw}	SMB	HML	$\bar{R}^2$
1	1.87	1.33	0.47	1.46				0.80
	(1.31)	(0.83)	(0.94)	(3.24)				0.77
	(1.21)	(0.76)	(0.86)	(2.98)				
2	5.75	-2.60	0.54	1.52	0.31	-0.05	0.11	0.83
	(4.03)	(-1.70)	(1.08)	(3.40)	(1.56	(-0.26)	(0.78)	0.77
	(3.28)	(-1.38)	(0.88)	(2.77)	(1.27	(-0.22)	(0.63)	

Notes for Table 5: This table presents estimates of cross-sectional Fama-MacBeth regressions using returns of 25 Fama-French portfolios:

$$E[R_{i,t+1}] = E[R_{0,t}] + \boldsymbol{\beta}'\boldsymbol{\lambda}.$$

The time-series betas $\boldsymbol{\beta}$ are computed in one multiple regression. The factors for each model are indicated in the figure heading. The set of factors include the return of the value-weighted CRSP index and returns on the HML and SMB portfolios as constructed in Fama and French (1993). The scaling variable is $\widehat{cay}$. The table reports the Fama-MacBeth cross sectional regression coefficient and two t-statistics in parentheses. The top statistic uses uncorrected Fama-MacBeth standard errors while to bottom statistic uses the Shanken (1992) correction. R^2 denotes the unadjusted cross-sectional R-square while $\bar{R}^2$ adjusts for the degrees of freedom. The model is estimated using data from 1963:Q3 to 1998:Q3. The coefficient estimates of the factors are multiplied by 100 while the estimates of the scaled terms are multiplied by 1000.

Table 6: Fama-MacBeth Regressions including Characteristics

Panel A: Size

		factors$_{t+1}$			$\widehat{cay}_t \cdot$ factors$_{t+1}$				R^2
#	CONST	R_{vw}	Δy	Δc	R_{vw}	Δy	Δc	SIZE	$\bar{R}^2$
1	14.18 (4.77) (4.35)	-3.60 (-2.78) (-2.54)						-0.57 (-3.46) (-3.15)	0.70 0.67
2	13.10 (4.71) (3.79)	-3.05 (-2.49) (-2.01)			0.82 (3.14) (2.52)			-0.49 (-3.24) (-2.61)	0.75 0.73
3	12.03 (4.56) (3.73)	-3.00 (-2.52) (-2.06)	0.51 (2.00) (1.63)					-0.41 (-2.81) (-2.30)	0.74 0.70
4	10.33 (3.78) (2.97)	-2.68 (-2.33) (-1.84)	0.33 (1.36) (1.07)		0.59 (2.63) (2.07)	-0.02 (-0.59) (-0.46)		-0.33 (-1.93) (-1.52)	0.80 0.76
5	5.59 (2.04) (2.03)			0.04 (0.35) (0.35)				-0.18 (-1.11) (-1.10)	0.22 0.15
6	6.09 (2.21) (1.66)			-0.16 (-1.45) (-1.09)			0.08 (3.23) (2.42)	-0.15 (-0.87) (-0.65)	0.72 0.68

Panel B: Book-to-Market Ratio

		factors$_{t+1}$			$\widehat{cay}_t \cdot$ factors$_{t+1}$				R^2
#	CONST	R_{vw}	Δy	Δc	R_{vw}	Δy	Δc	BM	$\bar{R}^2$
1	2.25 (2.06) (2.01)	1.47 (1.08) (1.06)						1.17 (3.62) (3.57)	0.82 0.81
2	2.22 (2.01) (1.95)	1.45 (1.05) (1.02)			0.15 (0.77) (0.75)			1.12 (3.51) (3.41)	0.83 0.81
3	1.91 (1.68) (1.52)	2.00 (1.41) (1.29)	0.41 (1.61) (1.44)					1.38 (3.89) (3.53)	0.83 0.80
4	2.81 (2.56) (2.36)	0.97 (0.71) (0.66)	-0.23 (-0.94) (-0.86)		0.14 (0.70) (0.64)	-0.05 (-1.56) (-1.44)		1.09 (3.13) (2.88)	0.85 0.81
5	3.69 (5.98) (5.70)			0.14 (0.81) (0.77)				0.83 (2.81) (2.67)	0.75 0.73
6	3.90 (6.29) (5.95)			0.08 (0.55) (0.52)			0.02 (1.40) (1.32)	0.61 (1.86) (1.75)	0.78 0.75

Notes for Table 6: This table presents estimates of cross-sectional Fama-MacBeth regressions using returns of 25 Fama-French portfolios:

$$E[R_{i,t+1}] = E[R_{0,t}] + \boldsymbol{\beta}'\boldsymbol{\lambda} + dC_i,$$

where C_i denotes a characteristic variable. The time-series betas $\boldsymbol{\beta}$ are computed in one multiple regression. The factors are the return of the value-weighted CRSP index (R_{vw}) in the top panel and per capita consumption growth (Δc) in the bottom panel. The scaling variable is $\widehat{cay}$. The cross-sectional regressions also include the log of the portfolio size SIZE (in the top panel) and the log of the book-to-market ratio BM (in the bottom panel). The table reports the Fama-MacBeth cross sectional regression coefficient and two t-statistics in brackets. The top statistic uses uncorrected Fama-MacBeth standard errors while to bottom statistic uses the Shanken (1992) correction. The model is estimated using data from 1963Q3 to 1998Q3. The coefficient estimates of the factors are multiplied by 100 while the estimates of the scaled terms are multiplied by 1000.

Table 7: Alternative Scaling Variables

Panel A: Dividend-Price Ratio

		factors$_{t+1}$			$(d_t - p_t) \cdot$ factors$_{t+1}$			R^2
#	CONST	R_{vw}	Δy	Δc	R_{vw}	Δy	Δc	$\bar{R}^2$
1	2.64	-0.37			-7.32			0.02
	(2.70)	(-0.31)			(-1.20)			-0.07
	(2.59)	(-0.29)			(-1.15)			
2	2.97	-1.21	0.90		-4.39	-2.89		0.73
	(3.26)	(-1.05)	(2.90)		(-0.75)	(-2.91)		0.67
	(1.76)	(-0.56)	(1.56)		(-0.41)	(-1.57)		
3	6.09			0.17			-0.34	0.14
	(2.21)			(1.14)			(-0.78)	0.07
	(1.66)			(1.06)			(-0.73)	

Panel A: Default Spread

		factors$_{t+1}$			SPR$_t \cdot$ factors$_{t+1}$			R^2
#	CONST	R_{vw}	Δy	Δc	R_{vw}	Δy	Δc	$\bar{R}^2$
1	2.21	0.29			-0.22			0.05
	(2.35)	(0.24)			(-2.31)			0.00
	(2.09)	(0.22)			(-2.05)			
2	2.31	-0.55	1.24		-0.09	0.02		0.59
	(2.50)	(-0.47)	(3.27)		(-1.07)	(2.22)		0.50
	(1.40)	(-0.27)	(1.83)		(-0.60)	(1.25)		
3	2.69			-0.00			-0.03	0.37
	(3.92)			(-0.03)			(-3.84)	0.31
	(3.08)			(-0.02)			(-3.02)	

Notes for Table 6: This table presents estimates of cross-sectional Fama-MacBeth regressions using returns of 25 Fama-French portfolios:

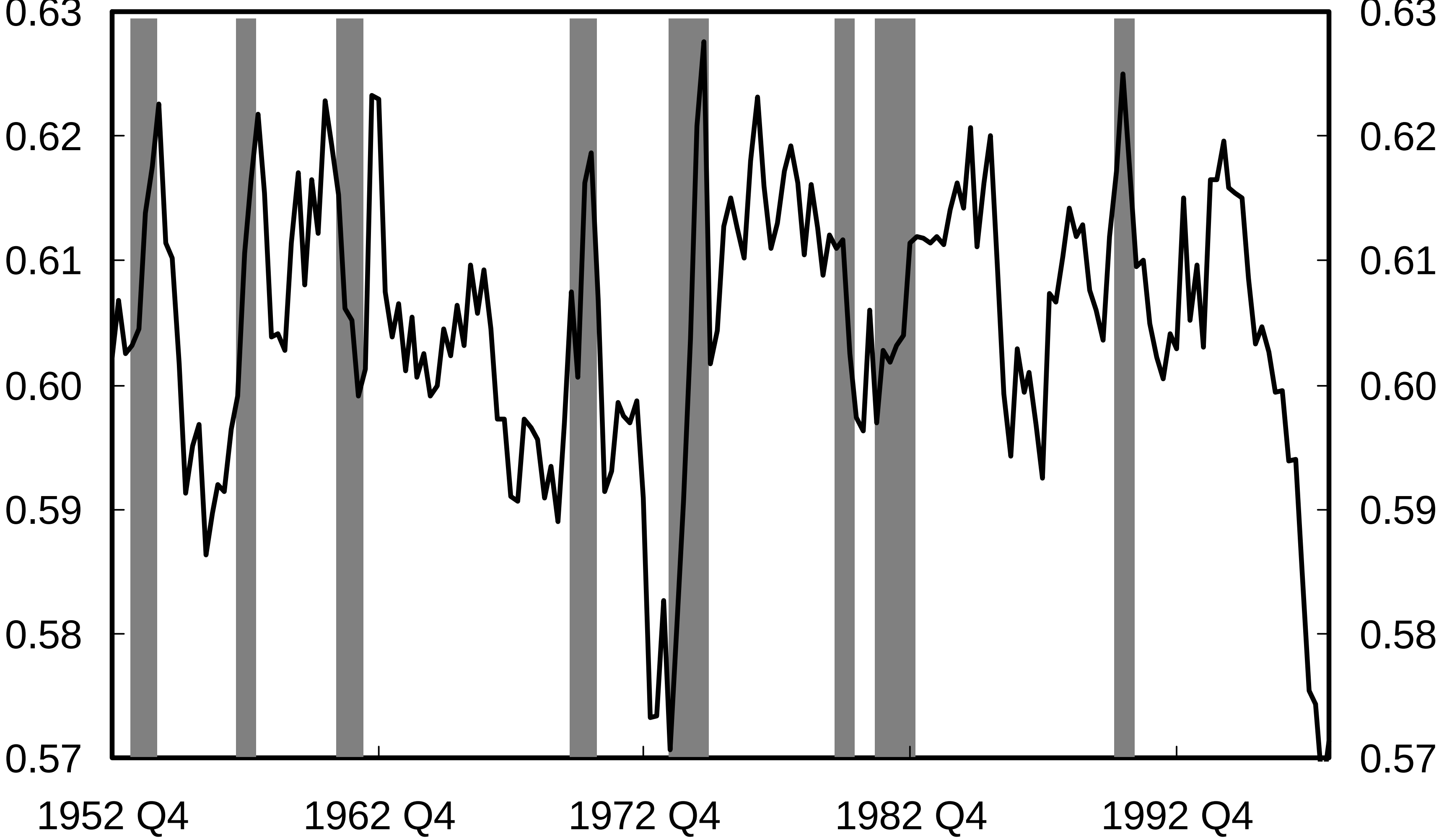
$$E[R_{i,t+1}] = E[R_{0,t}] + \boldsymbol{\beta}'\boldsymbol{\lambda}.$$

The time-series betas $\boldsymbol{\beta}$ are computed in one multiple regressions. The factors are the return of the value-weighted CRSP index (R_{vw}), labor income growth (Δy_{t+1}) and per capita consumption growth (Δc). In the top panel the log dividend-price ratio of the CRSP value-weighted index is used as scaling variable z, in the bottom panel we use the yield spread SPR of BAA and AAA bonds. The table reports the Fama-MacBeth cross sectional regression coefficient and two t-statistics in brackets. The top statistic uses uncorrected Fama-MacBeth standard errors while to bottom statistic uses the Shanken (1992) correction. The model is estimated using data from 1963Q3 to 1998Q3. The coefficient estimates of the factors are multiplied by 100 while the estimates of the scaled terms are multiplied by 1000.

Figure 1: Trend Deviation in Wealth

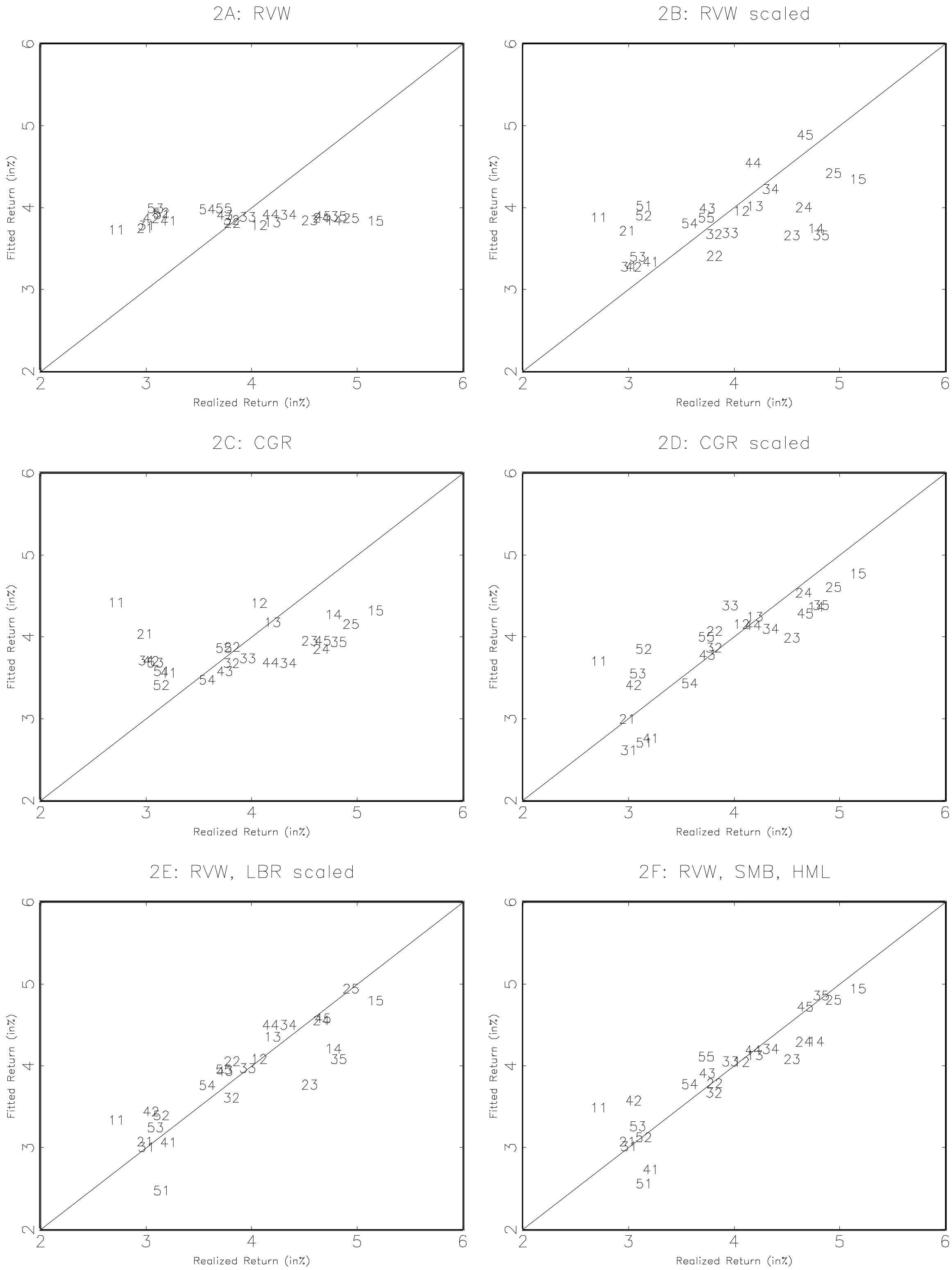
$\widehat{cay}_t = c_t^* - 0.31a_t^* - 0.59y_t^*$

1952:Q4 - 1998:Q3



Shading indicates NBER recessions

Figure 2: Realized versus Fitted Returns: 25 FF Portfolios



Notes for Figure 2: The figure shows the pricing errors for each of the 25 Fama-French portfolios in six different models. Each two-digit number represents one portfolio. The first digit refers to the size quintiles (1 indicating the smallest firms, 5 the largest), the second digit refers to book-to-market quintiles (1 indicating the portfolio with the lowest book-to-market ratio, 5 with the highest). The pricing errors are generated using the Fama-MacBeth regressions in Table 2. The factors for each model are indicated in the figure heading. The set of factors include the return of the value-weighted CRSP index (RVW), per capita consumption growth (CGR), labor income growth (LBR) and the Fama-French factors SMB and HML. The scaling variable is $\widehat{cay}$.