Cross-Sectional Asset Pricing with Individual Stocks: Betas versus Characteristics*

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Abstract

We develop a methodology for estimating bias-corrected premium estimates from cross-sectional regressions of individual stock returns on time-varying conditional betas. For a comprehensive sample of stocks over the post-war period from 1946 through 2011, we find fairly consistent evidence of a positive risk premium on the size factor, but limited evidence for the book-to-market and momentum factors (none for the market factor). Firm characteristics explain a much larger proportion of variation in estimated expected returns than factor loadings when return premia are taken to be constant. However, we find evidence of predictability in the premia for characteristics as well as loadings. Taking this into account, the gap between characteristics and loadings narrows (56% versus 44%) for the three-factor model and loadings take the lead (56% to 39%) with the addition of the momentum factor.

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A fundamental paradigm in finance is that of risk and return: riskier assets should earn higher expected returns. It is the systematic or nondiversifiable risk that should be priced, and under the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) this systematic risk is measured by an asset's market beta. While Black, Jensen, and Scholes (1972) and Fama and MacBeth (1973) do find a significant positive cross-sectional relation between security betas and expected returns, more recently Fama and French (1992) find that the relation between betas and returns is negative, though not reliably different from zero. This calls into question the link between risk and expected returns.

There is also considerable evidence of cross-sectional patterns (so-called anomalies) in stock returns that raises doubts about the risk-return paradigm. Specifically, price momentum, documented by Jegadeesh and Titman (1993), represents the strong abnormal performance of past winners relative to past losers. Earnings momentum, documented by Ball and Brown (1968), describes the subsequent outperformance of firms reporting unexpectedly high earnings relative to firms reporting unexpectedly low earnings. The size and book-to-market effects have been empirically established by, among others, Fama and French (1992). In particular, small market capitalization stock returns have historically exceeded big market capitalization stock returns, and high book-to-market (value) stocks have outperformed their low book-to-market (growth) counterparts. Brennan, Chordia, and Subrahmanyam (1998) find that investments based on anomalies[1] result in reward-to-risk (Sharpe) ratios that are about three times as high as that obtained by investing in the market, too large it would seem, to be consistent with a risk-return model (also see MacKinlay (1995)).

The behavioral finance literature points to psychological biases on the part of investors to explain the breakdown of the risk-return relationship. In contrast, Fama and French (1993) propose a three-factor model that includes risk factors proxying for the size- and value-effects, in addition to the market excess-return factor, Mkt. The size factor, SMB, is a return spread between small firms and big firms, while the value factor, HML, is a return spread between high and low book-to-market stocks. There is controversy in the literature as to whether these two additional factors are really risk factors, however.

Although there's a mechanical relation between loadings and characteristics at the portfolio level, there need not be a direct correspondence between loadings and market cap for

[1] Other anomalies include the accruals anomaly of Sloan (1996), the analyst forecast dispersion anomaly of Diether, Malloy, and Scherbina (2002), the asset growth anomaly of Cooper, Gulen, and Schill (2008), and the capital investment anomaly of Titman, Wei, and Xie (2004) amongst others. See also Fama and French (2008).

any given individual stock (similarly for HML).[2] Thus, the average small-firm loading on SMB must be higher than that for big firms (appropriately weighted), but a particular large-cap stock's price may tend to move more closely with the prices of small-firm stocks than with those of other big-firm stocks. Therefore, it's legitimate to ask whether the underlying firm characteristics or the corresponding factor loadings do a better job of tracking expected returns. While Fama and French (1993) and Davis, Fama and French (2000) argue that it is factor loadings that explain expected returns, Daniel and Titman (1997) contend that it is characteristics. On the other hand, Brennan, Chordia, and Subrahmanyam (1998) present evidence that firm characteristics explain deviations from the three-factor model, whereas Avramov and Chordia (2006) find that size and book-to-market have no incremental effect (momentum and liquidity do) when the model's loadings are time varying.

While some researchers are inclined to view expected return variation associated with factor loadings (betas) as due to risk, and variation captured by characteristics like book-to-market as due to mispricing, we adopt a more agnostic perspective on this issue. The reason is that the betas on an ex-ante efficient portfolio (a potential "factor") will *always* fully "explain" expected returns as a mathematical proposition (see Roll (1977)), whatever the nature of the underlying economic process. This makes it difficult to be sure that a beta effect is truly driven by risk. Conversely, if a characteristic is shown to have substantial explanatory power, it is difficult to rule out the possibility that this variable lines up well with stock return loadings on some omitted risk factor. Thus, the interpretation of such asset pricing results depends on the extent to which the particular factor employed *plausibly* correlates with some notion of aggregate marginal utility and whether there is evidence that a given characteristic actually reflects investor perceptions or behavior that deviates from rationality.

Whatever the interpretation, important gaps remain in our knowledge about the relevant empirical relations. In fact, we know of no study that directly evaluates how much of the cross-sectional variation in expected returns is "explained" by betas and how much by characteristics in a head-to-head competition. The main goal of this paper is to provide evidence on this issue. We do not *impose* a particular pricing model in this context but, rather, evaluate the role of loadings and of characteristics in the cross-sectional relation that best fits the data when both are included as explanatory variables.

[2] The regression of SMB on the three Fama-French factors must produce a perfect fit, with a loading of one on itself and zero on the other factors. Since the SMB loading equals the difference between the small-firm and big-firm portfolio loadings, that difference must equal one.

A number of methodological issues arise in this setting. Indeed, the lack of a consensus on the betas versus characteristics question stems, in part, from issues of experimental design. For example, Brennan Chordia, and Subrahmanyam and Avramov and Chordia work with individual stocks and employ risk-adjusted returns as the dependent variable in their cross-sectional regressions (CSRs). In computing the risk-adjustment, the prices of risk for the given factors are constrained to conform to a model's pricing relation and the zero-beta rate is taken to be the risk-free rate. A virtue of this approach is that the well-known errors-in-variables (EIV) problem is avoided since the betas do not serve as explanatory variables. Estimates of the characteristic premia are thus unbiased. However, the relative contributions of loadings and characteristics cannot be inferred from such an experiment.

More typically, in asset pricing tests, returns are employed as the dependent variable. Stocks are grouped into portfolios to improve the estimates of beta and thereby mitigate the EIV problem. However, the particular method of portfolio grouping can dramatically influence the results (see Lo and MacKinlay (1990) and Lewellen, Nagel, and Shanken (2010)). Using individual stocks as test assets avoids this somewhat arbitrary element. Ang, Liu, and Schwarz (2010) also advocate the use of individual stocks, but from a statistical efficiency perspective, arguing that greater dispersion in the cross-section of factor loadings reduces the variability of the risk-premium estimator. Simulation evidence in Kim (1995) indicates, though, that mean-squared error is higher with individual stocks than it is with portfolios, due to the greater small-sample bias, unless the risk premium estimator is corrected for EIV bias.[3] Thus, we employ EIV corrections that build on the early work of Litzenberger and Ramaswamy (1979), perhaps the first paper to argue for the use of individual stocks, and extensions by Shanken (1992).

The fact that betas change over time is another important consideration in empirical asset pricing, one that is particularly relevant to the debate about betas and characteristics. A study that does not accommodate time variation related to underlying firm characteristics like size and book-to-market (see Gomes, Kogan, and Zhang (2003) for theoretical motivation) may conclude that these characteristics provide incremental explanatory power for expected returns, but only because the characteristics proxy for mismeasurement of the true betas (see related work by Ferson and Harvey (1998), Lewellen (1999), and Avramov and Chordia (2006)). An important

[3] Ang, Liu, and Schwarz (2010) use an MLE framework with constant betas to develop analytical formulas for EIV correction to standard errors, but they do not address the bias in the estimated coefficients. Also, they seem to implicitly assume that the factor mean is known, which might explain the huge *t*-statistics that they report (see Jagannathan and Wang (2002) for a similar critique in the context of SDF models).

contribution of our paper, in this regard, is the development of an EIV correction for CSRs with time-varying conditional betas. Furthermore, we examine the implications of time-varying *premia* for both betas and characteristics.

Still another methodological issue arises when we estimate betas for each stock using the entire time series of returns, in an attempt to improve estimation efficiency. Given some surprising early results, we explored the possibility of some sort of contemporaneous bias by estimating betas using data separate from the returns in the CSR for a given month. This involved a computationally intensive procedure of re-computing betas every month by excluding the data for that one month from the time-series factor-model regressions. When it became clear that the CSR results were greatly affected by this modification, we looked for an explanation. We found that a "one-month bias" can be induced with all data included if the return disturbances are heteroskedastic conditional on the factors. This analysis has given rise to an additional bias correction that we employ in conjunction with a heteroskedastic version of the EIV correction.[4]

We conduct our tests for a comprehensive sample of NYSE, AMEX and NASDAQ stocks over the sample period September 1946 through December 2011. The independent variables in our CSRs consist of loadings as well as firm characteristics. The asset pricing model betas examined in the paper are those of the CAPM, the Fama and French (1993) three-factor model, and a four-factor model that also includes a momentum factor, as in Carhart (1997) and Fama and French (2011). While the CAPM is firmly grounded in theory, the multifactor models are more empirically driven, but have proven useful in many contexts. The firm characteristics that we examine are firm size, book-to-market ratio, and past six-month returns, the latter motivated by the work of Jegadeesh and Titman (1993) on momentum.

The rest of the paper is organized as follows. The next section presents the methodology. Section II provides simulation evidence on the finite-sample behavior of the bias corrections that we employ. Section III presents the data and Section IV discusses the results. Section V explores the impact of time-varying premia. Section VI concludes.

[4] Independent research by Gagliardinia, Ossola, and Scaillet (2011) addresses many of the issues considered here. They conclude, however, that the premium for market beta is significant (as do Ang, Liu, and Schwartz (2011)), in contrast to our bias-corrected results below.

I. Methodology

We run CSRs of individual stock returns on their factor loadings and characteristics, correcting for the various biases discussed above.

I.A. Underlying model

Time-series regression

Let F_t be a $k \times 1$ vector of factors. The factors may be traded portfolio return spreads, but we do not impose the restriction that their price of risk is equal to the factor mean. Incorporating this restriction makes sense when testing the null hypothesis that an asset pricing model provides an exact description of expected returns. Here, however, we take it as well established in past studies that these models can indeed be rejected. Our focus, instead, is on the competition between factor loadings and characteristics in accounting for empirically observed variation in expected returns with unconstrained cross-sectional coefficients.

Traditionally, factor loadings/betas are estimated through time-series regressions of excess stock returns on the factors:

$$R_{it} = B_{0i} + B_i F_t + \varepsilon_{it} . \tag{1}$$

This regression can be estimated using the entire sample (Black, Jensen, and Scholes (1972)) or rolling windows (Fama and MacBeth (1973)). Rolling betas are intended to capture the time-variation in betas. However, it is unlikely that time-variation in true betas is completely captured by the use of rolling betas; dramatic changes in firm fundamentals will only be reflected in these betas gradually, whereas the impact on size, book-to-market and implied conditional betas will be immediate. Conditioning is done here using macroeconomic variables as well as firm-level attributes. While business-cycle variables have been widely used to capture the current state of the economy,[5] the use of firm-level attributes is motivated by Gomes, Kogan, and Zhang (2003) who develop a general equilibrium model in which firm-level size and book-to-market ratio are correlated with the factor loadings.[6]

At this stage, we keep the notation general and let zts_{it} be a $p \times 1$ vector of firm-specific characteristics (macro variables are accommodated by getting rid of the i subscript). The first

[5] See, for instance, Shanken (1990) or Ferson and Harvey (1991).
[6] See Rosenberg and Guy (1976) for one of the first attempts at using firm characteristics to improve beta forecasts.

element of the zts vectors is a constant, so $p \geq 1$; let $zts_{(p-1)it}$ denote the corresponding $(p-1)\times 1$ subvector that excludes the constant. It is useful to define F_{it}^{*} as:

$$F_{it}^{*} \equiv [zts_{(p-1)it-1}, zts_{i1t-1}F_t', \; \ldots, zts_{ipt-1}F_t']', \tag{2}$$

a $(p-1+kp)\times 1 \equiv k^{*}\times 1$ vector of independent variables. Then our time-series model for excess stock returns R_{it} can be compactly represented as:

$$R_{it} = B_{0i} + B_i^{*}F_{it}^{*} + \varepsilon_{it} \,, \tag{3}$$

where B_i^{*} is a $1\times k^{*}$ vector of slope coefficients on the scaled intercept (excluding the constant) and the scaled factors (we sometimes refer to these together as the "expanded factors"). In effect, we allow for the possibility that the intercept, as well as the betas on each of the factors, vary with (lagged) firm characteristics. We can recover the time-varying betas implied by this model as follows. Define the $k^{*}\times k$ matrix Zts_{it} as:[7]

$$Zts_{it} = \begin{bmatrix} 0_{p-1\times k} \\ I_k \otimes zts_{it} \end{bmatrix}.$$

Then the $1\times k$ vector of implied betas B_{it-1} on the original factors is given as a function of the lagged firm characteristics by:

$$B_{it-1} \equiv B_i^{*}Zts_{it-1} \,. \tag{4}$$

Note that the original time-series model can be rewritten as:

$$R_{it} = (B_{0i} + B_{i1:p-1}^{*}zts_{(p-1)it-1}) + B_{it-1}F_t + \varepsilon_{it} \,, \tag{5}$$

with both the intercept and betas time-varying. Here, $B_{i1:p-1}^{*}$ is the subvector of B_i^{*} consisting of the first $p-1$ components following the constant.

A typical asset-pricing relation would specify the expected excess returns in terms of loadings and factor risk premia. Allowing for the possibility that the zero-beta rate is different from the risk-free rate, the asset pricing restriction using time-varying betas can be written as:

$$E_{t-1}(R_{it}) = \gamma_0 + B_{it-1}\gamma_1 \,, \tag{6}$$

[7] The submatrix of zeroes captures the fact that the scaled intercept coefficients are not needed here. The $\otimes$ reflects the fact that the beta on each original factor is linear in the same conditioning variables.

where γ_0 is the excess zero-beta rate over the risk-free rate, and γ_1 is a $k \times 1$ vector of factor risk premia. As in the more traditional empirical asset pricing literature, we initially consider models with constant cross-sectional coefficients. Later in the paper, we explore the impact of relaxing this assumption and obtain some interesting findings.

The use of firm-level attributes distinguishes our conditional models from those proposed by Shanken (1990), Ferson and Harvey (1999), as well as Lettau and Ludvigson (2001). These studies use macro predetermined or information variables to either scale the factor loadings or the coefficients in the model for the stochastic discount factor. Since our conditional-beta models include firm attributes, the econometrics must allow for the fact that the scaled factors need not be common across the test assets (also see Fama and Fench (1997), Lewellen (1999), and Avramov and Chordia (2006)).[8]

Cross-sectional regression

The factor prices of risk are traditionally estimated using a two-pass procedure. We adapt the Fama and MacBeth (1973) methodology to our setting and utilize the time-varying betas, as well as firm characteristics, in CSRs every month. For each month t, using N_t active stocks, define $\hat{B}_{t-1}$ to be the $N_t \times k$ matrix of estimated conditional betas. In addition, we utilize a $k_2 \times 1$ vector of stock characteristics, zcs_{it-1}. The firm characteristics utilized in the cross-section, zcs, may or may not be the same as those used in the time-series regression, zts. Define Zcs_{t-1} to be the $N_t \times k_2$ matrix of these characteristics and define the matrix of independent variables, $\hat{X}_t$, as:

$$\hat{X}_t \equiv [1_{N_t} : \hat{B}_{t-1} : Zcs_{t-1}]. \tag{7}$$

Each month, estimates of the return premia, γ_1 on factor loadings and γ_2 on characteristics, are calculated by running a CSR of excess stock returns, R_t, on $\hat{X}_t$. Specifically, the cross-sectional coefficients $\hat{\Gamma}_t \equiv \left(\hat{\gamma}_{0t}, \hat{\gamma}_{1t}', \hat{\gamma}_{2t}'\right)'$, are estimated using OLS as:

$$\hat{\Gamma}_t = \hat{A}_t R_t, \text{ where } \hat{A}_t \equiv (\hat{X}_t' \hat{X}_t)^{-1} \hat{X}_t', \tag{8}$$

[8] Fama and French (1997) allow SMB beta to vary with size and HML beta to vary with book-to-market in their analysis of industry betas. Our approach in calculating conditional beta is closer to that of Avramov and Chordia (2006), except that we cross-sectionally demean firm-specific variables (see equation (13)).

a $(1+k+k_2)\times N_t$ matrix. The time-series average of these estimates yields the overall estimate of Γ. The usual asset-pricing null hypothesis of expected return linearity in the loadings implies that the return premium on characteristics, γ_2, is zero. In principle, the average zero-beta rate in excess of the risk-free rate, γ_0, can be different from zero. Employing OLS on individual stocks, rather than a more complicated weighted estimator or portfolio-based approach, is consistent with our aim of evaluating the relative contributions of loadings and characteristics to the expected return for a typical stock.[9]

Note that with betas linearly related to firm size and book-to-market, variables that are also included as cross-sectional characteristics, there is an identification issue. The corresponding risk and characteristic premia would not be separately estimable if the time-series relations were the same for each stock, as this would create perfect multicollinearity in the CSRs. Therefore, identification of γ_1 and γ_2 requires some cross-sectional variation in the relevant elements of the $B_i^* s$, which we estimate individually for each stock.

I.B. Errors-in-variables problem

The literature has largely followed the lead of Black, Jensen, and Scholes (1972) and Fama and MacBeth (1973) in dealing with the EIV problem by using portfolios as test assets for two-pass estimation. As a result, there are relatively few studies using individual stocks in cross-sectional tests. Fama and French (1992) use individual assets but compute factor loadings from test portfolios. This procedure effectively amounts to running CSRs on test portfolios, despite using individual stocks in the second-stage regressions (see Ang, Liu, and Schwartz (2010)).

<u>Standard error calculation</u>

A measure of precision for the risk premia can be obtained by simply calculating the standard error from the time-series of monthly estimates. This is the traditional Fama and MacBeth (1973) approach. However, as demonstrated in Shanken (1992), this ignores the EIV problem that is introduced by the fact that the betas in the second-stage regressions are estimated variables.

Analytical solutions for correcting the asymptotic standard errors to accommodate the EIV problem exist for balanced panels. Shanken provides a correction for the case of constant

[9] We will explore the possible benefits of weighted-least squares estimators in future research.

betas. Jagannathan and Wang (1998) provide extensions to deal with non-iid errors. We report standard errors based on the Shanken correction. Prelminary exploration of modifications to this procedure that exploit the unbalanced panel error structure and estimation of conditional betas suggests that these changes make little difference. In fact, the various standard errors are close to those of Fama-MacBeth, a typical finding in the literature when *traded* factors are employed. More work needs to be done on this issue, however.[10]

Bias-corrected coefficients

EIV not only causes the standard errors to be biased, but also leads to a bias in the estimated coefficients – toward zero when the factors are orthogonal. In our empirical work, we find that the corrections for this bias are sometimes substantial, even though the EIV standard error correction is quite small. Our approach builds on Theorem 5 in Shanken (1992), now allowing for estimation of conditional betas and for heteroskedasticity of ε_{it} conditional on F_t. Relegating the details to Appendix B, the EIV-corrected OLS coefficients are given by:

$$\hat{\Gamma}_t^{\text{EIV}} = \left(\hat{X}_t'\hat{X}_t - \sum_{i=1}^{N_t} M'\hat{\Sigma}_{\hat{B}_{it-1}} M \right)^{-1} \hat{X}_t'R_t \,, \tag{9}$$

where M is a $k \times (1 + k + k_2)$ matrix defined as:

$$M = \begin{bmatrix} 0_{k\times 1} & I_{k\times k} & 0_{k\times k_2} \end{bmatrix},$$

and $\hat{\Sigma}_{\hat{B}_{it-1}}$ is the $k \times k$ covariance matrix for $\hat{B}_{it-1}$:

$$\hat{\Sigma}_{\hat{B}_{it-1}} = Zts_{it-1}'\hat{\Sigma}_{\hat{B}_i^*}^{\text{White}} Zts_{it-1},$$

where $\hat{\Sigma}_{\hat{B}_i^*}^{\text{White}}$ is the $k^* \times k^*$ White (1980) heteroskedasticity-consistent covariance matrix for the OLS time-series estimate of B_i^* in equation (5). M serves to insert zeros where needed, as the EIV correction only affects the $k \times k$ term, $\hat{B}_{t-1}'\hat{B}_{t-1}$.

We mentioned earlier, that when the factor-model disturbances are conditionally heteroskedastic, an additional bias can be induced due to correlation between the disturbances in a given cross-section of returns and the estimates of beta that serve as the explanatory variables in that CSR. The basic idea in the case of a one-factor market model is as follows. As with any regression, the slope estimate will be greater (less) than a stock's true beta if market returns, R_{md}, measured as deviations from the mean, happen to be

[10] Substantial standard error adjustments can be obtained with non-traded factors. See, for example Kan, Robotti, and Shanken (2010).

positively (negatively) related to the return disturbances, $\varepsilon_{i,}$ in the given sample. Now, a positive link between beta estimates and the level of returns will be generated if, in addition, this covariability between market deviations and non-market returns tends to be higher when the non-market return is itself higher, i.e., $E[(R_{md}\varepsilon_i)\varepsilon_i] > 0$. But this condition amounts to saying that the squared disturbances increase with market return deviations. This is precisely the form of conditional heteroskedasticity that we observe empirically for the majority of stocks, imparting an upward bias to the estimated market premium.

Whereas the usual EIV problem relates to the "denominator" of the CSR estimator, this one-month bias involves the "numerator." The correction developed in Appendix C subtracts the following term from $\hat{X}_t' R_t$ in equation (9):

$$bias_t = \begin{pmatrix} 0 \\ \sum_{i=1}^{N_t} Zts_{it-1}' (F_{di}^{*\prime} F_{di}^*)^{-1} F_{dit}^{*\prime} e_{it}^2 \\ 0_{k_2 \times 1} \end{pmatrix}, \tag{10}$$

where F_{di}^* is the $T_i \times k^*$ matrix of the time series of expanded factors (measured as deviations from the sample means) for stock i, F_{dit}^* is row t of this matrix, and e_{it} is the OLS factor-model residual for stock i at time t. Any systematic relation between the factors and the residual variance will be reflected in the product term, $F_{dit}^{*\prime} e_{it}^2$. With conditionally homoskedastic errors and a balanced panel, however, we show that the corresponding terms must average to zero in the overall CSR estimator. This is consistent with the classic scenario analyzed in Shanken (1992).

In Section II, we present evidence from simulations indicating that the proposed corrections substantially reduce the bias and mean-squared error of the CSR estimator.

I.C. Relative contribution of betas and characteristics

Our main goal is to calculate measures of the relative contribution that loadings or characteristics make toward a combined model's ability to explain cross-sectional expected return variation. We approach this problem in the following way.

We first compute time-series averages of the premia, $\hat{\gamma}$, for the factor loadings as well as the characteristics. The motivation is that we are interested in the explanatory power of the model based on the true return premia and the average estimates will better approximate that ideal than the individual monthly estimates. Using these average return premia, we calculate the expected return each month as:

$$E_{t-1}\left[R_t\right] = \hat{\gamma}_0 + E_{t-1}^{\text{beta}}\left[R_t\right] + E_{t-1}^{\text{char}}\left[R_t\right],$$

where (11)

$$E_{t-1}^{\text{beta}}\left[R_t\right] = \hat{B}_{t-1}\hat{\gamma}_1\,, \text{ and } E_{t-1}^{\text{char}}\left[R_t\right] = Zcsr_{t-1}\hat{\gamma}_2\,.$$

We then calculate the cross-sectional variance of expected return $E_{t-1}\left[R_t\right]$ using the fitted values in (11). Likewise, we compute variances for each component of measured expected return.

A complication arises, however. To see this, note that the cross-sectional variance of the beta-based component of expected returns can be written as $\hat{\gamma}_1'\hat{B}_{t-1}'\hat{B}_{t-1}\hat{\gamma}_1 / N_t - (1'\hat{B}_{t-1}\hat{\gamma}_1 / N_t)^2$. As in the CSR context, estimation error in the $k \times k$ term $\hat{B}_{t-1}'\hat{B}_{t-1}$ gives rise to a systematic bias. Here, it causes cross-sectional variation in the true loadings to be overstated. Fortunately, however, a correction to the variance estimator can be obtained using the same "trick" employed in equation (9).

The ratio of the variance of expected returns computed using the beta component, $E_{t-1}^{\text{beta}}\left[R_t\right]$, to the variance of expected returns $E_{t-1}\left[R_t\right]$ based on the full model, gives the contribution that factor loadings make to the explanatory power of the full model in month *t*. Similarly, the ratio of the variance of expected returns computed using the characteristics component, $E_{t-1}^{\text{char}}\left[R_t\right]$, to the variance of expected returns, $E_{t-1}\left[R_t\right]$, gives the contribution of characteristics to the explanatory power of the model. These ratios are averaged over all months to obtain a more precise aggregate measure. Note that, without the EIV correction discussed above, the role of loadings in the model relative to that of characteristics would be exaggerated. Also, keep in mind that the ratios need not add up to one because of covariation between the two components of expected return.[11]

It is important to note that sampling error in our estimates of the relative contributions of betas and characteristics is induced by the fact that we use estimates of the premia.[12] Deriving analytical formulas for the standard errors of the relative contributions appears to be infeasible,

[11] A similar issue arises when decomposing returns into cash flow news and expected return news, as in Campbell (1991).

[12] Although estimation error in $\hat{\gamma}$ should be the primary source of sampling variability, there is also some variation due to the fact that betas are estimated with error. However, we ignore this error in our computations.

as these ratios are highly non-linear and time-dependent functions of $\hat{\gamma}$. However, we can use our knowledge of the (approximate) distribution of $\hat{\gamma}$ to develop an approximate numerical solution. The procedure is as follows. We draw 1,000 normally distributed risk premia with moments matched to the average $\hat{\gamma}$ s and their standard errors. We then repeat the calculations in equation (11) for these risk premia and obtain empirical distributions for the corresponding relative contributions, as well as their differences. The standard deviations of these empirical distributions then serve as our rough standard errors.

II. Simulation Evidence

In order to gauge the statistical properties of our bias-corrected estimator of Γ for the sample sizes employed in empirical work, we resort to simulations. A simple data generating process is posited, in which returns are governed by factor models with constant betas:

$$R_{it} = B_i F_t + \varepsilon_{it}. \tag{12}$$

We consider a one-factor CAPM model and the three-factor Fama and French (1993) model. At the beginning of the simulation, for each stock, market betas are drawn from a *N*(1.1, 0.5) distribution, and the three-factor betas are drawn from *N*(1.1, 0.4), *N*(0.9, 0.7), and *N*(0.2, 0.7) distributions, respectively. These parameters are based on the distribution of betas estimated with actual data.

Although we typically focus on *ex-ante* expected return models like (6) in asset pricing analysis, it can be informative to consider expected returns conditional on the factor realizations. In this context, the ex-post price of risk, $\gamma_{1t} = \gamma_1 + (F_t - E(F))$, replaces the usual risk premium vector, differing only by the unexpected factor component. If the betas were known, there would be no bias and the expected value of the CSR estimator for month *t*, conditional on F_t, would simply be γ_{1t}. Increasing the number of stocks in a CSR can increase the precision of the estimator, but it does not provide any information about that month's factor surprise. Therefore, in comparing various estimators, it makes sense to focus on estimation conditional on the factors. Accordingly, we use the actual factor realizations from 1946 to 2011 (792 months) in equation (11).

To incorporate conditional heteroskedasticity, for each stock we need a function that will map the realized factors for a given month into a corresponding residual variance. This is implemented as follows. In the actual data, for every stock we run a time-series regression of the squared one or three-factor model residuals on the market return and the squared market return. This generates a cross-sectional distribution of coefficient vectors and random draws from this distribution define the conditional variance function for each simulated stock. The simulation then proceeds with the following steps.

First, for each stock, we randomly select a subset of 144 months from the 792 month sample to reflect the actual estimation period for the median stock. Since returns are assumed iid over time, the months need not be consecutive. For each simulated stock and each month, we calculate a conditional residual variance based on the factors for that month and then randomly draw a residual return from a normal distribution with mean zero and the given variance. The actual return for the month is computed, as in equation (12), from the stock's beta(s), the realized factor(s), and this residual return. Given the resulting time series of simulated returns, beta(s) can then be estimated.

In this way, beta estimates are generated for all stocks and CSRs are then run, both with and without correction for biases, as described in Section I.B. Note that since the number of stocks present in any given month is random, the simulation reflects the empirical reality of an unbalanced panel of data. Table 1 reports the mean bias (estimate – true value) and root mean squared error (RMSE) of the estimated risk premia (across 1,000 simulations) in percent per month. We repeat the exercise for different numbers of stocks ranging from 500 to 10,000. Since every stock has only 144 out of 792 months of valid data, the average number of stocks in the cross-sectional regressions is a bit less than 20% of the total number of stocks. For reference, the (ex-post) risk premia for the three factors Mkt, SMB, and HML equal 0.57%, 0.15%, and 0.36% per month, the respective factor means over the original sample.

Panel A of Table 1 shows the results for the one-factor model. Consistent with the EIV perspective, the estimated risk premium without bias correction is consistently lower than its true value, by roughly 0.10. Also, this attenuation bias is not eliminated or even reduced as the number of stocks increases. Though not shown, there is a persistent upward bias if we only use the EIV correction. In contrast, using the one-month correction as well, the bias in the corrected risk-premium estimator is much closer to zero (always less than 0.02 in magnitude), though surprisingly it increases somewhat with the number of stocks. Bias correction has little effect on RMSE with 500 stocks. As the number of stocks increases, however, RMSE declines substantially (from 0.14 to 0.03) for the corrected risk premium, while the uncorrected RMSE, which is dominated by the huge EIV bias, barely declines beyond 1,000 stocks. These observations are consistent with the discussion in Section I.B.

Results for the three-factor model are reported in Panel B of Table 1. The bias in the uncorrected risk premia is negative for all three factors. For the market factor, it is substantially larger than in Panel A (around −0.17) and fairly large for HML as well (around −0.13). With bias correction, it is negative as well, apart from one 500-stock scenario, but greatly reduced for all three factors. For example, the bias for HML is around −0.01. With bias correction, RMSE again declines sharply as the number of stocks increases, and it is always lower (often much lower) than the uncorrected RMSE for the Mkt and HML factors. Improvement for SMB is more modest and does not kick in until the number of stocks exceeds 2,000.[13]

To summarize, the desirability of employing bias correction when estimating risk premia with even a moderately high number of stocks is strongly supported by our simulation experiments.

III. Data

The data consist of monthly returns, size, book-to-market ratio, and lagged six-month returns for a sample of common stocks of NYSE, AMEX, and NASDAQ-listed companies. Book values are from Compustat and are calculated following the procedure described in Fama and French (1992).[14] The rest of the stock data come from CRSP. Factors are downloaded from Ken French's website.

The book-to-market ratio is calculated as the ratio of the most recently available (assumed to be available six months after the fiscal year-end) book value of equity divided by the current market capitalization. Book-to-market ratios greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and the 0.005 fractile values, respectively. We take natural logs of size and book-to-market before using them in time-series or CSRs. The sample spans the period July 1946 through December 2011. The start date reflects the fact that there are very few companies with valid book-to-market ratios before 1946 (and our simulation evidence in Section II suggests large biases and RMSE for CSRs involving only few hundred stocks).

[13] Use of the homoskedastic version of the EIV correction usually gives slightly higher RMSEs.

[14] Book values from Compustat are supplemented with hand-collected values from Moody's, whenever available (see Davis, Fama, and French (2000) for the exact description of these data). These are available on Kenneth French's website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

We include only common stocks with share codes 10 or 11 on CRSP. This criterion filters out ADRs, units, Americus Trust components, closed-end funds, preferred stocks and REITs. To be included in the sample, a stock must also have sufficient data to calculate market capitalization and book-to-market ratio for at least 5 years (the observations do not have to be continuous). Stocks with prices less than one dollar in a month are not included in the CSR for that month (they are included in other months when their prices exceed the one dollar limit). This screening process yields an average of 2,715 stocks (1,527 for the sample of NYSE/AMEX stocks) per month. The total number of different stocks in the 792-month sample period is 11,602 (5,644 for the sample of NYSE/AMEX stocks).

The macroeconomic variables include term spread (Term) which is the difference in yields of 10-year T-notes and three month T-bill, and default spread (Def) which is the difference in yields of BBB-rated and AAA-rated corporate bonds. The data for Term and Def are obtained from FRED. Fama and French (1989) argue that Def track similar variation in long-term business conditions, while Term is related to shorter-term business cycles.

We use three versions of factor loadings in our regressions. The first is the unconditional beta, a natural starting point. This beta is calculated using the entire sample available for each stock ($zts_{it} = 1 \forall i, t$). The other approaches to estimating loadings condition on ex-ante information. Many conditioning variables could be considered in this context, opening the door to over fitting, as the estimation approach discussed below involves a large number of interaction terms in the time-series regressions. We were also concerned that the EIV correction might be less reliable with too many coefficients to estimate in the expanded factor model. Therefore, we limited ourselves to the two sets of variables for which there is some clear economic motivation. One method conditions on the firm characteristics, size and book-to-market. We standardize these characteristics each month before using them in the time-series regression. That is, $zts_{it} = [1, Sz^*_{it}, B/M^*_{it}]'$, where *Sz* is ln(market capitalization) and *B/M* is ln(book-to-market), and a star superscript refers to cross-sectional standardization as follows:

$$Sz^*_{it} = \frac{Sz_{it} - m_t}{s_t}, \tag{13}$$

where m_t (s_t) is the cross-sectional mean (standard deviation) of *Sz* in month *t*, computed using only NYSE stocks, and B/M^* is defined analogously. The other approach conditions on macroeconomic variables, as well as firm characteristics, in the time-series regressions. Here, $zts_{it} = [1, Sz^*_{it}, B/M^*_{it}, Def_t, Term_t]' \; \forall i$.

Our CSRs also use two different versions of *zcs* variables. The first set of regressions does not utilize *zcs* at all and the CSRs are run using only factor loadings as independent variables. The second set of regressions uses size, book-to-market, and six-month return *Ret6* as firm characteristics ($zcsr_{it} = [Sz_{it}, B/M_{it}, Ret6_{it}]'$), and consistent with most of the literature, the firm-characteristics are not cross-sectionally standardized.

Table 2 presents summary statistics for all stocks in Panel A and for NYSE/AMEX stocks in Panel B. The reported numbers are the time-series means of the monthly cross-sectional statistics except for the factor loadings. The loadings are computed for each stock over its entire time series and then the summary statistics are computed over the cross-section. The mean excess return is 1.25% per month for all stocks and 1.24% for NYSE/AMEX stocks; the median excess return for NYSE/AMEX stocks is 0.53% and it is 0.32% for all stocks. Note that the median excess returns are far smaller than the means, suggesting that there are some stocks with very large monthly returns over the sample period. NYSE/AMEX stocks are larger, with average market capitalization of $1.86 billion as compared to $0.98 billion for all stocks. The mean (median) book-to-market ratio for all stocks is 1.00 (0.76). Not surprisingly, the mean and the median values of the unconditional market betas are approximately one for all stocks, as well as for NYSE/AMEX stocks.

IV. Cross-sectional Results

We present results for the one-factor CAPM beta, the Fama and French (1993) three-factor betas, and the four-factor model betas. Separate analysis of these factor models helps in analyzing the additional importance of the size, book-to-market and momentum factors using conditional betas. We present the standard Fama and MacBeth (1973) coefficients as well as bias-corrected coefficients side by side in all our results. This facilitates an evaluation of the importance of bias correction to estimated premia. Finally, we report *t*-statistics based on the methodology in Shanken (1992). As mentioned earlier, other standard errors that we considered are all close to those reported.

Although we show findings with constant betas, along with the conditional beta results, the constant beta assumption is almost surely misspecified, which may lead to spurious relations.

Therefore, while we include these results for completeness, we give them little weight in our conclusions.

IV.A. CAPM

Table 3 reports results for the one-factor market model. Estimation error in the betas should bias the estimated market risk premium downwards. Indeed, correcting for this bias substantially increases the risk premium estimates, sometimes by as much as 100% (results not shown). There is a second source of bias, however. Conditional residual heteroskedasticity, together with the fact that time-series estimation of the betas includes the month of each CSR, imparts an upward bias. We find that correcting for both of these offsetting biases (the "bias-corrected" results shown in the table) yields weakened results for the market premium.

Consider first the results in Panel A for all stocks. The average number of stocks in the cross-section is more than 2,700. The results without bias correction suggest that the market beta is priced, with two of the three estimates close to 0.4% per month and *t*-statistics over two. Upon correcting for the two sources of bias, we find that the estimated risk premia are smaller and statistically insignificant. Using firm-level conditional betas, the bias-corrected risk premium is 0.23% and it is just 0.04% per month conditioning on both firm-level and macro variables. Henceforth, for brevity, we refer to the latter scenario as firm/macro conditioning on betas.

The sample size is an average of 1,527 stocks per month when using NYSE/AMEX stocks as test assets (Panel B of Table 3). The estimates of the risk premium are lower in this case and, again, are statistically insignificant.[15] Thus, our conclusions about market beta are consistent with the results of Fama and French (1992), who use individual stocks, but assign each stock a portfolio-based beta estimate as a way to deal with the EIV problem.

Note that, due apparently to the impact of heteroskedasticity, bias correction always decreases the risk premium and increases the zero-beta rate in Table 3. The intercepts in second-pass regressions are around 6% to 11% per year, with *t*-statistics of 5 or more. Such large differences between the zero-beta rate and the risk-free rate, common in the literature going back

[15] As in most of the literature, our *t*-statistics do not take into account the possibility of deviations from the expected return relation. As shown in Kan, Robotti, and Shanken (2011), the impact is likely to be small in applications with traded factors that can be closely mimicked by the test assets (also see Shanken and Zhou (2007)). More work is needed, however, to derive the implications for our conditional specifications.

to Black, Jensen and Scholes (1972) and Fama and MacBeth (1973), are hard to fully reconcile with more general versions of the CAPM that incorporate restrictions on borrowing.[16]

IV.A.1. CAPM with additional controls

In Table 4, we add firm characteristics along with the market beta as explanatory variables in the monthly CSRs. Panel A of Table 4 shows that bias-corrected estimates of the market risk premium remain statistically insignificant in the case of the conditional models. Bias correction again has a significant impact on coefficient estimates. Conditioning on the firm-level attributes or firm/macro variables yields a market risk premium of 0.23% (0.04%) per month compared to the sample average return of 0.57%. The premia on firm characteristics are also noteworthy—as usual, large firms earn lower returns, value firms earn higher returns, and firms with higher past returns continue to earn higher returns and the estimates are highly statistically significant. In economic terms, a one standard deviation increase in firm size decreases monthly returns by 34 basis points, a one standard deviation increase in the book-to-market ratio leads to an increase in returns of 17 basis points per month, and a standard deviation increase in the past six month returns raises returns by 32 basis points per month.

The results for the firm characteristics are similar to those in Brennan, Chordia, and Subrahmanyam (1998) and imply rejection of the simple CAPM relation. These authors relate *beta-adjusted* returns to characteristics, with risk premia restricted to equal the factor means and the zero-beta rate equal to the riskless rate. In contrast, we let the loadings and characteristics compete without constraints on the risk premia or the zero-beta rate. What we learn from the new results is that the premia on firm characteristics (specifically size and book-to-market) remain significant even when betas are conditioned on the same firm-specific attributes. In other words, the explanatory power of firm-specific characteristics documented in the prior literature is not only due to an indirect effect on betas, but also manifests itself directly. Next, we will evaluate the relative contributions of loadings and characteristics toward explaining cross-sectional differences in expected returns.

The average cross-sectional adj-R^2 values (not reported) for Table 4 are higher than those for Table 3. This might seem to provide prima-facie evidence about the additional explanatory power of characteristics (beyond market beta) in the cross-section of returns. However, one cannot draw conclusions about the relative explanatory power of characteristics and betas by

[16] See also Frazzini and Pedersen (2011), who show that high zero-beta rates are obtained for most countries.

comparing these adj-R^2s. To see this, consider a scenario in which the ex-post coefficient on an explanatory variable is positive (+x, for instance) and significant in half the sample and negative (-x, for instance) and significant in the other half. The computed average of the cross-sectional adj-R^2s could be high even though the coefficient is zero on average and carries no *ex-ante* premium.

To address these problems with adj-R^2s, it is common in the literature to report the adj-R^2 from a single regression of *average* returns on unconditional betas for a set of test asset portfolios (see Kan, Robotti, and Shanken (2012)). This is problematic in our context, however, as we have time-varying betas and characteristics, and these are for individual stocks. One approach would be to report the adj-R^2 for a regression of average returns on average betas and average characteristics. However, a momentum characteristic averaged over time would display minimal cross-sectional variation and, therefore, its highly significant explanatory power would essentially be neglected by such an adj-R^2 measure. For these reasons, we do not report adj-R^2 for our regressions. Instead, we report measures of the relative contributions of loadings or characteristics, as discussed in Section I.C.

The last six rows of Table 4 present the contributions that the factor loadings and characteristics make toward explaining the variation in expected returns, as well as the contribution differences. Numbers in parenthesis below the contributions/differences are rough standard errors computed following the procedure in Section I.C. Focusing on bias-corrected coefficients with firm/macro conditioning variables, we find that the conditional market beta explains only 0.3% (standard error = 3.93%) and the characteristics explain 99.8% (standard error = 3.34%) of the variation. With conditioning on firm characteristics only, betas explain a bit more, but the 4.4% estimate is still less than one standard error from zero. Clearly, the characteristics explain an overwhelming majority of the variation in expected returns. The results for NYSE/AMEX stocks in Panel B are similar.

IV.B. Fama-French three-factor model

Next, we turn our attention to analysis of the Fama and French (1993) three-factor model. Table 5 shows the second-stage CSR risk premia estimates for the three factors. Panel A gives the results for all stocks. The market risk premium for this (multiple regression) beta is statistically significant with constant betas. It is no longer statistically or economically significant with bias correction and conditional betas, however, which we find more credible.

The risk premium on SMB is large when estimated with conditional betas. For example, the bias-corrected estimate of the monthly risk premium on SMB is 0.40% with a *t*-statistic of 3.64 (0.33% with a *t*-statistic of 3.15) when conditioning is done with firm attributes (firm/macro). The sample average of the SMB returns is 0.15%, considerably lower than the risk premium estimates.

A surprising feature of Table 5 is that the estimates of the risk premium on HML are reliably negative using unconditional betas, whereas the average HML return over our sample period is 0.36% per month. A positive premium for HML is obtained when conditioning on firm-level variables, but the estimate is not reliably different from zero. Conditioning on firm/macro variables produces a small positive premium of 0.15% per month with a *t*-statistic of 1.5. Keep in mind, however, that the SMB and HML cross-sectional risk premia need not equal the factor means unless the three-factor expected return model holds exactly, a restriction that is rejected below.

The bias-corrected market risk premium for the conditional models with NYSE/AMEX stocks in Panel B of Table 5 is once again indistinguishable from zero. The bias-corrected SMB risk premium is 0.31% with a *t*-statistic of 2.84 (0.25% with a *t*-statistic of 2.36) when estimated from betas conditioned on firm-level attributes (firm/macro). When betas are conditioned on firm/macro variables the HML premium is 0.26% per month with a *t*-statistic of 2.49.

IV.B.1. Fama-French model with additional controls

Next, we include firm characteristics along with the three-factor loadings in our CSRs. Panel A of Table 6 presents the results for all stocks. Skipping over the rather odd unconditional results, we find that the market risk premium is neither statistically nor economically significant for the conditional models. The risk premium for SMB is a statistically significant 0.23% per year whether conditioning on firm attributes or on firm/macro variables. The risk premium for HML is insignificant for the conditional models. Keep in mind, however, that this coefficient captures the *partial* effect of HML beta, controlling for the book-to-market variable. As earlier, the premia on firm characteristics are all statistically and economically significant. A comparison of Tables 4 and 6 reveals that these premia are, surprising, not very sensitive to which factor model is employed. The premia on firm characteristics are also not much affected by bias correction of the coefficients with conditional betas.

There is a controversy in the literature about the interpretation of the size- and value-effects. Fama and French (1993) and Davis, Fama, and French (2000) argue that these empirical phenomena point to the existence of other risk factors, proxied for by SMB and HML. In other words, these studies claim that factor loadings explain cross-sectional variation in expected returns. Daniel and Titman (1997), on the other hand, show that portfolios of firms with similar characteristics but different loadings on the Fama and French factors have similar average returns. They conclude from this finding that it is characteristics that drive cross-sectional variation in expected returns. None of the studies, however, runs a direct horse race between these two competing hypothesis. Our approach using individual stocks is designed so as to directly address this controversy. Not only do we allow both factor loadings and characteristics to jointly explain the cross-section of returns, but we also permit characteristics to impact stock returns indirectly through their effect on conditional betas.

The economic magnitudes and statistical significance reported thus far suggest that both factor loadings and characteristics matter. But how much? Again, we utilize the methodology explained in Section I.C to calculate the relative contributions of factor loadings and characteristics in explaining the variation in expected returns.[17] Betas conditioned on firm-level attributes (firm/macro) explain 15% (20%) and characteristics explain 71% (64%) of the model's cross-sectional variation in expected returns. Thus, even after allowing the SMB and HML loadings to vary with the associated firm characteristics, characteristics are still dominant, with the differences in contributions more than two standard errors above zero.[18]

Compared to the CAPM results (Table 4), the fraction of expected return variation explained by three-factor betas is larger, even though the risk premium on HML is not robust. Overall, our results suggest that it is the characteristics that are most useful for explaining expected returns. Moreover, these results highlight the importance of using a methodology that includes bias correction and conditioning of betas on firm attributes.

Panels B of Table 6 presents the results for NYSE/AMEX stocks. The market risk premium estimates continue to be insignificant for the conditional models. The SMB and HML risk premium estimates are positive in the case of the conditional models, and the premium on the HML beta is now more than two standard errors above zero with firm/macro betas. Premia

[17] A comparison between our results and those in Daniel and Titman (1997) is complicated by the fact that we use additional characteristics (six-month return and turnover) in our cross-sectional regressions.
[18] It is conceivable that incorporating the estimation error in betas would render the differences statistically insignificant in close calls.

on firm characteristics continue to be significant, with the same signs as earlier. The dominance of characteristics over betas in explaining expected returns is reduced somewhat compared to the all-stock findings, and the contribution differences are now less than two standard errors above zero. This is partly a reflection of the higher factor risk premium estimates for the HML beta, especially when the betas are conditioned on firm/macro variables.

Thus, while characteristics are the clear winner when all stocks are included in the analysis, there is some statistical uncertainty for the NYSE/AMEX universe.

IV.C. The four-factor model

Our focus thus far has been on the popular CAPM and Fama and French (1993) three-factor model betas. In this section, we report results for tests conducted on a four factor model that includes the Fama-French factors as well as a momentum factor, MOM (downloaded from Ken French's website). For brevity, we report results only for the entire sample of stocks with additional controls in the CSR. Results without cross-sectional controls and/or those using only NYSE/AMEX stocks are available upon request.

We make one additional modification for tests of this model. We allow betas on the momentum factor in the time-series regression to vary with past six-month returns as well as the earlier variables. The motivation in this case is based solely on a mechanical argument, rather than an economic one – loadings on MOM must be higher overall for winners as compared to losers.[19] The results are reported in Panel A of Table 7.

Using bias-corrected coefficients, the MOM risk premium (0.29%) is significant at the 10% level with firm/macro betas. Although it is still much lower than the MOM sample mean (0.76%), the overall contribution of betas rises to 31%, while characteristics explain about 53% of the variation in expected returns (20% vs. 64%, earlier for the three-factor model). Interestingly, even after inclusion of the momentum factor, six-month return remains highly significant as a characteristic in explaining the cross-section of returns. Nonetheless, the additional explanatory power for betas is enough to render the contribution difference statistically insignificant.

[19] Reasoning as in footnote 2, the difference between the winner and loser portfolio loadings on MOM must equal one. Therefore, knowing a stock's past six-month return, and hence whether it is a winner or loser, provides some (albeit imperfect) information about the magnitude of its loading on MOM.

IV.D. Additional robustness checks

In this subsection, we first take up the task of looking at the importance of the manner in which we estimate betas. For brevity, we only report the salient results in the text rather than in a tabular format.

Another common way of estimating (potentially) time-varying betas is through rolling betas. However, as has been noted before, rolling betas reflect new conditioning information with a substantial lag. We re-estimate our CSRs with rolling betas calculated using the previous five years of monthly data (minimum two years of data). Employing all stocks to estimate a one-factor model, with firm-specific characteristics as controls in the CSRs, we find that the market risk premium is 0.08% per month with a *t*-statistic of 0.82. The risk premium estimates of the three-factor model using all stocks are also economically small and statistically insignificant (Mkt=0.11%, SMB=−0.01%, and HML=0.05% per month).

In addition, we tried using one year of daily data in estimating rolling betas. Our estimate of the market risk premium in this case is only 0.06% per month (*t*-statistic = 0.57). Cosemans, Frehen, Schotman, and Bauer (2009) suggest a modification to this basic approach by using a MIDAS weighting scheme (where more weight is placed on more recent observations). We follow a similar approach in estimating market betas but again find a market risk premium of only 0.04% per year (*t*-statistic = 0.39). To summarize, rolling betas using monthly or daily data do not produce economically meaningful risk premium estimates.

Two final issues concern inclusion in the CSRs. First, relaxing the constraint that only stocks with price greater than $1 are included does not have a material impact on our results. Second, recall from Section III that, with estimation of conditional betas in mind, a stock is required to have 5 years of data to be in our sample. Once this data threshold is achieved, stocks enter the CSRs from the beginning of their return history. This could induce a survivor bias in the level of returns although, empirically, the difference in average returns between stocks with less than 5 years and stocks that already have 5 years of data, averaged over all months, is just 0.05% with *t*-statistic 0.68. That there would be a measureable impact on the betas, return premia and, most importantly, the relative contributions of loadings and characteristics, is less clear a priori. To explore this issue, we compare three-factor CSR results from 1951-2011, with and without the 5-year requirement for inclusion in CSRs imposed. We find a lower contribution difference between characteristics and betas with the restriction, paralleling the findings in Table

6 for NYSE/AMEX versus all stocks, Whether this simply reflects the fact that anomalies are often stronger in certain subsets of stocks cannot easily be determined, however.

V. Allowing for time-varying premia

In this section, we consider the possibility that the expected return premia for loadings or cross-sectional characteristics are time varying and we examine the impact that this has on our measures of the relative contributions to cross-sectional expected return variation. Following Ferson and Harvey (1991), we estimate changing premia via time-series regressions of the monthly CSR estimates on a set of predictive variables. The idea is that the premium estimate for a given month is equal to the true conditional premium plus noise. Therefore, regressing that series on relevant variables known at the beginning of each month identifies the expected component.

As predictive variables (x), we use the dividend-price ratio (D/P), term spread (Term), default spread (Def). These variables have frequently been used in predictive regressions for aggregate stock and bond returns, e.g., Fama and French (1989). Thus, the time-series regression of the γ coefficients is:

$$\hat{\gamma}_t = c_0 + c_1' x_{t-1} + v_t. \tag{14}$$

Using this time-series regression, each month we calculate the fitted values of the prices of risk and characteristics as $\hat{\gamma}_{t-1}^{fit} = \hat{c}_0 + \hat{c}_1' x_{t-1}$. We then recalculate the relative contributions as detailed in Section I.C using these fitted values $\hat{\gamma}_{t-1}^{fit}$ rather than average values $\hat{\gamma}$ as the expected premia:

$$\begin{gathered} E_{t-1}\left[R_t\right] = \hat{\gamma}_0 + E_{t-1}^{\text{beta}}\left[R_t\right] + E_{t-1}^{\text{char}}\left[R_t\right], \text{where} \\ E_{t-1}^{\text{beta}}\left[R_t\right] = \hat{B}_{t-1}\hat{\gamma}_{1t-1}^{fit}, \text{and } E_{t-1}^{\text{char}}\left[R_t\right] = Zcs_{t-1}\hat{\gamma}_{2t-1}^{fit}. \end{gathered} \tag{15}$$

To conserve space, we present results only for the bias-corrected coefficients and for the sample of all stocks. The t-statistics in parentheses below the coefficients are corrected for possible heteroskedasticity. Results for the one-factor model are given in Panel A of Table 7. With firm-attribute conditional betas, there is only a hint of predictability in the market premium related to Def, but more reliable evidence that the size and momentum premia vary negatively over time with Def. There is also some evidence that the momentum premium is related to D/P, and that the size and value premia are related to Term. Conditioning betas on firm/macro variables yields fairly similar evidence except that the momentum coefficient on Def is no longer reliably different from zero. As the three predictive variables are positively correlated, it is difficult to develop intuition about their partial effects. Of greater interest is the net impact on our relative contribution measures.

As in Table 4, the contribution of characteristics is over 90% with conditional betas and even higher with unconditional betas. For example, the contributions are 94% characteristics and 11% betas when conditioning betas on Sz and B/M, whereas it was 96%/4% earlier with constant premia. The contribution differences continue to be many standard errors above zero.[20]

Turning to the three-factor model results in Panel B, we see some evidence of predictability in the factor risk premia. For both sets of conditioning variables the *t*-statistics for the market premium on D/P and the SMB premium on DEF are greater than two. There is also evidence of time-varying characteristic premia. The *t*-statistics for the size premium on Term are less than −3 for both conditional beta approaches. Moreover, each of the characteristic premia appears to be related to at least one of the macro predictors when betas are conditioned on firm attributes. In fact, the *t*-statistics on Def exceed two in magnitude for all three characteristics. The contribution numbers are 37% betas and 63% characteristics in this case (15%/71% earlier), and the difference is now less than two standard errors from zero. With firm/macro betas, DEF is no longer significantly related to the characteristic premia. The contribution measures are 44% betas and 56% characteristics (20%/64% earlier) and the difference is less than a standard error above zero. Thus, the relative contribution of betas has been substantially enhanced in both cases by allowing for time-varying premia.

The four-factor results are given in Panel C. Although there's at most a hint of time-variation in the MOM premia, inclusion of the momentum factor eliminates the statistical significance of several of the coefficients for time-varying characteristic premia. With betas conditioned on firm attributes only, the contribution numbers are 43% betas, 50% characteristics (22%/64% earlier), and with firm/macro betas they are 56% betas, 39% characteristics (31%/53% earlier). As in the three-factor model, the role of betas is greatly enhanced by

[20] To accommodate the time-varying premia, the procedure in Section I.C is modified as follows. Rather than repeatedly sample (unconditional) premia coefficients, we sample values of the coefficients in equation (14) from a multivariate normal distribution with mean vector equal to the coefficient estimates and covariance matrix equal to the heteroskedasticity-consistent asymptotic covariance matrix for those estimates. The sampled coefficient values are then combined with the historical values of the predictive variables to obtain corresponding conditional risk premia that are used to recompute values of the contribution numbers based on equation (13). Similar results are obtained also allowing for autocorrelation of the disturbances in (12).

allowing the premia to vary over time. Although firm/macro betas finally beat out characteristics, the difference is not reliably different from zero.

Thus far, we have not adjusted for small-sample bias of the sort analyzed by Stambaugh (1999). This bias arises when a predictor is autocorrelated and innovations in the predictor are contemporaneously correlated with return surprises. To explore this issue, we used techniques for multiple predictors developed by Amihud and Hurvich (2004) and Amihud, Hurvich and Wang (2008). The simpler approach assumes that the best forecast of each predictor only requires its own lagged value and accommodates correlation between predictors only through the forecast errors. The more general approach relaxes this restriction. Results using the simpler approach and firm/macro betas are as follows (not tabulated). For the one-factor model, the contribution of beta declines and that of characteristics increases by about 1 percentage point. For the three and four-factor models, the contribution of betas actually increases by about 1 percentage point, while changes in the characteristic contributions are minimal. Applying the more general procedure, the declines are even smaller. Thus, the substantial increase in the contribution of betas with time-varying premia appears to be a robust finding.[21]

VI. Summary and Conclusions

Despite strong theoretical and practical reasons for conducting asset pricing tests using individual stocks, there are relatively few studies doing so. The flexibility of the two-pass methodology is an advantage over the more general GMM approach in this context. However, the major difficulty in two-pass regressions is to properly account for the bias introduced by imprecisely estimated individual betas. Therefore, we employ bias-corrected coefficient estimators that are adjusted to reflect these estimation errors. One methodological contribution of this paper is showing how to do this in a setting that accommodates an unbalanced panel dataset of individual stock returns, as well as betas that vary over time with firm characteristics and macroeconomic variables. We also identify and develop a correction for an additional bias that arises if a researcher wishes to exploit the full time series of returns for each stock in estimating conditional betas. Simulations indicate that our corrections for these biases are effective and also reduce the mean-square error in estimating the risk premia.

[21] In implementing both approaches, the autocorrelation of D/P is so high that the upward "correction" to this parameter implies a non-stationary process. Therefore, we leave the coefficient on D/P unadjusted while correcting the other coefficients. If we set the autocorrelation for D/P equal to 1, changes in the relative contributions described above are just a bit bigger – half a percentage point or less.

We document a number of important findings. As in many other studies, the market risk premium is never reliably different from zero with our conditional betas (we're inclined to dismiss evidence based on the implausible constant-beta specification). The risk premium for the Fama-French size factor, SMB is, for the most part, reliably positive, even when competing with the firm size characteristic. The case for the book-to-market factor HML is weak, however. With all stocks included in the estimation, the *t*-statistics for a positive premium range from −0.07 to 1.50, depending on the specification. There is some evidence of a reliably positive HML premium in the NYSE/AMEX universe if we condition betas on both firm-specific and macroeconomic variables. We also examine a momentum-factor, but the evidence of a positive premium is not quite significant at the 5% level when the MOM loading competes with past 6-month return. On the other hand, coefficients on the size, book-to-market, and 6-month past return characteristics are all highly significant, with the usual signs. This is true even when the three- or four-factor loadings are allowed to vary with those same firm characteristics.

While rejection of these beta-pricing models is not news, we do offer new results on the "loadings versus characteristics" controversy. The previous literature has tended to focus on whether it is one or the other that ultimately explains differences in expected returns. In contrast, we provide an intuitive and simple way to disentangle the *relative importance* of betas and firm characteristics in explaining the cross-section of expected returns. Not surprisingly, there is no contest with only a single market beta. The Fama-French factor loadings fare better, however, with beta contributions ranging from 15% to 31% (characteristics 59% to 71%) when conditioning betas on firm attributes and macro variables. Adding a momentum factor to the competition increases the beta contribution from 20% to 31% for the all-stock universe and firm/macro betas. Given the substantial error in estimating risk premia, this is enough to make the race with characteristics (53% contribution) too close to call statistically.

We also provide some analysis for the all-stock universe, in which expected return premia vary over time with macro variables. Using conditional betas, some evidence of predictable premia is found for the market factor, SMB and all three characteristic variables: size, book-to-market, and past return. Interestingly, we see a substantial rise in the expected return contribution of betas in this context, from 20% with constant premia to 44% with changing premia for the three-factor model and from 31% to 56% for the four-factor model (all with firm/macro betas). Though betas finally edge out characteristics in the latter case, the difference is well below two standard errors from zero. In future work, we hope to gain a better understanding of the manner in which time-varying premia manage to enhance the explanatory power of the betas. For now, the bottom line is that *both* betas and characteristics account for considerable cross-sectional variation in expected returns with time-varying premia, and their contributions may well be comparable in magnitude.

We have focused mainly on the CAPM, the Fama and French (1993) model, and the four-factor models in this paper. It would be of interest to examine the performance and risk premia for other asset pricing models as well, using individual stocks and conditional betas. Also, our goal here has been to explore the role of conditional betas in cross-sectional asset pricing. The properties and uses of conditional betas, for the purposes of portfolio optimization and cost of capital calculations deserve an independent study.

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Table 1: Simulation Results

The data generating process is:

$$R_{it} = B_i F_t + \varepsilon_{it} ,$$

where we use the market excess return in the one-factor model and the Fama and French (1993) factors in the three-factor model. At the beginning of the simulation, 1-factor betas are drawn from a $N(1.1,0.5)$ distribution, and the three 3-factor betas are drawn from $N(1.1,0.4)$, $N(0.9,0.7)$, and $N(0.2,0.7)$ distribution, respectively. We use the actual factor realizations from 1946 to 2011 (792 months) in the above equation. The residuals are drawn from a normal distribution with mean zero and heteroskedastic standard deviation following the procedure described in the text. For each stock, we randomly select a subset of 144 months from the 792 month sample (the months need not be consecutive) and generate returns for these months. Betas estimated from the first-pass time-series regressions are used in the second-pass cross-sectional regressions. The table reports the mean bias and root mean squared error (across 1,000 simulations) in percent per month of the estimated risk premiums, both without and with EIV correction. The ex-post risk premia for Mkt, SMB, and HML equal, 0.57%, 0.15%, and 0.36% per month, respectively.

	Bias		RMSE	
Number of stocks	Bias Uncorrected	Bias Corrected	Bias Uncorrected	Bias Corrected
Panel A: 1-factor model				
	Risk premium on B_{Mkt}			
500	-0.1022	-0.0018	0.1457	0.1416
1,000	-0.0867	-0.0079	0.1127	0.0957
2,000	-0.1009	-0.0107	0.1128	0.0679
5,000	-0.1160	-0.0172	0.1207	0.0482
10,000	-0.1108	-0.0146	0.1130	0.0333
Panel B: Three-factor model				
	Risk premium on B_{Mkt}			
500	-0.1668	-0.0048	0.2044	0.1995
1,000	-0.1891	-0.0219	0.2079	0.1396
2,000	-0.1603	-0.0182	0.1711	0.0936
5,000	-0.1682	-0.0243	0.1724	0.0628
10,000	-0.1743	-0.0268	0.1764	0.0496
	Risk premium on B_{SMB}			
500	-0.0438	-0.0044	0.0834	0.1053
1,000	-0.0423	-0.0019	0.0650	0.0687
2,000	-0.0369	-0.0019	0.0528	0.0538
5,000	-0.0392	-0.0001	0.0457	0.0330
10,000	-0.0378	-0.0015	0.0411	0.0227
	Risk premium on B_{HML}			
500	-0.1270	0.0016	0.1479	0.1127
1,000	-0.1246	-0.0064	0.1335	0.0692
2,000	-0.1301	-0.0106	0.1350	0.0526
5,000	-0.1346	-0.0131	0.1366	0.0355
10,000	-0.1270	-0.0118	0.1281	0.0257

Table 2: Descriptive statistics

This table presents the descriptive statistics of the main variables used in the paper. Panel A presents the monthly results for all stock and Panel B presents results for only NYSE/AMEX stocks. Size is the market capitalization in billions of dollars, book-to-market is calculated as the ratio of most recently available book-value (assumed available six months after fiscal year-end) divided by the current market capitalization, Ret6 is the last six-month return, and turnover is calculated as the ratio of shares traded to shares outstanding. Book-to-market ratios greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and the 0.005 fractile values, respectively. Unconditional betas are calculated from a time-series regression on the Fama and French (1993) three-factor model. For all variables, we first calculated the cross-sectional means, medians, and standard deviations. The numbers reported in the table are the time-series averages of these statistics. The sample period is 1946–2011. The sample includes only common stocks that have sufficient data to calculate market capitalization and book-to-market ratio for at least 5 years (the observations do not have to be continuous).

	Mean	Median	StdDev
Panel A: All stocks			
Excess Return (in %)	1.246	0.324	12.013
Firm Size ($ billions)	0.975	0.102	4.557
Book-to-market	0.999	0.757	0.997
Ret6 (in %)	7.804	4.102	31.420
Unconditional B_{Mkt}	0.992	0.987	0.399
Unconditional B_{SMB}	0.766	0.684	0.764
Unconditional B_{HML}	0.317	0.362	0.655
Panel B: NYSE/AMEX stocks			
Excess Return (in %)	1.238	0.525	10.000
Firm Size ($ billions)	1.855	0.325	6.244
Book-to-market	0.997	0.773	0.945
Ret6 (in %)	7.717	4.854	26.095
Turnover (in %)	0.577	0.412	0.686
Unconditional B_{Mkt}	1.023	1.017	0.343
Unconditional B_{SMB}	0.668	0.611	0.676
Unconditional B_{HML}	0.407	0.404	0.524

Table 3: Cross-sectional regression of one-factor model with no controls

This table presents the time-series averages of γ coefficients from the following individual stock cross-sectional regression:

$$R_{it} - R_{ft} = \gamma_{0t} + \gamma_{1t}\hat{B}_{it-1} + u_{it}.$$

Panel A presents the monthly results for all stock and Panel B presents results for only NYSE/AMEX stocks. Only stocks with price greater than $1 at the end of time *t* are used in the regression at time *t*. The first row is the coefficient (multiplied by 100) and the second row is *t*-statistic calculated as described in the main text. Left-hand side of the table reports bias uncorrected coefficients from a regular OLS regression while the right-hand side of the panel reports coefficients corrected for the EIV-bias following the procedure described in the text. The time-series stock specific-variables are size (Sz), and book-to-market (B/M). Size is the logarithm of market capitalization, and book-to-market is calculated as the ratio of most recently available book-value (assumed available six months after fiscal year-end) divided by the current market capitalization. Book-to-market ratios greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and the 0.005 fractile values, respectively. The macro variables are default spread (Def, difference between BAA- and AAA-rated bonds) and term spread (Term, difference between long-term government bond yield and 3-month Treasury-bill rate). All time-series variables are cross-sectionally standardized (using only NYSE stocks) before being used in the first-stage time-series regression. Nstocks is the average number of stocks used in the regression. The sample period is 1946–2011. The sample includes only common stocks that have sufficient data to calculate market capitalization and book-to-market ratio for at least 5 years (the observations do not have to be continuous).

	Bias uncorrected			Bias corrected		
ztsr→	—	Sz, B/M	Sz, B/M, Def, Term	—	Sz, B/M	Sz, B/M, Def, Term
			Panel A: All stocks			
Cnst	0.575	0.586	0.699	0.654	0.758	0.937
	(5.93)	(6.57)	(7.79)	(5.45)	(6.81)	(8.53)
B_{Mkt}	0.396	0.376	0.260	0.322	0.225	0.044
	(2.15)	(2.28)	(1.67)	(1.58)	(1.20)	(0.25)
Nstocks	2,715	2,715	2,715	2,715	2,715	2,715
			Panel B: NYSE/AMEX stocks			
Cnst	0.558	0.497	0.600	0.641	0.689	0.859
	(5.91)	(6.17)	(7.64)	(5.43)	(6.11)	(7.76)
B_{Mkt}	0.295	0.341	0.231	0.219	0.166	-0.017
	(1.59)	(2.05)	(1.48)	(1.08)	(0.87)	(-0.09)
Nstocks	1,527	1,527	1,527	1,527	1,527	1,527

Table 4: Cross-sectional regression of one-factor model with controls

This table presents the time-series averages of γ coefficients from the following individual stock cross-sectional OLS regression:

$$R_{it} - R_{ft} = \gamma_{0t} + \gamma_{1t}\hat{B}_{it-1} + \gamma_{2t}' zcs_{it-1} + u_{it}.$$

The single factor is the market factor. Panel A presents the monthly results for all stock and Panels B and C present results for only NYSE/AMEX stocks. Only stocks with price greater than \$1 at the end of time *t* are used in the regression at time *t*. The first row is the coefficient (multiplied by 100) and the second row is *t*-statistic calculated as described in the main text. Left-hand side of the table reports bias uncorrected coefficients from a regular OLS regression while the right-hand side of the panel reports coefficients corrected for EIV-bias following the procedure described in the text. The time-series stock specific-variables are size (Sz), and book-to-market (B/M). Size is the logarithm of market capitalization, and book-to-market is calculated as the ratio of most recently available book-value (assumed available six months after fiscal year-end) divided by the current market capitalization. Book-to-market ratios greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and the 0.005 fractile values, respectively. The macro variables are default spread (Def, difference between BAA- and AAA-rated bonds) and term spread (Term, difference between long-term government bond yield and 3-month Treasury-bill rate). All time-series variables are cross-sectionally standardized (using only NYSE stocks) before being used in the first-stage time-series regression. The cross-sectional variables (zcs_{it}) include size, book-to-market, and the last six-month return (Ret6). The cross-sectional variables are not standardized in the regression. Nstocks is the average number of stocks used in the regression. The last rows in each panel report the fraction of cross-sectional variation in expected returns given by betas and characteristics (the numbers do not add up to 100 because of covariation). Numbers in parenthesis below the fractions are their standard errors. Please refer to the text for further details. The sample period is 1946–2011. The sample includes only common stocks that have sufficient data to calculate market capitalization and book-to-market ratio for at least 5 years (the observations do not have to be continuous).

	Bias uncorrected			Bias corrected		
zts→	—	Sz, B/M	Sz, B/M, Def, Term	—	Sz, B/M	Sz, B/M, Def, Term
Panel A: All stocks						
Cnst	0.581	0.639	0.756	0.620	0.782	0.969
	(6.12)	(7.16)	(8.50)	(5.43)	(7.20)	(9.01)
B_{Mkt}	0.434	0.390	0.275	0.387	0.243	0.056
	(2.62)	(2.52)	(1.85)	(2.12)	(1.40)	(0.33)
Sz	-0.183	-0.177	-0.174	-0.184	-0.182	-0.180
	(-6.00)	(-5.94)	(-5.90)	(-6.07)	(-6.17)	(-6.09)
B/M	0.326	0.307	0.284	0.334	0.313	0.289
	(7.04)	(6.85)	(6.40)	(7.40)	(7.33)	(6.83)
Ret6	0.972	1.056	1.105	0.936	0.978	1.044
	(6.73)	(7.66)	(7.86)	(6.33)	(6.95)	(6.49)
Nstocks	2,701	2,701	2,701	2,701	2,701	2,701
% Betas	12.14	17.52	12.64	7.42	4.40	0.30
	(7.61)	(10.25)	(9.95)	(5.74)	(5.64)	(3.93)
% Chars	89.16	83.48	88.22	93.96	96.37	99.80
	(7.18)	(10.03)	(9.61)	(5.04)	(4.91)	(3.34)
% Diff	77.02	65.95	75.58	86.54	91.97	99.50
	(14.77)	(20.27)	(19.55)	(10.76)	(10.53)	(7.26)
Panel B: NYSE/AMEX stocks						
Cnst	0.693	0.624	0.712	0.806	0.875	1.021
	(7.54)	(7.22)	(8.30)	(7.50)	(8.14)	(9.12)
B_{Mkt}	0.201	0.283	0.194	0.073	0.017	-0.145
	(1.25)	(1.84)	(1.31)	(0.42)	(0.10)	(-0.86)
Sz	-0.100	-0.098	-0.097	-0.103	-0.106	-0.104
	(-3.64)	(-3.55)	(-3.51)	(-3.81)	(-3.95)	(-3.87)
B/M	0.266	0.250	0.236	0.269	0.251	0.244
	(5.73)	(5.66)	(5.38)	(5.85)	(5.74)	(5.56)
Ret6	1.142	1.218	1.249	1.081	1.116	1.128
	(7.27)	(8.19)	(8.38)	(6.45)	(7.13)	(7.04)
Nstocks	1,519	1,519	1,519	1,519	1,519	1,519
% Betas	3.87	12.21	7.93	0.41	0.03	2.62
	(5.37)	(10.38)	(9.85)	(3.16)	(3.77)	(6.58)
% Chars	94.48	86.01	91.09	99.83	99.77	99.29
	(6.31)	(10.95)	(10.24)	(3.97)	(3.96)	(4.61)
% Diff	90.61	73.80	83.17	98.41	99.74	96.67
	(11.65)	(21.31)	(20.07)	(6.97)	(7.44)	(11.11)

Table 5: Cross-sectional regression of three-factor model with no controls

This table presents the time-series averages of γ coefficients from the following individual stock cross-sectional regression:

$$R_{it} - R_{ft} = \gamma_{0t} + \gamma_{1t}' \hat{B}_{it-1} + u_{it}.$$

The three factors are Mkt, SMB, and HML (Fama and French (1993)). Panel A presents the monthly results for all stock and Panel B presents results for only NYSE/AMEX stocks. Only stocks with price greater than \$1 at the end of time *t* are used in the regression at time *t*. The first row is the coefficient (multiplied by 100) and the second row is *t*-statistic calculated as described in the main text. Left-hand side of the table reports bias uncorrected coefficients from a regular OLS regression while the right-hand side of the panel reports coefficients corrected for EIV-bias following the procedure described in the text The time-series stock specific-variables are size (Sz), and book-to-market (B/M). Size is the logarithm of market capitalization, and book-to-market is calculated as the ratio of most recently available book-value (assumed available six months after fiscal year-end) divided by the current market capitalization. Book-to-market ratios greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and the 0.005 fractile values, respectively. The macro variables are default spread (Def, difference between BAA- and AAA-rated bonds) and term spread (Term, difference between long-term government bond yield and 3-month Treasury-bill rate). All time-series variables are cross-sectionally standardized (using only NYSE stocks) before being used in the first-stage time-series regression. Nstocks is the average number of stocks used in the regression. The sample period is 1946–2011. The sample includes only common stocks that have sufficient data to calculate market capitalization and book-to-market ratio for at least 5 years (the observations do not have to be continuous).

	Bias uncorrected			Bias corrected		
zts→	—	Sz, B/M	Sz, B/M, Def, Term	—	Sz, B/M	Sz, B/M, Def, Term
			Panel A: All stocks			
Cnst	0.548	0.415	0.507	0.666	0.613	0.650
	(6.36)	(6.37)	(8.45)	(6.26)	(5.95)	(7.56)
B_{Mkt}	0.423	0.272	0.195	0.444	0.036	0.000
	(2.49)	(1.76)	(1.32)	(2.36)	(0.21)	0.00
B_{SMB}	0.130	0.357	0.291	0.008	0.403	0.328
	(1.15)	(3.39)	(2.90)	(0.06)	(3.64)	(3.15)
B_{HML}	-0.225	0.026	0.082	-0.365	0.037	0.151
	(-2.07)	(0.26)	(0.85)	(-3.06)	(0.33)	(1.50)
Nstocks	2,715	2,715	2,715	2,715	2,715	2,715
			Panel B: NYSE/AMEX stocks			
Cnst	0.536	0.434	0.516	0.570	0.595	0.668
	(6.03)	(6.87)	(9.09)	(5.16)	(6.59)	(7.84)
B_{Mkt}	0.383	0.237	0.158	0.446	0.043	-0.046
	(2.20)	(1.51)	(1.05)	(2.32)	(0.25)	(-0.29)
B_{SMB}	0.048	0.273	0.219	-0.036	0.313	0.248
	(0.44)	(2.64)	(2.19)	(-0.32)	(2.84)	(2.36)
B_{HML}	-0.152	0.088	0.137	-0.255	0.174	0.257
	(-1.39)	(0.88)	(1.41)	(-2.11)	(1.61)	(2.49)
Nstocks	1,527	1,527	1,527	1,527	1,527	1,527

Table 6: Cross-sectional regression of three-factor model with controls

This table presents the time-series averages of γ coefficients from the following individual stock cross-sectional OLS regression:

$$R_{it} - R_{ft} = \gamma_{0t} + \gamma_{1t}' \hat{B}_{it-1} + \gamma_{2t}' zcs_{it-1} + u_{it}.$$

The three factors are Mkt, SMB, and HML (Fama and French (1993)). Panel A presents the monthly results for all stock and Panels B and C present results for only NYSE/AMEX stocks. Only stocks with price greater than \$1 at the end of time t are used in the regression at time t. The first row is the coefficient (multiplied by 100) and the second row is t-statistic calculated as described in the main text. Left-hand side of the table reports bias uncorrected coefficients from a regular OLS regression while the right-hand side of the panel reports coefficients corrected for EIV-bias following the procedure described in the text. The time-series stock specific-variables are size (Sz), and book-to-market (B/M). Size is the logarithm of market capitalization, and book-to-market is calculated as the ratio of most recently available book-value (assumed available six months after fiscal year-end) divided by the current market capitalization. Book-to-market ratios greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and the 0.005 fractile values, respectively. The macro variables are default spread (Def, difference between BAA- and AAA-rated bonds) and term spread (Term, difference between long-term government bond yield and 3-month Treasury-bill rate). All time-series variables are cross-sectionally standardized (using only NYSE stocks) before being used in the first-stage time-series regression. The cross-sectional variables (zcs_{it}) include size, book-to-market, and the last six-month return (Ret6). The cross-sectional variables are not standardized in the regression. Nstocks is the average number of stocks used in the regression. The last rows in each panel report the fraction of cross-sectional variation in expected returns given by betas and characteristics (the numbers do not add up to 100 because of covariation). Numbers in parenthesis below the fractions are their standard errors. The sample period is 1946–2011. The sample includes only common stocks that have sufficient data to calculate market capitalization and book-to-market ratio for at least 5 years (the observations do not have to be continuous).

	Bias uncorrected			Bias corrected		
zts→	—	Sz, B/M	Sz, B/M, Def, Term	—	Sz, B/M	Sz, B/M, Def, Term
Panel A: All stocks						
Cnst	0.582	0.497	0.572	0.444	0.616	0.696
	(6.68)	(7.30)	(9.02)	(3.54)	(6.52)	(7.78)
B_{Mkt}	0.704	0.325	0.228	1.525	0.192	0.053
	(4.23)	(2.13)	(1.55)	(7.01)	(1.13)	(0.33)
B_{SMB}	-0.212	0.294	0.254	-1.011	0.228	0.225
	(-1.99)	(2.85)	(2.58)	(-8.22)	(2.00)	(2.14)
B_{HML}	-0.384	-0.034	0.043	-0.730	-0.007	0.102
	(-3.71)	(-0.34)	(0.45)	(-5.95)	(-0.07)	(0.97)
Sz	-0.253	-0.109	-0.108	-0.437	-0.126	-0.116
	(-11.45)	(-5.87)	(-6.10)	(-12.73)	(-5.48)	(-5.63)
B/M	0.370	0.303	0.257	0.375	0.275	0.211
	(10.73)	(10.70)	(9.47)	(8.96)	(7.92)	(6.30)
Ret6	0.910	1.079	1.127	0.893	1.081	1.244
	(6.87)	(9.34)	(10.09)	(5.77)	(8.91)	(10.28)
Nstocks	2,701	2,701	2,701	2,701	2,701	2,701
% Betas	36.51	35.35	36.84	111.34	15.02	19.52
	(10.37)	(11.79)	(12.39)	(13.49)	(9.68)	(9.96)
% Chars	110.31	53.04	50.14	161.58	70.59	64.02
	(9.79)	(13.20)	(13.77)	(8.29)	(13.53)	(12.39)
% Diff	73.80	17.69	13.30	50.24	55.57	44.49
	(15.29)	(24.48)	(25.88)	(17.77)	(22.30)	(22.07)

	Bias uncorrected			Bias corrected		
zts→	—	Sz, B/M	Sz, B/M, Def, Term	—	Sz, B/M	Sz, B/M, Def, Term
			Panel B: NYSE/AMEX stocks			
Cnst	0.700	0.514	0.572	0.679	0.657	0.711
	(7.64)	(7.55)	(9.10)	(5.25)	(6.76)	(7.71)
B_{Mkt}	0.563	0.230	0.148	1.262	-0.009	-0.107
	(3.34)	(1.49)	(0.99)	(5.82)	(-0.05)	(-0.66)
B_{SMB}	-0.355	0.214	0.178	-1.108	0.212	0.176
	(-3.74)	(2.13)	(1.82)	(-9.29)	(1.81)	(1.65)
B_{HML}	-0.324	0.037	0.108	-0.681	0.125	0.246
	(-3.25)	(0.37)	(1.13)	(-5.80)	(1.11)	(2.29)
Sz	-0.210	-0.053	-0.054	-0.393	-0.060	-0.055
	(-10.58)	*(-3.30)*	*(-3.54)*	*(-11.71)*	*(-2.62)*	*(-2.81)*
B/M	0.285	0.215	0.180	0.292	0.179	0.123
	(7.73)	(7.51)	(6.64)	(6.51)	(4.85)	(3.47)
Ret6	1.063	1.193	1.240	0.996	1.125	1.310
	(7.24)	(9.34)	(10.15)	(5.60)	(8.15)	(10.08)
Nstocks	1,519	1,519	1,519	1,519	1,519	1,519
% Betas	53.58	30.05	32.60	153.62	21.13	31.33
	(15.72)	(13.28)	(13.21)	(14.82)	(12.18)	(11.74)
% Chars	130.01	58.00	56.19	182.27	60.42	58.75
	(9.53)	(15.37)	(15.20)	(12.14)	(14.52)	(12.77)
% Diff	76.43	27.96	23.59	28.65	39.29	27.43
	(19.36)	(28.28)	(28.17)	(22.30)	(26.11)	(23.92)

Table 7: Cross-sectional regression of four-factor model with controls

This table presents the time-series averages of γ coefficients from the following individual stock cross-sectional OLS regression:

$$R_{it} - R_{ft} = \gamma_{0t} + \gamma_{1t}' \hat{B}_{it-1} + \gamma_{2t}' zcs_{it-1} + u_{it}.$$

This table presents the results from a four-factor model where the factors are Mkt, SMB, HML, and MOM. The sample includes all stocks listed on NYSE, AMEX, and NASDAQ. Only stocks with price greater than $1 at the end of time *t* are used in the regression at time *t*. The first row is the coefficient (multiplied by 100) and the second row is *t*-statistic calculated as described in the main text. Left-hand side of the table reports bias uncorrected coefficients from a regular OLS regression while the right-hand side of the panel reports coefficients corrected for EIV-bias following the procedure described in the text. The time-series stock specific-variables are size (Sz), book-to-market (B/M), and last six-month return (Ret6). Size is the logarithm of market capitalization, and book-to-market is calculated as the ratio of most recently available book-value (assumed available six months after fiscal year-end) divided by the current market capitalization. Book-to-market ratios greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and the 0.005 fractile values, respectively. The macro variables are default spread (Def, difference between BAA- and AAA-rated bonds) and term spread (Term, difference between long-term government bond yield and 3-month Treasury-bill rate). All time-series variables are cross-sectionally standardized (using only NYSE stocks) before being used in the first-stage time-series regression. The cross-sectional variables are not standardized in the regression. Nstocks is the average number of stocks used in the regression. The last row reports the fraction of cross-sectional variation in expected returns given by betas and characteristics (the numbers do not add up to 100 because of covariation). Numbers in parenthesis below the fractions are their standard errors. The sample period is 1946–2011. The sample only includes common stocks that have sufficient data to calculate market capitalization and book-to-market ratio for at least 5 years (the observations do not have to be continuous).

	Bias uncorrected			Bias corrected		
		Sz, B/M, Ret6	Sz, B/M, Ret6, Def, Term		Sz, B/M, Ret6	Sz, B/M, Ret6, Def, Term
zts→	—			—		
			4-factor model			
Cnst	0.584	0.515	0.566	0.288	0.589	0.689
	(6.89)	(7.93)	(9.38)	(2.19)	(6.17)	(7.99)
B_{Mkt}	0.709	0.305	0.233	1.855	0.196	0.078
	(4.30)	(2.00)	(1.60)	(8.05)	(1.12)	(0.49)
B_{SMB}	-0.193	0.282	0.255	-1.016	0.252	0.237
	(-1.80)	(2.77)	(2.62)	(-8.10)	(2.21)	(2.26)
B_{HML}	-0.386	-0.007	0.059	-0.763	0.044	0.116
	(-3.73)	(-0.08)	(0.64)	(-5.71)	(0.38)	(1.14)
B_{MOM}	0.268	0.166	0.157	0.689	0.267	0.285
	(1.81)	(1.20)	(1.18)	(2.21)	(1.17)	(1.86)
Sz	-0.247	-0.102	-0.097	-0.465	-0.107	-0.100
	(-11.52)	(-5.62)	(-5.64)	(-13.38)	(-4.44)	(-5.06)
B/M	0.362	0.308	0.261	0.373	0.275	0.231
	(11.10)	(11.84)	(10.34)	(8.64)	(8.00)	(7.40)
Ret6	0.890	1.147	1.210	0.861	1.250	1.298
	(6.87)	(11.88)	(13.00)	(5.36)	(7.54)	(11.48)
Nstocks	2,701	2,701	2,701	2,701	2,701	2,701
% Betas	37.22	37.31	44.24	110.05	21.56	31.37
	(10.22)	(10.98)	(10.64)	(12.99)	(10.53)	(9.47)
% Chars	107.87	51.69	44.14	157.99	63.61	53.21
	(9.92)	(11.73)	(11.13)	(9.76)	(12.87)	(10.53)
% Diff	70.65	14.38	-0.11	47.94	42.04	21.84
	(15.29)	(22.36)	(21.59)	(17.54)	(22.89)	(19.79)

Table 8: Time variation in prices of risk and characteristics

This table presents the results from a time-series regression of γ coefficients on macro variables:

$$\hat{\gamma}_t = c_0 + c_1' x_{t-1} + v_t.$$

The macro variables (x) are dividend-price ratio of the S&P500 index (D/P), default spread (difference between BAA- and AAA-rated bonds, Def), and term spread (difference between long-term government bond yield and 3-month Treasury-bill rate, Term). The γ coefficients are the premia for betas and characteristics. The one-factor/ three-factor/ four-factor model results in Panels A/B/C should be compared to the constant premia results in Panels A of Table 4/6/7, respectively. We show results only for EIV-bias corrected γcoefficients and all stocks. The first row is the coefficient (multiplied by 100) and the second row is the hetersoskedasticity consistent *t*-statistic. We use the fitted values from these regressions to calculate the contributions to cross-sectional variation in expected returns made by betas and characteristics. These fractions are reported in the last row of each panel (the numbers do not add up to 100 because of covariation) with standard errors in parentheses. The sample period is 1946–2011. The sample includes all common stocks that have sufficient data to calculate market capitalization and book-to-market ratio for at least 5 years (the observations do not have to be continuous).

	B_{Mkt}	Sz	B/M	Ret6
Panel A.1: Unconditional betas (*zts* = —)				
Cnst	0.381	-0.183	0.332	0.925
	(2.10)	(-6.14)	(7.42)	(6.41)
D/P	-0.052	0.067	-0.035	0.327
	(-0.22)	(1.65)	(-0.64)	(2.28)
Def	0.577	-0.113	0.090	-0.676
	(3.12)	(-3.85)	(1.39)	(-2.94)
Term	0.127	-0.060	0.085	-0.292
	(0.64)	(-1.86)	(1.81)	(-2.14)
adj-R^2	1.09	2.99	0.96	3.98
%Betas= 9.01 (4.69), %Chars= 97.10 (3.97), %Diff= 88.09 (8.37)				
Panel A.2: Conditional betas (*zts* = Sz, B/M)				
Cnst	0.238	-0.181	0.312	0.969
	(1.38)	(-6.23)	(7.33)	(7.02)
D/P	0.078	0.059	-0.016	0.311
	(0.37)	(1.54)	(-0.32)	(2.22)
Def	0.443	-0.108	0.062	-0.636
	(2.02)	(-3.83)	(1.18)	(-3.44)
Term	0.254	-0.061	0.100	-0.175
	(1.40)	(-1.95)	(2.23)	(-1.30)
adj-R^2	1.00	2.90	0.85	3.29
%Betas= 10.80 (6.15), %Chars= 94.27 (5.33), %Diff= 83.47 (11.26)				
Panel A.3: Conditional betas (*zts* = Sz, B/M, Def, Term)				
Cnst	0.053	-0.179	0.287	1.034
	(0.31)	(-6.14)	(6.81)	(6.46)
D/P	0.213	0.057	0.017	0.360
	(1.05)	(1.49)	(0.34)	(2.58)
Def	0.356	-0.105	0.061	-0.398
	(1.25)	(-3.74)	(1.34)	(-0.98)
Term	0.266	-0.063	0.101	-0.044
	(1.49)	(-2.04)	(2.27)	(-0.32)
adj-R^2	0.86	2.79	0.83	0.97
%Betas= 14.76 (8.19), %Chars= 88.86 (7.57), %Diff= 74.10 (15.60)				

	B_{Mkt}	B_{SMB}	B_{HML}	Sz	B/M	Ret6
Panel B.1: Unconditional betas (*zts* = —)						
Cnst	1.525	-1.014	-0.736	-0.436	0.374	0.884
	(7.67)	(-8.62)	(-6.38)	(-15.37)	(10.59)	(6.85)
D/P	0.247	0.144	0.263	0.018	-0.041	0.343
	(1.04)	(0.74)	(1.42)	(0.48)	(-1.05)	(2.68)
Def	1.008	-0.282	-0.299	-0.180	0.071	-0.438
	(3.31)	(-2.43)	(-1.81)	(-5.30)	(1.81)	(-2.74)
Term	-0.027	0.294	0.409	-0.005	0.031	-0.226
	(-0.13)	(2.43)	(2.92)	(-0.14)	(0.77)	(-1.84)
adj-R^2	3.10	0.70	1.55	4.54	0.50	2.67
%Betas= 102.76 (8.61), %Chars= 138.06 (8.36), %Diff= 35.50 (13.25)						
Panel B.2: Conditional betas (*zts* = Sz, B/M)						
Cnst	0.186	0.222	-0.014	-0.127	0.276	1.076
	(1.10)	(1.96)	(-0.13)	(-5.60)	(8.07)	(8.97)
D/P	0.416	-0.290	0.240	-0.024	-0.108	0.206
	(2.25)	(-1.77)	(1.49)	(-0.96)	(-2.85)	(1.70)
Def	0.353	0.259	-0.069	-0.062	0.086	-0.376
	(1.48)	(2.28)	(-0.43)	(-2.55)	(2.36)	(-2.16)
Term	0.262	-0.045	0.110	-0.080	0.050	-0.180
	(1.57)	(-0.42)	(0.92)	(-3.06)	(1.39)	(-1.52)
adj-R^2	1.41	0.86	0.21	2.75	2.16	1.79
%Betas= 36.79 (7.92), %Chars= 63.23 (8.77), %Diff= 26.44 (15.71)						
Panel B.3: Conditional betas (*zts* = Sz, B/M, Def, Term)						
Cnst	0.046	0.219	0.096	-0.117	0.212	1.239
	(0.29)	(2.11)	(0.91)	(-5.72)	(6.39)	(10.33)
D/P	0.420	-0.270	0.168	-0.016	-0.073	0.285
	(2.34)	(-1.79)	(1.08)	(-0.72)	(-1.94)	(2.35)
Def	0.349	0.336	0.013	-0.026	0.022	-0.252
	(1.52)	(3.16)	(0.09)	(-1.22)	(0.67)	(-1.21)
Term	0.184	-0.099	0.037	-0.082	0.065	-0.117
	(1.15)	(-0.99)	(0.34)	(-3.63)	(1.75)	(-1.00)
adj-R^2	1.43	1.34	-0.05	2.13	1.02	1.12
%Betas= 43.80 (6.95), %Chars= 56.47 (7.71), %Diff= 12.67 (13.98)						

	B_{Mkt}	B_{SMB}	B_{HML}	B_{MOM}	Sz	B/M	Ret6
			Panel C.1: Unconditional betas (*zts* = —)				
Cnst	1.855	-1.019	-0.769	0.694	-0.464	0.373	0.851
	(9.05)	(-8.61)	(-6.31)	(2.62)	(-16.95)	(10.62)	(6.60)
D/P	-0.229	0.193	0.363	-1.026	0.064	-0.072	0.386
	(-0.94)	(1.07)	(1.86)	(-2.82)	(2.17)	(-1.90)	(3.00)
Def	1.135	-0.231	-0.309	-0.290	-0.202	0.068	-0.390
	(4.02)	(-1.90)	(-1.79)	(-0.70)	(-5.57)	(1.70)	(-2.50)
Term	-0.128	0.276	0.370	-0.617	-0.005	0.026	-0.160
	(-0.58)	(2.34)	(2.76)	(-2.24)	(-0.17)	(0.68)	(-1.30)
adj-R^2	3.18	0.56	1.56	2.18	6.43	0.76	2.24
	%Betas= 108.21 (9.28), %Chars= 133.72 (9.36), %Diff= 25.51 (13.21)						
			Panel C.2: Conditional betas (*zts* = Sz, B/M)				
Cnst	0.189	0.246	0.037	0.258	-0.108	0.276	1.253
	(1.08)	(2.16)	(0.33)	(1.13)	(-4.57)	(8.11)	(7.64)
D/P	0.403	-0.296	0.208	0.030	-0.015	-0.071	0.094
	(2.15)	(-1.80)	(1.33)	(0.11)	(-0.60)	(-2.00)	(0.57)
Def	0.368	0.181	-0.050	-0.330	-0.064	0.055	-0.387
	(1.51)	(1.69)	(-0.32)	(-1.08)	(-2.48)	(1.56)	(-2.01)
Term	0.212	-0.119	0.034	-0.311	-0.090	0.053	-0.060
	(1.25)	(-1.14)	(0.30)	(-1.70)	(-3.91)	(1.55)	(-0.53)
adj-R^2	1.21	0.58	0.02	0.26	3.01	1.03	0.41
	%Betas= 42.96 (8.04), %Chars= 50.08 (9.72), %Diff= 7.12 (17.09)						
			Panel C.3: Conditional betas (*zts* = Sz, B/M, Def, Term)				
Cnst	0.069	0.232	0.110	0.274	-0.101	0.230	1.302
	(0.44)	(2.22)	(1.08)	(1.80)	(-5.19)	(7.44)	(11.63)
D/P	0.318	-0.262	0.176	0.026	-0.007	-0.042	0.118
	(1.83)	(-1.73)	(1.22)	(0.13)	(-0.33)	(-1.28)	(1.08)
Def	0.379	0.311	0.028	-0.432	-0.021	-0.022	-0.132
	(1.75)	(3.14)	(0.21)	(-1.72)	(-1.01)	(-0.67)	(-0.89)
Term	0.122	-0.147	0.082	-0.235	-0.089	0.036	-0.071
	(0.76)	(-1.48)	(0.79)	(-1.50)	(-4.43)	(1.08)	(-0.70)
adj-R^2	1.10	1.13	0.06	1.23	2.63	0.13	0.04
	%Betas= 55.73 (6.78), %Chars= 39.07 (6.77), %Diff= -16.66 (13.07)						