Asset Pricing Models and Financial Market Anomalies

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This article develops a framework that applies to single securities to test whether asset pricing models can explain the size, value, and momentum anomalies. Stock level beta is allowed to vary with firm-level size and book-to-market as well as with macroeconomic variables. With constant beta, none of the models examined capture any of the market anomalies. When beta is allowed to vary, the size and value effects are often explained, but the explanatory power of past return remains robust. The past return effect is captured by model mispricing that varies with macroeconomic variables.

The capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) has long been a basic tenet of finance. However, subsequent work by Basu (1977), Banz (1981), Jegadeesh (1990), and Fama and French (FF) (1992) suggests that cross-sectional differences in average returns are determined not only by the market risk, as prescribed by the CAPM, but also by firm-level market capitalization, book-to-market, and prior return. Some interpret the predictive ability of these variables as evidence against market efficiency. Support for market efficiency has been provided by Fama–French (1993, 1996) who show that, except for the momentum effect, the impact of security characteristics on expected returns can be explained within a risk-based multifactor model. However, there is still an ongoing debate about whether expected returns are explained by risk factors or by non-risk firm characteristics.

The failure of the CAPM has also been attributed to its static nature, and, thus, to its incomplete description of asset prices. Indeed, both theoretical and empirical work support the use of dynamic pricing models. For example, Hansen and Richard (1987) show that even if the static CAPM fails, a dynamic version of the CAPM could be perfectly valid. In addition, Gomes, Kogan, and Zhang (henceforth GKZ) (2003) develop a

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general equilibrium model in which the firm-level size and book-to-market ratio are correlated with the market beta. Ball (1978) and Fama and French (1992) also recognize the association between market evaluation ratios and expected return. Ball argues that such ratios pick up expected return variation, because prices move opposite to expected returns, and Fama and French indicate that size and the book-to-market ratio extract the information in prices about risk and expected return.

Motivated by that support for firm-level risk and expected return variations, this article assesses the empirical performance of conditional asset pricing models in a framework where factor loadings may vary with firm-specific market capitalization and the book-to-market ratio as well as with business cycle-related variables. An open question is whether such beta modeling in a risk-based framework applied to single securities can explain the size, book-to-market, turnover, and momentum effects on expected returns, all of which have been perceived to be financial market anomalies.

To pursue this question, we develop and apply a framework extending that of Brennan, Chordia, and Subrahmanyam (1998) (henceforth BCS). In particular, we first run regressions of excess stock return on asset pricing factors with loadings that may vary cross sectionally and over time with stock-level size and the book-to-market ratio as well as with macroeconomic variables. We then run cross-sectional regressions of risk-adjusted returns, rather than gross returns, as dependent variables on the equity characteristics size, the book-to-market ratio, turnover, and variables related to past return. Under the null hypothesis of exact pricing, all these characteristics should be insignificant in the cross-sectional regressions. The use of risk-adjusted returns in asset pricing tests also appears in Shanken (1992). It is intended to address the error-in-variables bias in estimating the cross-section regression coefficients in finite samples. To account for the bias in the standard errors, we implement the corrections proposed by Shanken (1992) and Jagannathan and Wang (1998).

The use of single securities in empirical tests of asset pricing models guards against the data-snooping biases inherent in portfolio-based asset pricing tests (Lo and MacKinlay 1990) and avoids the loss of information that results when stocks are sorted into portfolios (Litzenberger and Ramaswamy 1979). Relative to previous work, our framework allows factor loadings in first-pass time series regressions to change with firm-level size and book-to-market as well as with business conditions. In the second-pass cross-sectional regressions, risk-adjusted returns are regressed on size, book-to-market, turnover, and prior return variables. If the predictive power of such firm attributes is explained by asset pricing models, then firm attributes should be statistically insignificant. Support for using firm characteristics in cross-sectional regressions to detect model misspecification is provided by Jagannathan and Wang (1998). They show that when the beta pricing model is misspecified, the *t*-statistics for the coefficients on the firm characteristics generally converge to infinity in probability.

Our asset pricing framework is the first to use single securities in cross-sectional tests that allow risk and expected return to vary with conditioning information. Indeed, previous tests have not modeled factor loadings as a function of size, book-to-market, and the business cycle in individual stocks; these tests [Ferson and Harvey (1991, 1998, 1999)] have either modeled the interaction between loadings and macroeconomic variables or they have modeled the interaction between loadings and firm characteristics, but they have focused on portfolios, not individual stocks. In addition, we examine a rich set of models, extending the tests in Fama and French (1992, 1993), BCS (1998), and Ferson and Harvey (1999).

Here are the models we consider: (i) CAPM, (ii) Fama and French (1993) three factor model, (iii) Fama and French model augmented by the Pastor–Stambaugh (2003) liquidity factor,[1] (iv) Fama and French model augmented by the winners-minus-losers (WML) portfolio to proxy for momentum, (v) a version of Jagannathan and Wang (1996) that uses excess market return and labor income growth as factors, (vi) a linear version of the consumption CAPM (CCAPM) of Rubinstein (1976), Lucas (1978), and Breeden (1979), and (vii) Fama and French model augmented by the liquidity and momentum factors. The analysis uses a total of 7875 NYSE, AMEX, and NASDAQ stocks traded over the period August 1964 through December 2001.

The evidence shows that conditional and unconditional versions of the (C)CAPM do not capture any of the size, book-to-market, turnover, and past return effects. All these variables are highly significant in cross-sectional regressions, even when the market or consumption beta may vary with (i) the default spread, (ii) firm-level size and book-to-market, and (iii) firm-level size and book-to-market and default spread. Indeed, Lettau and Ludvigson (2001) show that (C)CAPM scaled by the consumption-wealth ratio, cay, do capture the size and book-to-market effects. However, they use 25 size and book-to-market portfolios as test assets. In unreported tests (available upon request), we confirm that the C(CAPM) scaled by their consumption-wealth ratio do not capture expected return and risk variations at the individual stock level.

Moving to multifactor models, the evidence suggests that the predictive ability of size, book-to-market, turnover, and past returns is also unexplained by the Fama–French (1993) three-factor model with constant risk

[1] We do not use the Pastor–Stambaugh non-traded liquidity factor (non-traded innovations in liquidity) but we use a traded portfolio that is long on stocks with high sensitivities and short on stocks with low sensitivities to the non-traded liquidity factor.

and expected return. In contrast, a version of Fama–French that allows for time-varying risk in a fashion described earlier does capture the impact of firm size and the book-to-market ratio. At the monthly frequency, an unconditional version of the Jagannathan and Wang (1996) model captures neither the size nor the value effect, and a conditional version explains only the size effect. Indeed, the *conditional* Fama–French model provides the greatest improvement over the CAPM in its ability to capture the size and book-to-market effects.

Focusing on the size and value effects, our results shed light on the research controversy: What explains expected returns, risk factors, or equity characteristics? Daniel and Titman (1997) argue that the security characteristics size and book-to-market, not the loadings on Small-Minus-Big (SMB) and High-Minus-Low (HML), have an impact on the cross-section of security returns. That the time-varying beta version of the Fama–French model captures the predictive ability of size and book-to-market lends support to a risk-based story. In essence, the literature has recognized the importance of modeling beta variation. For example, Ghysels (1998) argues that if the dynamics of beta are appropriately captured, then a time-varying beta model outperforms constant beta models. However, if beta is inherently misspecified, serious pricing errors, potentially larger than with a constant beta model, may result. Of course, one will never know the true dynamics of beta. Even so, we show that economic theory that associates size and book-to-market as well as the business cycle with factor loadings could provide guidance about the empirical modeling of beta. In particular, the type of modeling proposed here considerably improves the pricing abilities of virtually all models tested. From a time series perspective, we document intertemporal variation in the Fama–French factor loadings and show that the market and SMB betas are significantly correlated with a recession variable formed using the business cycle dates obtained from the National Bureau of Economic Research (NBER).

Even when beta variation improves pricing abilities, none of the models examined are able to capture the impact of turnover or momentum on the cross-section of stock returns, even when a liquidity factor, or the WML portfolio, or both are included in the first-pass time series regression. While we have shown that the Pastor–Stambaugh liquidity factor does not capture the impact of turnover on expected returns, there are some caveats. With turnover as an explanatory variable in the second pass cross-sectional regression, we have focused on the impact of the level of liquidity on returns, whereas the Pastor–Stambaugh measure is designed to capture the impact of liquidity risk. Also, we have used the value-weighted average return on stocks with high sensitivities to liquidity less the value-weighted average return on stocks with low sensitivities to liquidity as a proxy for the Pastor–Stambaugh non-traded liquidity factor. A different proxy for the liquidity factor may capture the turnover effect, though we note that the turnover effect is also robust when the liquidity factor is formed as the return differential between high- and low-turnover stocks.

Finally, we show that when model mispricing is allowed to vary with business-cycle variables in the first-pass regression, then this variation captures the impact of momentum on returns. Put differently, if in the cross-sectional regression the dependent variables is the risk-adjusted return minus the time-varying component of alpha, then past return variables become insignificant in this regression. This suggests that there is indeed a business cycle pattern to the momentum payoffs. This finding is important because the momentum phenomenon has defied rational explanations and has led to numerous behavioral models based on the cognitive biases of investors. Our evidence suggests that it may be premature to discard risk-based models to explain momentum. We point to the possibility that there may exist a yet undiscovered risk factor related to the business cycle that may capture the impact of momentum on the cross-section of individual stock returns. In contrast, the turnover effect is highly significant in the cross-sectional regression even when the time-varying component of model mispricing is subtracted from risk-adjusted returns. The impact of liquidity on average returns does not diminish after controlling for business cycle effects. Indeed, liquidity may be more of a trading phenomenon that is unrelated to the state of the economy. Liquidity is likely to be a function of market design, competition amongst liquidity suppliers, and the degree of information asymmetry in financial markets.

The rest of the article proceeds as follows: the next section provides a discussion of the various asset pricing models we examine; section 2 describes methodology; section 3 describes the data; section 4 presents the empirical findings; and section 5 concludes.

1. Asset Pricing Models

We study the CAPM of Sharpe (1964) and Lintner (1965) and the CCAPM of Rubinstein (1976), Lucas (1978), and Breeden (1979). Theoretically, CCAPM appears preferable to the CAPM because it takes into account the dynamic nature of portfolio decisions because it integrates the many forms of wealth beyond financial asset wealth. Empirically, however, the unconditional version of the CCAPM has been questioned. Hansen and Singleton (1982, 1983) reject the CCAPM based on US data, finding that it cannot simultaneously explain the time-variation of interest rates and the cross-sectional pattern of average returns on stocks and bonds. Several other papers document that the canonical consumption CAPM performs no better, and often even worse, than the static CAPM.[2] In contrast, as shown by Lettau and Ludvigson (2001), the conditional version of the CCAPM performs relatively well. While Lettau and Ludvigson run their analysis using 25 size and book-to-market portfolios as test assets, we focus on individual stocks in a framework that is reasonably robust to various criticisms about asset pricing tests, as noted in the introduction.

We then test multifactor models, starting with Fama and French (1993). Fama and French (1993, 1996, 1998) have shown that the cross-sectional variation in expected returns associated with most equity characteristics (except momentum) can be captured within a three-factor model, the market, size (SMB), and value (HML) premiums, using US as well as international data.[3] Fama and French (1993) argue that SMB and HML are state variables in an intertemporal asset pricing model. However, rational asset pricing theories have been silent about how SMB and HML are related to the underlying undiversifiable macroeconomic risks. The Fama–French model, though, has gained some support in recent work. Liew and Vassalou (2000) show that SMB and HML predict future economic growth even in the presence of traditional business cycle variables. Lettau and Ludvigson (2001) document the sensitivity of HML to bad news at times of economic distress. Vassalou (2002) shows that once news related to future GDP growth is removed from SMB and HML, the Fama–French model no longer prices equities significantly better than the CAPM.

We also examine the pricing abilities of the Fama–French model augmented with a liquidity factor. With the extensive availability of transactions data, there has been a recent surge in interest in pricing models that account for the impact of liquidity on returns. Amihud and Mendelson (1986) document the impact of the level of (il)liquidity, as measured by the bid-ask spread, on the cross-section of returns. Subsequently, Chordia, Roll, and Subrahmanyam (2000) document correlated movements in liquidity. Drawing on the commonality in liquidity argument, Pastor and Stambaugh (2003) form a liquidity factor that appears to have a significant impact on returns. They show that the decile portfolio with the highest sensitivity to their liquidity factor earns a return that exceeds the return on the decile portfolio with the lowest sensitivity to liquidity risk by 7.5% per year. As a proxy for the Pastor–Stambaugh's non-traded liquidity factor, we have used the value-weighted average return on stocks with high

[2] Mankiw and Shapiro (1986) regress the average returns of the 464 NYSE stocks on their market betas, on consumption growth betas, and on both betas. They find that the market betas are more strongly and robustly associated with the cross-section of average returns. They also find that market beta drives out consumption beta in multiple regressions. Breeden, Gibbons, and Litzenberger (1989) find comparable performance of the CAPM and a model that uses a mimicking portfolio for consumption growth as the single factor.

[3] The international framework (Fama and French 1998) focuses on the market and value premia.

sensitivities to the Pastor–Stambaugh liquidity factor less the value-weighted average return on stocks with low sensitivities to the same factor.

Next, we augment the Fama–French model with the WML portfolio. Jegadeesh and Titman (1993) show that past returns have a strong ability to predict future returns; a strategy of buying past winners and selling past losers results in abnormal returns of about 1% per month. Fama and French (1996) show that their three-factor model is able to capture most CAPM-related anomalies but is unable to capture the momentum effect. Thus, even when WML is purely empirically motivated and is devoid of economic content, it is natural to ask whether including WML explains the impact of momentum on the cross-section of individual stock returns. This exercise allows us to examine whether it is the firm-level past returns or the factor sensitivity to WML that impacts the cross-section of average returns.

The models described so far assume that the market portfolio captures return on financial wealth. Because the market portfolio may not capture the return on human capital, we account for human capital, as in Jagannathan and Wang (1996), which is a large fraction of an individual's wealth. Specifically, we consider a pricing specification that incorporates, along with financial wealth, human capital given by the capitalized value of labor income. The additional factor is the growth rate in labor income computed as $R_t^{\text{labor}} = L_{t-1} + L_{t-2}/L_{t-2} + L_{t-3}$, where L_t is the difference between the NIPA measure of monthly total personal income and total dividends, normalized by total US population.

In sum, we will examine conditional and unconditional versions of the following models: (i) CAPM, (ii) CCAPM, (iii) Fama and French, (iv) Fama and French augmented by the Pastor–Stambaugh liquidity risk factor, (v) Fama and French augmented by WML, (vi) Fama and French augmented by the Pastor–Stambaugh liquidity risk factor as well as by WML, and (vii) a version of Jagannathan and Wang.

2. Methodology

Our asset pricing tests extend the approach of BCS (1998). BCS test factor models by regressing risk-adjusted returns on firm-level attributes such as size, book-to-market, and turnover. Under the null of exact pricing, such attributes should be statistically insignificant in the cross-section. The practice of using risk-adjusted returns, rather than gross or excess returns, is also applied by Shanken (1992). It is intended to address the finite sample bias attributable to errors in estimating factor loadings in the first-pass time series regressions. As noted earlier, the focus on single securities avoids the data-snooping biases that are inherent in portfolio-based approaches, as noted by Lo and MacKinlay

(1990), and is robust to the sensitivity of asset pricing tests to the portfolio grouping procedure.

To address the bias in the estimated standard errors, we implement the corrections of Shanken (1992) and Jagannathan and Wang (1998). Shanken assumes homoscedasticity in the variance of asset returns conditional upon the realization of factors. Under this assumption, he shows that the standard errors based on the Fama–MacBeth procedure overstate the precision of the estimated parameters. Jagannathan and Wang (1998) relax the homoscedasticity assumption and show that the Fama–MacBeth-based standard errors need not overestimate the precision of the estimates. Indeed, in our empirical examinations, we show that t-ratios based on the Jagannathan and Wang correction are typically greater (in absolute value) than those based on the Shanken correction.

We now develop our conditional framework for testing asset pricing models. We assume that returns are generated by a conditional version of a K-factor model

$$R_{jt} = E_{t-1}(R_{jt}) + \sum_{k=1}^{K} \beta_{jkt-1} f_{kt} + e_{jt}, \tag{1}$$

where E_{t-1} is the conditional expectations operator, R_{jt} is the return on security j at time t, f_{kt} is the unanticipated (with respect to information available at $t-1$) time t return on the k th factor, and β_{jkt-1} is the conditional beta corresponding to the k th factor. $E_{t-1}(R_{jt})$ is modeled using the exact pricing specification

$$E_{t-1}(R_{jt}) - R_{Ft} = \sum_{k=1}^{K} \lambda_{kt-1}\, \beta_{jkt-1}, \tag{2}$$

where R_{Ft} is the risk-free rate and λ_{kt} is the risk premium for factor k at time t. The estimated risk-adjusted return on each security for month t is then calculated as

$$R^*_{jt} \equiv R_{jt} - R_{Ft} - \sum_{k=1}^{K} \hat{\beta}_{jkt-1} F_{kt}, \tag{3}$$

where $F_{kt} \equiv f_{kt} + \lambda_{kt-1}$ is the sum of the factor innovation and its corresponding risk premium and $\hat{\beta}_{jkt}$ is the conditional beta estimated by a first-pass time-series regression over the entire sample period as per the specification given below. Our risk adjustment procedure imposes the assumptions that the conditional zero-beta return equals the conditional risk-free rate, and that the factor premium is equal to the excess return on the factor, as is the case when factors are portfolio based.

Next, we run the cross-sectional regression

$$R^*_{jt} = c_{0t} + \sum_{m=1}^{M} c_{mt} Z_{mjt-1} + e_{jt}, \tag{4}$$

where Z_{mjt-1} is the value of characteristic m for security j at time $t-1$ and M is the total number of characteristics. Under exact pricing, equity characteristics do not explain risk-adjusted return and are thus insignificant in the specification (4). To examine significance, we estimate the vector of characteristics rewards each month as

$$\hat{c}_t = (Z'_{t-1} Z_{t-1})^{-1} Z'_{t-1} R^*_t, \tag{5}$$

where Z_{t-1} is a matrix including the M firm characteristics for N_t test assets and R^*_t is the vector of risk-adjusted returns on all test assets. The standard Fama–MacBeth (1973) estimators are the time-series averages of these coefficients, $\hat{c}_t$. The standard errors of the estimators are traditionally obtained from the time series of monthly estimates. As noted earlier, we correct the Fama–MacBeth (1973) standard errors, attributable to the error in the estimation of factor loadings in the first-pass regression, using the approaches in Shanken (1992) as well as Jagannathan and Wang (1998).

To formalize the conditional beta framework developed here let us rewrite the specification in Equation (4) using the generic form

$$R_{jt} - [R_{Ft} + \beta(\theta, z_{t-1}, X_{jt-1})' F_t] = c_{0t} + c_t Z_{jt-1} + e_{jt}, \tag{6}$$

where X_{jt-1} and Z_{jt-1} are vectors of firm characteristics, z_{t-1} denotes a vector of macroeconomic variables, and θ represents the parameters that capture the dependence of β on the macroeconomic variables and the firm characteristics. Ultimately, the null to test is $c_t = 0$. While we have checked the robustness of our results for the general case where $X_{jt-1} = Z_{jt-1}$, we will focus on the case where the factor loadings depend upon firm-level size, book-to-market, and business-cycle-related variables. That is, the vector X_{jt-1} stands for size and book-to-market and the vector Z_{jt-1} for size, book-to-market, turnover, and various lagged return variables.

The dependence on size and book-to-market is motivated by the general equilibrium model of GKZ (2003), which justifies separate roles for size and book-to-market as determinants of beta. In particular, firm size captures the component of a firm's systematic risk attributable to its growth option, and the book-to-market ratio serves as a proxy for risk of existing projects. Incorporating business-cycle variables follows the extensive evidence on time series predictability (Keim and Stambaugh 1986; Fama and French 1989; and Chen 1991).

To describe the beta modeling in the time series regressions, let us focus on the one factor CAPM, and let us assume that there is a single macroeconomic predictor z_{t-1}. The conditional beta of security j is modeled as

$$\beta_{jt-1} = \beta_{j1} + \beta_{j2} z_{t-1} + (\beta_{j3} + \beta_{j4} z_{t-1})\ Size_{jt-1} + (\beta_{j5} + \beta_{j6} z_{t-1}) BM_{jt-1}, \quad (7)$$

where $Size_{jt-1}$ and BM_{jt-1} are the market capitalization and the book-to-market ratio at time $t-1$. In the empirical examinations, beta is modeled under four specifications. In the first, the unconditional one, all βs except for β_{j1} are restricted to be zero. The next three are conditional versions: (i) $\beta_{j2} = \beta_{j4} = \beta_{j6} = 0$, (ii) $\beta_{j3} = \beta_{j4} = \beta_{j5} = \beta_{j6} = 0$, (iii) all βs are allowed to depart from zero. To illustrate, the first pass time series regression for the very last specification is

$$r_{jt} = \alpha_j + \beta_{j1} r_{mt} + \beta_{j2} z_{t-1} r_{mt} + \beta_{j3}\ Size_{jt-1} r_{mt} + \beta_{j4} z_{t-1}\ Size_{jt-1} r_{mt} + \beta_{j5}\ BM_{jt-1} r_{mt} + \beta_{j6} z_{t-1} BM_{jt-1} r_{mt} + u_{jt}, \quad (8)$$

where $r_{jt} = R_{jt} - R_{Ft}$ and r_{mt} is excess return on the value-weighted market index. Note that the firm characteristics size and book-to-market ratio and the macroeconomic predictor are all lagged one period as compared to the excess market and individual stock returns. Moreover, not only do we condition betas on size and the book-to-market ratio, but we also allow this conditioning to vary over time with z_{t-1}.

Then, R^*_{jt} in Equation (4), the dependent variable in the cross-section regression, is given by $\alpha_j + u_{jt}$. The time series regression (8) is run over the entire sample. While this entails the use of future data in calculating the factor loadings, Fama and French (1992) have shown that this forward looking does not impact any of the results. We can confirm that this is indeed true for a handful of random cases we have examined.

For perspective, it is useful to compare our approach to earlier studies

- Fama and French (1992) estimate beta by assigning the firm to one of 100 size-beta sorted portfolios. Firm's beta (proxied by the portfolio's beta) is allowed to evolve over time when the firm changes its portfolio classification.
- Fama and French (1993) focus on 25 size and book-to-market sorted portfolios, which allow firms' beta to change over time as they move between portfolios.

- BCS (1998) estimate beta each year in a first-pass regression using 60 months of past returns. They do not explicitly model how beta changes as a function of size and book-to-market, as we do, but their rolling regressions do allow beta to evolve over time.

We should also distinguish our beta-scaling procedure from those proposed by Shanken (1990) and Ferson and Harvey (1999) as well as Lettau and Ludvigson (2001). Shanken and Ferson and Harvey use predetermined variables to scale factor loadings in asset pricing tests. Lettau and Ludvigson use information variables to scale the pricing kernel parameters. In both procedures, a one-factor conditional CAPM can be interpreted as an unconditional multifactor model. Our conditional beta factor model does not have that unconditional multifactor interpretation since the firm-level $Size_j$ and BM_j are not common across all test assets. Thus, the economic quantity obtained by multiplying these firm-specific variables by the factors does not constitute an additional risk factor in an unconditional representation.

We note that we are able to estimate risk-adjusted stock returns in Equation (3) only if factors are portfolio based. Consequently, we construct maximally correlated portfolios also known as factor-mimicking portfolios for consumption growth and the growth in per capita labor income. The notion of using factor-mimicking portfolios in place of factors in an exact pricing relation is characterized by Breeden (1979) and Huberman, Kandel, and Stambaugh (1987). Breeden, Gibbons, and Litzenberger (1989) estimate a mimicking portfolio for consumption growth as the fitted value of the regression of consumption growth on a set of base assets. Recently, Lamont (2001) has proposed to extend this regression framework by including variables that can forecast future returns on the test assets. This approach has been implemented by Vassalou (2002) in creating mimicking portfolios for GDP growth. Here, we build on Lamont in estimating factor-mimicking portfolios when information variables are accounted for.

Specifically, a factor-mimicking portfolio in unconditional and conditional asset pricing tests is obtained by running the time series regressions

$$f_t = a + b'B_t + \eta_t \tag{9}$$

$$f_t = a + b'B_t + c'z_{t-1} + \eta_t, \tag{10}$$

respectively, where f_t is the realized value of the nonportfolio-based factor such as consumption growth or labor income growth, B_t denotes the time t excess returns (zero cost) on a vector of base assets. Under unconditional and conditional models, the factor-mimicking portfolio is the estimated value of $a + b'B_t$. The fitted value based on Equation (9) has the maximum unconditional correlation with f_t, and the fitted value based on Equation (10) has the maximum correlation with f_t conditioned upon z_{t-1}.

We use eight base assets to estimate factor-mimicking portfolios. Following Lamont (2001) and Vassalou (2002), the base assets include the six value-weighted Fama–French portfolios constructed from the intersections of two market value and three book-to-market portfolios. The remaining are the default and term premia. The former is the return differential between BAA and AAA rate bonds (by Moodys). The latter is the return differential between Treasury bonds with more than 10 years to maturity and Treasury bills that mature in three months. Of course, the true factor-mimicking portfolio is unknown. Hence, estimation errors could emerge. There is no reason to expect, however, any systematic biases in our empirical examinations. In addition, for robustness checks, we have created different portfolios to examine whether the empirical findings are sensitive to the choice of base assets from amongst the above eight assets along with industry portfolios. The empirical evidence is found to be robust to the choice of base assets.

Before concluding this section, we note that the methodological contribution of this article is two-fold. First, beta is allowed to change in cross-sectional regressions applied to single stocks. Previous cross-sectional tests have not explicitly modeled beta as a function of firm characteristics; time-series tests have modeled this interaction, but they have focused on portfolios. Second, it brings together several models, extending the tests in Fama and French (1993), BCS (1998), and Ferson and Harvey (1999). As noted earlier, our empirical tests are motivated by empirical and theoretical work that points to time-varying beta. Under fixed and time-varying beta models, we are able to examine the impact of size, book-to-market, turnover, and prior returns when contemporaneous returns are risk-adjusted by alternative factor specifications.

3. Data

The basic data consist of monthly returns, size, book-to-market, turnover, and lagged returns for a sample of common stocks of NYSE, AMEX, and NASDAQ-listed companies. The sample spans the period July 1964 through December 2001. NASDAQ stocks enter the sample only from January 1983 since the NASDAQ trading volume, one of the firm characteristics, is unavailable in Center for Research in Security Prices (CRSP) before November 1982.

We run the analysis using monthly observations for the most part. We test the CCAPM using quarterly data because data on consumption growth is available only at the quarterly frequency. To be included in the monthly analysis, a stock has to satisfy the following criteria. First, its return in the current month, t, and over the past 36 months has to be available from CRSP. Second, sufficient data has to be available to calculate the size as measured by market capitalization and to calculate the month $t-2$ trading volume as measured by turnover. Third, sufficient data has to be available on the Compustat tapes to calculate the book-to-market ratio as of December of the previous year. In quarterly asset pricing tests, at least 36 observations of returns and firm-level variables noted above are required. Otherwise, with a small number of observations, the estimates of individual firm factor loadings can be noisy.[4] Following Fama and French (1992) and Kothari, Shanken, and Sloan (1995) we control for the Compustat survival bias by dropping the first two years of Compustat data for every firm. In any case, the results are robust to dropping the first two years of Compustat data. This screening process yields an average of 2871 stocks (1818 for a sample of only the NYSE-AMEX stocks) per month. The total number of different stocks over the 450-month sample period is 7875.

Table 1 presents the summary statistics. Panel A presents the results for all stocks, whereas panel B limits the sample to NYSE-AMEX stocks only. We report the time-series averages of the cross-sectional means, medians, and standard deviations of the security characteristics. The mean excess return of all (NYSE-AMEX) stocks is 0.85% (0.76%) per month. The mean firm market capitalization of NYSE-AMEX and NASDAQ stocks is \$0.87 billion while that of NYSE-AMEX stocks is higher at \$1.38 billion. NASDAQ stocks generally have lower market capitalization than the NYSE-AMEX stocks. The average monthly turnover for NYSE-AMEX (NASDAQ) stocks is 4.40% (8.73%) while the median is 2.94% (4.58%). As in Fama and French (1992), the value of BM for July of year t to June of year $t+1$ was computed using accounting data at the end of year $t-1$, and book-to-market ratio values greater than the 0.995 fractile or less than the 0.005 fractile were set equal to the 0.995 and 0.005 fractile values, respectively. The mean book-to-market ratio of all stocks is 1.43 and that of the NYSE-AMEX stocks is 1.46.

The variables display considerable skewness. Therefore, in our cross-sectional analysis, which applies to individual firms, we employ the logarithmic transforms of all the variables except the lagged returns (proxy for momentum). Thus, SIZE is the logarithm of the individual firm market capitalization measured in billions of dollars; BM is the logarithm of the book-to-market ratio; NYTURN (NASDTURN) is the logarithm of the NYSE-AMEX (NASDAQ) share turnover. We separate the NYSE-AMEX and the NASDAQ turnover because Atkins and Dyl (1997) have argued that trading volume reported for NASDAQ

[4] We have confirmed the robustness of our results to different minimum data requirements ranging from 20 through 72 months. The requirement of the full 72 data points is mostly important for the most general specification in Equation (6).

Table 1
Summary statistics

	Mean	Median	Standard deviation	Regression coefficients
Panel A: NYSE-AMEX and NASDAQ stocks				
Excess return (%)	0.85	−0.14	5.61	
Firm size ($ billions)	0.87	0.09	0.83	−0.164 (−3.51)
Book-to-market ratio	1.43	0.83	0.58	0.177 (3.35)
NYSE-AMEX turnover (%)	4.40	2.94	1.86	−0.092 (−1.82)
NASDAQ turnover (%)	8.73	4.58	3.49	−0.111 (−1.26)
RET2-3 (%)	2.64	1.12	8.62	0.526 (1.86)
RET4–6 (%)	4.06	1.94	11.33	0.705 (3.01)
RET7–12 (%)	8.72	4.16	17.46	0.846 (6.07)
$\bar{R}^2$(%)				5.18
Panel B: NYSE-AMEX stocks				
Excess return (%)	0.76	0.00	5.45	
Firm size ($ billions)	1.38	0.20	1.47	−0.111 (−2.47)
Book-to-market ratio	1.46	0.86	0.60	0.167 (3.27)
NYSE-AMEX turnover (%)	4.40	2.94	1.90	−0.121 (−2.36)
RET2-3 (%)	2.46	1.30	8.31	0.601 (1.92)
RET4–6 (%)	3.76	2.18	10.84	0.883 (3.40)
RET7–12 (%)	8.12	4.63	16.61	1.014 (6.63)
$\bar{R}^2$(%)				5.59

This table presents the time-series averages of the cross-sectional means, medians, and standard deviations for an average of 2871 NYSE-AMEX and NASDAQ stocks in Panel A and 1818 NYSE and AMEX stocks in Panel B over 450 months from July 1964 through December 2001. The last column represents the time-series averages of slope coefficients in cross-sectional OLS regressions of excess return on various equity characteristics, t ratios (in parenthesis), and the adjusted R^2, denoted $\bar{R}^2$. Size represents the market capitalization in billions of dollars. Turnover is the monthly share trading volume divided by shares outstanding in percent. RET2-3, RET4-6, and RET7-12 are the cumulative returns over the second through third, fourth through sixth, and seventh through twelfth months before the current quarter, respectively. To be included in the sample, each stock has to satisfy the following criteria: (i) its return in the current month t and in the previous 36 months be available from Center for Research in Security Prices (CRSP), (ii) sufficient data be available to calculate the size and turnover as of the month $t-2$, and (iii) sufficient data be available on the Compustat tapes to calculate the book-to-market ratio as of December of the previous year. The book-to-market ratio provides summary statistics for this variable after book-to-market values greater than the 0.995 fractile or less than the 0.005 fractile are set to equal the 0.995 and 0.005 fractile values, respectively.

stocks may be overstated due to interdealer trading. In the cross-sectional regressions, we use a dummy for NASDAQ stocks because Loughran (1993) documents that returns on NASDAQ stocks are lower due to a larger fraction of new issues that subsequently underperform. Also, following BCS, the firm characteristics are deviations from the cross-sectional means and are lagged two months with respect to the excess returns or the risk-adjusted returns that are the dependent variables in our regressions.

Table 1 also summarizes the Fama–MacBeth coefficients from regressing the excess returns on the firm characteristics. Consistent with prior results in BCS and Chordia, Subrahmanyam, and Anshuman (2001), small firms and value firms (those with high book-to-market ratio) have higher excess returns.[5] Also, higher liquidity as measured by turnover leads to lower excess returns although the impact of turnover on NASDAQ stocks is statistically insignificant. Finally, consistent with the momentum phenomenon documented by Jegadeesh and Titman (1993), prior returns are positively related to excess returns. The average adjusted R^2 for all (NYSE-AMEX) stocks is 5.18% (5.59%).

A remaining task is to specify z_{t-1} in Equations (7), (8), and (10). Several variables may help predict future economic conditions. Nonetheless, attention must be restricted to a small number of such variables to ensure some precision in the estimation procedure. We follow Jagannathan and Wang (1996) and focus on the default spread as an indicator of the state of the economy. The default spread is the yield differential between low-graded and high-graded corporate bonds. The use of default spread is motivated by the studies of Stock and Watson (1989) and Bernanke (1990). Both run a horse race across a number of potential candidates in predicting future business conditions. They find that a variable similar to default spread does the best job. We should emphasize that we have run the analysis using dividend yield, term spread, and Treasury bill rate separately in the time series regressions. We report that all our results are robust to the choice of predictors.

In unreported tests (results available upon request), we also run quarterly regressions using the Lettau and Ludvigson (2001) consumption-wealth ratio (cay) as a conditioning variable. Scaling the market and consumption beta by this variable has been shown to capture much of the cross-section variation in expected returns when 25 size and book-to-market portfolios serve as test assets.[6] It is interesting to examine performance of C(CAPM) scaled by cay when tests assets are individual stocks. As in monthly regressions, firm characteristics in the quarterly regressions are lagged two months from the beginning of the quarter in which the excess returns or risk-adjusted returns are measured.

4. Results

Here, we empirically assess the pricing abilities of various time-varying beta models. We also report evidence based on fixed beta models as a benchmark for comparison. Here are the models examined: (i) CAPM, (ii) Fama–French three-factor model, (iii) Fama–French augmented by the liquidity factor of Pastor and Stambaugh (2003), (iv) Fama–French

[5] Note that the sign of the coefficient on firm size is different depending on whether dollar trading volume or turnover is used as a measure of liquidity. See Chordia, Subrahmanyam, and Anshuman (2001) for details.

[6] Avramov (2002) and Brennan and Xia (2005) show that the cay variable displays an impressive predictive power only when the shares of asset wealth and labor income (in total wealth) are based on data realized subsequent to the prediction period. However, it has poor predictive power when constructed using quantities available at the time of prediction.

augmented by a momentum factor, (v) Jagannathan and Wang (1996) with excess market return and labor income growth as risk factors, (vi) CCAPM, and (vii) Fama–French augmented by a liquidity and a momentum factors. The models are estimated at the monthly and quarterly frequency for NYSE-AMEX and NASDAQ stocks and at the monthly frequency for the NYSE-AMEX stocks. The CCAPM tests are based on quarterly observations only.

As suggested by Jagannathan and Wang (1998), the metric used to assess model pricing abilities is the significance of coefficient estimates in the cross-sectional regression of risk-adjusted returns on size, book-to-market, turnover, and past returns. A significant coefficient implies that the firm characteristic under consideration is related to the cross-section of individual risk-adjusted returns. Insignificant coefficients would point to the efficacy of the model. In addition, we use the cross-sectional average-adjusted R^2, denoted $\bar{R}^2$, as an informal and intuitive measure that shows the fraction of the variation in risk-adjusted returns explained by the firm characteristics. A high $\bar{R}^2$ suggests that the firm-level predictors do affect risk-adjusted returns (bad news for model validity); if the examined model captures size, turnover, book-to-market, and momentum effects, then the cross-sectional slope coefficients will be insignificant and $\bar{R}^2$ will be low. A high $\bar{R}^2$ and significant Fama–MacBeth coefficient estimates point to the failure of the particular model to adequately explain the impact of firm characteristics on risk-adjusted returns. We note that under all pricing models, the number of explanatory variables, that is, firm-level characteristics, in the cross-section regressions is the same. This facilitates a fair comparison of models regardless of the number of factors included in the first-pass time series regression. When $\bar{R}^2 = 0$, the presence of time-invariant pricing errors is not ruled out. Thus, $\bar{R}^2 = 0$ need not imply that the ultimate model has been found, but it does imply the model under consideration explains the predictive ability of size, book-to-market, turnover, and past return.

In the following subsections we discuss each asset pricing model in turn.

4.1 CAPM

Table 2 summarizes the Fama–MacBeth coefficient estimates for the cross-sectional regressions with risk-adjusted returns as the dependent variable and excess market return as the risk factor. In panel A, the cross-sectional regressions are conducted at a monthly frequency. The second column presents the fixed-beta results, in column three, we scale betas by size and the book-to-market ratio, in column four, betas are scaled by the default spread, and in the last column, the scaling is as described in Equation (7).

Table 2
Fama–MacBeth regression estimates with excess market return as the risk factor

	Unscaled	Size + BM	def	(Size + BM) def
Panel A: NYSE-AMEX and NASDAQ stocks–monthly frequency				
Intercept	0.355	−0.624	−0.618	0.340
	(2.80)	(−3.77)	(−3.49)	(−2.98)
	[3.46]	[−4.21]	[−4.00]	[−3.27]
Nasd	0.106	0.126	0.072	0.092
	(1.29)	(1.33)	(0.85)	(0.95)
	[1.10]	[1.25]	[0.71]	[0.92]
SIZE	−0.155	−0.154	−0.150	−0.141
	(−3.29)	(−3.29)	(−3.19)	(−3.11)
	[−3.34]	[−3.38]	[−3.19]	[−3.14]
BM	0.183	0.170	0.184	0.136
	(3.75)	(3.56)	(3.79)	(2.91)
	[3.80]	[3.70]	[3.98]	[3.02]
NYTURN	−0.124	−0.118	−0.118	−0.113
	(−3.24)	(−3.24)	(−3.12)	(−3.13)
	[−3.31]	(−3.64)	[−3.18]	[−3.22]
NASDTURN	−0.187	−0.175	−0.199	−0.187
	(−2.37)	(−2.28)	(−2.60)	(−2.51)
	[−2.84]	[−2.37]	[−2.69]	[−2.60]
RET2-3	0.663	0.762	0.656	0.875
	(2.45)	(2.86)	(2.46)	(3.30)
	[2.59]	[3.03]	[2.58]	[3.47]
RET4-6	0.773	0.830	0.794	0.924
	(3.75)	(4.20)	(3.89)	(4.66)
	[3.75]	[4.33]	[4.10]	[4.83]
RET7-12	0.822	0.819	0.819	0.858
	(6.32)	(6.32)	(6.29)	(6.79)
	[6.44]	[6.78]	[6.73]	[7.25]
$\bar{R}^2$(%)	4.42	4.31	4.37	4.26
Panel B: NYSE-AMEX stocks–Monthly Frequency				
Intercept	0.313	0.315	0.298	0.284
	(2.62)	(2.72)	(2.53)	(2.57)
	[2.69]	[2.79]	[2.55]	[2.63]
SIZE	−0.097	−0.095	−0.095	−0.091
	(−2.21)	(−2.19)	(−2.16)	(−2.13)
	[−2.25]	[−2.21]	[−2.21]	[−2.19]
BM	0.180	0.171	0.177	0.146
	(3.79)	(3.69)	(3.75)	(3.23)
	[3.95]	[3.81]	[3.91]	[3.34]
NYTURN	−0.170	−0.167	−0.162	−0.161
	(−4.56)	(−4.67)	(−4.42)	(−4.59)
	[−4.63]	[−4.74]	[−4.46]	[−4.67]
RET2-3	0.783	0.876	0.795	0.973
	(2.71)	(3.11)	(2.79)	(3.53)
	[2.86]	[3.29]	[2.93]	[3.67]
RET4-6	0.936	0.965	0.962	1.018
	(3.96)	(4.23)	(4.12)	(4.54)
	[4.18]	[4.44]	[4.35]	[4.73]

Table 2
(continued)

	Unscaled	Size + BM	def	(Size + BM) def
RET7-12	1.0162	1.066	1.067	1.090
	(7.32)	(7.56)	(7.35)	(7.84)
	[7.46]	[8.04]	[7.84]	[8.29]
$\bar{R}^2(\%)$	4.70	4.56	4.66	4.50

This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates. Panel A (B) presents the monthly results for NYSE-AMEX and NASDAQ (NYSE-AMEX) stocks over 450 months from July 1964 through December 2001. In the second column, the dependent variable is the excess return risk-adjusted using the excess market return as the risk factor. In the third, the dependent variable is the excess return risk-adjusted using the excess market return when the market beta is scaled by size and book-to-market ratio. In the fourth, default spread (yield differential between BBB- and AAA- rated bonds) is used as a scaling variable. In the last column, beta of stock j is modeled as

$$\beta_{jt-1} = \beta_{j1} + \beta_{j2}z_{t-1} + (\beta_{j3} + \beta_{j4}z_{t-1})\ Size_{jt-1} + (\beta_{j5} + \beta_{j6}z_{t-1})\ BM_{jt-1},$$

where z is the default spread. Size represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio with the exception that 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. NYTURN (NASDTURN) is turnover of NYSE-AMEX (NASDAQ) stocks. RET2-3, RET4-6, and RET7-12 are the cumulative returns over the second through third, fourth through sixth, and seventh through twelfth months before the current month or quarter respectively. $\bar{R}^2$ is the time-series average of the monthly adjusted R^2. The t-statistics in parenthesis use standard errors as per Shanken (1990), and the t-statistics in the square brackets use standard errors as in Jagannathan and Wang (1998). All coefficients are multiplied by 100.

Panel A of Table 2 documents that with the unscaled excess market return as a risk factor in monthly cross-sectional regressions, the coefficient on size is significantly negative; it is significantly positive on the book-to-market ratio; significantly negative on NYSE-AMEX and NASDAQ turnovers; and significantly positive on all lagged returns. Moreover, time-varying beta has virtually no impact on the significance of the firm characteristics in the cross-sectional regressions. There is a marginal decline in the average-adjusted R^2 from 4.42 to 4.26% as conditioning variables are added. Overall, conditional and unconditional versions of the single-factor CAPM do not capture any of the size, book-to-market, turnover, and momentum effects in individual stock returns. The failure of the CAPM is further reinforced below.

Panel B of Table 2 summarizes the Fama–MacBeth coefficient estimates of the monthly cross-sectional regressions for the NYSE-AMEX sample. As before, small, value firms with low-turnover and high past returns earn higher risk-adjusted returns. Also, conditioning does not call into question the significance of the above firm characteristics, although there is a marginal reduction in $\bar{R}^2$ from 4.70% in the unconditional model to 4.50% when the conditioning is as described in Equation (7). We conclude that the CAPM, both conditionally and unconditionally, altogether fails to capture the impact of firm characteristics on risk-adjusted returns.

4.2 Fama–French three-factor model

Panel A of Table 3 summarizes that the Fama–MacBeth coefficient estimates, when using the unscaled Fama–French risk factors, are qualitatively similar to those based on CAPM. Although the coefficient estimates are lower in absolute value terms (−0.10 as opposed to −0.16 for size and 0.10 as opposed to 0.18 for book-to-market) all the coefficients are significant as before. The big difference is that the average-adjusted R^2 is 2.43% as opposed to 4.42%, suggesting that the Fama–French model, although not perfect, is at least better than the CAPM in capturing the predictive power of firm attributes.

When the Fama–French factors are scaled by the firm-specific size and book-to-market ratio, the coefficient on the firm characteristic book-to-market is no longer significant. Moreover, when the relationship between betas and size as well as book-to-market is allowed to vary over the business cycle with the default spread in the last column of Table 3, the characteristics firm size and the book-to-market ratio, both, are no longer important in explaining the cross-section of returns under all scenarios. The t-statistics on SIZE and BM are −1.93 and 0.31, respectively, when the Fama–MacBeth standard errors are corrected using the methodology in Jagannathan and Wang (1998).[7] $\bar{R}^2$ also decreases from 2.43% for the unscaled model to 2.23% for the scaled model with time-varying scaling. Note that the unscaled model shows that the Fama–French factors related to size, SMB, and book-to-market, HML, do not capture the impact of the firm characteristics size and book-to-market on the cross-section of individual stock returns; it is only when the factor loadings are conditioned on size, book-to-market, and the default spread that the scaled Fama–French model is able to capture the impact of the size and book-to-market characteristics. Using default spread only does not help explain any of the so-called financial market anomalies.

Panel B of Table 3 focuses on NYSE-AMEX firms only. There is no impact of size and book-to-market on the cross-section of individual stock returns when the factor loadings are conditioned on (i) size and book-to-market or (ii) size, book-to-market, and the default spread. Also, $\bar{R}^2$ declines from 2.62% in the case of the unconditional model to 2.26% when factor loadings vary as described in Equation (7).

One may argue that it is not surprising that conditioning on size and book-to-market captures the size and book-to-market effects. However,

[7] We present the OLS, Shanken (1992) corrected and Jagannathan and Wang (1998) corrected t-statistics. In general, the Jagannathan and Wang (1998) corrected t-statistics are higher than those using the Shanken correction and are often higher than the OLS t-statistics.

Table 3
Fama–MacBeth regression estimates with excess market return, SMB, and HML as risk factors

	Unscaled	Size + BM	def	(Size + BM) def
Panel A: NYSE-AMEX and NASDAQ stocks—monthly frequency				
Intercept	0.008	−0.360	−0.350	−0.339
	{0.65}	{−3.44}	{−3.33}	{−2.51}
	(0.63)	(−3.34)	(−3.24)	(−2.44)
	[0.15]	[−3.44]	[−3.15]	[−2.39]
Nasd	0.193	0.291	0.254	0.277
	{2.58}	{3.40}	{2.80}	{3.55}
	(2.51)	(3.30)	(2.72)	(3.45)
	[2.44]	[3.93]	[2.63]	[3.56]
SIZE	−0.099	−0.065	−0.086	−0.047
	{−3.24}	{−2.36}	{−2.88}	{−1.85}
	(−3.15)	(−2.29)	(−2.80)	(−1.80)
	[−3.74]	[−2.44]	[−3.14]	[−1.93]
BM	0.096	0.052	0.069	0.008
	{2.78}	{1.70}	{2.10}	{0.28}
	(2.70)	(1.65)	(2.04)	(0.27)
	[2.88]	[1.76]	[2.25]	[0.31]
NYTURN	−0.123	−0.113	−0.122	−0.115
	{−3.49}	{−3.49}	{−3.51}	{−3.81}
	(−3.39)	(−3.39)	(−3.41)	(−3.70)
	[−3.62]	[−3.52]	[−3.60]	[−4.08]
NASDTURN	−0.106	−0.083	−0.099	−0.087
	{−2.06}	{−1.80}	{−1.98}	{−2.07}
	(−2.00)	(−1.75)	(−1.92)	(−2.01)
	[−2.39]	[−1.86]	[−2.04]	[−2.07]
RET2-3	0.639	0.834	0.557	0.859
	{2.67}	{3.71}	{2.36}	{3.74}
	(2.59)	(3.60)	(2.29)	(3.63)
	[2.75]	[3.76]	[2.40]	[3.78]
RET4-6	0.755	0.880	0.755	0.902
	{4.21}	{5.31}	{4.34}	{5.48}
	(4.09)	(5.16)	(4.22)	(5.32)
	[4.45]	[5.62]	[4.75]	[5.77]
RET7-12	0.742	0.796	0.716	0.768
	{6.14}	{7.26}	{5.93}	{7.37}
	(5.97)	(7.05)	(5.76)	(7.16)
	[5.95]	[7.17]	[5.82]	[7.38]
$\bar{R}^2$(%)	2.43	2.25	2.38	2.23
Panel B: NYSE-AMEX stocks—monthly frequency				
Intercept	−0.038	−0.041	−0.051	−0.024
	{−0.80}	{−1.10}	{−1.16}	{−0.74}
	(−0.78)	(−1.07)	(−1.13)	(−0.72)
	[−0.71]	[−0.90]	[−1.10]	[−0.82]
SIZE	−0.041	−0.018	−0.036	−0.012
	{−1.65}	{−0.81}	{−1.48}	{−0.57}
	(−1.60)	(−0.79)	(−1.44)	(−0.55)
	[−1.84]	[−0.87]	[−1.65]	[−0.63]
BM	0.100	0.018	0.065	0.003
	{2.93}	{0.63}	{2.01}	{0.11}
	(2.85)	(0.61)	(1.95)	(0.11)
	[3.19]	[0.66]	[2.21]	[0.12]

Table 3
(continued)

	Unscaled	Size + BM	def	(Size + BM) def
NYTURN	−0.166	−0.180	−0.162	−0.143
	{−4.89}	{−5.52}	{−4.85}	{−4.96}
	(−4.75)	(−5.36)	(−4.71)	(−4.82)
	[−5.02]	[−5.63]	[−5.01]	[−5.06]
RET2-3	0.769	0.991	0.678	0.969
	{3.00}	{4.11}	{2.69}	{4.05}
	(2.92)	(3.99)	(2.61)	(3.94)
	[3.12]	[4.21]	[2.79]	[4.12]
RET4-6	0.919	1.079	0.907	1.060
	{4.47}	{5.50}	{4.54}	{5.82}
	(4.34)	(5.34)	(4.41)	(5.66)
	[4.84]	[5.75]	[4.92]	[6.05]
RET7-12	0.987	1.023	0.942	0.972
	{7.37}	{8.55}	{7.05}	{8.53}
	(7.16)	(8.31)	(6.85)	(8.29)
	[7.46]	[8.63]	[7.06]	[8.53]
$\bar{R}^2$(%)	2.62	2.34	2.54	2.26

This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates. Panel A (B) presents the monthly results for NYSE-AMEX and NASDAQ (NYSE-AMEX) stocks over 450 months from July 1964 through December 2001. In the second column, the dependent variable is the excess return risk-adjusted using the Fama–French (1993) factors. In the third, the dependent variable is the excess return risk-adjusted using the Fama–French factors with loadings scaled by size and book-to-market ratio. In the fourth, default spread (yield differential between BBB- and AAA-rated bonds) is used as a scaling variable. In the last column, each of the factor loadings of stock j is modeled as

$$(\beta_{jt-1} = \beta_{j1} + \beta_{j2}z_{t-1} + (\beta_{j3} + \beta_{j4}z_{t-1})Size_{jt-1} + (\beta_{j5} + \beta_{j6}z_{t-1})BM_{jt-1},$$

where z is the default spread. Size represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio with the exception that 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. NYTURN (NASDTURN) is turnover of NYSE-AMEX (NASDAQ) stocks. RET2-3, RET4-6, and RET7-12 are the cumulative returns over the second through third, fourth through sixth, and seventh through twelfth months before the current month or quarter, respectively. $\bar{R}^2$ is the time-series average of the monthly adjusted R^2. The OLS t-statistics are presented under the coefficient estimates, t-statistics in parenthesis use standard errors as per Shanken (1990), and the t-statistics in the square brackets use standard errors as in Jagannathan and Wang (1998). T-statistics in curly brackets are unadjusted by a potential error-in-variables bias. All coefficients are multiplied by 100.

there is no mechanical reason for why such conditioning would capture the impact of the characteristics, firm size and book-to-market ratio, on the cross-section of returns. It can very well be the case that the value effect and the size effect represent mispricing that is completely unrelated to risk. Conditioning factor loadings on size and book-to-market simply attempts to better characterize risk, as suggested by the theoretical model of GKZ (2003). If risk is completely unrelated to the size and value effects, then conditional versions of pricing models will not capture the size and value effects.

Also, observe from Table 2 that scaling the market beta by size and book-to-market does not capture any of the size and book-to-market effects. It is only when the excess market return is augmented by SMB and HML and when the factor loadings on SMB and HML are scaled by macroeconomic and firm-level variables, does the impact of size and book-to-market disappear.[8] Note also from the unconditional Fama–French model that SMB and HML do not capture the size and book-to-market effects in individual stock returns, even when Fama and French (1996) show that SMB and HML capture the size and book-to-market effects on portfolio returns.[9]

Why does the conditional Fama–French model capture the impact of size and book-to-market? It must be due to the time variation in factor loadings. In Figure 1, we plot the cross-sectional averages of the factor

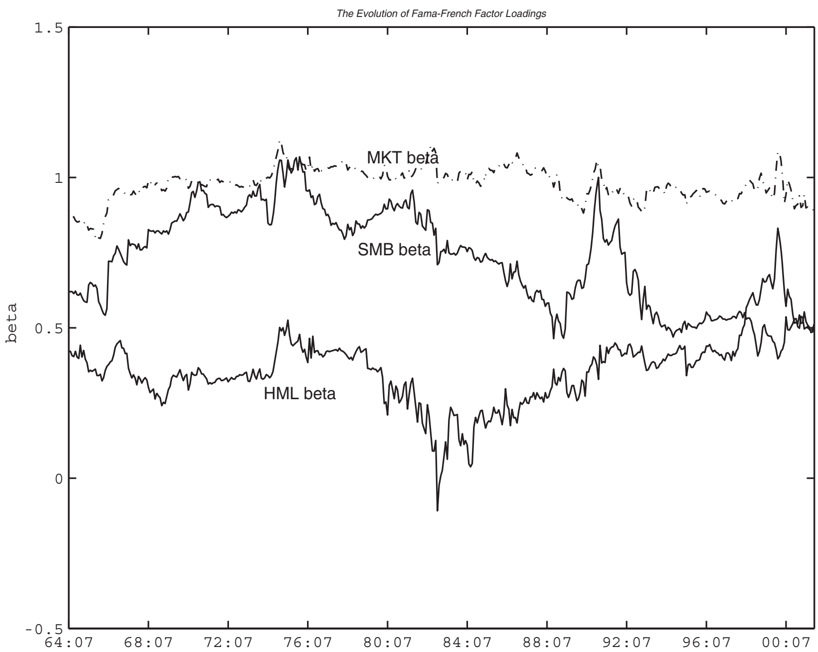

Figure 1
The figure plots the cross-sectional averages of the Fama–French factor loadings over the sample period when beta is scaled by firm-level size and book-to-market and by the default spread.

[8] We have also conditioned the excess market return and the Fama–French factors by turnover and the past twelve-month returns to find that the strong impact of turnover and momentum on the cross-section of individual stock returns remains undiminished.

[9] Even Fama and French (1993) use the Gibbons, Ross, and Shanken test statistic to show that their three-factor model rejects the null of (joint) zero intercepts for their test portfolios (see page 41 in their paper). However, they do argue that the rejection is marginal and suggest that the model can be useful in practical applications.

loadings for the Fama–French factors over the sample period. We demonstrate that there is substantial intertemporal variation in the factor loadings of SMB and HML. Moreover, the time variation in the market beta and the SMB beta appears to be related to the business cycle. To see this, we form a time series variable, denoted Recession, that is set to one during recessions and zero otherwise.[10] The correlation between Recession and the factor loading on the excess market return (SMB) is a statistical significant 0.19 (0.30) suggesting that the betas on the excess market return and the SMB increase during recessions.

The evidence is important, among other things, because there is a research controversy about what explains expected returns, risk factors, or equity characteristics. Daniel and Titman (1997) question the risk-based Fama–French model, arguing that it is the security characteristics, size and book-to-market, and not the loadings on SMB and HML that have an impact on the cross-section of security returns. Here, we document that a conditional Fama–French model captures the impact of size and book-to-market on expected returns, providing support to a risk-based story.

Let us point out that given the strong persistence in firm-level debt and shares outstanding, one may argue that firm size and the book-to-market ratio fluctuate mainly with recent past stock returns. Thus, one may conjecture that factor loadings should be conditioned on past returns, not on size and book-to-market. Indeed, we have estimated a model where the Fama–French factor loadings are conditioned by past twelve-month returns. We have found that such a specification *does not* capture the impact of size and book-to-market on the cross-section of expected returns.

4.3 Fama–French model plus a liquidity factor

Conditional and unconditional versions of the CAPM and the Fama–French model are unable to capture the impact on expected returns, of the firm predictor related to liquidity, the monthly trading volume as measured by the share turnover. Thus, it is natural to ask whether the introduction of a factor related to liquidity would be able to eliminate the impact of turnover. Here, we augment the Fama–French model with a proxy for the Pastor–Stambaugh (2003) liquidity factor. Pastor and Stambaugh show that the average return on stocks with high sensitivities to liquidity exceeds that for stocks with low sensitivities by 7.5% annually. Our liquidity factor is the difference between value-weighted average return on stocks with high sensitivities to liquidity less the value-weighted average return on stocks with low sensitivities to liquidity.[11]

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[10] The business cycle expansions and contractions are dated by the NBER and can be obtained from http://www.nber.com/cycles/cyclesmain.html.

[11] We thank Lubos Pastor for providing this factor.

The monthly results for NYSE-AMEX and NASDAQ stocks are in panel A of Table 4. The unscaled model has the same average $\bar{R}^2$ as the Fama–French model, suggesting that the inclusion of the liquidity factor does not improve the model ability to explain the predictive power of equity characteristics. Also, the coefficient estimates for NYTURN and NASDTURN are in general larger in absolute value and more significant than if the liquidity factor were not included. This continues to hold even when the conditional versions of the model are used. Thus, the liquidity factor does not capture the impact of turnover on the cross-section of individual stock returns.

Panel B of Table 4 summarizes that for the NYSE-AMEX sample, conditioning beta on size and book-to-market captures the impact of the firm characteristics size and book-to-market. In fact, when conditioning is allowed to vary over time with the default spread, the average $\bar{R}^2$ is the lowest across all models and frequencies; it should be noted, however,

Table 4
Fama–MacBeth regression estimates with excess market return, SMB, HML, and liquidity as risk factors

	Unscaled	Size + BM	def	(Size + BM) def
Panel A: NYSE-AMEX and NASDAQ stocks—Monthly frequency				
Intercept	−0.045	−0.312	−0.397	−0.243
	(−3.79)	(−2.75)	(−2.69)	(−1.51)
	[−3.82]	[−2.77]	[−2.70]	[−1.45]
Nasd	0.209	0.242	0.192	0.209
	(1.84)	(2.52)	(1.78)	(2.35)
	[2.57]	[2.72]	[2.53]	[3.07]
SIZE	−0.094	−0.056	−0.082	−0.031
	(−3.07)	(−2.09)	(−2.76)	(−1.31)
	[−3.38]	[−2.32]	[−3.05]	[−1.47]
BM	0.099	0.050	0.065	0.003
	(2.66)	(1.61)	(1.87)	(0.10)
	[3.00]	[1.75]	[2.08]	[0.12]
NYTURN	−0.127	−0.114	−0.122	−0.109
	(−3.64)	(−3.77)	(−3.58)	(−3.93)
	[−4.08]	[−4.20]	[−4.02]	[−4.38]
NASDTURN	−0.117	−0.106	−0.098	−0.119
	(−2.51)	(−2.64)	(−2.20)	(−3.46)
	[−2.85]	[−2.90]	[−2.39]	[−3.76]
RET2-3	0.686	0.846	0.543	0.783
	(2.75)	(3.53)	(2.17)	(3.18)
	[3.03]	[3.87]	[2.39]	[3.40]
RET4-6	0.855	1.021	0.840	0.983
	(4.38)	(5.79)	(4.46)	(5.72)
	[5.08]	[6.49]	[5.15]	[6.42]
RET7-12	0.765	0.810	0.696	0.776
	(5.89)	(7.03)	(5.38)	(7.20)
	[6.78]	[7.87]	[6.21]	[8.20]
$\bar{R}^2$(%)	2.43	2.03	2.21	2.03

Table 4
(continued)

	Unscaled	Size + BM	def	(Size + BM) def
Panel B: NYSE-AMEX stocks — Monthly Frequency				
Intercept	−0.016	−0.024	−0.026	−0.027
	(−0.38)	(−0.68)	(−0.67)	(−0.92)
	[−0.40]	[−0.63]	[−0.79]	[−1.21]
SIZE	−0.042	−0.008	−0.038	−0.005
	(−1.61)	(−0.36)	(−1.47)	(−0.23)
	[−1.77]	[−0.40]	[−1.66]	[−0.27]
BM	0.102	0.020	0.067	−0.039
	(2.74)	(0.68)	(1.90)	(−1.43)
	[3.09]	[0.73]	[2.14]	[−1.54]
NYTURN	−0.171	−0.195	−0.159	−0.149
	(−4.98)	(−5.88)	(−4.77)	(−5.26)
	[−5.57]	[−6.49]	[−5.32]	[−5.86]
RET2-3	0.837	0.982	0.682	1.007
	(3.06)	(3.76)	(2.54)	(3.86)
	[3.36]	[4.18]	[2.78]	[4.23]
RET4-6	1.018	1.167	1.004	1.183
	(4.51)	(5.56)	(4.61)	(6.14)
	[5.09]	[6.13]	[5.26]	[6.91]
RET7-12	1.032	0.978	0.957	0.926
	(7.11)	(7.68)	(6.69)	(7.82)
	[8.12]	[8.59]	[7.69]	[8.77]
$\bar{R}^2$ (%)	2.51	2.07	2.40	1.99

This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates. Panel A (B) presents the monthly results for NYSE-AMEX and NASDAQ (NYSE-AMEX) stocks over 450 months from July 1964 through December 2001. The dependent variable in the second column (unscaled) is the excess return risk-adjusted using the Fama–French (1993) factors augmented by the Pastor–Stambaugh (2003) liquidity factor. In the third, the dependent variable is the excess return risk-adjusted using the above factors with loadings scaled by size and book-to-market ratio. In the fourth, default spread (yield differential between BBB- and AAA-rated bonds) is used as a scaling variable. In the last column, each of the factor loadings of stock j is modeled as

$$\beta_{jt-1} = \beta_{j1} + \beta_{j2} z_{t-1} + (\beta_{j3} + \beta_{j4} z_{t-1})\ Size_{jt-1} + (\beta_{j5} + \beta_{j6} z_{t-1})\ BM_{jt-1},$$

where z is the default spread. Size represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio with the exception that 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. NYTURN (NASDTURN) is turnover of NYSE-AMEX (NASDAQ) stocks. RET2-3, RET4-6, and RET7-12 are the cumulative returns over the second through third, fourth through sixth, and seventh through twelfth months before the current month or quarter, respectively. $\bar{R}^2$ is the time-series average of the monthly adjusted R^2. The t-statistics in parenthesis use standard errors as per Shanken (1990), and the t-statistics in the square brackets use standard errors as in Jagannathan and Wang (1998). All coefficients are multiplied by 100.

that the improvement in capturing the impact of the firm characteristics may be marginal when the liquidity factor is included in the asset pricing specification. Most of the improvement in explaining the impact of size and book-to-market is already captured by the Fama–French three-factor model. Ultimately, including liquidity factor does not capture the impact of turnover and past returns in the cross-section of individual stock returns.

While we have shown that the liquidity factor does not capture the impact of turnover on expected returns, we would like to issue some caveats. With turnover as an explanatory variable in the second stage regression, we have focused on the impact of the level of liquidity on returns, whereas the Pastor–Stambaugh measure is designed to capture the impact of liquidity risk.[12] We have used the value-weighted average return on stocks with high sensitivities to liquidity less the value-weighted average return on stocks with low sensitivities to liquidity as a proxy for the Pastor–Stambaugh's non-traded liquidity factor. We do not rule out a case where a different choice of a liquidity factor may capture the impact of turnover on expected returns.

4.4 Fama–French model plus a Momentum factor

No model examined thus far has been able to explain the impact of past returns on the cross-section of individual stock returns. Here, we ask whether a commonly used factor created on the basis of past returns can capture the impact of past returns. More specifically, we use a factor for momentum obtained from Ken French's website.[13] This factor will be denoted WML for winners minus losers on the basis of the momentum strategy of buying winners and selling losers as depicted by Jegadeesh and Titman (1993). Note that there is no theoretical basis for using WML as a risk factor. Even so, it is instructive to ask whether the extensively used momentum factor can capture the impact of past returns on the cross-section of returns.

The results are summarized in Table 5. It is immediately clear from both panels that past returns continue to have an impact on expected returns, even when WML is included in the first-pass time series regressions. Thus, for the sample of NYSE-AMEX and NASDAQ stocks as well as for the sample of NYSE-AMEX stocks, WML does not capture the impact of past three-, six-, and twelve-month returns on the cross-section of returns. Similarly, conditioning beta on size, book-to-market, and default spread does not explain the predictive power of past returns. The only benefit from using WML in an asset pricing context is that it seems to capture the impact of NASDAQ turnover on returns. The coefficient on NASDTURN is no longer significantly different from zero even under the unscaled specification. The average $\bar{R}^2$, although an improvement upon the Fama–French model, is slightly higher than that of Table 4 when the Fama–French model is augmented by the

[12] We have also experimented with a value-weighted portfolio that is long on high turnover decile stocks and is short on low turnover decile stocks. This liquidity factor performed worse than the Pastor–Stambaugh factor in terms of capturing the impact of characteristics on the cross-section of returns.

[13] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

liquidity factor. Ultimately, a factor based on momentum, WML, does not capture the impact of past returns on the cross-section of individual stock returns.

Table 5
Fama–MacBeth regression estimates with excess market return, SMB, HML, and momentum as risk factors

	Unscaled	Size + BM	def	(Size + BM) def
Panel A: NYSE-AMEX and NASDAQ stocks—monthly frequency				
Intercept	0.158	0.105	0.125	0.070
	(2.64)	(2.14)	(2.22)	(1.63)
	[2.53]	[2.06]	[2.15]	[1.59]
Nasd	0.231	0.312	0.259	0.279
	(2.60)	(3.91)	(3.02)	(3.82)
	[2.66]	[4.07]	[3.18]	[4.09]
SIZE	−0.101	−0.050	−0.077	−0.015
	(−3.14)	(−1.77)	(−2.47)	(−0.59)
	[−3.24]	[−1.98]	[−2.54]	[−0.67]
BM	0.099	0.021	0.082	0.000
	(2.68)	(0.68)	(2.37)	(0.01)
	[2.99]	[0.74]	[2.56]	[0.01]
NYTURN	−0.098	−0.113	−0.097	−0.108
	(−2.65)	(−3.41)	(−2.69)	(−3.60)
	[−2.69]	[−3.68]	[−2.75]	[−3.96]
NASDTURN	−0.048	−0.169	−0.033	−0.040
	(−0.91)	(−0.37)	(−0.65)	(−0.98)
	[−1.02]	[−1.07]	[−0.71]	[−1.13]
RET2-3	0.606	0.714	0.474	0.754
	(2.46)	(3.11)	(1.98)	(3.24)
	[2.22]	[2.98]	[1.78]	[3.21]
RET4-6	0.743	0.765	0.691	0.717
	(4.11)	(4.72)	(3.98)	(4.56)
	[4.73]	[5.53]	[4.51]	[5.31]
RET7−12	0.720	0.701	0.670	0.666
	(5.80)	(6.54)	(5.47)	(6.74)
	[5.54]	[6.52]	[5.15]	[6.72]
$\bar{R}^2$(%)	2.41	2.09	2.31	2.06
Panel B: NYSE−AMEX stocks—monthly frequency				
Intercept	0.078	0.064	0.061	0.107
	(1.75)	(1.89)	(1.49)	(1.44)
	[2.05]	[2.01]	[1.68]	[1.03]
SIZE	−0.044	−0.013	−0.028	0.024
	(−1.68)	(−0.56)	(−1.11)	(0.87)
	[−1.94]	[−0.69]	[−1.26]	[1.36]
BM	0.107	0.015	0.086	−0.118
	(2.95)	(0.50)	(2.48)	(−1.27)
	[3.32]	[0.56]	[2.87]	[−1.47]
NYTURN	−0.138	−0.137	−0.132	−0.117
	(−3.84)	(−4.27)	(−3.77)	(−2.58)
	[−4.06]	[−4.73]	[−4.01]	[−4.41]
RET2-3	0.700	0.820	0.558	1.033
	(2.63)	(3.37)	(2.16)	(1.84)
	[2.45]	[3.34]	[2.03]	[3.50]

Table 5
(continued)

	Unscaled	Size + BM	def	(Size + BM) def
RET4-6	0.881	0.903	0.803	0.699
	(4.17)	(4.97)	(3.95)	(2.54)
	[4.62]	[5.87]	[4.36]	[4.66]
RET7-12	0.958	0.925	0.890	0.795
	(6.88)	(7.86)	(6.54)	(4.14)
	[6.82]	[8.22]	[6.28]	[7.26]
$\bar{R}^2$(%)	2.58	2.20	2.46	2.03

This table presents the timeseries averages of individual stock crosssectional OLS regression coefficient estimates. Panel A (B) presents the monthly results for NYSE-AMEX and NASDAQ (NYSE-AMEX) stocks over 450 months from July 1964 through December 2001. The dependent variable in the second column (unscaled) is the excess return risk-adjusted using the Fama–French (1993) factors augmented by a momentum factor obtained from Ken French's web page. In the third, the dependent variable is the excess return risk-adjusted using the above factors with loadings scaled by size and book-to-market ratio. In the fourth, default spread (yield differential between BBB- and AAA-rated bonds) is used as a scaling variable. In the last column, each factor loading of stock j is modeled as

$$\beta_{jt-1} = \beta_{j1} + \beta_{j2}z_{t-1} + (\beta_{j3} + \beta_{j4}z_{t-1})\ Size_{jt-1} + (\beta_{j5} + \beta_{j6}z_{t-1})\ BM_{jt-1},$$

where z is the default spread. Size represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio with the exception that 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. NYTURN (NASDTURN) is turnover of NYSE-AMEX (NASDAQ) stocks. RET2-3, RET4-6, and RET7-12 are the cumulative returns over the second through third, fourth through sixth, and seventh through twelfth months before the current month or quarter, respectively. $\bar{R}^2$ is the time-series average of the monthly adjusted R^2. The t-statistics in parenthesis use standard errors as per Shanken (1990), and the t-statistics in the square brackets use standard errors as in Jagannathan and Wang (1998). All coefficients are multiplied by 100.

4.5 Jagannathan and Wang Model

Here, the time series regressions use the excess return on the market portfolio and return on a zero cost portfolio that is maximally correlated with growth in per capita labor income as risk factors. The results are summarized in Table 6.

Starting with panel A, at the monthly frequency when all stocks are included, we find that firm characteristics are *all* important in explaining the cross-section of stock returns. Moving to panel B, when the monthly sample is limited to NYSE-AMEX stocks, the evidence based on the unscaled version is similar to that based on the entire sample; all characteristics are important in explaining the cross-section of returns. When betas vary with size and book-to-market, the size effect in stock returns is explained, but the value effect is still prominent. The average-adjusted R^2 is lower than when only the excess market return is used as a risk factor. However, the Fama–French factor with or without the liquidity risk factor or WML does have better explanatory power for the firm characteristics under consideration, generating a lower adjusted R^2. Overall, including human capital in the overall market wealth could improve the

Table 6
Fama–MacBeth regression estimates with the market portfolio and the maximally correlated portfolio with labor income as risk factors

	Unscaled	Size + BM	def	(Size + BM) def
Panel A: NYSE-AMEX and NASDAQ stocks—monthly frequency				
Intercept	0.343	0.325	0.302	0.264
	(2.71)	(2.66)	(2.45)	(2.31)
	[2.46]	[2.48]	[2.54]	[2.67]
Nasd	0.182	0.139	0.059	0.097
	(1.47)	(1.44)	(0.82)	(1.08)
	[1.92]	[1.03]	[1.03]	[1.13]
SIZE	−0.149	−0.130	−0.132	−0.106
	(−3.29)	(−2.96)	(−2.96)	(−2.56)
	[−3.44]	[−3.04]	[−3.14]	[−2.65]
BM	0.168	0.159	0.176	0.137
	(3.49)	(3.48)	(3.74)	(3.15)
	[3.70]	[3.59]	[4.12]	[3.33]
NYTURN	−0.139	−0.143	−0.140	−0.141
	(−3.79)	(−4.11)	(−3.90)	(−4.19)
	[−3.87]	[−4.06]	[−4.13]	[−4.35]
NASDTURN	−0.168	−0.163	−0.194	−0.187
	(−2.32)	(−2.38)	(−2.91)	(−3.10)
	[−2.47]	[−2.59]	[−3.00]	[−3.25]
RET2-3	0.627	0.715	0.633	0.817
	(2.34)	(2.69)	(2.38)	(3.04)
	[2.53]	[2.88]	[2.55]	[3.23]
RET4-6	0.757	0.787	0.736	0.788
	(3.73)	(4.01)	(3.68)	(4.07)
	[4.03]	[4.23]	[3.97]	[4.30]
RET7-12	0.720	0.704	0.714	0.686
	(5.56)	(5.69)	(5.53)	(5.68)
	[5.99]	[5.89]	[6.15]	[6.05]
$\bar{R}^2$(%)	4.20	4.06	4.13	3.99
Panel B: NYSE-AMEX stocks—monthly frequency				
Intercept	0.283	0.254	0.244	0.209
	(2.42)	(2.29)	(2.13)	(2.01)
	[2.54]	[2.31]	[2.30]	[2.09]
SIZE	−0.090	−0.066	−0.077	−0.059
	(−2.11)	(−1.60)	(−1.85)	(−1.51)
	[−2.20]	[−1.64]	[−1.94]	[−1.55]
BM	0.173	0.185	0.174	0.147
	(3.63)	(4.14)	(3.72)	(3.42)
	[3.86]	[4.21]	[3.83]	[3.61]
NYTURN	−0.185	−0.185	−0.184	−0.184
	(−5.17)	(−5.45)	(−5.26)	(−5.67)
	[−5.28]	[−5.38]	[−5.55]	[−5.82]
RET2-3	0.768	0.918	0.798	0.974
	(2.69)	(3.29)	(2.82)	(3.56)
	[2.89]	[3.47]	[3.07]	[3.77]
RET4-6	0.919	0.965	0.908	0.929
	(3.93)	(4.27)	(3.94)	(4.23)
	[3.79]	[4.50]	[4.26]	[4.48]

Table 6
(continued)

	Unscaled	Size + BM	def	(Size + BM) def
RET7-12	0.956	0.921	0.952	0.913
	(6.63)	(6.69)	(6.61)	(6.76)
	[7.13]	[6.89]	[7.35]	[7.19]
$\bar{R}^2(\%)$	4.47	4.31	4.45	4.26

This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates. Panel A (B) presents the monthly results for NYSE-AMEX and NASDAQ (NYSE-AMEX) stocks over 450 months from July 1964 through December 2001. In the second column, the dependent variable is the excess return risk-adjusted using the excess market return as well as a factor that is maximally correlated with labor income growth. In the third, the dependent variable is the excess return risk-adjusted using the above factors with loadings scaled by size and book-to-market ratio. In the fourth, default spread (yield differential between BBB- and AAA-rated bonds) is used as a scaling variable. In the last column, beta of stock j is modeled as

$$\beta_{jt-1} = \beta_{j1} + \beta_{j2}z_{t-1} + (\beta_{j3} + \beta_{j4}z_{t-1})\ Size_{jt-1} + (\beta_{j5} + \beta_{j6}z_{t-1})\ BM_{jt-1},$$

where z is the default spread. Size represents the logarithm of market capitalization in billions of dollars, BM is the logarithm of the book-to-market ratio with the exception that 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. NYTURN (NASDTURN) is turnover of NYSE-AMEX (NASDAQ) stocks. RET2-3, RET4-6, and RET7-12 are the cumulative returns over the second through third, fourth through sixth, and seventh through twelfth months before the current month or quarter, respectively. $\bar{R}^2$ is the time-series average of the monthly adjusted R^2. The t-statistics in parenthesis use standard errors as per Shanken (1990), and the t-statistics in the square brackets use standard errors as in Jagannathan and Wang (1998). All coefficients are multiplied by 100.

pricing ability of a model to explain the impact of firm size if one considers the time-varying beta version of the model.

4.6 Consumption-based CAPM

The Consumption Capital Asset Pricing Model (CCAPM) is theoretically appealing because it accounts for intertemporal consumption portfolio decisions, and unlike the CAPM, it integrates other forms of wealth beyond financial wealth. The consumption data is available at a quarterly frequency, and we use a factor-mimicking portfolio that is maximally correlated with consumption growth in the time series regressions.

Table 7 summarizes the results. All of the coefficients are highly significant and, moreover, the size effect is reversed. Large firms earn higher returns. The value effect, the liquidity effect, and the momentum effect are all strongly present in the data. The average-adjusted R^2 is over 14% compared to 2.5% for the Fama–French three-factor model. The evidence thus suggests that the linear version of the CCAPM fails to explain the impact of size, book-to-market, turnover, and past return, even when the consumption beta varies with the default spread. In unreported tests, we have also checked for robustness by conditioning beta on the consumption-wealth ratio of Lettau and Ludvigson (2001). This does not alter the evidence against the CCAPM.

Table 7
Fama–MacBeth regression estimates with the maximally correlated portfolio with consumption growth as the risk factor

	Unscaled	Size + BM	def	(Size + BM) def
Intercept	−0.332	−0.545	−0.332	−0.539
	(−37.43)	(−71.13)	(−39.10)	(−79.98)
	[−38.42]	[−73.10]	[−40.14]	[−82.21]
Nasd	0.046	0.002	0.046	−0.007
	(5.89)	(0.30)	(6.44)	(−0.91)
	[6.00]	[0.30]	[6.56]	[−0.92]
SIZE	3.319	4.276	3.519	4.447
	(18.20)	(23.32)	(20.48)	(26.18)
	[18.72]	[23.98]	[21.06]	[26.90]
BM	3.060	4.503	1.860	3.054
	(10.62)	(13.41)	(7.07)	(9.87)
	[10.84]	[13.69]	[7.22]	[10.06]
NYTURN	−1.757	−3.976	−1.774	−3.931
	(−7.80)	(−17.90)	(−8.51)	(−20.17)
	[−8.00]	[−18.34]	[−8.73]	[−20.65]
NASDTURN	−3.004	−7.268	−2.583	−7.337
	(−7.65)	(−15.09)	(−7.14)	(−15.99)
	[−7.87]	[−15.41]	[−7.35]	[−16.30]
RET2-3	8.494	10.232	8.848	10.553
	(5.04)	(4.19)	(5.34)	(4.49)
	[5.13]	[4.27]	[5.45]	[4.57]
RET4-6	4.987	5.633	5.685	6.412
	(3.28)	(2.73)	(3.77)	(3.15)
	[3.34]	[2.78]	[3.84]	[3.21]
RET7-12	3.107	3.478	4.060	4.427
	(3.13)	(2.79)	(4.24)	(3.72)
	[3.20]	[2.84]	[4.33]	[3.79]
$\bar{R}^2$(%)	18.12	18.98	14.90	17.40

This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates. The sample contains 150 quarterly observations from the third quarter of 1964 through the fourth quarter of 2001. In the second column, the dependent variable is the excess return risk-adjusted using a factor that is maximally correlated with consumption growth. In the third, the dependent variable is the excess return risk-adjusted using the above factor with loadings scaled by size and book-to-market ratio. In the fourth, default spread (yield differential between BBB- and AAA-rated bonds) is used as a scaling variable. In the last column, each of the factor loadings of stock j is modeled as

$$\beta_{jt-1} = \beta_{j1} + \beta_{j2} z_{t-1} + (\beta_{j3} + \beta_{j4} z_{t-1})\ Size_{jt-1} + (\beta_{j5} + \beta_{j6} z_{t-1})\ BM_{jt-1},$$

where z is the default spread, def. Size represents the logarithm of market capitalization in billions of dollars, BM is the logarithm of the book-to-market ratio with the exception that 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. NYTURN (NASDTURN) is turnover of NYSE-AMEX (NASDAQ) stocks. RET2-3, RET4-6, and RET7-12 are the cumulative returns over the second through third, fourth through sixth, and seventh through twelfth months before the current month or quarter, respectively. $\bar{R}^2$ is the time-series average of the monthly adjusted R^2. The t-statistics in parenthesis use standard errors as per Shanken (1990), and the t-statistics in the square brackets use standard errors as in Jagannathan and Wang (1998). All coefficients are multiplied by 100.

4.7 Fama–French model plus a liquidity and a momentum factor

In this section, we ask the question whether the conditional version of the Fama–French three-factor model augmented by the Pastor–Stambaugh liquidity factor as well as the momentum factor can capture the impact of the turnover and past returns on stock returns. As conditioning variables, we include size, book-to-market ratio as well as turnover and past twelve-month returns and we allow the scaling to vary over time with the default spread. The results are summarized in Table 8.[14]

The adjusted R^2 for the unconditional and conditional versions of the above-described specification are the lowest amongst all the models considered. Specifically, the $\bar{R}^2$ for the fully conditional model at 1.55% is the lowest recorded here, suggesting that the most general specification of the model in Equation (6) performs the best in terms of explaining the impact of characteristics on the cross-section of returns. However, the coefficient estimates for turnover of NYSE-AMEX stocks as well as the past returns are all highly significant. Ultimately, the impacts of liquidity as measured by turnover and of momentum as measured by past returns on the cross-section of returns remain robust.

In unreported tests (available upon request), we have also considered the most general specification described in Equation (6), setting $X_{jt-1} = Z_{jt-1}$, that is, we use all the right-hand side firm characteristics as conditioning variables as well. Past returns and turnover continue to be highly significant, suggesting that the impact of momentum and liquidity on the cross-section of individual stock returns remains robust.

4.8 Time-varying alphas

The documented inability of well-known risk-based asset pricing models to explain the momentum effect at the stock level is consistent with the evidence in Chordia and Shivakumar (2002). Using a linear time series predictive regression framework, they show that profits to momentum strategies can be explained by macroeconomic predictive variables. In their framework, predictability could be traced to either time-varying risk premia or time-varying asset pricing misspecification, or both [see equation (10) in Avramov (2004)]. Thus, asset pricing misspecification (alpha) could vary with the business cycle in a fashion consistent with profitable momentum strategies. This is precisely what we document in this subsection.

We modify the first-pass regression (8) to account for time-varying alpha

[14] We present results for NYSE-AMEX and NASDAQ stocks. We have checked the results for NYSE-AMEX stocks alone, and the results are qualitatively identical.

Table 8
Fama–MacBeth regression estimates with excess market return, SMB, HML, liquidity, and momentum as risk factors

	Unscaled	Size + BM	def	(Size + BM) def
NYSE-AMEX and NASDAQ stocks - Monthly frequency				
Intercept	0.142	0.123	0.119	0.080
	(2.62)	(3.02)	(2.32)	(2.48)
	[3.01]	[3.29]	[2.68]	[2.79]
Nasd	0.146	0.221	0.151	0.222
	(1.58)	(2.91)	(1.71)	(3.61)
	[1.69]	[3.13]	[1.91]	[4.04]
SIZE	−0.093	−0.051	−0.075	−0.008
	(−3.00)	(−2.10)	(−2.50)	(−0.43)
	[−3.51]	[−2.49]	[−2.93]	[−0.50]
BM	0.106	−0.075	0.075	−0.026
	(2.78)	(−0.03)	(2.13)	(−1.12)
	[3.16]	[−0.03]	[2.40]	[−1.27]
NYTURN	−0.115	−0.093	−0.114	−0.079
	(−3.24)	(−3.43)	(−3.29)	(−3.41)
	[−3.62]	[−3.96]	[−3.73]	[−3.98]
NASDTURN	−0.102	−0.045	−0.084	−0.043
	(−2.21)	(−1.27)	(−1.92)	(−1.59)
	[−2.51]	[−1.47]	[−2.18]	[−1.89]
RET2-3	0.643	0.761	0.486	0.772
	(2.57)	(3.47)	(1.96)	(3.63)
	[3.04]	[4.10]	[2.30]	[4.15]
RET4-6	0.841	0.752	0.772	0.669
	(4.35)	(5.21)	(4.13)	(5.00)
	[5.37]	[6.40]	[4.95]	[6.04]
RET7-12	0.749	0.554	0.677	0.542
	(5.71)	(5.99)	(5.24)	(6.75)
	[6.18]	[6.47]	[5.44]	[7.34]
$\bar{R}^2$(%)	2.23	1.63	2.14	1.55

This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates. The sample includes NYSE-AMEX and NASDAQ stocks over 450 months from July 1964 through December 2001. The dependent variable in the second column (unscaled) is the excess return risk-adjusted using the Fama–French (1993) factors augmented by the Pastor–Stambaugh liquidity factor and a momentum factor obtained from Ken French's web page. In the third, the dependent variable is the excess return risk-adjusted using the above factors with loadings scaled by firm-level size, book-to-market ratio, turnover, and the past twelve month returns. In the fourth, default spread (yield differential between BBB- and AAA-rated bonds) is used as a scaling variable. In the last column, each factor loading of stock j is modeled as

$$\beta_{jt-1} = \beta_{j1} + \beta_{j2}z_{t-1} + (\beta_{j3} + \beta_{j4}z_{t-1})\ Size_{jt-1} + (\beta_{j5} + \beta_{j6}z_{t-1})\ BM_{jt-1} + (\beta_{j7} + \beta_{j8}z_{t-1})\ Turn_{jt-1} + (\beta_{j9} + \beta_{j10}z_{t-1})\ Mom_{jt-1},$$

where z is the default spread. Size represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio with the exception that 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. Turn is turnover, and Mom is past twelve-month return. NYTURN (NASDTURN) is turnover of NYSE-AMEX (NASDAQ) stocks. RET2-3, RET4-6, and RET7-12 are the cumulative returns over the second through third, fourth through sixth, and seventh through twelfth months before the current month or quarter, respectively. $\bar{R}^2$ is the time-series average of the monthly adjusted R^2. The t-statistics in parenthesis use standard errors as per Shanken (1990) and, the t-statistics in the square brackets use standard errors as in Jagannathan and Wang (1998). All coefficients are multiplied by 100.

$$r_{jt} = \alpha_{j0} + \alpha_{j1}BC_{t-1} + \beta_{j1}FF_t + \beta_{j2}z_{t-1}FF_t + \beta_{j3}Size_{jt-1}FF_t + \beta_{j4}z_{t-1}Size_{jt-1}FF_t + \beta_{j5}BM_{jt-1}FF_t + \beta_{j6}z_{t-1}BM_{jt-1}FF_t + u_{jt}, \quad (11)$$

where FF is a vector representing the three Fama–French factors, BC is vector of business cycle variables, including dividend yield, default spread, term spread, and the three month Treasury-bill yield. The betas are all row vectors. Then, R_{jt}^{*} in Equation (3), the dependent variable in the cross-section regressions, is given by $\alpha_{j0} + u_{jt}$. The regression in Equation (11) uses only the Fama–French benchmarks because the conditional three factor model seems to have the best performance in capturing the impact of size and book-to-market on the cross-section of returns. The results are presented in Table 9.

Specifically, Table 9 describes the impact of firm attributes on the component of risk-adjusted returns that is unrelated to business cycle variation. Strikingly, lagged returns are no longer or are even negatively related to the fixed component of risk-adjusted returns. For instance, when the Fama–French factors are scaled by either size and book-to-market ratio or only by the default spread, the coefficient on RET2-3 is significantly negative and the coefficients on RET4-6 and RET7-12 are statistically insignificant. In addition, when beta varies with both firm-level size and book-to-market as well as with macroeconomic variables, as proposed by economic theory, none of the lagged return variables is significant.

The evidence thus suggests that when alpha varies with macroeconomic variables the impact of firm-level lagged returns on the cross-section of expected returns unrelated to business cycle variation is completely eliminated.[15] This in itself does not suggest that momentum is explained within a rational asset pricing model or that momentum represents reward for risk. However, it does suggest that the payoffs to a momentum strategy vary with the business cycle. This evidence is important because the momentum phenomenon, as evidenced by lagged returns, has defied rational explanations and has led to numerous behavioral-based models. We argue that it may be premature to discard rational asset pricing models. It is possible that there exists a yet undiscovered risk factor related to the business cycle that may capture the impact of momentum on the cross-section of individual stock returns.

On the contrary, the coefficient on turnover in Table 9 is highly significant and negative. In fact, compared to Table 3, the absolute

[15] Similarly, Avramov and Chordia (2006) show that optimal portfolios based on time-varying alpha hold stock with high previous year returns. That is, firm-level momentum is captured by alpha that varies with aggregate macroeconomic variables.

Table 9
Fama–MacBeth regression estimates with the Fama–French three factor model and time-varying alpha

	Unscaled	Size + BM	def	(Size + BM) def
Intercept	0.438	0.151	0.476	0.347
	(6.36)	(2.59)	(7.16)	(6.12)
	[6.56]	[2.63]	[7.26]	[6.25]
Nasd	0.899	0.977	0.775	0.550
	(7.15)	(8.54)	(6.05)	(5.31)
	[7.28]	[8.69]	[6.45]	[5.42]
SIZE	−0.292	−0.230	−0.372	−0.285
	(−8.60)	(−7.35)	(−10.98)	(−9.53)
	[−9.63]	[−7.99]	[−11.85]	[−10.36]
BM	−0.118	−0.129	−0.188	−0.175
	(−2.29)	(−2.70)	(−3.68)	(−3.93)
	[−2.41]	[−2.98]	[−3.96]	[−4.29]
NYTURN	−0.244	−0.284	−0.269	−0.311
	(−6.48)	(−8.08)	(−7.29)	(−9.44)
	[−6.83]	[−8.59]	[−7.82]	[−10.05]
NASDTURN	−0.350	−0.480	−0.469	−0.787
	(−5.39)	(−8.41)	(−7.67)	(−14.90)
	[−5.72]	[−8.66]	[−8.10]	[−15.79]
RET2-3	−1.141	−0.694	−1.100	−0.423
	(−3.05)	(−1.97)	(−2.93)	(−1.16)
	[−3.24]	[−2.06]	[−3.08]	[−1.21]
RET4-6	−0.426	−0.231	−0.355	−0.095
	(−1.45)	(−0.83)	(−1.20)	(−0.34)
	[−1.57]	[−0.87]	[−1.28]	[−0.40]
RET7-12	0.273	0.315	0.312	0.370
	(1.27)	(1.55)	(1.44)	(1.86)
	[1.29]	[1.61]	[1.46]	[1.89]
$\bar{R}^2(\%)$	2.91	2.55	2.88	2.37

This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates for NYSE-AMEX and NASDAQ stocks over 450 months from July 1964 through December 2001. The dependent variable in the cross-sectional regression is $\alpha_{j0} + u_{jt+1}$ based on the following time series regression

$$r_{jt} = \alpha_{j0} + \alpha_{j1} BC_{t-1} + \beta_{j1} FF_t + \beta_{j2} z_{t-1} FF_t + \beta_{j3} Size_{jt-1} FF_t + \beta_{j4} z_{t-1} Size_{jt-1} FF_t + \beta_{j5} BM_{jt-1} FF_t + \beta_{j6} z_{t-1} BM_{jt-1} FF_t + u_{jt},$$

where z is the default spread, and BC is a vector of business cycle variables including, default spread, term spread, dividend yield, and the three-month Treasury bill yield. In the second column, the dependent variable has no conditioning variables. In the third, size and book-to-market ratio are the conditioning variables for the factor loadings. In the fourth, default spread is used as a scaling variable for the betas. In the last column, scaling by size and book-to-market is allowed to vary over the business cycle. Size represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio with the exception that 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. NYTURN (NASDTURN) is turnover of NYSE-AMEX (NASDAQ) stocks. RET2-3, RET4-6, and RET7-12 are the cumulative returns over the second through third, fourth through sixth, and seventh through twelfth months before the current month or quarter, respectively. $\bar{R}^2$ is the time-series average of the monthly adjusted R^2. The t-statistics in parenthesis use standard errors as per Shanken (1990), and the t-statistics in the square brackets use standard errors as in Jagannathan and Wang (1998). All coefficients are multiplied by 100.

coefficient on NYTURN is over twice as large and the absolute coefficient on NASDTURN is over eight times as large. This suggests that the impact of liquidity on returns does not diminish after controlling for potential business cycle effects. One potential explanation is that liquidity is more of trading phenomenon, unrelated to the state of the economy. Liquidity is likely to be a function of market design, competition amongst liquidity suppliers, and the degree of information asymmetry or the lack thereof.

Moreover, in the presence of time-varying alpha, the book-to-market ratio has a negative impact on expected stock return.[16] This is consistent with the fact that the value premium is indeed related to the business cycle, as shown by Liew and Vassalou (2000) and others. The notion is that the positive impact of book-to-market on total risk-adjusted returns turns negative when total returns are replaced by non-business cycle-related returns.

Indeed, in Table 9, we have presented the results only at a monthly frequency focusing on the Fama–French three-factor model. We have conducted a number of robustness checks and found that qualitatively the results hold at the quarterly frequency, with only the NYSE-AMEX sample, and with the CAPM as well as the Fama–French model augmented by the Pastor–Stambaugh liquidity risk factor. Moreover, we have experimented with using only the default spread as the business cycle variable in regression (3). While using only default spread does capture the impact of past returns over the months $t-2$ to $t-3$ and over months $t-4$ to $t-6$, the returns over months $t-7$ through $t-12$ are still positive, but much less significant.

5. Conclusions

This article develops and applies a framework in which to examine whether the predictive ability of size, book-to-market, turnover, and past returns is explained by various asset pricing models. Following recent developments in economic theory, our framework allows factor loadings in first-pass time series regressions to change with firm-level size and book-to-market as well as business cycle-related variables. Risk-adjusted returns based on the first-pass regressions are then regressed on size, book-to-market, turnover, and prior returns. If the predictive power of such firm-level variables is explained by asset pricing models, then they should be statistically insignificant in the second-pass cross-sectional regressions.

[16] Note that the difference in the signs and significance of some of the variables in Table 9 as compared to (say) Table 3 should not be surprising. The dependent variable in the cross-sectional regressions is different. In Table 3, the dependent variable is the risk-adjusted return while in Table 9 the dependent variable is the asset mispricing purged of the business cycle variation.

The empirical evidence shows that

- The conditional and unconditional versions of the single-factor CAPM and CCAPM do not capture any of the size, book-to-market ratio, turnover, and past return effects, even when the market or consumption beta may vary with (i) the default spread, (ii) firm-level size and book-to-market, and (iii) both firm-level variables and the default spread.
- The predictive ability of size, book-to-market, turnover, and past returns is also unexplained by Fama–French model with constant risk and expected return.
- The conditional Fama–French model does capture the impact of firm size and book-to-market ratio on the cross-section of individual stock returns.
- Consistent with economic theory, allowing beta to vary with size, book-to-market, and business cycle variables can substantially improve the pricing abilities of most examined models.
- Even when beta variation helps, none of the examined models capture the impact of liquidity or momentum on the cross-section of individual stock returns, even when returns are risk-adjusted by liquidity and momentum factors.
- Momentum profits are consistent with asset pricing misspecification that varies with the business cycle. This could point to a systematic rather than idiosyncratic source of momentum profits.
- Time-varying business conditions do not capture the liquidity effect on stock returns.

To summarize, time-varying beta versions of multifactor models can capture the size and book-to-market effects. Even so, turnover and past returns are important determinants of the cross-section of stock returns even when return is adjusted by a liquidity factor or a momentum factor, or both. The fact that time-varying alpha captures the impact of past returns points to a potential business-cycle related explanation for the impact of momentum on the cross-section of individual stock returns. Ultimately, the search for a risk-based asset pricing model that captures the impact of turnover and/or momentum goes on.

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