The cross section of expected stock returns

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This version: August 2014
Forthcoming in *Critical Finance Review*

Tel: 603-646-8650; email: jon.lewellen@dartmouth.edu. I am grateful to Eugene Fama, Ken French, Bob Resutek, Jay Shanken, Ivo Welch, an anonymous referee, and workshop participants at Arrowstreet Capital, Columbia University, Dimensional Fund Advisors, McGill University, Purdue University, Rice University, and the University of Washington for helpful comments and suggestions.

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Abstract

This paper studies the cross-sectional properties of return forecasts derived from Fama-MacBeth regressions. These forecasts mimic how an investor could, in real time, combine many firm characteristics to obtain a composite estimate of a stock's expected return. Empirically, the forecasts vary substantially across stocks and have strong predictive power for actual returns. For example, using ten-year rolling estimates of Fama-MacBeth slopes and a cross-sectional model with 15 firm characteristics (all based on low-frequency data), the expected-return estimates have a cross-sectional standard deviation of 0.87% monthly and a predictive slope for future monthly returns of 0.74, with a standard error of 0.07.

Electronic copy available at: http://ssrn.com/abstract=2511246

1. Introduction

The asset-pricing literature finds significant cross-sectional predictability in stock returns. Firm characteristics such as size, book-to-market (B/M), past returns, and investment are correlated with a firm's subsequent stock returns, effects that show up both in the performance of characteristic-sorted portfolios and in slopes from Fama-MacBeth (FM) cross-sectional regressions (see Fama and French, 2008, for a recent review). Many of the documented patterns are highly significant and seem almost certainly to be real, i.e., they are unlikely to be due to random chance or data-snooping biases.

This paper provides new evidence on the cross-sectional properties of expected stock returns, focusing on two closely related questions that, to date, do not have clear answers in the literature: (1) How much cross-sectional variation in expected returns can we actually predict?, and (2) How reliable are estimates of expected returns from FM regressions? These questions are not answered either by the portfolio sorts common in the literature—which consider one or two pre-selected characteristics at a time—or by traditional cross-sectional tests. As an alternative, I study the distribution and out-of-sample predictive ability of expected-return estimates derived from FM regressions, based on slopes estimated in prior years. The primary question I consider is whether these estimates line up with true expected returns, i.e., do they predict subsequent realized returns with a slope of one, as they should if they truly provide good estimates of expected returns? My results contribute to the literature in several ways:

First, the literature shows that many firm characteristics are correlated with subsequent stock returns, but little evidence exists on whether the characteristics can actually be used, individually or in combination, to estimate expected stock returns in real time. For example, even though we know that B/M and accruals are significantly related to subsequent returns, we do not know whether forecasts derived from those variables line up well with true expected returns. If past cross-sectional slopes are poor estimates of the true slopes going forward, either because of noise in the estimates or because of time-variation in the true parameters, the out-of-sample predictive power of estimated expected returns could be low even if firm characteristics have historically been significant predictors of returns.

Second, we know that trading strategies based on one or two characteristics taken at a time have performed quite well historically, but there has been much less work on how an investor could combine many characteristics into a composite trading strategy, based only on information available at the time (i.e., without knowing how strong the predictive power of each characteristic would turn out to be). Out-of-sample forecasts from FM regressions provide a simple, yet surprisingly effective, way to form a composite trading strategy—going long high-expected-return stocks and short low-expected-return stocks—again using only slope estimates available in real time. My tests consider regressions with up to 15 firm characteristics, many of which turn out not to be significant predictors of stock returns, in order to capture the idea that an investor did not know ex ante which variables were best.

Third, there has been much work in recent years attempting to infer a firm's expected stock return (or cost of equity) from its observed stock price and forecasts of its dividends and earnings, but there has not been a similar effort to estimate expected returns from known predictors of stock returns. My results suggest that cross-sectional regressions provide quite reliable estimates of expected returns—indeed, the estimates appear to be much more reliable than prior work has found for the implied cost of capital, though a direct comparison is beyond the scope of the paper.

My tests focus on the period 1964–2013, either pooling all stocks together or looking at just those larger than the NYSE 20th percentile ('all-but-tiny' stocks) or the NYSE median ('large' stocks). I consider three specifications of FM regressions based on progressively larger sets of predictor variables. The first model includes only size, B/M, and past 12-month returns; the second model adds accruals, stock issuance, profitability, and asset growth; and the third model includes a host of additional characteristics that an investor might have thought—it turns out erroneously—could help to predict returns, such as dividend yield, beta, and market leverage (15 variables in total). All of the variables are relatively slow-moving, representing either level variables (like size and B/M) or flow variables measured over at least an annual horizon (like accruals, asset growth, and dividend yield).

My primary tests focus on monthly forecasts derived from 10-year rolling averages of FM slopes. These forecasts have a cross-sectional standard deviation of roughly 0.80% for all stocks, 0.60% for all-but-tiny stocks, and 0.50% for large stocks using all three sets of predictor variables, increasing only slightly as the number of characteristics expands (forecasts from the three models are highly correlated with each other). The estimates suggest considerable dispersion in expected returns, compared, for example, with average returns of just over 1.00% per month.

More importantly, the expected-return estimates line up well with true expected returns: In out-of-sample FM regressions, I find slopes of 0.74–0.80 for all stocks, slopes of 0.57–0.64 for all-but-tiny stocks, and slopes of 0.44–0.66 for large stocks when subsequent returns are regressed on the three sets of expected-return forecasts (the estimates are highly significant with t-statistics of 3.64–10.65). Results are similar when cumulative average slopes starting in 1964 are used instead, and even just the prior 1-, 3-, or 5-years of FM slopes are useful in estimating expected returns.

For additional perspective, I sort stocks into deciles based on the expected-return forecasts. Focusing again on estimates derived from 10-year rolling FM slopes, the spread between the *predicted* monthly returns of the top and bottom deciles is 2.70% using the small set of predictors (size, B/M, and momentum) and 3.09% using the full set of 15 characteristics. The spread in their subsequent *realized* returns is almost as large, 2.19% monthly in the first case and 2.36% monthly in the second. (The spread in their value-weighted returns is 1.21% in the first case and 1.54% in the second.) Forecasts based on all three sets of predictor variables line up closely with average returns, and the incremental predictive power of accruals, asset growth, and the other characteristics included in the more complete models is surprisingly modest.

For the subset of stocks larger than the NYSE median, the spread between the predicted monthly returns of the top and bottom deciles is 1.54% using the small set of predictors and 1.87% using the full set of 15 variables. The spread between their subsequent realized returns is smaller but highly significant, ranging from 0.79% to 1.04%. Thus, FM-based estimates of expected returns appear to be somewhat more accurate for smaller stocks—reflecting, in part, the substantial cross-sectional variation in their true expected returns—but are also informative about true expected returns even among larger stocks.

My final tests explore whether the results carry over to longer horizons. Forecasts of 6- and 12-month returns seem to be noisier than their monthly counterparts yet still have strong predictive power for returns. For example, in out-of-sample FM regressions, I find statistically strong slopes of 0.70–0.91 for all stocks, 0.43–0.60 for all-but-tiny stocks, and 0.36–0.68 for large stocks when annual returns are regressed on predicted returns (the slopes vary depending on how the forecasts are constructed, e.g., which set of predictors is used and how many years of past data are averaged to get the FM slopes). Forecasts based on longer histories of FM slopes work best and, statistically, are quite strongly related to subsequent annual returns.

My tests are most closely related to those of Haugen and Baker (1996) and Hanna and Ready (2005), who also study the usefulness of past FM regressions. However, those papers differ from mine in key ways: (1) They focus on the profitability of high-turnover trading strategies, driven largely by short-lived predictors such as a stock's prior 1-month return, and do not study the distribution or accuracy of FM expected-return estimates; (2) they focus on strategies derived from 1-year rolling averages of FM slopes, which seem to provide in my data very noisy estimates of expected returns and to pick up transitory patterns in returns. In addition, my paper provides new evidence on predictability among larger stocks, on the predictability of long-horizon returns, and on the incremental role of characteristics such as accruals, asset growth, and stock issuance that have received significant attention in recent years.

My paper also relates to Fama and French (1997), Simin (2008), and Levi and Welch (2014), who show that the CAPM and Fama-French (1993) three-factor model do not provide reliable estimates of expected returns. My results suggest that forecasts from characteristic-based regressions have better out-of-sample predictive power than either of the asset-pricing models.

The remainder of the paper is organized as follows: Section 2 describes the data; Section 3 studies monthly return forecasts and tests how well they line up with subsequent realized returns; Section 4 extends the tests to semiannual and annual returns; and Section 5 concludes.

2. Data

My tests use all common stocks on the Center for Research in Security Prices (CRSP) monthly files, merged with accounting data from Compustat (thereby restricting the tests to 1964–2013). I also consider two sub-samples of larger firms: ‘all-but-tiny’ stocks are those larger than the NYSE 20th percentile and ‘large’ stocks are those larger than the NYSE 50th percentile based on market equity at the beginning of the month. Fama and French (2008) suggest using these groups as a simple way to check whether predictability is driven by micro-cap stocks or also exists among the economically more important population of large stocks. At the end of 2013, the NYSE 20th percentile is $693 million and the NYSE median is $2,757 million. Those breakpoints roughly partition the sample into the popular definitions of micro-cap vs. small-cap vs. mid- and large-cap stocks (see, e.g., Investopedia.com).

Return forecasts are derived from FM regressions of stock returns on lagged firm characteristics. I consider three regression models that encompass a progressively larger set of predictors. The first two models use characteristics that prior studies find to be significant: Model 1 includes size, B/M, and past 12-month stock returns, while Model 2 adds three-year share issuance and one-year accruals, profitability, and asset growth. Model 3 includes eight additional characteristics that have a weaker relation historically to subsequent returns, including beta, dividend yield, one-year share issuance, three-year stock returns, 12-month volatility, 12-month turnover, market leverage, and the sales-to-price ratio. The logic of the three specifications is that the first two models are most relevant if we believe an investor identified the best predictors early in the sample—perhaps based on theory rather than empirical evidence—while the third model is most relevant if an investor considered a larger number of predictors, even those we now know did not add significant explanatory power to the model.

The variables are defined below. Stock prices, returns, shares outstanding, dividends, and trading volume come from CRSP, and sales, earnings, assets, and accruals come from the Compustat annual file. Market data are assumed to be known immediately; accounting data are assumed to be known four months after the end of the fiscal year (thus, sales, earnings, etc. are assumed to be observable by the end of April for a firm whose fiscal year ends in the prior December).

LogSize_{-1} = Log market value of equity at the end of the prior month,

LogB/M_{-1} = Log book value of equity minus log market value of equity at the end of the prior month,

$\text{Return}_{-2,-12}$ = Stock return from month -12 to month -2,

$\text{LogIssues}_{-1,-36}$ = Log growth in split-adjusted shares outstanding from month -36 to month -1,

Accruals_{Yr-1} = Change in non-cash net working capital minus depreciation in the prior fiscal year,

ROA_{Yr-1} = Income before extraordinary items divided by average total assets in the prior fiscal year,

LogAG_{Yr-1} = Log growth in total assets in the prior fiscal year,

$\text{DY}_{-1,-12}$ = Dividends per share over the prior 12 months divided by price at the end of the prior month,

$\text{LogReturn}_{-13,-36}$ = Log stock return from month -36 to month -13,

$\text{LogIssues}_{-1,-12}$ = Log growth in split-adjusted shares outstanding from month -12 to month -1,

$\text{Beta}_{-1,-36}$ = Market beta estimated from weekly returns from month -36 to month -1,

$\text{StdDev}_{-1,-12}$ = Monthly standard deviation, estimated from daily returns from month -12 to month -1,

$\text{Turnover}_{-1,-12}$ = Average monthly turnover (shares traded/shares outstanding) from month -12 to month -1,

Debt/Price_{Yr-1} = Short-term plus long-term debt divided by market value at the end of the prior month,

$\text{Sales/Price}_{Yr-1}$ = Sales in the prior fiscal year divided by market value at the end of the prior month.

A couple of observations might be useful. First, all of the characteristics are highly persistent in monthly data because they either represent level variables that change slowly (like size and B/M) or flow variables measured over at least a year (like earnings and sales). This suggests that any predictability in monthly returns is likely to extend to longer horizons, a possibility I test directly using semiannual and annual returns in Section 4. Second, many of the characteristics are highly correlated with each other either because they are mechanically related (like short-term and long-term stock issuance) or capture related features of the firm (like beta and standard deviation, or asset growth and accruals). However, the resulting multicollinearity in the regressions is not a significant concern here because I am primarily interested in the overall predictive power of the model, not the slopes on individual variables.

The Appendix provides a brief survey of prior work that uses these or similar variables to predict stock returns. I do not know of any paper that simultaneously considers all of the characteristics, but my goal is not to break new ground in defining the predictors.

Table 1 reports summary statistics for monthly returns and the 15 characteristics defined above. The numbers

Table 1
Descriptive statistics, 1964–2013

The sample includes all common stocks on CRSP with current-month returns (Return, %) and beginning-of-month market value, book-to-market equity, and lagged 12-month returns. 'All-but-tiny' stocks are those larger than the NYSE 20th percentile (based on a firm's market value of equity) and 'Large' stocks are those larger than the NYSE median. Stock prices, returns, shares outstanding, dividends, and turnover come from CRSP and book equity, total assets, debt, sales, earnings, and accruals come from Compustat (annual data). Accounting data are assumed to be known four months after the end of the fiscal year. The numbers represent the time-series averages of the cross-sectional mean ('Avg'), standard deviation ('Std') and sample size ('N') for each variable.

	All stocks			All-but-tiny stocks			Large stocks		
	Avg	Std	N	Avg	Std	N	Avg	Std	N
Return (%)	1.27	14.79	3,955	1.12	9.84	1,706	1.03	8.43	876
LogSize_{-1}	4.63	1.93	3,955	6.38	1.18	1,706	7.30	0.90	876
LogB/M_{-1}	-0.51	0.84	3,955	-0.73	0.73	1,706	-0.81	0.71	876
$\text{Return}_{-2,-12}$	0.13	0.48	3,955	0.20	0.41	1,706	0.19	0.36	876
$\text{LogIssues}_{-1,-36}$	0.11	0.25	3,519	0.10	0.22	1,583	0.09	0.21	837
$\text{Accruals}_{\text{Yr-1}}$	-0.02	0.10	3,656	-0.02	0.08	1,517	-0.03	0.07	778
$\text{ROA}_{\text{Yr-1}}$	0.01	0.14	3,896	0.05	0.08	1,679	0.06	0.07	865
$\text{LogAG}_{\text{Yr-1}}$	0.12	0.26	3,900	0.15	0.22	1,680	0.14	0.20	865
$\text{DY}_{-1,-12}$	0.02	0.02	3,934	0.02	0.02	1,702	0.03	0.02	875
$\text{LogReturn}_{-13,-36}$	0.09	0.58	3,417	0.23	0.46	1,556	0.25	0.41	828
$\text{LogIssues}_{-1,-12}$	0.04	0.12	3,953	0.03	0.10	1,706	0.03	0.10	876
$\text{Beta}_{-1,-36}$	0.96	0.55	3,720	1.06	0.50	1,639	1.05	0.46	854
$\text{StdDev}_{-1,-12}$	0.15	0.08	3,954	0.11	0.04	1,706	0.09	0.03	876
$\text{Turnover}_{-1,-12}$	0.08	0.08	3,666	0.10	0.08	1,635	0.09	0.08	857
$\text{Debt/Price}_{\text{Yr-1}}$	0.83	1.59	3,908	0.64	1.16	1,677	0.61	1.09	864
$\text{Sales/Price}_{\text{Yr-1}}$	2.53	3.56	3,905	1.59	1.95	1,677	1.37	1.52	865

LogSize_{-1} = Log market value of equity at the end of the prior month
LogB/M_{-1} = Log book equity minus log market value of equity at the end of the prior month
$\text{Return}_{-2,-12}$ = Stock return from month -12 to month -2
$\text{LogIssues}_{-1,-36}$ = Log growth in split-adjusted shares outstanding from month -36 to month -1
$\text{Accruals}_{\text{Yr-1}}$ = Working capital accruals, à la Sloan (1996), in the prior fiscal year
$\text{ROA}_{\text{Yr-1}}$ = Income before extraordinary items divided by average total assets in the prior fiscal year
$\text{LogAG}_{\text{Yr-1}}$ = Log growth in total assets in the prior fiscal year
$\text{DY}_{-1,-12}$ = Dividends per share over the prior 12 months divided by price at the end of the prior month
$\text{LogReturn}_{-13,-36}$ = Log stock return from month -36 to month -13
$\text{LogIssues}_{-1,-12}$ = Log growth in split-adjusted shares outstanding from month -12 to month -1
$\text{Beta}_{-1,-36}$ = Market beta estimated from weekly returns from month -36 to month -1
$\text{StdDev}_{-1,-12}$ = Monthly standard deviation, estimated from daily returns from month -12 to month -1
$\text{Turnover}_{-1,-12}$ = Average monthly turnover (shares traded/shares outstanding) from month -12 to month -1
$\text{Debt/Price}_{\text{Yr-1}}$ = Short-term plus long-term debt divided by market cap at the end of the prior month
$\text{Sales/Price}_{\text{Yr-1}}$ = Sales in the prior fiscal year divided by market value at the end of the prior month

represent time-series averages of the monthly cross-sectional mean, standard deviation, and sample size for each variable. Since the smallest set of predictors I consider includes size, B/M, and 12-month momentum, I restrict the sample to firms with valid data for those variables. All characteristics, except monthly returns, are winsorized monthly at their 1st and 99th percentiles.

The table shows that all-but-tiny stocks make up just under half the sample and large stocks roughly half of those (i.e., just under a quarter of the sample). Except for turnover, the cross-sectional variation of the characteristics is highest in the full sample and lowest among large stocks. That property will be inherited by their expected-return estimates as well.

3. Expected stock returns

My primary tests, described in this section, focus on monthly stock returns. I first summarize basic FM cross-sectional regressions and then explore the properties and out-of-sample predictive power of return forecasts derived from these regressions.

3.1. FM regressions

Table 2 reports average slopes, R^2s, and sample sizes for 596 monthly cross-sectional regressions, 1964:05–2013:12. The t-statistics are based on the time-series variability of the slope estimates, incorporating a Newey-West correction with four lags to account for possible autocorrelation in the slopes. As explained above, I show results for three groups of firms (all stocks, all-but-tiny stocks, and large stocks) and for three specifications of the regressions.

The results are consistent, qualitatively and quantitatively, with prior research. In the first two models, the slopes on B/M, past 12-month returns, and profitability are significantly positive, while the slopes on size, share issuance, accruals, and asset growth are significantly negative. In general, the estimates are reasonably similar for the three groups of firms. The predictive ability of size, B/M, and asset growth is somewhat weaker among larger stocks (both the point estimates and t-statistics), while the predictive ability of share issuance and profitability is somewhat stronger.

Adding the remaining characteristics to the regression, in the third model, has a modest effect on the slopes of the seven variables included in Models 1 and 2. Among the new variables, beta is the only one that is at least marginally significant for all three groups of stocks (t-statistics of 1.73–3.05). A firm's volatility over the prior

Table 2
Fama-MacBeth regressions, 1964–2013

This table summarizes Fama-MacBeth cross-sectional regressions (average slopes, R^2s, and number of stocks) when monthly returns (in %) are regressed on lagged firm characteristics. t-statistics for the slopes are based on the time-series variability of the estimates, incorporating a Newey-West correction with four lags to account for possible autocorrelation in the estimates. The full sample includes all common stocks on CRSP with the necessary data to estimate the cross-sectional regression in each panel (i.e., the firm must have data for returns and all predictor variables in a given month). 'All-but-tiny' stocks are those larger than the NYSE 20th percentile (based on beginning-of-month market value) and 'Large' stocks are those larger than the NYSE median. Stock prices, returns, shares outstanding, dividends, and turnover come from CRSP and book equity, total assets, debt, sales, earnings, and accruals come from Compustat (annual data). Accounting data are assumed to be known four months after the end of the fiscal year. The variables are defined in Table 1.

	All stocks			All but tiny stocks			Large stocks		
	Slope	t-stat	R^2	Slope	t-stat	R^2	Slope	t-stat	R^2
Model 1: Three predictors									
LogSize_{-1}	-0.13	-2.80	0.033	-0.06	-1.40	0.046	-0.05	-1.33	0.056
LogB/M_{-1}	0.54	7.07		0.33	4.11		0.29	3.62	
$\text{Return}_{-2,-12}$	1.06	5.70		1.05	5.35		1.01	4.54	
N	3,955			1,706			876		
Model 2: Seven predictors									
LogSize_{-1}	-0.13	-3.38	0.042	-0.09	-2.38	0.062	-0.09	-2.21	0.076
LogB/M_{-1}	0.44	6.26		0.31	3.82		0.29	3.47	
$\text{Return}_{-2,-12}$	0.88	5.32		0.93	4.88		0.93	4.37	
$\text{LogIssues}_{-1,-36}$	-0.39	-3.77		-0.39	-3.46		-0.59	-4.39	
Accruals_{Yr-1}	-1.44	-5.66		-1.66	-5.01		-1.27	-3.37	
ROA_{Yr-1}	1.34	2.54		2.57	4.38		2.32	3.49	
LogAG_{Yr-1}	-0.78	-6.40		-0.45	-2.94		-0.35	-1.86	
N	3,254			1,409			745		
Model 3: Fifteen predictors									
LogSize_{-1}	-0.15	-5.01	0.076	-0.16	-4.68	0.115	-0.13	-3.84	0.147
LogB/M_{-1}	0.35	6.18		0.18	2.78		0.17	2.31	
$\text{Return}_{-2,-12}$	0.96	6.86		0.93	5.70		0.90	5.05	
$\text{LogIssues}_{-1,-36}$	-0.35	-3.52		-0.23	-1.90		-0.43	-3.23	
Accruals_{Yr-1}	-1.38	-5.69		-1.67	-5.15		-1.32	-3.75	
ROA_{Yr-1}	1.43	3.57		1.94	4.36		1.76	2.89	
LogAG_{Yr-1}	-0.54	-4.49		-0.29	-2.17		-0.13	-0.82	
$\text{DY}_{-1,-12}$	-0.46	-0.27		-1.24	-0.70		0.61	0.34	
$\text{LogReturn}_{-13,-36}$	-0.07	-1.00		-0.06	-0.81		0.01	0.07	
$\text{LogIssues}_{-1,-12}$	0.02	0.10		-0.31	-1.38		-0.22	-0.88	
$\text{Beta}_{-1,-36}$	0.33	3.05		0.34	2.70		0.23	1.73	
$\text{StdDev}_{-1,-12}$	-1.45	-1.40		-5.90	-4.63		-5.90	-3.76	
$\text{Turnover}_{-1,-12}$	-4.49	-3.68		-1.18	-1.02		-0.37	-0.26	
Debt/Price_{Yr-1}	-0.03	-1.21		0.02	0.58		0.03	0.65	
$\text{Sales/Price}_{Yr-1}$	0.04	3.10		0.03	1.51		0.03	1.16	
N	2,967			1,348			728		

year is significantly negative for all-but-tiny and large stocks, but not in the full sample, while past turnover and the sales-to-price ratio are significant only in the full sample. The remaining variables—dividend yield, long-term returns, 12-month share issuance, and market leverage—are not significant for any group of stocks, with t-statistics ranging from -1.38 to 0.65 after controlling for the other characteristics.

Several features of the results are worth highlighting. First, it would be wrong to interpret the FM R^2 as informative about the overall predictive power of the variables. The FM R^2 provides information mostly about the fraction of *contemporaneous* volatility explained by characteristic-based portfolios, not about the *predictive ability* of the characteristics. A simple example illustrates why: Suppose all stocks have the same expected return but different betas and a one-factor market model explains all return volatility (stocks have no idiosyncratic residuals). In FM regressions, beta would have perfect explanatory power month-by-month even though it has no predictive power for returns; beta would be perfectly positively related to returns half the time, when the market goes up, and perfectly negatively related to returns half the time, when the market drops, because realized returns always line up exactly with beta. More generally, FM slopes can be interpreted as returns on characteristic-based portfolios (Fama 1976) and the FM R^2 reflects, in large part, how much ex post volatility these portfolios explain.[1]

Second, the slopes on B/M and 12-month momentum depend somewhat on how B/M is measured. In particular, some studies follow Fama and French (1992) and calculate B/M once a year at the end of June, using book equity for the prior fiscal year and market equity as of the prior December. My measure is based, instead, on the latest observations for both market and book equity (the latter updated four months after the fiscal year). Thus, my variable reflects recent stock-price changes in a more timely way than the Fama and French measure and, consequently, is more negatively correlated with momentum (which is updated monthly

[1] A better measure of a model's predictive power is given by the R^2 from a pooled time-series, cross-sectional regression, using returns and characteristics de-meaned relative to their monthly cross-sectional means in order to remove marketwide movement in the variables through time (mimicking what FM regressions do). This pooled R^2 is appropriate because the variance of the fitted values in the numerator reflects a single set of slopes estimated for all months, rather than month-by-month realizations of FM slopes, while the variance in the denominator reflects the cross-sectional variance of returns (implicitly weighting each month by the number of firms in the sample at the time). For the specifications in Table 2, these R^2s range from 0.0017–0.0024 for all stocks, 0.0012–0.0021 for all-but-tiny stocks, and 0.0012–0.0024 for large stocks, about 20–50 times smaller than the FM R^2s.

in most studies, including this one). This fact strengthens the FM slopes on both B/M and momentum. For example, in Model 1, the full-sample slope on B/M drops from 0.54 to 0.31 and the slope on momentum drops from 1.06 to 0.74 if I redefine B/M using Fama and French's approach (the slopes remain strongly significant for all three groups of stocks).

A related observation concerns the impact of the year 2009 on momentum. Several months in 2009 were disastrous for momentum strategies and have a sizable effect on the results. For example, using all stocks, the slope on past 12-month returns in Model 1 jumps to 1.24 if 2009 is dropped from the sample. (The monthly slope hits a low of -33.58 in April 2009, and the average slope for all of 2009 is -7.41 because losers but not winners rebounded strongly in March, April, and May of 2009.) Although slopes on other variables are much less sensitive to the inclusion of 2009, the extremely poor predictive performance of momentum in that year tends to reduce the overall out-of-sample performance of return forecasts from the regressions, especially among larger stocks.

Fig. 1 shows how the slopes on selected characteristics change through time (see also McLean and Pontiff 2013). The figure plots 10-year rolling averages of the slopes from Model 2, which includes the seven characteristics with the strongest predictive power. (All seven characteristics are included in the regressions, but the figure omits the slopes on size and ROA for visual clarity.) Most of the slopes shrink toward zero over time, including those on size and ROA, but the 10-year rolling estimates lie almost entirely on one side of the x-axis or the other, i.e., the magnitudes but not the signs change through time. The relatively steady decline in the slopes suggests that past estimates will tend to overstate the cross-sectional dispersion in true expected returns going forward, exactly the pattern I document below.

3.2. Estimates of expected stock returns

Table 3 explores the distribution and out-of-sample predictive ability of forecasts derived from the FM regressions above. These forecasts—i.e., estimates of expected returns—are based on a firm's beginning-of-month characteristics and either the prior 10-year rolling average or the cumulative average, starting in 1964, of intercepts and slopes from the three models in Table 2. (I consider estimates based on alternative rolling

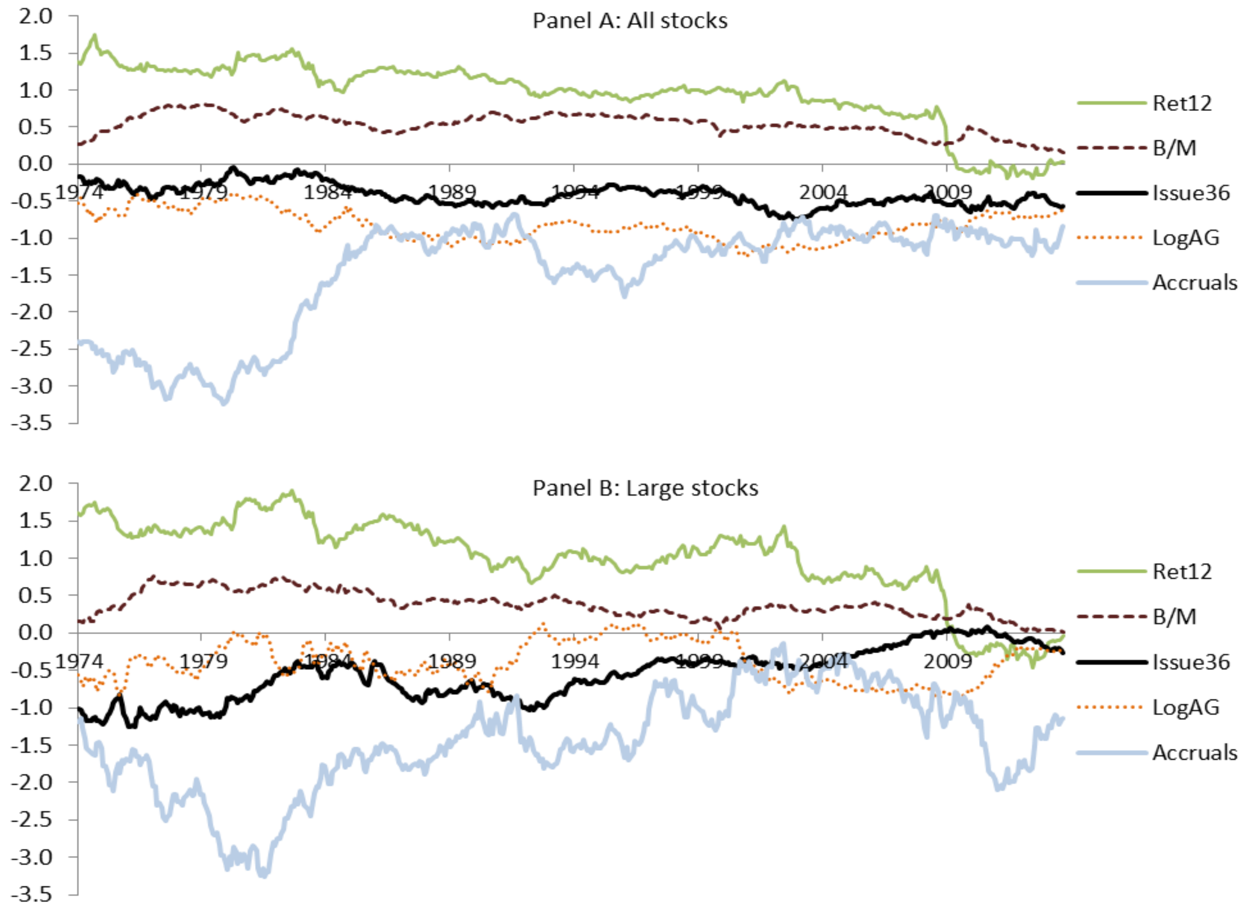

Fig. 1. Ten-year rolling slope estimates, 1974–2013
The figure plots ten-year rolling averages of Fama-MacBeth slopes on selected characteristics (the x-axis indicates the ending date for the ten-year window). Panel A shows estimates using all stocks and Panel B shows estimates using large stocks, defined as those larger than the NYSE median based on market value at the beginning of the month. The estimates come from Model 2: Monthly returns (in %) are regressed on size, B/M, 12-month momentum (Ret12), three-year stock issuance (Issue36), accruals, ROA, and asset growth (LogAG). Market data come from CRSP and accounting data come from Compustat. The variables are defined in Table 1.

windows later.) Again, the goal is to mimic what an investor could have forecast for expected returns, in real time, using only slopes from prior FM regressions.

The left-hand columns in Table 3 summarize the distribution of the forecasts, in particular, the average of their monthly cross-sectional means, standard deviations, and 10th and 90th percentiles. I report the mean mostly for descriptive purposes; the cross-sectional dispersion is more important for understanding how well the estimates capture variation in expected returns across stocks (an analyst could shift all of the estimates up or down to reflect different beliefs about overall market returns).

Table 3
Expected stock returns, 1974–2013

This table reports the distribution (average, standard deviation, 10th and 90th percentiles) and predictive ability (slope, standard error, t-statistic, R^2) of monthly return forecasts derived from a firm's current characteristics and slopes from past FM regressions (10-year rolling estimates or cumulative averages starting in 1964). All point estimates equal time-series averages of monthly cross-sectional parameters. Predictive slopes and R^2s come from (out-of-sample) FM regressions of monthly returns on the expected-return estimates; standard errors are based on the time-series variability of the estimates, incorporating a Newey-West correction with four lags. The full sample includes all common stocks on CRSP. 'All but tiny' stocks are those larger than the NYSE 20th percentile based on market cap and 'Large' stocks are those larger than the NYSE median. Accounting data come from Compustat. Model 1 includes size, B/M, and 12-month momentum; Model 2 adds three-year stock issuance and one-year accruals, profitability, and asset growth; Model 3 adds beta, dividend yield, market leverage, sales/price, three-year returns, and one-year stock issuance, volatility, and turnover.

		Univariate properties (%)				Predictive ability			
FM estimate	Model	Avg	Std	p10	p90	Slope	S.E.	t-stat	R^2
Panel A: All stocks									
Rolling slopes	Model 1	1.19	0.76	0.28	2.09	0.77	0.09	8.63	0.007
	Model 2	1.24	0.80	0.29	2.17	0.80	0.08	10.06	0.007
	Model 3	1.12	0.87	0.11	2.13	0.74	0.07	10.65	0.009
Cumulative slopes	Model 1	1.11	0.80	0.18	2.06	0.82	0.07	11.40	0.007
	Model 2	1.10	0.84	0.14	2.06	0.81	0.06	13.40	0.007
	Model 3	0.70	1.04	-0.56	1.86	0.63	0.06	9.64	0.012
Panel B: All-but-tiny stocks									
Rolling slopes	Model 1	1.06	0.51	0.49	1.64	0.62	0.13	4.75	0.015
	Model 2	1.07	0.58	0.45	1.69	0.64	0.10	6.19	0.013
	Model 3	1.04	0.63	0.32	1.73	0.57	0.10	5.94	0.014
Cumulative slopes	Model 1	0.95	0.61	0.31	1.63	0.61	0.11	5.51	0.016
	Model 2	0.90	0.65	0.23	1.59	0.67	0.09	7.21	0.015
	Model 3	0.67	0.67	-0.11	1.40	0.68	0.10	6.95	0.018
Panel C: Large stocks									
Rolling slopes	Model 1	1.00	0.44	0.51	1.50	0.66	0.16	3.99	0.022
	Model 2	1.01	0.48	0.48	1.54	0.65	0.13	5.09	0.019
	Model 3	1.02	0.53	0.43	1.61	0.44	0.12	3.64	0.020
Cumulative slopes	Model 1	0.85	0.51	0.30	1.42	0.60	0.14	4.12	0.024
	Model 2	0.80	0.54	0.21	1.39	0.71	0.11	6.36	0.021
	Model 3	0.60	0.53	-0.02	1.18	0.72	0.12	5.91	0.025

Forecasts from all three models suggest considerable cross-sectional variation in expected returns. For the full sample, the cross-sectional standard deviations range from 0.76% using 10-year rolling slope estimates for Model 1 to 1.04% using cumulative slope estimates for Model 3. The 10th percentiles of the distributions are close to zero (positive for Models 1 and 2, zero or negative for Model 3), while the 90th percentiles range from 1.86% to 2.17% monthly. Thus, using the 10th and 90th percentiles as a guide, the estimates imply a spread of roughly 2% monthly between high and low expected returns.

Dropping tiny stocks from the sample reduces variability in the forecasts but the cross-sectional standard deviations are still 0.51–0.67% for all-but-tiny stocks and 0.44–0.54% for large stocks. An investor using FM-based estimates of expected return would forecast, on the low end, excess returns that are zero or negative for many large stocks and, on the high end, excess returns greater than 15% annualized (the average monthly Tbill rate during the sample is 0.41%).

Dispersion of the forecasts is higher when more characteristics are included in the model but the differences are surprisingly modest for all three samples. For example, using 10-year windows and all stocks, the cross-sectional standard deviation increases from 0.76% for Model 1 to 0.80% for Model 2 to 0.87% for Model 3. These numbers suggest that the characteristics added to Models 2 and 3 contribute only a small amount to the cross-sectional volatility of expected returns, surprising given the strong statistical significance of some of the variables in FM regressions. I discuss this result further below.[2]

The right-hand columns in Table 3 explore the critical question of whether the estimates actually pick up cross-sectional variation in true expected returns. An estimate that provides an unbiased forecast of returns should predict subsequent realized returns with a slope of one (better forecasts may or may not have greater statistical significance, due to the confounding effects of cross-sectional correlation in returns). The tests in Table 3 are based on out-of-sample FM regressions, again with t-statistics based on the time-series variability of the monthly slopes.

The return forecasts do a good job capturing variation in expected returns, especially in the full sample of stocks. In particular, in the full sample, the predictive slopes for the six specifications range from 0.63 to 0.82 and the t-statistics range from 8.63 to 13.40. The point estimate is highest (0.82) for return forecasts based on

[2] Variation in the forecasts is partially attributable to estimation error. Formally, the cross-sectional variance of the forecasts equals $\text{var}^{cs}(F) = g'\text{var}^{cs}(X)g$, where $\text{var}^{cs}(X)$ is the cross-sectional covariance matrix of firm characteristics and g is the vector of FM slopes, equal to the true slopes γ plus estimation error e_g. Under standard assumptions, g is unbiased and $E[\text{var}^{cs}(F)] = \gamma'\text{var}^{cs}(X)\gamma + E[e_g'\text{var}^{cs}(X)e_g]$. The last term can be rewritten as $E[\text{tr}(e_g'\text{var}^{cs}(X)e_g)] = E[\text{tr}(e_g e_g'\text{var}^{cs}(X))] = \text{tr}(\Sigma_g \text{var}^{cs}(X))$, where Σ_g is the covariance matrix of e_g, which can be estimated in the usual way based on the time-series variability of the FM slopes. For the 10-year rolling windows in Table 3, this formula suggests that noise in the slopes contributes modestly to dispersion in the forecasts, raising the cross-sectional standard deviations by roughly 0.05–0.06% for Models 1 and 2 and 0.09–0.13% for Model 3. The fraction of variance attributed to noise is slightly less than would be inferred from an errors-in-variables analysis of the predictive slopes discussed next.

cumulative FM estimates of Model 1, and the t-statistic is highest (13.40) for return forecasts based on cumulative FM estimates of Model 2 (with a slightly lower point estimate of 0.81). The slopes are reliably less than one—in untabulated tests, the minimum t-statistic testing that hypothesis is 2.45—but the results suggest that the vast majority of variation in the expected-return estimates does, in fact, reflect differences in stocks' true expected returns.

The same conclusions carry over to the all-but-tiny and large-stock samples but the predictive slopes tend to be lower. The slopes range from 0.57 to 0.68 for all-but-tiny stocks and from 0.44 to 0.72 for large stocks (t-statistics of 3.93–6.97). For these groups, cumulative FM estimates from Models 2 and 3 seem to capture variation in true expected returns the best (slope estimates of 0.67–0.72), but rolling FM estimates for Models 1 and 2 follow closely behind (slope estimates of 0.62–0.66). Again, the slopes are statistically less than one in all cases, with a minimum t-statistic testing that hypothesis of 2.08.

The evidence in Table 3 has several implications. At the most basic level, the tests show that FM-based expected-return estimates have strong predictive power for subsequent stock returns. Stocks estimated to have high expected returns based on prior FM regressions do, in fact, have significantly higher returns going forward. The predictive ability of the estimates is typically stronger than the predictive ability of any of the individual characteristics in the various models (see Table 2).

At the same time, the expected-return estimates vary more than the true expected returns they forecast. The cross-sectional dispersion of the estimates needs to be shrunk by about 20–35% (i.e., by one minus the slopes in Table 3) in order to get a sense of how much true expected returns, as forecast by the estimates, actually vary across stocks.

An additional implication of the results is that FM regressions are stable enough and estimated precisely enough to have strong out-of-sample predictive ability. Unlike time-series predictive regressions (Goyal and Welch 2008), prior FM regressions provide a reliable way to forecast subsequent returns. Put differently, FM regressions provide an effective way to combine many firm characteristics, in real time, into a composite forecast of a stock's expected return—recognizing that the estimate should be shrunk a bit toward the cross-sectional mean to account for apparent noise in the estimate.[3]

3.3. Comparing the models

As observed above, the three regression models capture similar variation in expected returns, despite the fact that several of the characteristics added to Models 2 and 3 have strong predictive power in standard FM regressions. Table 4 explores the relation between the models in greater detail, focusing on forecasts derived from 10-year rolling windows of past FM regressions.

Much of the predicted variation in expected returns is common to all three models, with pairwise correlations in their forecasts of 0.71–0.87 for all stocks, 0.67–0.84 for all-but-tiny stocks, and 0.65–0.80 for large stocks. The incremental component of Model 2's forecasts relative to Model 1 (the residual when Model 2's forecast is regressed on Model 1's forecast) has a cross-sectional standard deviation of 0.26–0.38% monthly. This is economically important but substantially less than the variation captured by Model 1 (see Table 3). The incremental component of Model 3 relative to Model 2 has a similar standard deviation (0.27–0.44%), whereas the incremental component of Model 3 relative to Model 1 is higher (0.35–0.57%).

The last three columns in Table 4 show that the incremental forecast from Model 2 relative to Model 1 has strong out-of-sample predictive power for returns, with slopes of 0.67–0.84 and t-statistics of 4.67–6.46 for the different samples. The incremental component of Model 3 is less informative, with strong significance relative

[3] The predictive slope in Table 3 is closely linked to the mean-squared-error (MSE) of the forecasts. In particular, suppose we ask how well a given forecast F_i performs relative to a null forecast that all stocks have the same expected return F, which I assume equals the cross-sectional mean of F_i (the question is whether F_i helps distinguish between high and low expected-return stocks, not whether the mean of F_i is a better estimate than F of average expected returns). The MSE of F versus F_i equals $\text{MSE}(F) - \text{MSE}(F_i) = (1/N)\ \Sigma_i[(R_i - F)^2 - (R_i - F_i)^2] = (2b-1)\text{var}^{cs}(F_i)$, where b is the predictive slope when returns are regressed on F_i. Thus, F_i has a smaller MSE if and only if the predictive slope is greater than 0.50. Further, if we shrink F_i toward its mean to obtain a shrinkage estimator $F_i' = F + s\,(F_i - F)$, the MSE of F_i' equals $\text{MSE}(F) - \text{MSE}(F_i') = (2bs - s^2)\ \text{var}^{cs}(F_i)$. This quantity is maximized when $s = b$, implying, naturally enough, that the optimal weight on F_i equals the predictive slope. In addition, F_i' outperforms the null forecast for all $s \in (0, 2b)$, so putting some weight on the forecast F_i is always better than using the null forecast as long as $b > 0$. Thus, the predictive slopes in Table 3 can be interpreted as the optimal weight to give FM return forecasts, and testing whether $b > 0$ is equivalent to testing whether putting positive weight on the forecasts helps to reduce the MSE relative to a null forecast.

Table 4
Model comparison, 1974–2013

This table compares return forecasts from the three models considered in Tables 2 and 3, referred to as Forecasts 1, 2, and 3 (forecasts are based on 10-year rolling windows of FM regressions). The first three columns summarize the correlation, slope, and residual standard deviation (in %) for Forecast 2 regressed on Forecast 1, Forecast 3 regressed on Forecast 1, and Forecast 3 regressed on Forecast 2. The last three columns report the slope, standard error, and t-statistic when residuals from those regressions are used to predict monthly stock returns. All point estimates equal time-series averages of monthly cross-sectional parameters. The full sample includes all common stocks with market data on CRSP and accounting data on Compustat. 'All-but-tiny' stocks are those larger than the NYSE 20th percentile based on market cap and 'Large' stocks are those larger than the NYSE median. Model 1 includes size, B/M, and 12-month momentum; Model 2 adds three-year stock issuance and one-year accruals, profitability, and asset growth; Model 3 adds beta, dividend yield, market leverage, sales/price, three-year returns, and one-year stock issuance, volatility, and turnover.

				Predict returns w/ residual		
	Correlation	Slope	Res. std.	Slope	S.E.	t-stat
Panel A: All stocks						
Forecast 2 regressed on Forecast 1	0.87	0.92	0.38	0.84	0.13	6.46
Forecast 3 regressed on Forecast 1	0.71	0.82	0.57	0.64	0.13	5.14
Forecast 3 regressed on Forecast 2	0.83	0.92	0.44	0.52	0.17	3.13
Panel B: All-but-tiny stocks						
Forecast 2 regressed on Forecast 1	0.80	0.92	0.32	0.76	0.13	5.85
Forecast 3 regressed on Forecast 1	0.67	0.85	0.42	0.52	0.11	4.58
Forecast 3 regressed on Forecast 2	0.84	0.94	0.30	0.30	0.22	1.37
Panel C: Large stocks						
Forecast 2 regressed on Forecast 1	0.79	0.89	0.26	0.67	0.14	4.67
Forecast 3 regressed on Forecast 1	0.65	0.82	0.35	0.30	0.13	2.27
Forecast 3 regressed on Forecast 2	0.80	0.89	0.27	0.09	0.20	0.44

to Model 1 but inconsistent significance relative to Model 2. Overall, the extra characteristics in Models 2 and 3 capture significant variation in expected returns beyond the information contained in size, B/M, and 12-month past returns (the variables in Model 1), but the incremental predictive power seems modest compared to their significance in FM regressions.

3.4. Alternative windows

Table 5 tests whether forecasts based on shorter—but more timely—rolling windows also provide good estimates of expected returns. The layout is the same as Table 3, with univariate statistics on the left and the predictive performance of the estimates on the right. I show results for forecasts based on 1-, 3-, 5-, and 7-year rolling averages of past FM slopes. The data are the same for all windows except that the tests start in May 1965 for the 1-year window (the 13th month of the sample), May 1967 for the 3-year window (the 37th month

Table 5
Estimates based on alternative rolling windows, 1965–2013
This table replicates Table 3 using return forecasts derived from alternative rolling averages of past Fama-MacBeth slopes (1-, 3-, 5-, or 7-year windows of monthly regressions). Statistics are based on the longest time period available (starting in 1965 for the 1-year rolling estimates, 1967 for the 3-year rolling estimates, etc.). Table 3 provides additional information about the sample and tests.

		Univariate properties				Predictive ability			
Model	FM estimate	Avg	Std	p10	p90	Slope	S.E.	t-stat	R^2
Panel A: All stocks									
Model 1	1-yr rolling	1.10	1.12	-0.28	2.42	0.70	0.09	7.62	0.015
	3-yr rolling	1.12	0.86	0.07	2.14	0.66	0.11	6.09	0.011
	5-yr rolling	1.07	0.77	0.14	1.98	0.59	0.11	5.14	0.009
	7-yr rolling	1.13	0.75	0.23	2.02	0.69	0.11	6.02	0.007
Model 2	1-yr rolling	1.19	1.21	-0.25	2.60	0.64	0.07	9.51	0.016
	3-yr rolling	1.19	0.92	0.07	2.26	0.64	0.08	7.74	0.011
	5-yr rolling	1.14	0.82	0.15	2.09	0.63	0.09	6.83	0.009
	7-yr rolling	1.19	0.79	0.24	2.11	0.79	0.09	8.78	0.008
Model 3	1-yr rolling	1.15	1.45	-0.57	2.87	0.57	0.06	10.12	0.022
	3-yr rolling	1.10	1.07	-0.15	2.33	0.59	0.07	8.53	0.014
	5-yr rolling	1.06	0.94	-0.03	2.15	0.64	0.08	8.45	0.013
	7-yr rolling	1.11	0.88	0.08	2.13	0.67	0.07	9.30	0.009
Panel B: All-but-tiny stocks									
Model 1	1-yr rolling	1.00	0.90	-0.03	2.05	0.52	0.08	6.24	0.023
	3-yr rolling	1.00	0.65	0.26	1.74	0.66	0.12	5.46	0.020
	5-yr rolling	0.95	0.55	0.33	1.58	0.36	0.25	1.46	0.018
	7-yr rolling	1.01	0.52	0.43	1.60	0.57	0.16	3.62	0.016
Model 2	1-yr rolling	1.04	1.02	-0.10	2.19	0.51	0.06	8.10	0.022
	3-yr rolling	1.02	0.72	0.21	1.83	0.66	0.09	7.40	0.018
	5-yr rolling	0.98	0.62	0.29	1.66	0.52	0.11	4.67	0.016
	7-yr rolling	1.03	0.59	0.39	1.67	0.65	0.11	5.76	0.015
Model 3	1-yr rolling	1.03	1.27	-0.45	2.49	0.41	0.06	6.99	0.032
	3-yr rolling	0.98	0.86	-0.01	1.94	0.51	0.08	6.42	0.022
	5-yr rolling	0.94	0.73	0.11	1.75	0.49	0.09	5.66	0.019
	7-yr rolling	1.00	0.66	0.25	1.73	0.50	0.10	4.92	0.017
Panel C: Large stocks									
Model 1	1-yr rolling	0.93	0.83	-0.01	1.90	0.50	0.10	5.18	0.028
	3-yr rolling	0.92	0.57	0.28	1.59	0.72	0.14	5.24	0.026
	5-yr rolling	0.89	0.48	0.34	1.44	0.49	0.21	2.28	0.025
	7-yr rolling	0.95	0.45	0.45	1.47	0.55	0.22	2.46	0.024
Model 2	1-yr rolling	0.98	0.95	-0.09	2.06	0.47	0.07	7.15	0.027
	3-yr rolling	0.95	0.64	0.23	1.67	0.65	0.10	6.33	0.025
	5-yr rolling	0.92	0.53	0.32	1.52	0.58	0.12	4.68	0.022
	7-yr rolling	0.98	0.50	0.43	1.53	0.66	0.13	5.08	0.021
Model 3	1-yr rolling	0.98	1.23	-0.42	2.38	0.36	0.06	5.82	0.040
	3-yr rolling	0.92	0.79	0.03	1.80	0.48	0.09	5.38	0.029
	5-yr rolling	0.91	0.64	0.21	1.62	0.49	0.10	4.96	0.026
	7-yr rolling	0.97	0.56	0.34	1.60	0.49	0.12	3.94	0.024

of the sample), and so forth.

The general pattern of the results suggests that forecasts based on longer windows of past FM slopes are more accurate: The cross-sectional dispersion of the forecasts declines monotonically as the window grows from one to seven years, while the predictive slopes tend to increase. Both patterns suggest that forecasts based on longer windows are less noisy.

At the same time, the forecasting ability of the estimates is surprisingly strong even for those based on just 12 months of past FM regressions. Across all windows and groups of stocks, the slopes range from 0.36 to 0.79. Three-quarters of the slopes (27/36) are above 0.50 and nearly half (15/36) are above 0.60. The t-statistics are greater than four with only five exceptions, and all but one of the t-statistics for the full sample are greater than six. As in Table 3, the slopes are significantly less than one, so the expected-return estimates vary more than the true expected returns they forecast, but the estimates do a reasonably good job of capturing variation in true expected returns.[4]

For the shortest windows, the return forecasts reflect some short-term persistence in FM slopes on individual characteristics. For example, in the full sample, FM slopes on 14 of the 15 variables in Model 3 have positive first-order autocorrelations, with an average value of 0.10 across the 15 variables (the average autocorrelation is 0.07 for all-but-tiny and large stocks; the standard error of the autocorrelations is about $1/596^{1/2} = 0.04$). The persistence essentially vanishes by lag 2, suggesting that it reflects higher-frequency properties of returns rather than long-lasting changes in the slopes.

As a robustness check, I have re-run the tests skipping a month between the rolling windows used to estimate FM regressions and the month used to explore the predictive ability of the return forecasts. The predictive

[4] The last few years of the sample have a large negative impact on the predictive slopes in Table 5, especially the estimates for Model 1 based on 5- and 7-year rolling windows (which are most sensitive to the poor performance of momentum in 2009). For example, if data for 2009–2013 are dropped, the predictive slope for 5-year rolling estimates of Model 1 jumps from 0.59 to 0.74 for all stocks, 0.36 to 0.63 for all-but-tiny stocks, and 0.49 to 0.70 for large stocks (all t-statistics become greater than four). The results prior to 2009 also provide stronger evidence that forecasts based on longer windows are more accurate than forecasts based on shorter windows.

ability of the forecasts drops somewhat for short-window estimates but the basic conclusions are quite robust. For example, using 12-month rolling estimates of Model 1, the predictive slopes in Table 5 drop from 0.70 to 0.56 for the full sample (t-statistic of 4.72), 0.52 to 0.43 for all-but-tiny stocks (t-statistic of 4.40), and 0.50 to 0.43 for large stocks (t-statistic of 4.07). The corresponding slopes in Table 3 using 10-year rolling windows drop from 0.77 to 0.76 (t-statistic of 8.69), 0.62 to 0.60 (t-statistic of 4.68), and 0.66 to 0.64 (t-statistic of 3.80) for the three groups of stocks. The results for Models 2 and 3 are similar.

3.5. Portfolios

For additional perspective on the predictive power of the return forecasts, Table 6 compares the predicted and actual returns of expected-return-sorted portfolios. To keep the output manageable, I show results only for Model 3, using all 15 firm characteristics as predictors (forecasts are based on 10-year rolling averages of past FM slopes). These results are representative of those from all three models: predicted returns from Models 1 and 2 exhibit a bit less cross-sectional dispersion across portfolios but the actual returns of the portfolios are similar (average returns and t-statistics for the high-minus-low strategies in the table tend to be marginally stronger using Model 2 and marginally weaker using Model 1).

The results in Table 6 convey, at a basic level, the same message as my earlier tests: FM-based estimates of expected returns have strong predictive power for subsequent returns but exhibit too much variation across portfolios relative to average realized returns. Actual returns line up almost monotonically with predicted returns for both equal- and value-weighted portfolios and for all three groups of stocks, with large spreads between the top and bottom deciles.

Focusing first on equal-weighted portfolios of all stocks, average *predicted* returns range from -0.46% to 2.64% monthly compared with average *realized* returns of 0.24–2.60%. The spread between the top and bottom deciles (H–L) is 3.09% for predicted returns and 2.36% for realized returns, yielding a ratio of 0.76 (2.36/3.09), almost identical to the cross-sectional slope estimated in Table 3. Statistically and economically, H–L's average return is extremely large. The point estimate is 10.21 standard errors above zero, and both the

Table 6
Expected-return sorted portfolios, 1974–2013
This table reports average predicted (Pred) and realized (Avg) returns for equal- and value-weighted deciles when stocks are sorted by predicted expected returns. The standard deviation (Std) and annualized Sharpe ratio (Shp) of returns are also reported, along with Newey-West t-statistics (t-stat) testing whether the risk premium is positive. Predicted expected returns are derived from a firm's current characteristics and slopes from past Fama-MacBeth regressions (10-year rolling estimates of Model 3, which includes all 15 characteristics). The full sample includes all common stocks on CRSP with the data necessary to forecast expected returns. 'All-but-tiny' stocks are those larger than the NYSE 20th percentile based on market cap and 'Large' stocks are those larger than the NYSE median. Market data come from CRSP and accounting data come from Compustat.

	Equal-weighted					Value-weighted				
	Pred	Avg	Std	Shp	t-stat	Pred	Avg	Std	Shp	t-stat
Panel A: All stocks										
Low (L)	-0.46	0.24	7.17	-0.08	-0.45	-0.32	0.65	5.93	0.14	0.84
2	0.33	0.91	5.75	0.30	1.75	0.33	0.97	4.70	0.42	2.61
3	0.63	1.10	5.38	0.44	2.55	0.63	1.10	4.56	0.52	3.27
4	0.86	1.25	5.24	0.56	3.19	0.85	1.16	4.63	0.56	3.43
5	1.04	1.31	5.28	0.59	3.39	1.04	1.26	4.95	0.59	3.72
6	1.22	1.48	5.31	0.70	4.01	1.22	1.34	5.22	0.62	3.72
7	1.41	1.58	5.47	0.74	4.16	1.40	1.45	5.58	0.65	3.76
8	1.63	1.79	5.95	0.80	4.52	1.62	1.63	6.06	0.70	4.05
9	1.92	2.07	6.58	0.87	4.75	1.91	1.77	6.70	0.70	4.06
High (H)	2.64	2.60	7.76	0.98	5.30	2.53	2.19	8.02	0.77	4.45
H–L	3.09	2.36	4.93	1.65	10.21	2.85	1.54	6.30	0.85	5.03
Panel B: All-but-tiny stocks										
Low (L)	-0.12	0.53	7.26	0.06	0.38	-0.02	0.49	6.41	0.05	0.29
2	0.48	1.00	5.90	0.35	2.16	0.49	0.86	4.99	0.31	2.01
3	0.71	1.09	5.24	0.45	2.71	0.71	0.87	4.58	0.35	2.12
4	0.87	1.26	5.12	0.57	3.44	0.86	1.02	4.55	0.47	2.90
5	1.00	1.27	5.01	0.59	3.62	0.99	1.03	4.63	0.47	2.94
6	1.12	1.35	4.95	0.66	3.99	1.11	1.14	4.76	0.53	3.26
7	1.24	1.36	4.95	0.67	4.03	1.24	1.16	4.85	0.54	3.30
8	1.38	1.54	5.08	0.77	4.75	1.38	1.32	5.05	0.62	3.74
9	1.58	1.60	5.59	0.74	4.59	1.58	1.42	5.64	0.62	3.63
High (H)	2.12	1.80	6.93	0.70	4.19	2.06	1.66	6.76	0.64	3.82
H–L	2.24	1.26	5.17	0.85	5.26	2.08	1.16	5.99	0.67	4.09
Panel C: Large stocks										
Low (L)	0.11	0.71	6.72	0.16	1.00	0.16	0.63	6.32	0.12	0.77
2	0.56	1.08	5.49	0.42	2.68	0.56	0.83	5.00	0.30	1.88
3	0.73	1.01	5.03	0.42	2.48	0.73	0.94	4.69	0.40	2.43
4	0.85	1.14	4.87	0.52	3.25	0.85	0.92	4.39	0.40	2.55
5	0.96	1.20	4.76	0.57	3.39	0.96	1.03	4.54	0.48	2.89
6	1.06	1.21	4.66	0.59	3.60	1.06	1.00	4.44	0.46	2.88
7	1.17	1.27	4.71	0.63	3.88	1.16	1.08	4.62	0.50	3.18
8	1.29	1.28	4.68	0.65	3.99	1.29	1.16	4.84	0.54	3.23
9	1.48	1.31	5.16	0.60	3.58	1.48	1.19	5.27	0.52	3.01
High (H)	1.98	1.71	6.73	0.67	4.00	1.95	1.56	6.65	0.60	3.53
H–L	1.87	1.00	5.68	0.61	3.70	1.80	0.93	6.01	0.54	3.25

return itself (2.36%) and the annualized Sharpe ratio (1.65) suggest a very profitable trading strategy. For comparison, the market portfolio has an average monthly excess return of 0.60% and an annualized Sharpe ratio of 0.45 from 1974 to 2013.

The cross-sectional dispersion in both predicted and realized average returns is less dramatic among larger stocks but the spread between the top and bottom deciles is still considerable. For all-but-tiny stocks, average predicted returns range from -0.12% to 2.12% compared with average realized returns of 0.53–1.80%. For large stocks, average predicted returns range from 0.11% to 1.98% compared with average realized returns of 0.71–1.71%. Again, the average returns of the H–L strategies, 1.26% for all-but-tiny stocks and 1.00% for large stocks, are statistically and economically large (t-statistics of 5.26 and 3.70, respectively, and annualized Sharpe ratios of 0.85 and 0.61).

Results for value-weighted portfolios are fairly similar to the results for equal-weighted portfolios of larger stocks. In particular, for value-weighted H–L strategies, the average predicted return is 2.85% using all stocks, 2.08% for all-but-tiny stocks, and 1.80% for large stocks. These compare with average realized returns of 1.54%, 1.16%, and 0.93%, respectively (t-statistics of 3.25–5.03). All of the results indicate that estimated expected returns have strong predictive power for subsequent realized returns.

While my paper is primarily concerned with how well the return forecasts line up with true expected returns—regardless of whether the predictive power is rational or not—Table 7 reports, for completeness, risk-adjusted returns on the portfolios relative to the CAPM and Fama-French (1993) three-factor models. The patterns are similar to those in average returns: Alphas are almost monotonically related to predicted returns in all six panels, and the alphas for H–L strategies are close to their average returns in Table 6. From a trading perspective, an important result in Table 7 is that the performance of the H–L strategies is driven as much by the long side of the strategy as by the short side. For example, for value-weighted portfolios of large stocks, the top decile has a three-factor alpha of 0.53% (t-statistic of 3.08) and the bottom decile has a three-factor alpha of -0.51% (t-statistic of -3.37). Thus, to the extent that positive abnormal returns are easier to exploit than negative abnormal returns, Table 7 suggests that trading strategies based on the expected-return estimates

Table 7
Alphas for expected-return sorted portfolios, 1974–2013
This table reports CAPM and Fama-French three-factor alphas for equal- and value-weighted deciles when stocks are sorted by predicted expected returns. Predicted expected returns are derived from a firm's current characteristics and the slopes from past Fama-MacBeth regressions (10-year rolling estimates of Model 3, which includes all 15 firm characteristics). The full sample includes all common stocks on CRSP with the data required to forecast returns. 'All-but-tiny' stocks are those larger than the NYSE 20th percentile based on market cap and 'Large' stocks' are those larger than the NYSE median. Market data come from CRSP, accounting data come from Compustat, and the Fama-French factors come from Kenneth French's website at Dartmouth College.

	Equal-weighted				Value-weighted			
	a_{CAPM}	$t(a_{CAPM})$	a_{FF}	$t(a_{FF})$	a_{CAPM}	$t(a_{CAPM})$	a_{FF}	$t(a_{FF})$
Panel A: All stocks								
Low (L)	-0.95	-5.20	-1.14	-7.99	-0.45	-3.47	-0.40	-3.12
2	-0.16	-1.26	-0.35	-3.50	-0.01	-0.07	0.04	0.52
3	0.06	0.50	-0.17	-1.91	0.13	1.87	0.12	1.76
4	0.23	1.99	-0.02	-0.21	0.18	2.44	0.11	1.59
5	0.30	2.39	0.02	0.31	0.25	2.96	0.15	1.87
6	0.47	3.73	0.18	2.82	0.32	3.24	0.22	2.39
7	0.57	4.03	0.27	3.92	0.39	3.44	0.24	2.37
8	0.74	4.51	0.43	4.92	0.54	3.62	0.42	2.76
9	1.00	4.87	0.68	5.44	0.63	3.46	0.49	3.06
High (H)	1.48	5.62	1.18	6.41	0.96	4.21	0.81	4.14
H–L	2.43	10.09	2.32	10.46	1.41	4.78	1.21	4.45
Panel B: All-but-tiny stocks								
Low (L)	-0.71	-4.62	-0.82	-6.10	-0.64	-4.09	-0.66	-4.35
2	-0.11	-0.89	-0.24	-2.13	-0.13	-1.25	-0.10	-0.89
3	0.06	0.53	-0.11	-1.14	-0.08	-0.96	-0.07	-0.90
4	0.23	2.34	0.04	0.52	0.07	0.91	0.07	0.94
5	0.25	2.69	0.06	0.87	0.06	0.82	0.02	0.29
6	0.35	3.56	0.15	2.24	0.17	1.87	0.13	1.45
7	0.36	3.56	0.15	2.47	0.17	2.06	0.11	1.40
8	0.52	5.36	0.32	5.32	0.31	3.13	0.26	2.83
9	0.55	5.01	0.39	5.91	0.35	2.99	0.33	3.06
High (H)	0.65	3.65	0.56	4.39	0.52	3.03	0.53	3.39
H–L	1.36	5.76	1.38	5.96	1.16	3.97	1.19	4.31
Panel C: Large stocks								
Low (L)	-0.47	-3.10	-0.55	-3.71	-0.49	-3.18	-0.51	-3.37
2	0.03	0.22	-0.07	-0.65	-0.14	-1.24	-0.17	-1.65
3	0.00	0.02	-0.13	-1.42	-0.01	-0.09	0.00	-0.02
4	0.14	1.56	0.02	0.19	0.00	-0.06	0.00	0.03
5	0.21	2.21	0.07	0.85	0.09	1.00	0.08	0.92
6	0.23	2.95	0.10	1.41	0.07	0.85	0.09	1.15
7	0.28	3.65	0.14	2.34	0.11	1.37	0.08	0.95
8	0.30	3.85	0.20	3.16	0.18	1.85	0.19	2.00
9	0.29	3.07	0.24	2.88	0.18	1.52	0.21	1.93
High (H)	0.58	3.36	0.60	3.91	0.43	2.43	0.53	3.08
H–L	1.04	3.88	1.15	4.35	0.92	3.08	1.04	3.62

might be profitable.[5]

3.6. Evolution through time

Fig. 2 explores how the predictive ability of the expected-return estimates changes through time. For brevity, I again focus on forecasts from Model 3. The top panel plots the out-of-sample predictive slopes discussed in Section 3.2, while the bottom panel plots returns on the equal- and value-weighted H–L strategies described in Section 3.5 (top minus bottom decile when all stocks are sorted by predicted expected returns). The graphs show 10-year rolling averages of the statistics starting with data in May 1974, implying the first 10-year window ends in April 1984.

The predictive power of the estimates is stable for most of the sample. Until 2008, the 10-year rolling average of the predictive slopes (Panel A) fluctuates in a fairly narrow range around 0.80 for all stocks and 0.60 for all-but-tiny and large stocks, reaching a low in the mid-1990s before peaking close to one in the early 2000s. Average returns for the equal-weighted H–L strategy are also quite steady (they peak near 3.6% monthly in 2004), while average returns for the value-weighted H–L strategy decline substantially in the 1980s and 1990s before rebounding in 2000.

The predictive ability deteriorates at the end of the sample, due in part to extremely poor performance among large stocks in 2007–2010. The average predictive slope in the final ten years is 0.38 for the full sample, 0.15 for all-but-tiny stocks, and -0.37 for large stocks (the yearly average hits a minimum value of -0.10 for the full sample in 2007 and -2.03 for large stocks in 2009). Returns on the H–L strategies also decline but remain positive from 2004–2013, equal to 1.20% monthly for equal-weighted portfolios and 0.71% monthly for value-weighted portfolios. In short, the forecasts have weaker predictive power at the end of the sample, but it is impossible to tell whether the decline is permanent or reflects the unusual behavior of returns during the financial crisis, especially the negative returns to momentum in 2009.

[5] Alphas from a four-factor model that includes Fama and French's UMD momentum factor can also be quite large but are less uniformly significant than CAPM and three-factor alphas. For equal-weighted H–L strategies, four-factor alphas are 2.04% (t-statistic of 8.49) using all stocks, 0.68% (t-statistic of 3.54) for all-but-tiny stocks, and 0.43% (t-statistic of 1.97) for large stocks. For value-weighted H–L strategies, four-factor alphas are 0.83% (t-statistic of 3.15), 0.46% (t-statistic of 1.97), and 0.29% (t-statistic of 1.17), respectively.

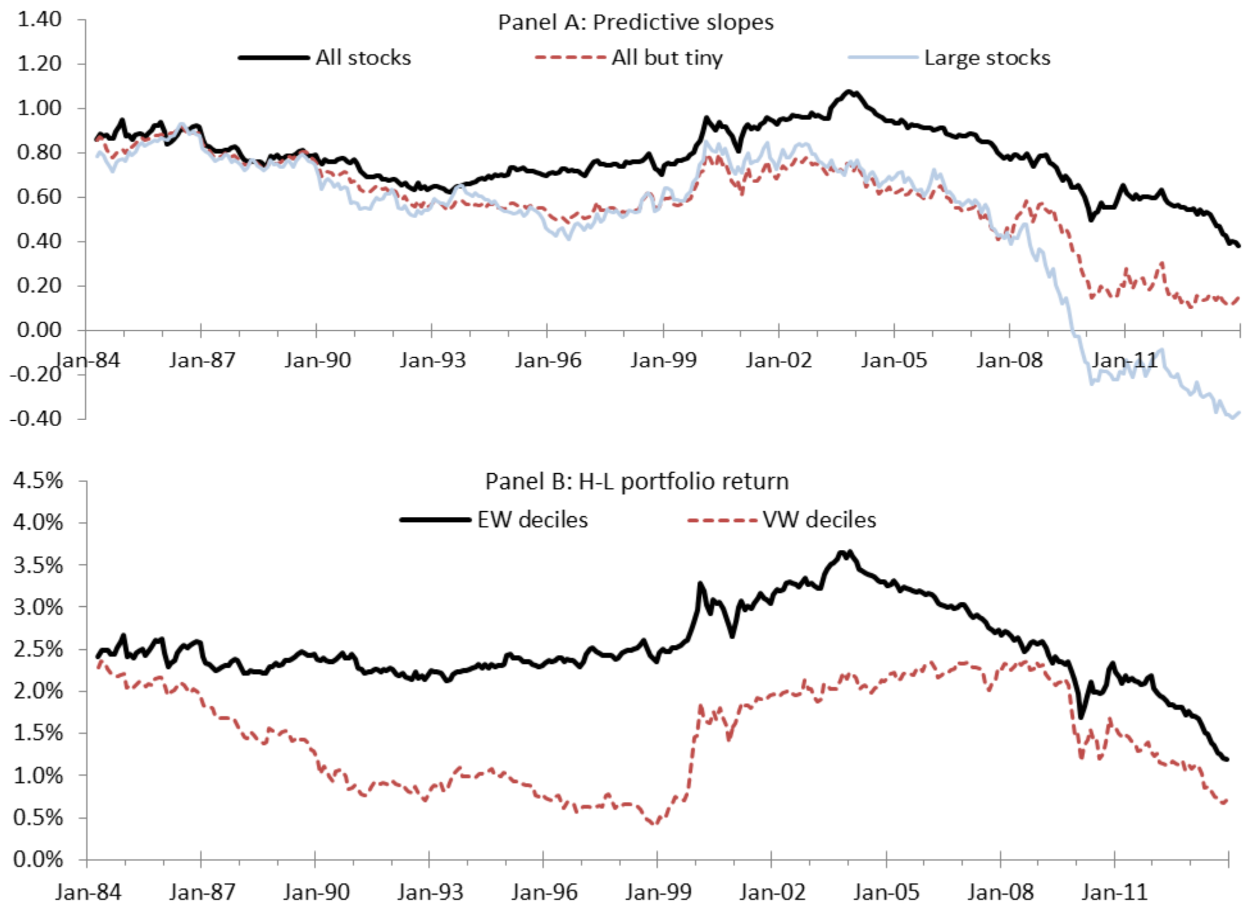

Fig. 2. Out-of-sample predictive slopes and portfolio returns, 1984–2013
Panel A plots ten-year rolling averages of the predictive slope on return forecasts from Model 3, which includes all 15 firm characteristics (the forecasts themselves are based on ten-year rolling windows of past Fama-MacBeth regressions). Panel B plots ten-year rolling averages of monthly returns on equal- and value-weighted H–L strategies (decile 10 minus decile 1) when stocks are sorted by return forecasts from Model 3. Market data come from CRSP and accounting data come from Compustat. The variables are defined in Table 1.

4. Longer-horizon expected returns

Estimates of expected monthly returns have many uses in asset-pricing research and investment practice, but longer-horizon expected returns are more important for some applications. For example, there has been much work in recent years attempting to infer a firm's cost of equity from its current stock price and earnings forecasts, focusing almost exclusively on annual stock returns. In addition, to the extent that an investor is interested in a buy-and-hold strategy—or, at least, in managing portfolio turnover and trading costs—expected returns beyond a month are important.

4.1. Forecasting long-horizon returns

I explore two ways of forecasting long-horizon returns. The first way simply repeats my earlier tests using long-horizon returns in place of monthly returns, i.e., forecasts are derived from FM regressions of 6- and 12-month returns on lagged characteristics. The second approach extrapolates long-horizon expected returns from forecasts of monthly returns, accounting for the fact that firm characteristics and expected returns may contain transitory components and, consequently, revert toward their cross-sectional means through time. The advantage of the second approach is that, by imposing structure on the behavior of expected monthly returns, we should be able to forecast long-horizon returns more precisely; the disadvantage, of course, is that imposing this structure will add noise if it is wrong.

For the second approach, I extrapolate from monthly to longer horizons assuming that expected returns decay geometrically toward the cross-sectional average expected return. The decay rate is based on the persistence of the monthly forecasts from Section 3: Using 10-year rolling averages of FM slopes, the monthly expected-return estimates have a first-order autocorrelation (in cross-sectional regressions) of 0.90–0.94 for the three groups of stocks and three regression models, which I round to 0.90 for simplicity. Stock i's predicted k-month return is then calculated as $F_{ik} = k\ F_1 + (1+.9+.9^2+\ldots+.9^{k-1})(F_{i1} - F_1)$, where F_{i1} is the monthly forecast for stock i and F_1 is the cross-sectional mean of F_{i1}.

It is useful to note that the mean-reversion (or shrinkage) embedded in the estimates affects only the cross-sectional dispersion of the forecasts, with an offsetting effect on their predictive slopes, but has no impact on the statistical tests. At a basic level, the tests simply ask whether the monthly forecasts help to predict longer-horizon returns. The calculation described in the prior paragraph just scales the forecasts in a way to make them interpretable as 6- or 12-month expected returns, recognizing that monthly expected returns seem to contain a mean-reverting component.

4.2. Results

Tables 8a and 8b report the first-step FM regressions of 6- and 12-month returns on lagged firm characteristics,

Table 8a
Fama-MacBeth regressions using 6-month returns, 1964–2013

This table summarizes Fama-MacBeth regressions (average slopes, R^2s, and number of stocks) when 6-month returns (in %) are regressed on lagged firm characteristics; t-statistics are based on the time-series variability of the slopes, incorporating a Newey-West correction with ten lags. The full sample includes all common stocks on CRSP. 'All-but-tiny' stocks are those larger than the NYSE 20th percentile and 'Large' stocks are those larger than the NYSE median. Accounting data come from Compustat. The variables are defined in Table 1.

	All stocks			All-but-tiny stocks			Large stocks		
	Slope	t-stat	R^2	Slope	t-stat	R^2	Slope	t-stat	R^2
Model 1: Three predictors									
LogSize_{-1}	-0.61	-2.07	0.044	-0.39	-1.64	0.057	-0.40	-1.68	0.068
LogB/M_{-1}	2.18	4.65		1.47	3.16		1.18	2.50	
$\text{Return}_{-2,-12}$	4.69	3.96		4.37	3.66		4.42	3.45	
N	3,956			1,704			875		
Model 2: Seven predictors									
LogSize_{-1}	-0.67	-2.71	0.057	-0.63	-2.67	0.077	-0.64	-2.72	0.097
LogB/M_{-1}	1.30	2.91		1.09	2.20		0.96	1.81	
$\text{Return}_{-2,-12}$	3.46	3.27		3.67	3.06		4.17	3.27	
$\text{LogIssues}_{-1,-36}$	-3.48	-6.13		-2.77	-4.21		-3.51	-4.60	
$\text{Accruals}_{\text{Yr-1}}$	-6.97	-4.61		-8.44	-4.80		-6.29	-2.92	
$\text{ROA}_{\text{Yr-1}}$	7.07	2.08		9.78	2.57		8.42	2.04	
$\text{LogAG}_{\text{Yr-1}}$	-5.06	-8.23		-2.49	-3.37		-1.81	-1.87	
N	3,253			1,407			743		
Model 3: Fifteen predictors									
LogSize_{-1}	-0.73	-3.67	0.097	-0.85	-3.85	0.137	-0.75	-3.33	0.176
LogB/M_{-1}	0.98	2.92		0.55	1.44		0.42	0.91	
$\text{Return}_{-2,-12}$	3.46	3.99		3.59	3.40		4.13	3.86	
$\text{LogIssues}_{-1,-36}$	-2.85	-4.30		-1.83	-2.30		-2.57	-3.37	
$\text{Accruals}_{\text{Yr-1}}$	-6.12	-4.56		-8.14	-4.70		-6.63	-3.45	
$\text{ROA}_{\text{Yr-1}}$	6.56	2.95		7.77	2.99		5.73	1.63	
$\text{LogAG}_{\text{Yr-1}}$	-3.45	-5.13		-1.65	-2.52		-0.83	-0.97	
$\text{DY}_{-1,-12}$	-25.04	-2.55		-22.66	-2.29		-3.76	-0.33	
$\text{LogReturn}_{-13,-36}$	-0.77	-1.78		-0.43	-0.92		-0.23	-0.44	
$\text{LogIssues}_{-1,-12}$	-1.41	-1.07		-2.36	-1.84		-2.34	-1.77	
$\text{Beta}_{-1,-36}$	1.57	2.39		1.47	2.30		1.00	1.52	
$\text{StdDev}_{-1,-12}$	-9.47	-1.67		-25.03	-3.32		-26.89	-2.96	
$\text{Turnover}_{-1,-12}$	-22.12	-3.49		-7.98	-1.04		-0.15	-0.02	
$\text{Debt/Price}_{\text{Yr-1}}$	-0.29	-1.48		0.20	1.01		0.31	1.32	
$\text{Sales/Price}_{\text{Yr-1}}$	0.13	1.58		0.13	1.10		0.08	0.61	
N	2,964			1,346			726		

replicating the tests from Table 2. The regressions are estimated monthly and the t-statistics incorporate a Newey-West correction with ten lags for 6-month returns and 16 lags for 12-month returns to account for the overlap in successive monthly regressions.

For the most part, the same variables that predict monthly returns also predict 6- and 12-month returns, though

Table 8b
Fama-MacBeth regressions using 12-month returns, 1964–2013

This table summarizes Fama-MacBeth regressions (average slopes, R^2s, and number of stocks) when 12-month returns (in %) are regressed on lagged firm characteristics; t-statistics are based on the time-series variability of the slopes, incorporating a Newey-West correction with 16 lags. The full sample includes all common stocks on CRSP. 'All-but-tiny' stocks are those larger than the NYSE 20th percentile and 'Large' stocks are those larger than the NYSE median. Accounting data come from Compustat. The variables are defined in Table 1.

	All stocks			All-but-tiny stocks			Large stocks		
	Slope	t-stat	R^2	Slope	t-stat	R^2	Slope	t-stat	R^2
Model 1: Three predictors									
LogSize_{-1}	-1.17	-1.81	0.044	-0.83	-1.60	0.057	-0.84	-1.57	0.067
LogB/M_{-1}	4.05	4.14		2.65	2.64		1.93	1.89	
$\text{Return}_{-2,-12}$	5.75	2.81		5.53	2.92		5.18	2.66	
N	3,958			1,703			874		
Model 2: Seven predictors									
LogSize_{-1}	-1.37	-2.41	0.060	-1.25	-2.38	0.080	-1.27	-2.41	0.098
LogB/M_{-1}	2.27	2.25		1.77	1.56		1.38	1.14	
$\text{Return}_{-2,-12}$	3.36	1.86		4.16	2.27		4.83	2.46	
$\text{LogIssues}_{-1,-36}$	-7.46	-6.70		-6.21	-4.49		-7.40	-4.54	
$\text{Accruals}_{\text{Yr-1}}$	-13.77	-4.98		-15.45	-4.69		-11.58	-3.04	
$\text{ROA}_{\text{Yr-1}}$	14.02	1.70		14.89	1.64		12.11	1.34	
$\text{LogAG}_{\text{Yr-1}}$	-9.69	-8.31		-4.56	-2.85		-3.11	-1.59	
N	3,251			1,404			742		
Model 3: Fifteen predictors									
LogSize_{-1}	-1.44	-3.11	0.097	-1.65	-3.28	0.136	-1.34	-2.68	0.174
LogB/M_{-1}	1.99	2.83		1.06	1.36		0.78	0.81	
$\text{Return}_{-2,-12}$	3.53	2.38		4.26	2.61		4.94	2.99	
$\text{LogIssues}_{-1,-36}$	-6.56	-4.76		-4.57	-3.08		-5.56	-3.76	
$\text{Accruals}_{\text{Yr-1}}$	-12.36	-5.14		-14.58	-4.53		-11.69	-3.41	
$\text{ROA}_{\text{Yr-1}}$	14.16	2.90		13.06	2.36		8.06	1.22	
$\text{LogAG}_{\text{Yr-1}}$	-6.59	-5.57		-3.03	-2.37		-1.07	-0.64	
$\text{DY}_{-1,-12}$	-68.97	-2.92		-55.64	-2.38		-18.61	-0.76	
$\text{LogReturn}_{-13,-36}$	-1.27	-1.43		-0.98	-0.85		-0.61	-0.50	
$\text{LogIssues}_{-1,-12}$	-1.72	-0.57		-4.09	-1.64		-5.47	-2.06	
$\text{Beta}_{-1,-36}$	2.55	1.94		2.57	1.91		1.24	0.98	
$\text{StdDev}_{-1,-12}$	-16.43	-1.47		-47.64	-3.60		-44.02	-2.61	
$\text{Turnover}_{-1,-12}$	-34.33	-2.56		-11.99	-0.71		2.55	0.13	
$\text{Debt/Price}_{\text{Yr-1}}$	-0.21	-0.44		0.65	1.49		0.75	1.47	
$\text{Sales/Price}_{\text{Yr-1}}$	0.24	1.34		0.20	0.80		0.04	0.14	
N	2,960			1,342			725		

their statistical significance here tends to be weaker. The drop in significance is especially striking for B/M, momentum, and ROA, with t-statistics that are often less than half those in Table 2 (but still greater than two). Accruals, share issuance, and asset growth continue to be highly significant—in fact, the latter two variables are more significant here than in the earlier monthly regressions. In Model 3, dividend yield also predicts 6- and 12-month returns more strongly than in monthly data, with slopes that are more than two standard errors below zero for all stocks and all-but-tiny stocks. The remaining variables have weak predictive power, similar to that found using monthly returns.

Tables 9a and 9b report the distribution and predictive ability of estimated 6- and 12-month expected returns. As before, I show results using 10-year rolling estimates and cumulative averages of past FM slopes. The top panel in each table is based on the first forecasting approach described above, with forecasts derived from the FM regressions in Tables 8a and 8b. The bottom panels use the second approach, with forecasts extrapolated from the monthly estimates in Table 3. The predictive slopes in the right-hand columns come from out-of-sample FM regressions with 6- or 12-month realized returns as the dependent variable (the t-statistics again incorporate a Newey-West correction with ten lags for 6-month returns and 16 lags for 12-month returns to account for the overlap in successive regressions).

The tables show that the monthly results extend to longer horizons: the expected-return estimates exhibit large cross-sectional variation and have strong predictive power for subsequent returns but vary too much relative to the actual expected returns they forecast. The dispersion and out-of-sample predictive slopes are strong using either of the two forecasting approaches.

Focusing on 12-month returns (Table 9b), the expected-return estimates have a cross-sectional standard deviation of 5.44–9.16% for the full sample, 3.64–5.80% for all-but-tiny stocks, and 3.02–5.35% for large stocks. The estimates tend to be more variable using the first forecasting approach (forecasts derived directly from long-horizon FM regressions) and using cumulative averages of FM slopes. Dispersion also rises when more characteristics are included in the model. The increase is modest in Panel B, reflecting the properties of the monthly forecasts on which they are based, but more substantial in Panel A when forecasts come directly from long-horizon FM regressions. The results suggest that the characteristics included in Models 2 and 3—in particular, share issuance, accruals, and asset growth—contribute more to the cross-sectional dispersion of long-horizon expected returns than of monthly expected returns, consistent with the stronger significance of the variables in Table 8b.

Table 9a
Expected 6-month stock returns, 1974–2013

This table reports the distribution (average, standard deviation, 10th and 90th percentiles) and predictive ability (slope, standard error, t-statistic, R^2) of 6-month return forecasts derived from a firm's current characteristics and slopes from past FM regressions. The forecasts in Panel A come from FM regressions using 6-month returns; the forecasts in Panel B come from FM regressions using monthly returns, extrapolating to 6-month forecasts as described in the text. All numbers other than t-statistics equal time-series averages of monthly cross-sectional parameters. Predictive slopes and R^2s come from (out-of-sample) FM regressions of 6-month returns on the return forecasts; t-statistics are based on the time-series variability of the predictive slopes, incorporating a Newey-West correction with 10 lags. The full sample includes all common stocks on CRSP. 'All but tiny' stocks are those larger than the NYSE 20th percentile and 'Large' stocks are those larger than the NYSE median. Accounting data come from Compustat. Models 1, 2, and 3 are defined in Table 8.

			Univariate properties				Predictive ability			
Sample	FM slopes	Model	Avg	Std	p10	p90	Slope	S.E.	t-stat	R^2
Panel A: Forecasting approach 1										
All stocks	Rolling	Model 1	7.16	3.50	3.05	11.22	0.67	0.12	5.38	0.010
		Model 2	7.30	4.06	2.60	11.76	0.73	0.09	7.85	0.012
		Model 3	6.79	4.59	1.33	11.92	0.66	0.08	7.83	0.015
	Cumulative	Model 1	6.96	3.67	2.73	11.30	0.74	0.09	8.20	0.010
		Model 2	6.99	3.96	2.46	11.49	0.81	0.07	11.52	0.012
		Model 3	5.56	4.97	-0.54	11.15	0.60	0.08	7.77	0.017
All-but-tiny stocks	Rolling	Model 1	6.43	2.46	3.70	9.19	0.48	0.14	3.39	0.015
		Model 2	6.46	2.90	3.31	9.55	0.52	0.11	4.60	0.016
		Model 3	6.30	3.23	2.64	9.86	0.44	0.10	4.21	0.015
	Cumulative	Model 1	5.55	2.76	2.60	8.65	0.56	0.14	3.96	0.018
		Model 2	5.48	2.95	2.28	8.72	0.66	0.12	5.59	0.018
		Model 3	4.59	3.26	0.71	8.25	0.57	0.11	4.99	0.020
Large stocks	Rolling	Model 1	6.04	2.21	3.61	8.53	0.56	0.17	3.39	0.024
		Model 2	6.12	2.57	3.30	8.95	0.53	0.13	4.18	0.023
		Model 3	6.36	2.97	3.14	9.74	0.28	0.12	2.43	0.022
	Cumulative	Model 1	4.89	2.28	2.44	7.44	0.61	0.18	3.38	0.026
		Model 2	4.75	2.56	1.95	7.59	0.68	0.14	4.97	0.025
		Model 3	4.34	2.52	1.41	7.16	0.61	0.14	4.30	0.026
Panel B: Forecasting approach 2										
All stocks	Rolling	Model 1	7.12	3.55	2.86	11.34	0.67	0.11	5.87	0.010
		Model 2	7.43	3.75	2.99	11.80	0.80	0.11	7.41	0.012
		Model 3	6.74	4.08	1.98	11.45	0.74	0.09	8.11	0.015
	Cumulative	Model 1	6.68	3.75	2.32	11.13	0.76	0.09	8.74	0.010
		Model 2	6.59	3.93	2.11	11.11	0.82	0.07	11.56	0.012
		Model 3	4.18	4.88	-1.72	9.61	0.65	0.07	8.79	0.016
All-but-tiny stocks	Rolling	Model 1	6.38	2.41	3.71	9.08	0.55	0.13	4.10	0.016
		Model 2	6.42	2.72	3.50	9.34	0.60	0.11	5.30	0.017
		Model 3	6.22	2.96	2.86	9.45	0.51	0.11	4.56	0.017
	Cumulative	Model 1	5.71	2.84	2.70	8.88	0.55	0.14	3.94	0.018
		Model 2	5.39	3.06	2.24	8.64	0.63	0.11	5.53	0.019
		Model 3	4.03	3.16	0.39	7.42	0.62	0.12	5.09	0.021
Large stocks	Rolling	Model 1	6.01	2.06	3.71	8.34	0.67	0.18	3.68	0.024
		Model 2	6.04	2.25	3.56	8.52	0.66	0.14	4.54	0.023
		Model 3	6.11	2.47	3.38	8.88	0.39	0.15	2.68	0.024
	Cumulative	Model 1	5.12	2.39	2.55	7.78	0.58	0.17	3.45	0.026
		Model 2	4.77	2.53	2.02	7.55	0.71	0.13	5.33	0.026
		Model 3	3.58	2.48	0.69	6.29	0.67	0.14	4.76	0.027

Table 9b
Expected 12-month stock returns, 1974–2013

This table reports the distribution (average, standard deviation, 10th and 90th percentiles) and predictive ability (slope, standard error, t-statistic, R^2) of 12-month return forecasts derived from a firm's current characteristics and slopes from past FM regressions. The forecasts in Panel A come from FM regressions using 12-month returns; the forecasts in Panel B come from FM regressions using monthly returns, extrapolating to 12-month forecasts as described in the text. All numbers other than t-statistics equal time-series averages of monthly cross-sectional parameters. Predictive slopes and R^2s come from (out-of-sample) FM regressions of 12-month returns on the return forecasts; t-statistics are based on the time-series variability of the predictive slopes, incorporating a Newey-West correction with 10 lags. The full sample includes all common stocks on CRSP. 'All-but-tiny' stocks are those larger than the NYSE 20th percentile and 'Large' stocks are those larger than the NYSE median. Accounting data come from Compustat. Models 1, 2, and 3 are defined in Table 8.

			Univariate properties				Predictive ability			
Sample	FM slopes	Model	Avg	Std	p10	p90	Slope	S.E.	t-stat	R^2
Panel A: Forecasting approach 1										
All stocks	Rolling	Model 1	15.13	5.90	7.89	22.14	0.65	0.18	3.69	0.011
		Model 2	15.10	7.29	6.51	23.04	0.76	0.13	5.88	0.014
		Model 3	14.40	8.30	4.36	23.82	0.56	0.09	6.48	0.014
	Cumulative	Model 1	14.58	6.20	6.98	22.16	0.66	0.13	4.87	0.010
		Model 2	14.64	7.27	6.01	23.11	0.77	0.09	8.34	0.013
		Model 3	13.21	9.16	2.04	23.84	0.54	0.09	5.95	0.017
All-but-tiny stocks	Rolling	Model 1	13.31	3.64	9.02	17.45	0.33	0.17	1.91	0.014
		Model 2	13.27	4.66	8.07	18.19	0.45	0.12	3.63	0.016
		Model 3	13.24	5.71	6.61	19.66	0.27	0.10	2.63	0.015
	Cumulative	Model 1	11.09	4.18	6.32	15.87	0.47	0.13	3.55	0.016
		Model 2	10.97	4.81	5.38	16.31	0.63	0.10	5.98	0.016
		Model 3	9.80	5.80	2.69	16.35	0.43	0.12	3.48	0.021
Large stocks	Rolling	Model 1	12.59	3.08	9.01	16.09	0.42	0.21	2.03	0.022
		Model 2	12.71	4.04	8.19	17.12	0.40	0.12	3.39	0.019
		Model 3	13.34	5.35	7.49	19.55	0.22	0.11	1.96	0.019
	Cumulative	Model 1	9.77	3.02	6.31	13.17	0.54	0.18	2.96	0.022
		Model 2	9.55	3.89	5.10	13.77	0.62	0.12	5.41	0.019
		Model 3	9.49	3.94	4.79	13.89	0.41	0.14	2.82	0.022
Panel B: Forecasting approach 2										
All stocks	Rolling	Model 1	14.25	5.44	7.72	20.71	0.70	0.14	4.92	0.010
		Model 2	14.86	5.74	8.06	21.56	0.88	0.13	6.68	0.013
		Model 3	13.47	6.25	6.19	20.69	0.78	0.11	7.06	0.015
	Cumulative	Model 1	13.37	5.74	6.68	20.17	0.79	0.12	6.73	0.010
		Model 2	13.18	6.02	6.32	20.09	0.91	0.10	8.70	0.014
		Model 3	8.35	7.48	-0.68	16.67	0.72	0.11	6.56	0.017
All-but-tiny stocks	Rolling	Model 1	12.76	3.69	8.67	16.90	0.43	0.15	2.96	0.015
		Model 2	12.84	4.16	8.36	17.31	0.55	0.12	4.75	0.017
		Model 3	12.44	4.54	7.30	17.39	0.44	0.11	4.08	0.017
	Cumulative	Model 1	11.42	4.35	6.80	16.28	0.46	0.15	3.09	0.017
		Model 2	10.78	4.68	5.95	15.75	0.60	0.12	4.80	0.018
		Model 3	8.07	4.84	2.49	13.26	0.57	0.15	3.91	0.021
Large stocks	Rolling	Model 1	12.01	3.15	8.50	15.58	0.57	0.20	2.84	0.022
		Model 2	12.07	3.44	8.27	15.87	0.62	0.15	4.28	0.022
		Model 3	12.22	3.78	8.03	16.46	0.36	0.16	2.29	0.022
	Cumulative	Model 1	10.25	3.65	6.31	14.32	0.49	0.17	2.80	0.024
		Model 2	9.54	3.87	5.33	13.79	0.68	0.13	5.11	0.024
		Model 3	7.16	3.80	2.73	11.31	0.60	0.15	4.05	0.026

The right-hand columns show that the expected-return estimates have strong predictive power for all groups of stocks and regression models, but the predictive slopes and t-statistics tend to be somewhat lower than in monthly data. The slopes in Table 9b range from 0.54 to 0.91 for the full sample (t-statistics of 3.69–8.70), from 0.27 to 0.63 for all-but-tiny stocks (t-statistics of 1.91–5.98), and from 0.22 to 0.68 for large stocks (t-statistics of 1.96–5.41). Forecasts based on Model 2 seem to work best, and forecasts based on cumulative average FM slopes typically work slightly better than those based on 10-year rolling averages. The differences across models, estimation windows, and forecasting approaches are typically small.

The predictive slopes in Tables 9a and 9b, like those in Table 3, are reliably less than one. The results again imply that FM-based forecasts exhibit too much cross-sectional variation, consistent with the presence of significant estimation error. An analyst would need to shrink the forecasts toward the cross-sectional mean by about 10–30% for all stocks, 40–55% for all-but-tiny stocks, and about 35–60% for large stocks to get a more accurate estimate of a firm's true expected return.

5. Conclusions

The time-series and cross-sectional properties of expected stock returns are important for many applications in finance, including testing asset-pricing models, devising trading strategies, and determining a firm's cost of capital. The primary goal of this paper is to test how well we can estimate expected returns, in real time, using a firm's current characteristics and the historical slopes from FM regressions.

My results show that FM-based return forecasts do, in fact, line up well with true expected returns, especially over the shorter horizons typically used in asset-pricing studies. The out-of-sample predictive slopes in cross-sectional regressions, as well as the return spreads for expected-return-sorted portfolios, are economically and statistically large using any of the three specifications studied in this paper. In addition, the expected-return estimates are quite persistent and their predictive power extends for at least a year.

Interpreted differently, the tests suggest that FM regressions provide an effective way to combine many firm characteristics into a composite estimate of a stock's expected returns in real time. The cross-sectional slopes seem to be sufficiently stable and estimated sufficiently well that historical FM slopes provide a reasonably accurate picture of a firm's expected return over the next month and a somewhat noisier estimate of the expected return over the next year. Empirically, for the specifications considered here, a stock's expected-return estimate would need to be shrunk toward the cross-sectional mean by about 20–30% for monthly expected returns and 20–50% for annual expected returns to obtain an unbiased forecast of the stock's true expected return.

Appendix

This appendix provides a brief survey of the empirical literature as it relates to the cross-sectional predictive power of the firm characteristics used in this paper. The variables are discussed in roughly the order they first appear in the literature.

Beta: Black, Jensen, and Scholes (1972), Fama and MacBeth (1973), and others provide evidence that beta is positively related to expected stock returns, though not as strongly as the CAPM predicts. More recent work shows that beta has no predictive power after 1960 and no predictive power back to 1926 after controlling for its correlation with size and B/M (e.g., Fama and French, 1992, 2006b).

Dividend yield: The relation between dividends and expected stock returns has a long history in the empirical literature (e.g., Litzenberger and Ramaswamy, 1982; Miller and Scholes, 1982). The bottom line seems to be that dividend yield has little predictive power for future returns.

Size: Banz (1981) and Fama and French (1992) show that a firm's market cap is negatively related to its subsequent returns. In cross-sectional regressions that are similar to Model 2 of my paper, Fama and French (2008) estimate slopes that are close to those reported here.

Book-to-market: Stattman (1980), Rosenberg, Reid, and Lanstein (1985), and Fama and French (1992) show that B/M is positively related to expected returns. The effect remains after controlling for many other variables and seems to be strongest among smaller stocks (e.g., Fama and French, 1993, 2008).

Long-term past returns: DeBondt and Thaler (1985, 1987) first study the predictive power of long-term past returns, finding evidence of price reversals. Fama and French (1996) suggest that long-term reversals can be explained by the Fama–French (1993) size and B/M factors (in time-series tests using portfolios, not cross-sectional tests using size and B/M directly).

Leverage: Bhandari (1988) and Fama and French (1992) provide evidence that leverage is positively related to expected stock returns. Fama and French argue that the predictive power of leverage is subsumed by the B/M effect in returns.

Momentum: Jegadeesh and Titman (1993) show that past 3- to 12-month returns are positively related to subsequent 3- to 12-month returns. This relation has been confirmed by many others (e.g., Fama and French, 1996, 2008; Jegadeesh and Titman, 2001; Novy-Marx, 2012).

Profitability: Many studies find that earnings surprises, earnings-to-price, and earnings-to-book-value are positively related to subsequent returns (e.g., Basu, 1983; Bernard and Thomas, 1990; Fama and French, 1992, 2006a, 2008; Lakonishok, Shleifer, and Vishny, 1994; Chan, Jegadeesh, and Lakonishok, 1996; Chen, Novy-Marx, and Zhang, 2010). The earnings-to-price result seems to be subsumed by the size and B/M effects in returns (Fama and French, 1992, 1996).

Accruals: Sloan (1996) shows that accruals, defined as the change in net working capital minus depreciation, is strongly negatively related to subsequent returns. This result has been confirmed and extended by many others (e.g., Fairfield, Whisenant, and Yohn, 2003; Richardson et al., 2005; Fama and French, 2008).

Stock issuance: Many studies find that equity sales and repurchases have predictive power for future returns over both the short and long run (see Fama, 1998, for a review). Daniel and Titman (2006), Pontiff and Woodgate (2008), and Fama and French (2008) show that a composite measure of net issuance, equal to the percentage change in shares outstanding, is strongly negatively related to expected returns after controlling for other known predictors of stock returns.

Turnover: Lee and Swaminathan (2000) show that turnover in the past three to 12 months is negatively related to subsequent returns, especially among stocks that performed poorly over the same past 3- to 12-months. The effect persists after controlling for size and B/M factors.

Asset growth: A variety of variables that measure a firm's investment and growth seem to be negatively related to expected stock returns, included capital expenditures (Titman, Wie, and Xie, 2004) and both current and long-term accruals (Sloan, 1996; Fairfield, Whisenant, and Yohn, 2003; Richardson et al., 2005; Dechow, Richardson, and Sloan, 2008). Cooper, Gulen, and Schill (2008) show that a composite measure, the growth in total assets, has strong predictive power for future returns (see, also, Daniel and Titman, 2006; Fama and

French, 2006, 2008). This measure is closely related to the broad measure of accruals advanced by Fairfield, Whisenant, and Yohn (2003) and Hirshleifer et al. (2004).

Volatility: Ang et al. (2006) find that idiosyncratic volatility over the past 1- to 12-months is a strong negative predictor of subsequent returns. The effect remains after controlling for a variety of other firm characteristics, such as beta, size, B/M, momentum, and turnover.

Sales-to-price. Fama and French (1992) and Lakonishok, Shleifer, and Vishny (1994) show that expected stock returns are positively related to a variety of scaled-price variables, including B/M, earnings-to-price, and cash-flow-to-price. The sales-to-price ratio is motivated by the same logic but should contain new information relative to the other fourteen variables.

References

Ang, Andrew, Robert Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006. The cross-section of volatility and expected returns. Journal of Finance 61, 259–299.

Banz, Rolf, 1981. The relationship between return and market value of common stocks. Journal of Financial Economics 9, 3–18.

Basu, Sanjoy, 1983. The relationship between earnings yield, market value, and return for NYSE common stocks: Further evidence. Journal of Financial Economics 12, 129–156.

Bernard, Victor and Jacob Thomas, 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. Journal of Accounting and Economics 13, 305–340.

Bhandari, Laxmi Chand, 1988. Debt/equity ratio and expected common stock returns: Empirical evidence. Journal of Finance 43, 507–528.

Black, Fischer, Michael Jensen, and Myron Scholes, 1972. The capital asset pricing model: Some empirical tests. In: M. Jensen, ed., Studies in the theory of capital markets (Praeger, New York, NY), 79–121.

Chan, Louis, Narashimhan Jegadeesh, and Josef Lakonishok, 1996. Momentum strategies. Journal of Finance 51, 1681–1713.

Chen, Long, Robert Novy-Marx, and Lu Zhang, 2010. An alternative three-factor model. Working paper (University of Washington in St. Louis).

Cooper, Michael, Huseyin Gulen, and Michael Schill, 2008. Asset growth and the cross-section of stock returns. Journal of Finance 63, 1609–1651.

Daniel, Kent and Sheridan Titman, 2006. Market reactions to tangible and intangible information. Journal of Finance 61, 1605–1643.

DeBondt, Werner and Richard Thaler, 1985. Does the stock market overreact? Journal of Finance 40, 793–808.

DeBondt, Werner and Richard Thaler, 1987. Further evidence on investor overreaction and stock market seasonality. Journal of Finance 42, 557–581.

Dechow, Patricia, Scott Richardson, and Richard Sloan, 2008. The persistence and pricing of the cash component of earnings. Journal of Accounting Research 46, 537–566.

Fairfield, Patricia, J. Scott Whisenant, and Teri Yohn, 2003. Accrued earnings and growth: Implications for future profitability and market mispricing. The Accounting Review 78, 353–371.

Fama, Eugene, 1976. Foundations of Finance (Basic Books, New York, NY).

Fama, Eugene, 1998. Market efficiency, long-term returns, and behavioral finance. Journal of Financial Economics 49, 283–306.

Fama, Eugene and Kenneth French, 1992. The cross-section of expected stock returns. Journal of Finance 47, 427–465.

Fama, Eugene and Kenneth French, 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, Eugene and Kenneth French, 1996. Multifactor explanations of asset pricing anomalies. Journal of

Finance 51, 55–84.

Fama, Eugene and Kenneth French, 1997. Industry costs of equity. Journal of Financial Economics 43, 153–193.

Fama, Eugene and Kenneth French, 2006a. Profitability, investment, and average returns. Journal of Financial Economics 82, 491–518.

Fama, Eugene and Kenneth French, 2006b. The value premium and the CAPM. Journal of Finance 61, 2163–2185.

Fama, Eugene and Kenneth French, 2008. Dissecting anomalies. Journal of Finance 63, 1653–1678.

Fama, Eugene and James MacBeth, 1973. Risk, return and equilibrium: Empirical tests. Journal of Political Economy 81, 607–636.

Goyal, Amit and Ivo Welch, 2008. A comprehensive look at the empirical performance of equity premium prediction. Review of Financial Studies 21, 1455–1508.

Hanna, J. Douglas and Mark Ready, 2005. Profitable predictability in the cross section of stock returns. Journal of Financial Economics 78, 463–505.

Haugen, Robert and Nardin Baker, 1996. Commonality in the determinants of expected stock returns. Journal of Financial Economics 41, 401–439.

Hirshleifer, David, Kewei Hou, Siew Hong Teoh, and Yinglei Zhang, 2004. Do investors overvalue firms with bloated balance sheets? Journal of Accounting and Economics 38, 297–331.

Jegadeesh, Narasimhan and Sheridan Titman, 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance 48, 65–91.

Jegadeesh, Narasimhan and Sheridan Titman, 2001. Profitability of momentum strategies: An evaluation of alternative explanations. Journal of Finance 56, 699–720.

Lakonishok, Josef, Andrei Shleifer, and Robert Vishny, 1994. Contrarian investment, extrapolation, and risk. Journal of Finance 49, 1541–1578.

Lee, Charles and Bhaskaran Swaminathan, 2000. Price momentum and trading volume. Journal of Finance 55, 2017–2069.

Levi, Yaron and Ivo Welch, 2014. Long-term capital budgeting. Working paper (University of California, Los Angeles).

Litzenberger, Robert and Krishna Ramaswamy, 1982. The effects of dividends on common stock prices: Tax effects or information effects? Journal of Finance 37, 429–443.

McLean, R. David and Jeffrey Pontiff, 2013. Does academic research destroy stock return predictability? Working paper (University of Alberta and Boston College).

Miller, Merton and Myron Scholes, 1982. Dividends and taxes: Some empirical evidence. Journal of Political Economy 90, 1118–1141.

Novy-Marx, Robert, 2012. Is momentum really momentum? Journal of Financial Economics 103, 429–453.

Pontiff, Jeffrey and Artemiza Woodgate, 2008. Share issuance and cross-sectional returns. Journal of Finance 63, 921–945.

Richardson, Scott, Richard Sloan, Mark Soliman, and İrem Tuna, 2005. Accrual reliability, earnings persistence, and stock prices. Journal of Accounting and Economics 39, 437–485.

Rosenberg, Barr, Kenneth Reid, and Ronald Lanstein, 1985. Persuasive evidence of market inefficiency. Journal of Portfolio Management 11, 9–17.

Simin, Timothy, 2008. The poor predictive performance of asset pricing models. Journal of Financial and Quantitative Analysis 43, 355–380.

Sloan, Richard, 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? The Accounting Review 71, 289–315.

Stattman, Dennis, 1980. Book values and stock returns. The Chicago MBA: A Journal of Selected Papers 4, 25–45.

Titman, Sheridan, K.C. John Wei, and Feixue Xie, 2004. Capital investment and stock returns. Journal of Financial and Quantitative Analysis 39, 677–700.