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Does It Pay to Bet Against Beta? On the Conditional Performance of the Beta Anomaly

SCOTT CEDERBURG and MICHAEL S. O'DOHERTY*

ABSTRACT

Prior studies find that a strategy that buys high-beta stocks and sells low-beta stocks has a significantly negative unconditional capital asset pricing model (CAPM) alpha, such that it appears to pay to "bet against beta." We show, however, that the conditional beta for the high-minus-low beta portfolio covaries negatively with the equity premium and positively with market volatility. As a result, the unconditional alpha is a downward-biased estimate of the true alpha. We model the conditional market risk for beta-sorted portfolios using instrumental variables methods and find that the conditional CAPM resolves the beta anomaly.

THE SHARPE-LINTNER CAPITAL asset pricing model (CAPM) implies that exposure to market risk, as measured by beta, should be compensated by the market risk premium. Based on the performance of portfolios formed on lagged firm-level beta, however, a number of empirical studies find that the risk-reward relation is too flat. For example, Friend and Blume (1970) and Black, Jensen, and Scholes (1972) demonstrate that portfolios of high-beta stocks earn lower returns than implied by the CAPM and therefore have negative alphas, whereas portfolios of low-beta stocks earn positive alphas. Fama and French (1992, 2006) extend these results by showing that the beta-return relation becomes even flatter after controlling for size and book-to-market characteristics. Finally, Frazzini and Pedersen (2014) confirm the underperformance of high-beta stocks over a long sample period extending from 1926 to 2012 and develop a "betting-against-beta" strategy, which has drawn substantial interest from academics and practitioners alike.[1]

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[1] For example, Asness, Frazzini, and Pedersen (2014), Bali et al. (2014), Huang, Lou, and Polk (2014), Novy-Marx (2014), Boguth and Simutin (2015), and Malkhozov et al. (2015) examine aspects of the betting-against-beta strategy. Dozens of funds have also been set up to take advantage of the low-beta and closely related low-volatility anomalies (see, for example, "Beat the Market—With

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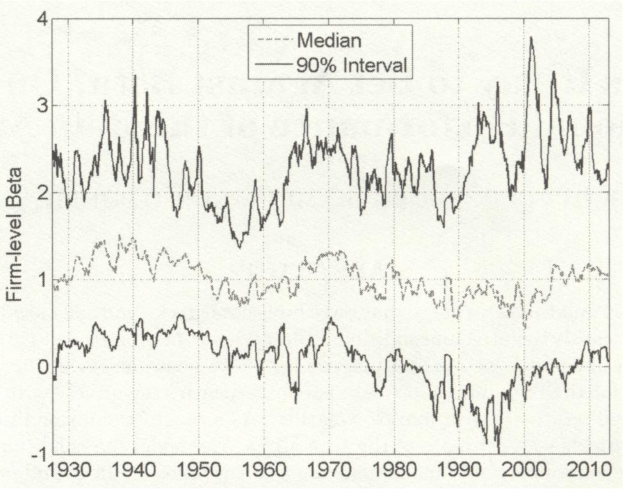

Figure 1. Cross-sectional distribution of firm betas, July 1927 to December 2012. The figure displays statistics for the cross-sectional distribution of firm betas. The dashed line is the median and the solid lines show the 5^{th} and 95^{th} percentiles of firm betas. Firm betas are estimated at the beginning of each month using daily returns over the previous 12 months.

In this paper, we reconsider the evidence on the abnormal performance of beta-sorted portfolios. Prior work focuses on the unconditional CAPM alphas of these strategies and finds a significantly negative alpha on a high-minus-low beta-spread portfolio. It is well known, however, that unconditional alphas are biased estimates of the true portfolio alphas if portfolio betas vary systematically with the market risk premium or market volatility (see Grant (1977), Jagannathan and Wang (1996), Lewellen and Nagel (2006), and Boguth et al. (2011)).[2] For the beta anomaly to be explained by a bias in unconditional alpha, the conditional beta for the high-minus-low strategy must display meaningful time-series variation. Consistent with this argument, we find that the betas of portfolios sorted on past firm beta vary substantially over time, largely as a result of the shifting cross-sectional variation in firm betas. For instance, Figure 1 reveals that the 90% interval of the cross section of firm betas exhibits pronounced changes over the sample period. We observe a relatively tight distribution of betas early in the postwar period, with a beta difference between the 95^{th} and 5^{th} percentiles of about 1.5, whereas this difference approximately doubles to a beta spread of around 3.0 in the 1990s and early 2000s. The betas of portfolios sorted on past firm beta inherit these time-series patterns, displaying large swings over the sample period.

Less Risk," *The Wall Street Journal*, October 1, 2011, and "High Hopes for 'Low Volatility' Funds," *The Wall Street Journal*, April 6, 2014).

[2] Given that unconditional and conditional CAPM inferences may differ, a recent literature reevaluates several other cross-sectional anomalies while allowing for time variation in betas. See, for example, Lettau and Ludvigson (2001), Avramov and Chordia (2006), Fama and French (2006), Lewellen and Nagel (2006), Ang and Chen (2007), Boguth et al. (2011), and O'Doherty (2012).

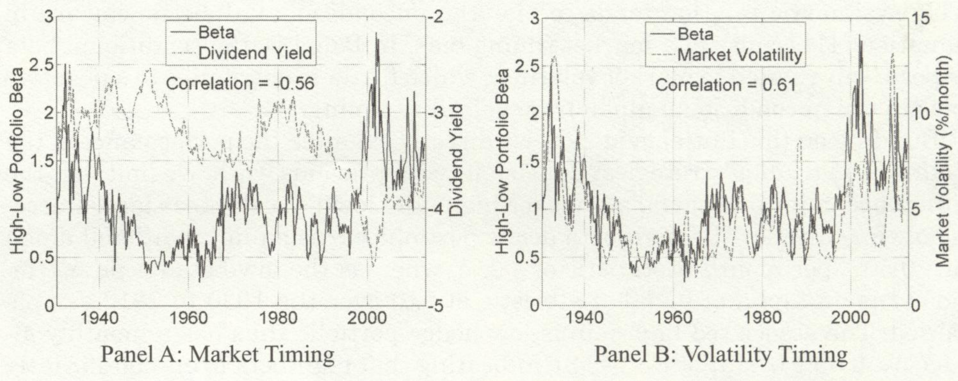

Figure 2. Systematic trends in portfolio betas, July 1930 to December 2012. Panel A (Panel B) shows the instrumental variables (IV) beta for the high-minus-low beta portfolio and the aggregate log dividend yield (volatility of the CRSP value-weighted portfolio). The conditional beta estimate corresponds to case 7 in Table 2, and the IV approach is outlined in Section I.A. The log dividend yield is the log of the sum of dividends accruing to the CRSP value-weighted portfolio over the previous 12 months scaled by the lagged level of this portfolio. Market volatility is the realized volatility using daily excess market returns over the previous 12 months.

As noted above, previous work establishes a formal link between time variation in market exposure for a given strategy and the bias in its unconditional CAPM alpha. Specifically, Lewellen and Nagel (2006), Boguth et al. (2011), and others show that, if the conditional CAPM holds, the unconditional alpha for a particular asset can be approximated by

$$\alpha_i^U \approx \mathrm{Cov}(\beta_{i,t}, E_{t-1}(R_{m,t})) - \frac{E(R_{m,t})}{\sigma_m^2}\mathrm{Cov}\left(\beta_{i,t}, \sigma_{m,t}^2\right), \tag{1}$$

where $\beta_{i,t}$ is the asset's conditional beta, $E(R_{m,t})$ and $E_{t-1}(R_{m,t})$ are the unconditional and conditional market expected excess returns, and σ_m^2 and $\sigma_{m,t}^2$ are the unconditional and conditional market volatilities. A negative bias in unconditional alpha arises when beta is negatively related to the expected excess return on the market ("market timing") and/or positively related to market volatility ("volatility timing"). In empirical applications, biases in unconditional alphas can be substantial, with the volatility timing channel having a particularly large potential effect (Boguth et al. (2011)).

Our tests focus on contrasting the unconditional and conditional performance of decile portfolios sorted on prior market beta. Figure 2 provides a preliminary indication that a negative unconditional CAPM alpha for a high-minus-low beta portfolio is plausibly attributable to market timing and volatility timing effects in the data.[3] Panel A shows that this strategy's beta is inversely related to the log dividend yield for the market portfolio, which is a positive predictor of the equity premium (e.g., Fama and French (1988) and Cochrane (2008)).

[3] We introduce our method for estimating conditional portfolio betas in Section I.A and detail the construction of the beta-sorted test assets in Section I.B.

This systematic relation tends to bias the unconditional alpha downward in equation (1) because of a market timing bias. In Panel B, the conditional beta is positively related to market volatility, which further contributes to a negative bias in the unconditional alpha from volatility timing.

Building on this initial evidence, we directly examine the performance of the beta-sorted trading strategies. Consistent with previous work, we find that the difference in unconditional alphas for high- and low-beta stocks is large in economic magnitude. The high-beta decile portfolio earns an unconditional alpha of −0.50% per month (*t*-statistic of −2.7), whereas the low-beta decile portfolio earns an alpha of 0.09% (*t*-statistic of 0.8) over the 1930 to 2012 sample period. The associated high-minus-low hedge portfolio thus has a monthly alpha of −0.59% (*t*-statistic of −2.3), indicating that high-beta firms significantly underperform their low-beta counterparts.

In contrast, conditional alphas for the high-minus-low strategy are statistically insignificant and substantially smaller in magnitude in comparison to the unconditional case. Our empirical approach is based on standard instrumental variables (IV) methods (e.g., Shanken (1990), Ferson and Schadt (1996), and Boguth et al. (2011)) in which portfolio betas are modeled as a function of lagged state variables. We specifically consider conditioning variables from the prior literature including lagged betas for each portfolio and macroeconomic variables. In our most comprehensive conditional model, the long-short beta portfolio earns a conditional alpha of −0.18% per month (*t*-statistic of −0.7), which represents a nearly 70% reduction in magnitude relative to the unconditional performance estimate of −0.59%. Our analysis suggests that the perceived abnormal performance from betting against beta is largely erased after properly incorporating conditioning information into the benchmark model.

We also demonstrate that conditioning remains critically important in evaluating the performance of beta-sorted portfolios relative to a multifactor benchmark. This analysis is motivated by Fama and French's (1992, 2006) evidence that the beta anomaly becomes stronger after controlling for firm size and book-to-market in portfolio sorts. Based on these results, a reasonable prior is that the poor performance for high-beta firms relative to the unconditional CAPM should become even more pronounced relative to the Fama-French (1993) three-factor model, which controls for exposure to the size and value effects in benchmarking performance. To further explore this issue, we analyze the performance of unconditional and conditional versions of the three-factor model in explaining the average returns for our beta-sorted portfolios. The results allow us to directly distinguish between the effects from conditioning and those from incorporating additional risk factors. As anticipated, the unconditional three-factor model displays poor performance in pricing the beta-spread portfolio, producing an alpha estimate of −0.75% per month (*t*-statistic of −3.0). This estimate is also significantly lower than the corresponding unconditional CAPM alpha for this strategy. The conditional version of the three-factor model performs reasonably well, however, with a conditional alpha of −0.26% (*t*-statistic of −1.7). Moreover, we find that over 80% of this improvement is attributable to systematic variation in betas on the market factor. In short, the multifactor results reinforce the importance of accounting for changes in conditional exposures to market risk in evaluating betting-against-beta strategies.

Our final objective is to characterize the economic mechanisms underlying our results. We are particularly interested in identifying state variables with predictive content for the observed dispersion in firm-level betas shown in Figure 1, as these variables should also be helpful in characterizing the market exposures for the high- and low-beta strategies. Based on the extensive literature on the determinants of individual firm betas, we propose that times of increased heterogeneity in firm-level investment opportunities, increased heterogeneity in firm leverage, and heightened average idiosyncratic risk across firms are likely to be associated with greater dispersion in betas, all else equal. Consistent with these predictions and the theoretical literature, state variables motivated by these explanations are robust predictors of betas for the strategies of interest and are valuable in accounting for the differences in unconditional and conditional performance for the beta portfolios.

Our paper contributes to the asset pricing literature by reevaluating the performance of beta-sorted portfolios while properly accounting for predictable time-series variation in portfolio betas. The CAPM's failure to explain the average returns of these strategies is widely viewed as one of the most damaging pieces of evidence against the model. In particular, the beta anomaly seems to provide direct and straightforward evidence against the primary prediction of the CAPM—that exposure to market risk is sufficiently rewarded—which suggests a broad rejection of the model on statistical and economic grounds. Our study provides an explanation for these results and shows that the market risk of beta-sorted portfolios is rewarded in a manner that is consistent with the conditional CAPM. To be clear, however, we focus exclusively on the performance of beta-sorted portfolios and do not consider whether beta is significantly rewarded among other sets of test assets. An alternative approach based on standard cross-sectional regressions (e.g., Fama and MacBeth (1973)) could be used to test whether beta is positively rewarded in a given cross section of assets. This framework can yield a broader assessment of the empirical success of the CAPM in pricing diverse sets of test assets and can be applied to test whether market risk is priced after controlling for firm characteristics or exposures to additional risk factors. Our focus on beta-sorted portfolios is narrower in scope, but our results on the beta anomaly are important as evidenced by the broad interest in this strategy.[4]

[4] An alternative approach to testing the CAPM focuses on whether the average return for the high-minus-low beta portfolio is significantly positive (e.g., Reinganum (1981) and Fama and French (1992)). We find that this strategy earns an average return of 0.44% per month with an associated t-statistic of 1.09. Thus, consistent with prior findings, we cannot reject the null hypothesis of a flat beta-return relation based on the average return of this hedge portfolio. As noted by Kothari, Shanken, and Sloan (1995), however, such a test suffers from low power given the high level of volatility of the long-short trading strategy (12.68% per month in our data). In fact, had the high-low beta portfolio earned an average return of 0.62% per month over 1930 to

We further add to the literature by documenting and investigating interesting trends in the cross-sectional dispersion of firm-level beta estimates. We propose several theoretical explanations underlying these changes and the associated systematic trends in market risk for beta-sorted portfolios. These results build on those of Chan and Chen (1988), who show how changes in the cross spectrum of conditional betas can impact tests of the unconditional CAPM. Finally, we contribute to the literature on the relative performance of factor models in explaining patterns in average returns.

The remainder of the paper is organized as follows. Section I introduces empirical methods for testing the conditional CAPM and discusses the data. Section II contains our main empirical results on the unconditional and conditional performance of portfolios sorted on past firm beta. Section III considers potential explanations for the systematic variation in portfolio betas that drives our results. Section IV concludes.

I. Empirical Methods and Data Description

The objective of the paper is to contrast the unconditional and conditional performance of portfolios formed on past values of equity beta. Section I.A introduces our IV approach for evaluating conditional portfolio performance, and Section I.B provides details on constructing the beta-sorted test assets.

A. Conditional Performance Evaluation

Our primary tests focus on the conditional performance of beta-sorted portfolios. The conditional CAPM implies that

$$\alpha_{i,t} \equiv E(R_{i,t}|I_{t-1}) - \beta_{i,t}E(R_{m,t}|I_{t-1}) = 0, \tag{2}$$

where $R_{i,t}$ is portfolio i's excess return during period t, $R_{m,t}$ is the excess market return, I_{t-1} is the investor information set at the end of period $t-1$, and $\beta_{i,t} = \mathrm{Cov}(R_{i,t}, R_{m,t}|I_{t-1})/\mathrm{Var}(R_{m,t}|I_{t-1})$ is the conditional beta of portfolio i. Several methods for estimating conditional portfolio risk have been proposed in the finance literature. The traditional implementation of the conditional CAPM follows Shanken (1990), Ferson and Schadt (1996), and Ferson and Harvey (1999) by modeling the portfolio beta as a linear function of instruments such as the aggregate dividend yield and default spread.

Boguth et al. (2011) build upon this literature and demonstrate improvements from incorporating lags of realized portfolio betas as additional state variables in the classical IV approach. Lewellen and Nagel (2006) and others directly characterize conditional portfolio risk using realized betas from short-window CAPM regressions, recognizing that the IV approach conditions on a subset of the investor information set (e.g., Cochrane (2005)). Realized beta estimates may capture variation in portfolio betas that is otherwise unmodeled

2012 such that its conditional CAPM alpha was zero in our most comprehensive IV model, this test would be unable to statistically reject a flat relation between beta and return.

by the econometrician, so including these variables can improve the performance of the IV approach. Boguth et al. (2011) further emphasize that lagging the realized beta estimates is essential in tests of the conditional CAPM. Including contemporaneously estimated betas may lead to an "overconditioning" bias in estimated alphas because these beta estimates are not in the investor information set at the beginning of the period. This bias can be severe when the returns for a particular strategy are nonlinear in market returns. Incorporating lagged realized betas as instruments in the IV implementation of the conditional CAPM avoids this overconditioning problem as these variables are known to investors ex ante.

We follow this approach and use both the one-step and two-step IV models outlined below to assess the performance of our beta-sorted test portfolios. As discussed in Section I.B.2, our primary analysis uses a time series of quarterly portfolio returns. The one-step IV (IV1) method is based on the conditional return regression

$$R_{i,\tau} = \alpha_i^{IV1} + (\gamma_{i,0} + \gamma_{i,1}' Z_{i,\tau-1}) R_{m,\tau} + u_{i,\tau}, \tag{3}$$

where τ indexes quarters, $R_{i,\tau}$ is the quarterly buy-and-hold excess return for portfolio i over quarter τ, $R_{m,\tau}$ is the quarterly buy-and-hold excess return for the market portfolio, and $Z_{i,\tau-1} \subseteq I_{\tau-1}$ is a $k \times 1$ vector of instruments. We thus assume that the conditional portfolio beta is a linear function of a portfolio-specific state variable vector, $\beta_{i,\tau}^{IV1} \equiv \gamma_{i,0} + \gamma_{i,1}' Z_{i,\tau-1}$, and the conditional portfolio alpha is constant.[5] Given that $Z_{i,\tau-1}$ is in the investor information set at the start of period τ, this method eliminates overconditioning bias in estimated alphas. Additionally, the unconditional CAPM is a special case of equation (3) in which $Z_{i,\tau-1}$ is the null information set, such that the portfolio beta is restricted to be constant. We denote the portfolio alpha in this case as α_i^U.

We estimate equation (3) using the generalized method of moments (GMM). Following Boguth et al. (2011), we use the moment conditions

$$E\left[\left(R_{i,\tau} - \alpha_i^{IV1} - \left(\gamma_{i,0} + \gamma_{i,1}' Z_{i,\tau-1}\right) R_{m,\tau}\right) X_{i,\tau}\right] = 0, \tag{4}$$

where $X_{i,\tau} \equiv [1 \quad R_{m,\tau} \quad Z_{i,\tau-1}' R_{m,\tau}]'$. The model is thus exactly identified and the GMM parameter estimates correspond to ordinary least squares estimates. For many of our empirical applications, we are interested in comparing estimates of α_i^{IV1} across portfolios or for a single portfolio under alternative information sets. In these cases, it is straightforward to combine multiple sets of moment conditions in the form of equation (4) into a single GMM estimation procedure.[6] Finally, we use Newey-West (1987) standard errors to statistically assess portfolio performance.

[5] This implementation of the conditional CAPM follows Ferson and Schadt (1996) and Boguth et al. (2011). Shanken (1990) and Ferson and Harvey (1999) also model conditional alpha as a linear function of state variables.

[6] See Appendix A.5 in Boguth et al. (2011) for estimation details.

Much of the empirical work that follows focuses on the difference in the performance between portfolios of high-beta firms and low-beta firms under alternative information sets. We specifically test whether the difference in conditional portfolio alphas, $\alpha_{HL}^{IV1} \equiv \alpha_H^{IV1} - \alpha_L^{IV1}$, is equal to zero as implied by the conditional CAPM (i.e., equation (2)). We also assess whether this difference in conditional alphas for a given set of instruments is significantly larger than the corresponding difference in unconditional alphas. That is, we test the null hypothesis that $\alpha_{HL}^{IV1} \le \alpha_{HL}^{U}$.

Our initial tests presented in Section II are largely atheoretical in the choice of instruments, $Z_{i,\tau-1}$, for each portfolio. As a starting point, Boguth et al. (2011) show that lagged betas from prior estimation windows are typically good predictors of beta, so we incorporate lagged short-term and long-term betas in the set of conditioning information. We also follow prior literature on the conditional CAPM and include common macroeconomic state variables in the IV specification. The estimates of $\gamma_{i,1}$ from the one-step IV model in equation (3) can then be used to assess the predictive content of various state variables for portfolio risk loadings.

Boguth et al. (2011) also introduce a two-step IV method that can be used to generate more direct evidence on the relation between the conditioning variables and portfolio betas. To implement this approach, we begin by estimating a separate CAPM regression for each quarter τ using daily portfolio return data to obtain a time series of nonoverlapping conditional CAPM regression parameters that spans the entire sample period. The regression model is

$$r_{i,j} = \alpha_i + \beta_{i,0} r_{m,j} + \beta_{i,1} r_{m,j-1} + \beta_{i,2}\left[\frac{r_{m,j-2} + r_{m,j-3} + r_{m,j-4}}{3}\right] + \varepsilon_{i,j}, \tag{5}$$

where $r_{i,j}$ is the excess return for a given portfolio and $r_{m,j}$ is the excess market return on day j of quarter τ. The portfolio beta estimate for quarter τ is

$$\hat{\beta}_{i,\tau} \equiv \hat{\beta}_{i,0} + \hat{\beta}_{i,1} + \hat{\beta}_{i,2}. \tag{6}$$

The regressions include lags of the excess market return to alleviate the impact of asynchronous trading, and the slopes on lags two through four are constrained to be equal following Lewellen and Nagel (2006).

In the first stage of the two-stage IV (IV2) approach, the estimated quarterly portfolio betas are regressed on a set of lagged instruments,

$$\hat{\beta}_{i,\tau} = \delta_{i,0} + \delta_{i,1}' Z_{i,\tau-1} + e_{i,\tau}. \tag{7}$$

The fitted betas from this regression, $\tilde{\beta}_{i,\tau}$, are then used in a second-stage return regression that is given by

$$R_{i,\tau} = \alpha_i^{IV2} + (\phi_{i,0} + \phi_{i,1}\tilde{\beta}_{i,\tau}) R_{m,\tau} + v_{i,\tau}. \tag{8}$$

The two-stage method is thus a restricted version of the IV approach in which the IV beta, $\beta_{i,\tau}^{IV2} \equiv \phi_{i,0} + \phi_{i,1}\tilde{\beta}_{i,\tau}$, is constrained to be linear in the fitted first-stage beta. The first-stage parameter estimates and R^2 from the regression model in equation (7) directly reflect the ability of a given set of instruments to describe beta dynamics. Additionally, regressing portfolio beta estimates on $Z_{i,\tau-1}$ in the first stage of the IV2 approach tends to produce more precise estimates of the conditional beta coefficients (i.e., $\delta_{i,1}$) compared to the corresponding IV1 coefficients from the return-based regression in equation (3), so the IV2 approach may be a more powerful test for evaluating potential determinants of portfolio betas. These features of the IV2 approach are particularly valuable for our analysis in Section III, which focuses on theoretical explanations for the observed time-series trends in systematic risk for the beta portfolios.

B. Data

Section I.B.1 provides details on the sample and portfolio construction, and Section I.B.2 reports summary statistics for the beta-sorted portfolios.

B.1. Sample Construction

The sample includes all NYSE, Amex, and NASDAQ ordinary common stocks with return data available on the CRSP daily and monthly stock files and sufficient historical return data to compute beta estimates to be used in forming the beta-based trading strategies. The empirical tests use daily, monthly, and quarterly returns on beta-sorted portfolios. Our test assets are based on formation-period betas estimated from the prior 12 months of daily return data following equations (5) and (6). A firm must have 150 valid return observations over the prior 12 months to be included in this trading strategy.

Each year at the beginning of July, we sort firms into 10 groups based on past beta using all listed firms for the break points. The portfolios are value weighted and held for 12 months before rebalancing. We use the CRSP daily file to construct a series of daily returns and the CRSP monthly file to construct monthly and quarterly return series for each portfolio. For each series, we follow the approach in Liu and Strong (2008) to ensure that the returns correspond to those actually realized by a buy-and-hold investor.

When a firm is delisted from an exchange during a given month, we replace any missing returns with the delisting returns provided by CRSP.[7] We convert all portfolio returns to excess returns by subtracting the corresponding risk-free rate. Data on the daily and monthly market return (i.e., the CRSP value-weighted index) and the risk-free rate are from Kenneth French's website.[8] We construct the quarterly buy-and-hold excess return series by compounding monthly returns for a given portfolio and the risk-free asset separately and then computing the difference. Our tests use return data from July 1926 to December 2012. Given that some of the empirical approaches rely on lagged estimates of

[7] See Shumway (1997) for a discussion of delisting bias.

[8] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/. We thank Kenneth French for making these data available.

conditional betas, the first portfolio formation date is July 1930, and the tables report portfolio performance over the period July 1930 to December 2012.

B.2. Portfolio Summary Statistics

Table I reports summary statistics for the value-weighted portfolios sorted on firm beta. Panels A and B present means and standard deviations of excess returns for the daily, monthly, and quarterly series. For purposes of comparison, the average returns and standard deviations are reported in percentage per month. That is, the daily average excess returns (standard deviations) are multiplied by 22 ($\sqrt{22}$), where 22 is the average number of trading days per month for the full sample period. Similarly, the average quarterly excess returns (standard deviations) are multiplied by 1/3 ($\sqrt{1/3}$). In each case, the long-short decile portfolio yields only modestly positive returns. A zero-cost portfolio that takes a long position in the high-beta decile and a short position in the low-beta decile earns an average excess return of 0.15%, 0.23%, or 0.44% per month using daily, monthly, or quarterly data, respectively.[9] These results are consistent with the findings of Fama and French (1992) and Frazzini and Pedersen (2014), who document a relatively flat relation between equity beta and realized return.

The observed differences in average excess returns for the daily, monthly, and quarterly series warrant additional analysis. Boguth et al. (2015) demonstrate that delayed incorporation of information into stock prices leads to a downward bias in short-horizon average portfolio returns. The bias produced by slow information diffusion is amplified for buy-and-hold strategies when stocks react to new information with differential delays. This bias tends to be particularly large for value-weighted portfolios and strategies concentrated in small and volatile stocks, so horizon effects in measured portfolio performance may impact our beta-based trading strategies (see, for example, Panel C of Table I).

Boguth et al. (2015) further emphasize the importance of selecting an appropriate return interval to mitigate any bias in measured average returns and alphas related to these effects. We adopt their proposed diagnostic tool and find that a quarterly return measurement interval is appropriate for our subsequent analysis. Specifically, for the low- and high-beta portfolios, we compute average n-day buy-and-hold returns scaled to a monthly equivalent for values of n ranging from one to 264 (i.e., up to one year). The results are shown in Figure 3.[10] Consistent with the results in Panel A of Table I, the high-beta portfolio exhibits pronounced horizon effects in average returns. The upward slope

[9] Blume and Stambaugh (1983) and Roll (1983) examine microstructure effects in average returns and demonstrate that bid-ask bounce can cause upward biases in average returns that are amplified when taking averages of short-horizon returns. Asparouhova, Bessembinder, and Kalcheva (2013) show that value weighting returns helps minimize this upward bias.

[10] The plots are constructed using the daily time series of portfolio returns. We refer the reader to Boguth et al. (2015) for computation details. We also note that, similar to our results, Boguth et al. (2015) find large biases in daily and monthly average returns for several U.S. = style portfolios.

Table I

Summary Statistics, July 1930 to December 2012

The table reports summary statistics for value-weighted decile portfolios sorted on past market beta. "H" refers to the high-beta portfolio, "L" refers to the low-beta portfolio, and "HL" refers to their difference. The formation-period betas are estimated using 12 months of daily data as described in Section I.B.1, and the portfolios are rebalanced at the beginning of each July using all listed firms for the break points. Panel A presents average excess returns for the daily, monthly, and quarterly return series. Average excess returns are reported in percentage per month (i.e., the daily average excess returns are multiplied by 22 and the quarterly average excess returns are multiplied by 1/3). Quarterly statistics are calculated by constructing a series of quarterly excess returns for each portfolio by compounding monthly returns. Panel B presents the standard deviation of excess returns for each portfolio in percentage per month (i.e., the daily standard deviations are multiplied by $\sqrt{22}$ and the quarterly standard deviations are multiplied by $\sqrt{1/3}$). Panel C reports the time-series average of the fraction of total market capitalization for each portfolio as of the portfolio formation date. Panel D presents time-series properties of the value-weighted, formation-period portfolio betas. Panel E presents unconditional CAPM beta estimates based on daily, monthly, and quarterly regressions for each portfolio. Panel F reports averages of conditional CAPM betas estimated from nonoverlapping windows based on daily data (three-month intervals), monthly data (12-month intervals), and quarterly data (30-month intervals). The daily betas are computed as the sum of slope coefficients from regressions of portfolio excess returns on the market excess return, its lag, and the average of lags two through four.

	Portfolio										
	L	2	3	4	5	6	7	8	9	H	HL
Panel A: Mean Excess Returns											
Daily	0.35	0.55	0.54	0.68	0.77	0.74	0.68	0.71	0.63	0.50	0.15
Monthly	0.38	0.57	0.56	0.69	0.77	0.76	0.70	0.76	0.66	0.61	0.23
Quarterly	0.40	0.61	0.60	0.73	0.82	0.83	0.77	0.86	0.78	0.84	0.44
Panel B: Standard Deviations											
Daily	3.46	3.56	4.30	4.84	5.37	6.00	6.49	7.29	8.05	9.55	8.43
Monthly	3.96	4.11	4.60	5.18	5.50	6.42	6.93	8.09	8.60	10.88	9.42
Quarterly	4.49	4.91	5.32	5.86	6.40	7.77	8.34	10.12	10.65	14.33	12.68
Panel C: Proportion of Total Market Capitalization											
Mean	0.07	0.10	0.12	0.12	0.13	0.12	0.12	0.10	0.08	0.05	
Panel D: Properties of Formation-Period Betas											
Mean	0.11	0.42	0.61	0.78	0.93	1.09	1.27	1.48	1.75	2.28	
Standard deviation	0.31	0.23	0.22	0.21	0.21	0.20	0.21	0.23	0.27	0.43	
Minimum	−0.91	−0.09	0.14	0.34	0.50	0.67	0.86	1.02	1.18	1.46	
Maximum	0.53	0.81	0.98	1.15	1.31	1.56	1.76	2.09	2.41	3.68	
Panel E: Unconditional CAPM Betas											
Daily	0.51	0.65	0.78	0.90	0.98	1.12	1.21	1.38	1.49	1.77	1.26
Monthly	0.49	0.66	0.78	0.90	0.97	1.13	1.23	1.42	1.50	1.83	1.34
Quarterly	0.47	0.67	0.75	0.85	0.94	1.15	1.24	1.49	1.56	2.02	1.55

(*Continued*)

Table I—*Continued*

	Portfolio										
	L	2	3	4	5	6	7	8	9	H	HL
Panel F: Average Conditional CAPM Betas											
Daily	0.54	0.64	0.76	0.87	0.97	1.08	1.17	1.32	1.45	1.66	1.12
Monthly	0.59	0.65	0.75	0.87	0.97	1.07	1.18	1.33	1.46	1.72	1.13
Quarterly	0.63	0.69	0.78	0.85	0.96	1.03	1.15	1.32	1.53	1.82	1.18

in the plot for low n suggests that the bias related to partial price adjustment would not be alleviated even in monthly returns. In contrast, the downward bias is largely absent in quarterly returns for the beta-sorted portfolios, and we base our analysis primarily on this return interval throughout the paper.[11]

Panel D of Table I reports the time-series properties of the value-weighted formation-period betas including the mean, standard deviation, minimum, and maximum beta for each portfolio as of the portfolio formation date in July of each year. The average formation-period betas show considerable time-series variation, which is likely to be reflected in the conditional market exposures for each portfolio.

Finally, Panels E and F of Table I show beta estimates from unconditional and conditional CAPM regressions based on daily, monthly, and quarterly excess portfolio returns. The conditional beta estimates in Panel F are time-series averages of beta estimates from nonoverlapping windows based on daily data (three-month intervals), monthly data (12-month intervals), and quarterly data (30-month intervals). The monotonically increasing patterns in portfolio betas suggest that the ranking betas are a good proxy for relative future exposure to market risk. The portfolio beta estimates also provide some indication that the average formation-period betas in Panel C overstate the true cross-sectional dispersion in betas. For example, the average formation-period betas estimated from daily data are 0.11 for the low-beta decile and 2.28 for the high-beta decile, whereas the daily holding-period conditional betas range from 0.54 to 1.66. This result is unsurprising as we expect a positive cross-sectional relation between measurement error in individual firm formation-period betas and portfolio rank (e.g., Black, Jensen, and Scholes (1972)).

Two additional aspects of these betas are worth noting. First, portfolio beta estimates exhibit some evidence of horizon effects, particularly among high-beta stocks. Boguth et al. (2015) show that the same slow information diffusion mechanism that produces the previously discussed horizon effects in average returns can also affect portfolio beta estimates. Specifically, daily sum betas with a small number of lags are likely to be biased. We are cognizant of these issues in developing our empirical design. The IV1 and IV2 estimation

[11] We note that, for average holding period returns in Figure 3 between two and six months, the largest absolute difference between the three-month return and any other holding period return is 1.2 basis points per month for the low-beta portfolio and 3.2 basis points for the high-beta portfolio.

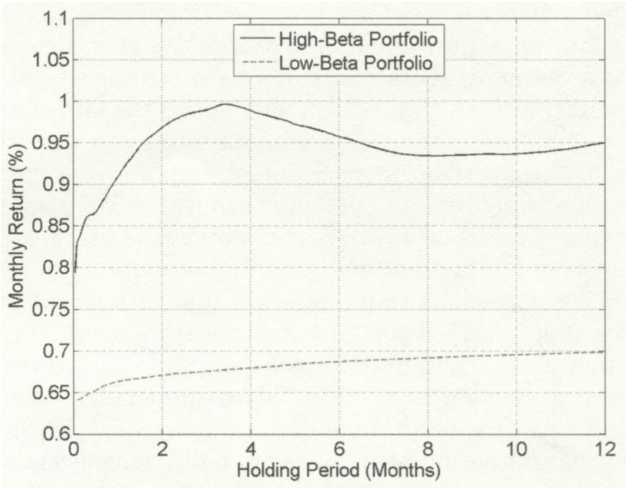

Figure 3. Mean buy-and-hold returns for beta portfolios scaled to a monthly holding period, July 1930 to December 2012. The figure plots average n-day buy-and-hold returns scaled to a monthly equivalent, $[E(r_{t-n+1}\ldots r_t)]^{22/n}-1$, for the high- and low-beta decile portfolios. The plots show mean monthly portfolio returns based on holding periods ranging from 1 to 264 days. The horizontal axis is scaled to months (i.e., the n-day holding periods are divided by 22).

approaches implicitly account for horizon effects in betas, as daily portfolio betas are used only as instruments for the IV betas, which are estimated directly from quarterly returns (see Boguth et al. (2011) for additional discussion on this topic). Second, the unconditional beta of the high-minus-low beta portfolio is 1.55 compared to an average conditional beta of 1.18 using quarterly data. This difference in unconditional and conditional betas provides direct evidence that volatility timing effects are likely to play a key role in our analysis of portfolio performance. That is, the volatility timing channel works primarily through a bias in unconditional beta, as the unconditional beta estimate tends to overstate the average risk of a strategy when the conditional beta is positively related to market volatility. This bias in unconditional beta, in turn, leads to a bias in unconditional alpha as seen in equation (1).

II. Portfolio Performance

Section II.A contains our main findings on the performance of the beta-sorted portfolios relative to the CAPM using the IV estimation approach. Section II.B extends this analysis to a multifactor setting by examining the pricing performance of unconditional and conditional versions of the Fama-French (1993) three-factor model.

A. CAPM Alphas

As a starting point, we investigate the impact of conditioning information on the performance of our beta strategies using a standard set of instruments introduced in prior literature. Boguth et al. (2011) show that short-term and long-term lagged beta estimates for a given portfolio are valuable instruments for predicting conditional portfolio risk exposure. We therefore consider lagged three-month and 36-month beta measures as instruments. We estimate the lagged-component (LC) betas for a given portfolio at the end of quarter $\tau - 1$ as the portfolio-weighted averages of lagged beta estimates for constituent firms to be included in the portfolio in period τ. As such, these betas account for changes in portfolio weights and portfolio turnover.[12] We also use two lagged macroeconomic state variables that are common in the literature: the dividend yield (DY) and the default spread (DS).[13]

An additional issue specific to our empirical application arises when measuring the LC betas of beta-sorted portfolios for use as instruments. Measurement error in formation-period beta and portfolio rank tend to be positively associated as discussed in Section I.B.2. In constructing the LC betas, we are thus careful to avoid using any firm return data that overlap with the data used to estimate the formation-period betas, as systematic measurement error in the lagged beta estimates would likely diminish their value as instruments. The short-term beta instruments, β^{LC3}, are based on firm betas estimated using daily return data within a lagged three-month period following equations (5) and (6). For the first, second, and fourth quarters of each year, β^{LC3} is calculated using firm betas from the most recent quarter. During the third quarter (i.e., July to September), the immediately preceding quarter falls within the period used to estimate the formation-period betas. We thus use firm betas from the second quarter in the prior year, which is the most recent quarter that falls outside the formation beta measurement period, to calculate β^{LC3} for the third quarter of each year. A natural concern with this empirical design is that the predictive content of β^{LC3} for realized portfolio beta may be diminished during the third quarter. As such, we include specifications with a third-quarter indicator ($I_{\{Q3\}}$) and interaction term ($I_{\{Q3\}} \times \beta^{LC3}$) to allow for a differential impact on the portfolio beta during this quarter. Finally, the long-term LC betas, β^{LC36}, are estimated from firm betas measured using daily data over the 36-month period immediately preceding the formation-beta estimation window.[14]

[12] We also investigated three-month and 36-month lagged-portfolio betas measured using past portfolio returns rather than constituent firm returns. The resulting inferences on portfolio alphas are similar to those obtained using the LC betas as instruments. We provide a discussion of these results in the Internet Appendix. The Internet Appendix is available in the online version of this article on the *Journal of Finance* website.

[13] The dividend yield is the difference between the log of the sum of dividends accruing to the CRSP value-weighted market portfolio over the prior 12 months and the log of the lagged index level. The default premium is the yield spread between Moody's Baa- and Aaa-rated bonds. The bond yields are obtained from the Federal Reserve Bank of St. Louis website. See http://research.stlouisfed.org/fred2/. We examined specifications that also included the term premium and the yield on a short-term Treasury bill, but these variables did not have a material impact on model fit or affect inferences. We omit these variables for parsimony but the results are available in the Internet Appendix.

[14] We require 36 (450) valid return observations during the three-month (three-year) period to include a firm's beta in the calculation for β^{LC3} (β^{LC36}).

Table II contains our main results on the performance of beta-sorted portfolios. Case 1 confirms the significant underperformance of high-beta stocks relative to the unconditional CAPM. With beta constrained to be constant, the low-beta portfolio has an estimated beta of 0.47 compared to 2.02 for the high-beta portfolio. The long-short beta portfolio has an unconditional alpha of −0.59% per month (−7.08% per year), which is statistically significant at the 5% level (*t*-statistic of −2.3).[15] These results are consistent with findings in prior literature that a betting-against-beta strategy generates abnormal returns relative to the unconditional CAPM (e.g., Black, Jensen, and Scholes (1972) and Frazzini and Pedersen (2014)).

Cases 2 to 8 consider alternative information sets in estimating conditional CAPM alphas. Case 2 includes the three-month LC beta, β^{LC3}, which is a positive predictor of beta with coefficients of about 0.6 for both portfolios. Using this single instrument, the estimated difference in conditional CAPM alphas is an insignificant −0.37% per month (*t*-statistic of −1.5). A test for improvements in the long-short alpha from conditioning indicates that the conditional alpha is significantly greater than its unconditional counterpart with a *p*-value of 0.021. When indicators for the third quarter are included in case 3, the model tends to put more weight on past beta during the first, second, and fourth quarters, whereas lagged beta has a more muted impact during the third quarter as expected.[16] The conditional alpha is −0.28% per month (*t*-statistic of −1.1) in this case, and the difference in unconditional and conditional alphas is strongly statistically significant with a *p*-value of 0.011. Instrumenting for portfolio betas using only recent short-term betas thus reduces the magnitude of the estimated CAPM alpha by more than half relative to case 1.

Cases 4 and 5 introduce the 36-month LC beta, β^{LC36}. This variable significantly forecasts the low-beta portfolio beta with a coefficient of 0.86 and reduces the coefficient estimate for β^{LC3} to 0.33 in case 4, but has little impact on the high-beta portfolio. The coefficients on the short-term and long-term lagged beta instruments suggest that market exposure for the low-beta portfolio tends to be relatively more stable over time. Conditional alphas are similar to cases 2 and 3, which exclude β^{LC36}, with estimates of −0.39% and −0.30% per month for the long-short beta portfolio.

Macroeconomic variables also have significant explanatory power for portfolio betas. Case 6 includes the dividend yield and default spread as the sole instruments. These variables have significant coefficients for both portfolios, and the R^2s for the portfolios in case 6 are similar to those for the specifications including all lagged betas. The conditional alpha of the long-short beta portfolio is −0.31% per month (*t*-statistic of −1.2), which is significantly greater than the unconditional alpha in case 1 with a *p*-value of 0.011. Case 7 contains

[15] We consider the performance of the low-beta, high-beta, and beta-spread portfolios for parsimony. IV1 regression results for all 10 decile portfolios are available in the Internet Appendix.

[16] The coefficients on $I_{\{Q3\}}$ and $I_{\{Q3\}} \times \beta^{LC3}$ are statistically insignificant for the IV1 estimation in case 3. The Internet Appendix shows that these variables are highly significant predictors of beta for the high-beta portfolio when betas are directly modeled in the first stage of the IV2 approach.

Table II

Instrumental Variables Regressions, July 1930 to December 2012

The table reports IV1 regression results for decile portfolios formed on past market beta. "H" refers to the high-beta portfolio, "L" refers to the low-beta portfolio, and "HL" refers to their difference. The formation-period betas are estimated using 12 months of daily data as described in Section I.B.1, and the portfolios are rebalanced at the beginning of each July using all listed firms for the break points. The return regression is given by $R_{i,\tau} = \alpha_i^{IV1} + (\gamma_{i,0} + \gamma_{i,1}' Z_{i,\tau-1}) R_{m,\tau} + u_{i,\tau}$ and is estimated from quarterly excess returns for the portfolios and factors. The instruments $Z_{i,\tau-1}$ for a given portfolio include the three-month and 36-month LC betas (β^{LC3} and β^{LC36}), an indicator variable equal to one for the third quarter of each year and zero otherwise ($I_{\{Q3\}}$), the interaction between the third-quarter indicator and the three-month LC beta ($I_{\{Q3\}} \times \beta^{LC3}$), the log dividend yield (DY), and the default spread (DS). The estimates of α_i^{IV1} are reported in percentage per month, and the numbers in parentheses are Newey-West (1987) corrected t-statistics with a lag length equal to five. For each regression, R^2 is the adjusted R^2 value. For each conditional model (i.e., cases 2 to 8), the table also reports a p-value ($p(\alpha_i \leq \alpha_i^U)$) for the one-sided test that the conditional HL alpha is less than or equal to the corresponding unconditional alpha from case 1.

				$R_{m,\tau} \times$							
Case		α_i^{IV1}	$p(\alpha_i \leq \alpha_i^U)$	1	β^{LC3}	$I_{\{Q3\}}$	$I_{\{Q3\}} \times \beta^{LC3}$	β^{LC36}	DY	DS	R^2
1	L	0.09		0.47							46.8
		(0.8)		(5.2)							
	H	−0.50		2.02							84.5
		(−2.7)		(15)							
	HL	−0.59	n/a								
		(−2.3)									
2	L	0.00		0.22	0.59						49.6
		(0.0)		(1.7)	(3.2)						
	H	−0.37		0.84	0.63						86.1
		(−2.1)		(2.9)	(3.6)						
	HL	−0.37	0.021								
		(−1.5)									
3	L	−0.04		0.30	0.64	−0.23	−0.16				53.6
		(−0.4)		(2.0)	(2.6)	(−1.0)	(−0.4)				
	H	−0.33		0.64	0.69	0.86	−0.28				86.6
		(−1.7)		(2.0)	(3.8)	(1.6)	(−1.0)				
	HL	−0.28	0.011								
		(−1.1)									

(*Continued*)

Table II—*Continued*

Case		α_i^{IV1}	$p(\alpha_i \leq \alpha_i^U)$	$R_{m,\tau} \times$ 1	β^{LC3}	$I_{\{Q3\}}$	$I_{\{Q3\}} \times \beta^{LC3}$	β^{LC36}	DY	DS	R^2
4	L	0.02		−0.13	0.33			0.86			51.6
		(0.2)		(−0.5)	(1.4)			(1.9)			
	H	−0.37		0.74	0.61			0.09			86.1
		(−2.1)		(1.3)	(2.5)			(0.2)			
	HL	−0.39	0.028								
		(−1.6)									
5	L	−0.02		−0.02	0.44	−0.14	−0.30	0.74			55.0
		(−0.2)		(−0.1)	(1.7)	(−0.7)	(−0.8)	(2.2)			
	H	−0.32		0.49	0.66	0.88	−0.29	0.12			86.5
		(−1.8)		(0.8)	(3.3)	(1.6)	(−0.9)	(0.3)			
	HL	−0.30	0.012								
		(−1.2)									
6	L	−0.01		1.47					0.20	−0.14	56.6
		(−0.1)		(4.5)					(2.1)	(−7.6)	
	H	−0.32		−0.31					−0.54	0.22	87.1
		(−1.8)		(−0.3)					(−2.0)	(5.0)	
	HL	−0.31	0.011								
		(−1.2)									
7	L	−0.03		1.00	0.16			0.47	0.17	−0.12	57.5
		(−0.3)		(3.1)	(0.7)			(1.5)	(1.8)	(−5.6)	
	H	−0.26		−0.97	0.33			0.32	−0.41	0.19	87.8
		(−1.4)		(−1.4)	(1.5)			(1.0)	(−1.7)	(3.7)	
	HL	−0.23	0.007								
		(−0.9)									
8	L	−0.05		0.88	0.27	−0.08	−0.26	0.44	0.14	−0.10	58.9
		(−0.5)		(2.7)	(1.1)	(−0.5)	(−0.8)	(1.6)	(1.4)	(−6.1)	
	H	−0.23		−1.37	0.48	1.05	−0.46	0.32	−0.44	0.19	88.0
		(−1.2)		(−1.6)	(2.0)	(2.3)	(−1.8)	(1.0)	(−1.9)	(4.4)	
	HL	−0.18	0.003								
		(−0.7)									

lagged betas and macroeconomic variables as instruments for portfolio betas. The macroeconomic variables maintain some significance for forecasting betas, with the default spread in particular showing strong predictive ability, and the coefficients on lagged betas remain positive but become statistically insignificant. The long-short alpha is −0.23% per month (t-statistic of −0.9) using this information set, and this conditional alpha is significantly greater than the alpha from case 1 at the 1% significance level.

Finally, case 8 uses the full information set to model portfolio betas. After including the third-quarter indicators, β^{LC3} is a significant predictor of the high-beta portfolio beta at the 5% level, whereas the third-quarter interaction term is significantly negative at the 10% level and nearly reduces the marginal effect of β^{LC3} to zero in the third quarter. The macroeconomic variables also continue to be important in modeling portfolio betas. Using the full information set, the conditional alpha estimate for the long-short beta portfolio is −0.18% per month (t-statistic of −0.7), which is significantly greater than the unconditional alpha (p-value of 0.003). This point estimate for alpha represents a nearly 70% reduction in magnitude relative to the unconditional model in case 1.[17,18]

Overall, the results in Table II suggest that accounting for time variation in portfolio risk explains much of the apparent underperformance of high-beta stocks. The approximation in equation (1) indicates that inferences from unconditional and conditional models may differ to the extent that portfolio betas are systematically related to the market risk premium and/or market volatility. In particular, the large negative unconditional alpha for the beta-spread portfolio may be entirely consistent with the conditional CAPM if the beta for this strategy covaries negatively with the expected market return or positively with market volatility. Figure 2 presents preliminary evidence that beta estimates for the long-short portfolio are correlated in the right direction with both the market risk premium and the volatility of the market portfolio.

Table III reports direct estimates of the market timing and volatility timing effects for the beta-sorted portfolios. Specifically, the difference in unconditional

[17] The tests in Table II consider whether market risk is priced in the manner predicted by the Sharpe-Lintner CAPM. Black (1972) develops an alternative version of the CAPM under borrowing constraints. In Black's CAPM, the expected return on a zero-beta asset may not be equal to the risk-free rate, and we may expect to see low-beta stocks perform well relative to the predictions of the Sharpe-Lintner CAPM. Even so, the −59 basis point difference in monthly performance for high- and low-beta stocks implied by the unconditional CAPM is quite large from an economic perspective. The −18 basis point difference in performance relative to the conditional CAPM seems more plausibly explained by borrowing constraints.

[18] In the Internet Appendix, we investigate the robustness of our results in case 8 of Table II to alternative portfolio formation rules. We specifically consider formation-period betas that are estimated over a prior five-year period following Fama and French (1992) and Frazzini and Pedersen (2014). Inferences are generally similar to our base results as the reductions in the magnitude of alpha moving from the unconditional to conditional models are large and statistically significant. Measured biases in unconditional alphas range from −0.18% to −0.23% per month depending on the specification, though the strategies earn conditional alphas that are statistically significant at the 10% level in some tests.

Table III
Alpha Bias Decomposition, July 1930 to December 2012

The table provides decompositions to demonstrate the biases in unconditional portfolio alphas attributable to market timing and volatility timing for portfolios sorted on past market beta. The IV alphas and betas correspond to case 8 in Table II. The unconditional alpha bias, $\alpha_i^U - \alpha_i^{IV1}$, is decomposed into the market timing effect and the volatility timing effect. The market timing effect is estimated as $(1 + \frac{\bar{R}^2_{m,\tau}}{\hat{\sigma}^2_m})\mathrm{Cov}(\hat{\beta}^{IV1}_{i,\tau}, R_{m,\tau})$, where $R_{m,\tau}$ is the buy-and-hold return on the CRSP value-weighted portfolio in excess of the risk-free rate, $\bar{R}_{m,\tau}$ is the average market risk premium, $\hat{\sigma}^2_m$ is the unconditional variance of the market risk premium, and $\hat{\beta}^{IV1}_{i,\tau}$ is the IV beta, $\hat{\gamma}_{i,0} + \hat{\gamma}'_{i,1} Z_{i,\tau-1}$. The estimated volatility timing effect is the quantity $\frac{\bar{R}_{m,\tau}}{\hat{\sigma}^2_m}\mathrm{Cov}(\hat{\beta}^{IV1}_{i,\tau}, R^2_{m,\tau})$. All results are reported in percentage per month.

	Market Timing		Volatility Timing						
Portfolio	$(1 + \frac{\bar{R}^2_{m,\tau}}{\sigma^2_m})\mathrm{Cov}(\beta^{IV1}_{i,\tau}, R_{m,\tau})$	−	$\frac{\bar{R}_{m,\tau}}{\sigma^2_m}\mathrm{Cov}(\beta^{IV1}_{i,\tau}, R^2_{m,\tau})$	=	Total	=	α_i^U	−	α_i^{IV1}
L	0.00	−	−0.14	=	0.14	=	0.09	−	−0.05
H	−0.07	−	0.20	=	−0.27	=	−0.50	−	−0.23
HL	−0.07	−	0.34	=	−0.41	=	−0.59	−	−0.18

and conditional alphas for a given portfolio can be decomposed into two terms (e.g., Boguth et al. (2011)),

$$\alpha_i^U - \alpha_i^{IV1} = \left(1 + \frac{\bar{R}_{m,\tau}^2}{\sigma_m^2}\right) \mathrm{Cov}\left(\beta_{i,\tau}^{IV1}, R_{m,\tau}\right) - \frac{\bar{R}_{m,\tau}}{\sigma_m^2} \mathrm{Cov}\left(\beta_{i,\tau}^{IV1}, R_{m,\tau}^2\right), \quad (9)$$

where $\beta_{i,\tau}^{IV1}$ is the conditional portfolio beta, $R_{m,\tau}$ is the excess market return for period τ, and $\bar{R}_{m,\tau}$ and σ_m^2 are the unconditional mean and variance of excess market returns, respectively. The first term accounts for the effect of market timing and the second term reflects the volatility timing effect. We estimate the market timing effect as $(1 + \frac{\bar{R}_{m,\tau}^2}{\hat{\sigma}_m^2})\mathrm{Cov}(\hat{\beta}_{i,\tau}^{IV1}, R_{m,\tau})$, where $\hat{\beta}_{i,\tau}^{IV1}$ is the fitted portfolio conditional beta from case 8 in Table II for quarter τ, and $\bar{R}_{m,\tau}$ and $\hat{\sigma}_m^2$ are the unconditional average and variance of excess market returns. The volatility timing effect is estimated as $\frac{\bar{R}_{m,\tau}}{\hat{\sigma}_m^2}\mathrm{Cov}(\hat{\beta}_{i,\tau}^{IV1}, R_{m,t}^2)$. Each effect is scaled to be expressed in percentage per month.

Table III presents estimates of the market timing and volatility timing effects for the low-beta, high-beta, and long-short portfolios. Exposure to market risk for the long-short portfolio covaries negatively with the market risk premium, and this pattern in portfolio betas produces a bias in the unconditional alpha estimate of −0.07% per month. Volatility timing has a larger effect on unconditional alphas of −0.34% per month, and both the low-beta (−0.14%) and high-beta (−0.20%) portfolios contribute to the negative bias in unconditional alphas. This effect is driven by a positive relation between the conditional beta of the high-low beta portfolio and market volatility. Intuitively, the volatility timing bias arises because returns in volatile periods tend to be more influential observations in the unconditional CAPM regressions. If conditional portfolio risk tends to be high in these volatile periods, the unconditional beta estimate will typically overstate the average conditional portfolio beta. These effects are observed for our beta-sorted portfolios, as the low-beta portfolio has an unconditional beta estimate of 0.47 compared to an average conditional beta of 0.68 and the high-beta portfolio has a larger unconditional beta of 2.02 compared to the average conditional beta of 1.71. The unconditional CAPM thus tends to overstate the average risk of a strategy that buys high-beta stocks and sells low-beta stocks. The market timing and volatility timing effects combine to produce the reported −0.41% per month difference between unconditional and conditional performance for this portfolio in Table II.

To summarize and interpret our results to this point, we show that, even though beta-sorted portfolios produce a relatively flat beta-return relation, exposure to market risk is still rewarded in a manner consistent with the conditional CAPM for these test assets. The high-minus-low beta portfolio's exposure to market risk exhibits not only considerable time-series variation but also systematic relations with expected market returns and volatility. Given these features of the data, the conditional CAPM implies a relatively low expected return for the long-short beta portfolio, which is consistent with the observed weak relation between beta and average return. The unconditional performance estimates emphasized in prior studies, on the other hand, fail to account for these systematic trends in factor exposures and lead to an incomplete assessment of the CAPM's ability to price beta-sorted portfolios.

Table IV contains robustness results for our findings in Table II. We investigate three alternatives to our base specification. The table reports estimates of alpha for the high-low beta portfolio under various information sets as well as p-values for the differences between conditional and unconditional alphas. The Internet Appendix contains full results with all parameter estimates for these specifications. For comparison, we reproduce a summary of our results from Table II in Panel A of Table IV.

Panel B presents alpha estimates from applying the IV2 approach discussed in Section I.A. The conditional alpha estimates in cases 2 to 8 are generally similar in magnitude to the corresponding one-step figures from Panel A. All of these long-short conditional alpha estimates are insignificant at conventional levels, and the null hypothesis of $\alpha_{HL}^{IV2} \leq \alpha_{HL}^{U}$ is rejected at the 5% level in each case.

In Panel C of Table IV, we present a set of IV1 results based on monthly portfolio returns for the high- and low-beta portfolios of interest. Although the analysis presented in Section I.B.2 suggests that slow information diffusion among high-beta firms makes a quarterly return measurement interval more appropriate for our empirical work, we would like to highlight the influence of this choice relative to monthly returns, which are a popular alternative in the literature. We estimate the model in equation (3) under alternative information sets with the state variables updated on a monthly basis. The unconditional alpha estimate of −0.59% per month in case 1 is nearly identical to the corresponding estimate based on quarterly data in Panel A. Conditioning continues to be important with monthly data, as each of the observed conditional alphas in Panel C is significantly greater than the unconditional alpha. The conditional alpha estimate of −0.30% in case 8 represents a reduction in magnitude of abnormal performance of roughly 50% relative to the unconditional alpha.

Finally, Panel D presents IV1 results for test portfolios formed using break points that are based on the formation-period betas for NYSE firms. This empirical design leads to slightly more diversified portfolios for the high- and low-beta groups, but the qualitative impact of conditioning information on portfolio alpha estimates is nearly identical to the base case in Panel A.

B. Fama-French Model Alphas

In this section, we examine the performance of the Fama-French (1993) three-factor model in explaining the average returns of the beta-sorted test portfolios. The Fama-French model is popular in empirical work, and multifactor models are a common risk-based alternative to conditional models for explaining CAPM anomalies. Further, Fama and French (1992) demonstrate that the beta-return relation becomes even flatter after controlling for firm size, and Fama and French (2006) extend this result to controlling for both size and book-to-market. We thus investigate the impact of controlling for

Table IV

Robustness Tests, July 1930 to December 2012

The table outlines robustness tests for the IV results in Table II. The reported alphas are the differences in alpha estimates for the top ("H") and bottom ("L") deciles for the beta-sorted portfolios. For ease of comparison, Panel A reproduces the one-step IV results from Table II, which are based on quarterly excess returns for each portfolio. The return regression is given by $R_{i,\tau} = \alpha_i^{IV1} + (\gamma_{i,0} + \gamma_{i,1}' Z_{i,\tau-1})R_{m,\tau} + u_{i,\tau}$, and the instruments $Z_{i,\tau-1}$ are defined in Table II. Panel B presents results for two-step IV regressions based on quarterly portfolio excess returns. In the first stage, contemporaneous portfolio betas are regressed on lagged state variables, $\hat{\beta}_{i,\tau} = \delta_{i,0} + \delta_{i,1}' Z_{i,\tau-1} + e_{i,\tau}$. The second-stage results are for the regression $R_{i,\tau} = \alpha_i^{IV2} + (\phi_{i,0} + \phi_{i,1}\tilde{\beta}_{i,\tau})R_{m,\tau} + v_{i,\tau}$. Panel C reports one-step IV results based on monthly portfolio and factor returns. Panel D shows one-step IV results for portfolios formed using only NYSE-listed firms to determine break points, and these regressions use quarterly portfolio excess returns. Alphas are expressed in percentage per month, and the numbers in parentheses are Newey-West (1987) corrected t-statistics with a lag length equal to five. For each conditional model (i.e., cases 2 to 8), the table also reports a p-value ($p(\alpha_i \leq \alpha_i^U)$) for the one-sided test that the conditional HL alpha is less than or equal to the corresponding unconditional alpha from case 1. The instruments included in each model are those included for the corresponding case from Table II.

	Panel A		Panel B		Panel C		Panel D	
	Quarterly Returns, All Break Points				Monthly Returns		NYSE Break Points	
Case	α_i^{IV1}	$p(\alpha_i \leq \alpha_i^U)$	α_i^{IV2}	$p(\alpha_i \leq \alpha_i^U)$	α_i^{IV1}	$p(\alpha_i \leq \alpha_i^U)$	α_i^{IV1}	$p(\alpha_i \leq \alpha_i^U)$
1	−0.59	n/a	−0.59	n/a	−0.59	n/a	−0.58	n/a
	(−2.26)		(−2.26)		(−2.71)		(−2.44)	
2	−0.37	0.021	−0.37	0.021	−0.44	0.018	−0.39	0.020
	(−1.52)		(−1.52)		(−2.20)		(−1.70)	
3	−0.28	0.011	−0.37	0.016	−0.40	0.008	−0.31	0.011
	(−1.11)		(−1.50)		(−1.96)		(−1.24)	
4	−0.39	0.028	−0.38	0.022	−0.43	0.023	−0.41	0.021
	(−1.62)		(−1.55)		(−2.20)		(−1.82)	
5	−0.30	0.012	−0.39	0.017	−0.40	0.012	−0.32	0.009
	(−1.22)		(−1.58)		(−1.98)		(−1.36)	
6	−0.31	0.011	−0.35	0.019	−0.40	0.004	−0.34	0.022
	(−1.22)		(−1.34)		(−1.91)		(−1.42)	
7	−0.23	0.007	−0.25	0.011	−0.32	0.003	−0.27	0.008
	(−0.92)		(−0.98)		(−1.60)		(−1.18)	
8	−0.18	0.003	−0.26	0.009	−0.30	0.002	−0.22	0.002
	(−0.72)		(−0.99)		(−1.51)		(−0.93)	

exposures to the size ($R_{smb,\tau}$) and value ($R_{hml,\tau}$) factors of the Fama-French model on inferences about the performance of the beta strategies. We also explore the linkages between exposures to the additional factors and the conditioning information that underlies our results in Section II.A.

We examine both unconditional and conditional versions of the three-factor model. This approach allows us to distinguish between the effects of adding the size and value factors and those obtained by accounting for time variation in risk exposures. Data on the daily and monthly Fama-French factor returns are from Kenneth French's website. We construct a quarterly version of each factor return by compounding the monthly returns for the long and short sides of the factor separately and then computing the difference. The IV1 estimation is based on the following regression:

$$R_{i,\tau} = \alpha_i^{IV1} + \left(\lambda_{i,0} + \lambda_{i,1}' Z_{i,\tau-1}^{\lambda}\right) R_{m,\tau} + \left(\theta_{i,0} + \theta_{i,1}' Z_{i,\tau-1}^{\theta}\right) R_{smb,\tau} + \left(\eta_{i,0} + \eta_{i,1}' Z_{i,\tau-1}^{\eta}\right) R_{hml,\tau} + u_{i,\tau}. \quad (10)$$

Table V presents the performance of the beta-sorted portfolios relative to the Fama-French three-factor model. The unconditional Fama-French alpha for the long-short portfolio in case 1 is -0.75% per month (t-statistic of -3.0). This performance estimate is significantly lower than the corresponding unconditional CAPM alpha of -0.59% from case 1 in Table II at the 10% level (p-value of 0.080). The high-beta portfolio has larger loadings on $R_{smb,\tau}$ and $R_{hml,\tau}$ compared to the low-beta portfolio (0.45 versus 0.04 for $R_{smb,\tau}$ and 0.31 versus -0.12 for $R_{hml,\tau}$), so including these additional factors amplifies the measured underperformance of high-beta stocks.

This result that the Fama-French model produces a larger negative alpha on the high-minus-low portfolio after controlling for exposures to $R_{smb,\tau}$ and $R_{hml,\tau}$ is broadly consistent with, and complementary to, the results of Fama and French (1992, 2006). In these studies, the beta-return relation becomes flatter after controlling for firm size and book-to-market in portfolio sorts, and a steeper negative pattern in CAPM alphas emerges across beta ranks. In a similar vein, controlling for exposures to the size and value factors in the Fama-French model amplifies the measured underperformance of high-beta stocks. Because the Fama-French model results in case 1 deepen the unconditional beta anomaly, we next examine the effect of conditioning information on measured portfolio performance.

The remaining three cases in Table V introduce instruments for factor loadings to estimate conditional versions of the Fama-French model. Case 2 includes three-month and 36-month LC betas for each of the three factors.[19] The estimated alpha in this case is -0.39%, which is significantly greater than the

[19] These instruments are estimated analogously to the CAPM LC betas after incorporating the two additional factors into equation (5). Given the similarity of results for specifications that include or exclude third-quarter indicators and interactions, for parsimony we exclude these variables in the remaining tests.

Table V
Fama-French Model Regressions, July 1930 to December 2012

The table reports IV regression results for decile portfolios formed on past market beta using the Fama-French (1993) three-factor model. "H" refers to the high-beta portfolio, "L" refers to the low-beta portfolio, and "HL" refers to their difference. The return regression is given by $R_{i,\tau} = \alpha_i^{IV1} + (\lambda_{i,0} + \lambda_{i,1}' Z_{i,\tau-1}^{\lambda}) R_{m,\tau} + (\theta_{i,0} + \theta_{i,1}' Z_{i,\tau-1}^{\theta}) R_{smb,\tau} + (\eta_{i,0} + \eta_{i,1}' Z_{i,\tau-1}^{\eta}) R_{hml,\tau} + u_{i,\tau}$ and is estimated from quarterly excess returns for the portfolios and factors. The instruments for a given portfolio include the three-month and 36-month LC factor loadings, the log dividend yield (DY), and the default spread (DS). The estimates of α_i^{IV1} are reported in percentage per month, and the numbers in parentheses are Newey-West (1987) corrected t-statistics with a lag length equal to five. For each regression, R^2 is the adjusted R^2 value. For each conditional model (i.e., cases 2 to 4), the table also reports a p-value ($p(\alpha_i \leq \alpha_i^U)$) for the one-sided test that the conditional HL alpha is less than or equal to the corresponding unconditional alpha from case 1.

				$R_{m,\tau} \times$					$R_{smb,\tau} \times$					$R_{hml,\tau} \times$					
Case		α_i^{IV1}	$p(\alpha_i \leq \alpha_i^U)$	1	β^{LC3}	β^{LC36}	DY	DS	1	s^{LC3}	s^{LC36}	DY	DS	1	h^{LC3}	h^{LC36}	DY	DS	R^2
1	L	0.12		0.49					0.04					−0.12					47.9
		(1.0)		(7.3)					(0.6)					(−0.9)					
	H	−0.63		1.76					0.45					0.31					87.1
		(−4.0)		(14)					(2.0)					(1.2)					
	HL	−0.75	n/a																
		(−3.0)																	
2	L	−0.01		−0.22	0.18	1.21			−0.08	0.03	0.56			−0.12	0.25	0.99			62.6
		(−0.1)		(−1.1)	(0.8)	(2.9)			(−1.3)	(0.3)	(2.9)			(−1.5)	(1.7)	(4.0)			
	H	−0.40		−0.16	0.51	0.68			0.27	0.03	0.42			0.05	0.12	1.00			92.0
		(−3.7)		(−0.4)	(3.1)	(2.7)			(2.9)	(0.2)	(2.8)			(0.4)	(0.8)	(3.8)			
	HL	−0.39	0.008																
		(−2.3)																	
3	L	−0.03		0.69			−0.01	−0.05	1.14			0.27	−0.07	−1.23			−0.43	−0.10	62.6
		(−0.4)		(2.0)			(−0.1)	(−1.9)	(2.0)			(1.7)	(−2.0)	(−3.3)			(−4.1)	(−3.8)	
	H	−0.37		−0.15			−0.45	0.10	2.29			0.36	−0.33	3.45			1.09	0.21	93.1
		(−3.3)		(−0.3)			(−3.2)	(1.4)	(2.4)			(1.3)	(−5.7)	(4.2)			(4.9)	(2.8)	
	HL	−0.33	0.004																
		(−1.8)																	
4	L	−0.04		0.28	0.09	0.73	0.02	−0.02	0.18	−0.12	0.98	0.03	−0.09	−1.05	0.12	0.53	−0.36	−0.09	70.0
		(−0.4)		(0.8)	(0.5)	(2.5)	(0.2)	(−0.7)	(0.4)	(−1.5)	(6.8)	(0.2)	(−3.1)	(−3.0)	(0.8)	(3.2)	(−3.8)	(−2.6)	
	H	−0.30		−0.54	0.26	0.16	−0.37	0.08	1.24	0.19	0.30	0.22	−0.15	1.65	0.20	0.41	0.57	0.19	94.1
		(−3.1)		(−1.2)	(2.6)	(0.8)	(−2.9)	(1.6)	(1.3)	(1.9)	(1.8)	(0.8)	(−2.3)	(1.5)	(1.8)	(1.8)	(1.7)	(2.9)	
	HL	−0.26	0.004																
		(−1.7)																	

alpha from case 1 (p-value of 0.008). The 36-month LC betas appear to be useful as instruments for modeling portfolio factor loadings, as all coefficients are large, positive, and significant. Three-month betas, on the other hand, are only significant at the 10% level for the high-beta portfolio's market loading and the low-beta portfolio's loading on the value factor. Increased measurement error in factor loadings for the multifactor model may explain the diminished effect of betas estimated over short windows. Case 3 includes the dividend yield and default spread as instruments. The conditional Fama-French alpha for the high-low portfolio is -0.33%, which is less than half of the unconditional alpha in magnitude. These standard instruments are significant in explaining several loadings, and the regression R^2s are as large as or larger than those from case 2, suggesting that the macroeconomic variables are valuable instruments.

Case 4 includes the full set of conditioning information. The 36-month factor loading estimates remain important for modeling portfolio betas, and the macroeconomic factors retain some predictive ability for portfolio betas, with the strongest effects occurring for value factor loadings. The estimated long-short alpha of -0.26% is marginally statistically significant (p-value of 0.095) but represents a 65% reduction in the magnitude of alpha relative to case 1 (p-value of 0.004). The conditional Fama-French alpha of -0.26% is also statistically indistinguishable from the corresponding CAPM alpha of -0.23% (i.e., case 7 in Table II). Overall, we find that allowing for time variation in risk exposures is important for evaluating the performance of beta-sorted portfolios using the Fama-French model.

We can also decompose the bias in unconditional Fama-French alphas to see which of the three factors drives the results. That is, the difference between unconditional and conditional three-factor performance for a given portfolio can be expressed as the sum of three terms:

$$
\begin{aligned}
\hat{\alpha}_i^U - \hat{\alpha}_i^{IV1} &= \frac{1}{T}\left(\sum_{\tau=1}^{T}\hat{\beta}_{i,\tau}^{IV1}R_{m,\tau} - \hat{\beta}_i^U\sum_{\tau=1}^{T}R_{m,\tau}\right) \\
&\quad + \frac{1}{T}\left(\sum_{\tau=1}^{T}\hat{s}_{i,\tau}^{IV1}R_{smb,\tau} - \hat{s}_i^U\sum_{\tau=1}^{T}R_{smb,\tau}\right) \\
&\quad + \frac{1}{T}\left(\sum_{\tau=1}^{T}\hat{h}_{i,\tau}^{IV1}R_{hml,\tau} - \hat{h}_i^U\sum_{\tau=1}^{T}R_{hml,\tau}\right),
\end{aligned}
\tag{11}
$$

where $\hat{\beta}_i^U$, $\hat{s}_i^U$, and $\hat{h}_i^U$ are the unconditional portfolio factor loadings on the market, size, and value factors, and $\hat{\beta}_{i,\tau}^{IV1}$, $\hat{s}_{i,\tau}^{IV1}$, and $\hat{h}_{i,\tau}^{IV1}$ are the fitted conditional loadings (e.g., $\hat{\beta}_{i,\tau}^{IV1} \equiv \hat{\lambda}_{i,0} + \hat{\lambda}_{i,1}' Z_{i,\tau-1}^{\lambda}$). Each of the three right-hand-side terms in equation (11) corresponds to a single factor. Table VI provides the results of this decomposition for the conditional alpha estimates in case 4 of Table V. The unconditional alpha for the long-short portfolio is biased by -49 basis points per month. Time variation in the market factor loading for this portfolio accounts for -41 basis points (84%) of this total. By comparison, the

Table VI

Decomposing Fama-French Alphas, July 1930 to December 2012

The table provides decompositions to demonstrate the biases in unconditional Fama-French (1993) model alphas ($\alpha_i^U - \alpha_i^{IV1}$) attributable to the market, size, and value factors. "H" refers to the high-beta portfolio, "L" refers to the low-beta portfolio, and "HL" refers to their difference. The IV alphas and factor loadings correspond to case 4 in Table V. The market factor bias is estimated as $\frac{\sum_{\tau=1}^{T}\hat{\beta}_{i,\tau}^{IV1}R_{m,\tau}}{T} - \hat{\beta}_i^U \bar{R}_{m,\tau}$, where $R_{m,\tau}$ is the buy-and-hold return on the CRSP value-weighted portfolio in excess of the risk-free rate, $\bar{R}_{m,\tau}$ is the average market risk premium, $\hat{\beta}_i^U$ is the unconditional market factor loading, and $\hat{\beta}_{i,\tau}^{IV1}$ is the IV loading for the market factor, $\hat{\lambda}_{i,0} + \hat{\lambda}_{i,1}' Z_{i,\tau-1}^{\lambda}$. The biases attributable to the size and value factors are computed analogously. All results are reported in percentage per month.

Portfolio	Market Factor Bias $\frac{\sum \beta_{i,\tau}^{IV1} R_{m,\tau}}{T} - \beta_i^U \bar{R}_{m,\tau}$	+	Size Factor Bias $\frac{\sum s_{i,\tau}^{IV1} R_{smb,\tau}}{T} - s_i^U \bar{R}_{smb,\tau}$	+	Value Factor Bias $\frac{\sum h_{i,\tau}^{IV1} R_{hml,\tau}}{T} - h_i^U \bar{R}_{hml,\tau}$	=	Total	=	α_i^U	−	α_i^{IV1}
L	0.13	+	−0.03	+	0.06	=	0.16	=	0.12	−	−0.04
H	−0.28	+	−0.03	+	−0.02	=	−0.33	=	−0.63	−	−0.30
HL	−0.41	+	0.00	+	−0.08	=	−0.49	=	−0.75	−	−0.26

contributions of the size and value terms of 0 basis points (0%) and −8 basis points (16%), respectively, are much less pronounced.

These results indicate that, even in a three-factor setup, the changing exposures to market risk among high- and low-beta firms account for most of the improvements obtained through conditioning. Given the nature of these findings, in the remainder of the paper, we focus on market factor loadings in a CAPM setting.

III. Determinants of Portfolio Betas

The prior section establishes that the previously documented poor performance of high-beta firms relative to low-beta firms is attributable to a bias in unconditional portfolio alphas. The relatively flat beta-return relation is simply an artifact of systematic variation in portfolio betas in relation to the market risk premium and market volatility. In this section, we attempt to identify the economic drivers underlying the observed changes in CAPM betas for our test assets. Our objective is to introduce and test a series of theoretically motivated conditioning variables with predictive content for the market exposures of the beta-sorted portfolios.

A. Portfolio Beta Decomposition

As a starting point, we introduce a simple decomposition to characterize potential sources of variation in the conditional betas for our trading strategies. The CAPM beta for a given portfolio can be expressed as the value-weighted average of N_τ constituent firm betas in quarter τ:

$$\beta_\tau = \sum_{n=1}^{N_\tau} w_{n,\tau}\beta_{n,\tau}, \tag{12}$$

where $\beta_{n,\tau}$ is the beta and $w_{n,\tau}$ is the portfolio weight for firm n in period τ. Using a covariance decomposition on the right-hand side, the portfolio beta can be expressed as

$$\beta_\tau = \bar{\beta}_{n,\tau} + N_\tau \mathrm{Cov}(w_{n,\tau}, \beta_{n,\tau}), \tag{13}$$

where $\bar{\beta}_{n,\tau}$ is the simple average of firm betas in period τ and $\mathrm{Cov}(w_{n,\tau}, \beta_{n,\tau})$ is the covariance between betas and weights within the portfolio.

The decomposition in equation (13) implies that variation in market risk for a given portfolio arises from changes in the average firm-level beta (i.e., the "beta distribution component," $\bar{\beta}_{n,\tau}$) or changes in the within-portfolio relation between betas and portfolio weights (i.e., the "valuation component," $N_\tau\mathrm{Cov}(w_{n,\tau}, \beta_{n,\tau})$). Figure 1 demonstrates that the distribution of firm betas is highly time varying, which will be reflected in the conditional market exposures of the beta-sorted portfolios through the distribution term, $\bar{\beta}_{n,\tau}$. Portfolio betas depend on the relative weights of higher- and lower-beta constituent firms through the valuation term, $N_\tau \mathrm{Cov}(w_{n,\tau}, \beta_{n,\tau})$, and a positive correlation between betas and weights will result in a conditional beta that exceeds the simple average beta of the constituent firms.

We thus investigate several theoretically motivated channels that may produce time variation in portfolio betas through the beta distribution and valuation components. Section III.B outlines how valuation effects can generate systematic changes in market exposure for beta-sorted portfolios, and Section III.C considers several potential economic mechanisms underlying the distribution effects in portfolio betas. Finally, Section III.D empirically examines these explanations for time-series variation in portfolio betas using the IV framework.

B. Valuation Effects for Portfolio Betas

The valuation component in equation (13) shows that a given portfolio's beta depends on the relation between the betas and weights of constituent firms. If firm values evolve as the present value of future cash flows with discount rates determined by the conditional CAPM, we would expect to observe systematic variation in this component in relation to the market risk premium. In the Internet Appendix, we introduce a model that formalizes these valuation-related effects. The valuation level for each firm in the cross section of the model economy is higher when the market risk premium is low, but the largest impact on valuations from a change in the market risk premium is felt by high-beta firms. The weights of firms in the high-beta portfolio therefore fluctuate systematically over time in relation to the market risk premium, with higher beta stocks receiving relatively larger weights during periods of low risk premiums.

The discussion above indicates that the market risk premium should be negatively related to the conditional beta for the high-beta strategy. To capture these valuation effects, we include the market risk premium as an instrument for modeling conditional betas in Section III.D. Specifically, the market risk premium is defined as the fitted value from the following regression of quarterly excess market returns on lagged state variables:

$$R_{m,\tau} = \pi_0 + \pi_1 DY_{\tau-1} + \pi_2 DS_{\tau-1} + \pi_3 TS_{\tau-1} + \pi_4 TB_{\tau-1} + \nu_\tau, \qquad (14)$$

where $DY_{\tau-1}$ and $DS_{\tau-1}$ are the dividend yield and default spread defined in Section II, $TS_{\tau-1}$ is the term spread, and $TB_{\tau-1}$ is the short-term risk-free rate.[20] Table VII provides summary statistics for the market risk premium, expressed in percentage per month, and the distribution-related state variables introduced below. Details regarding the construction of each state variable are available in the Internet Appendix.

[20] The term spread is the difference between the 10-year and 1-year Treasury constant maturity rates and the risk-free rate is the three-month Treasury bill yield. Data for these state variables come from the Federal Reserve Bank of St. Louis website. The regression in equation (14) is estimated from quarterly data over the period July 1930 to December 2012.

Table VII
Summary Statistics for Explanatory Variables, July 1971 to December 2012

The table reports summary statistics for the state variables used in characterizing the variation in market risk for beta-sorted portfolios. Panel A presents the time-series mean and standard deviation for the following variables: the fitted market risk premium ($\hat{R}_m$), the number of IPOs in the prior five years divided by the total number of sample firms (IPO), the cross-sectional standard deviation of firm-level log book-to-market ratios (σ_{BM}), the cross-sectional standard deviation of firm-level book leverage (σ_{LEV}), the cross-sectional average of firm-level idiosyncratic volatility computed from daily returns over the prior 12 months ($IVOL$), and the standard deviation of daily TED spread innovations over the prior three months ($\sigma_{\Delta TED}$). The fitted excess market return is estimated from a regression of quarterly excess market returns on the log dividend yield (DY), the default spread (DS), the term premium (TS), and the short-term interest rate (TB) using data from the period July 1930 to December 2012. Panel B reports pairwise correlations for the predictor variables. Each state variable is updated at a quarterly frequency.

Panel A: Distributional Statistics

	$\hat{R}_m$	IPO	σ_{BM}	σ_{LEV}	$IVOL$	$\sigma_{\Delta TED}$
Mean	0.429	0.172	0.886	0.319	3.360	0.126
Standard deviation	0.432	0.095	0.111	0.169	0.830	0.128

Panel B: Correlation Matrix

	$\hat{R}_m$	IPO	σ_{BM}	σ_{LEV}	$IVOL$	$\sigma_{\Delta TED}$
$\hat{R}_m$	1.000					
IPO	−0.534	1.000				
σ_{BM}	−0.081	0.516	1.000			
σ_{LEV}	−0.041	0.138	0.116	1.000		
$IVOL$	−0.180	0.665	0.701	0.043	1.000	
$\sigma_{\Delta TED}$	0.188	−0.438	−0.336	−0.328	−0.389	1.000

C. Determinants of the Cross-Sectional Distribution of Betas

As outlined in Section III.A, an important determinant of market exposures for beta-sorted portfolios is time variation in the dispersion of firm-level betas. In Sections III.C.1 to III.C.5, we propose characteristics of the cross section of stocks that are likely to forecast these shifts in the beta distribution. We specifically consider economic drivers related to initial public offering (IPO) activity, heterogeneity in investment opportunities, heterogeneity in firm leverage, idiosyncratic risk levels, and economy-wide funding conditions. For each of these five channels, we introduce a corresponding instrument and develop theoretical predictions for its relation with portfolio betas.

C.1. Initial Public Offerings

Our first proposed explanation links shifts in the distribution of firm-level betas to changes in the set of publicly traded firms. We argue that the intensity of recent IPO activity should positively predict the market exposure of the high-low beta portfolio. We proxy for IPO activity using the number of IPOs in the prior five years as a fraction of the total number of sample firms (IPO). Our model developed in the Internet Appendix formalizes this prediction. This model economy allows for the possibility of new entrants each period, and each potential entrant undertakes an IPO if its price-dividend ratio exceeds a threshold valuation ratio. Given that discount rates are determined by the conditional CAPM in this model, high-beta firms experience the largest changes in valuation given a shock to the market risk premium. As such, the IPO decisions of high-beta stocks are highly procyclical. The model predicts that IPO waves occur and more high-beta stocks undertake IPOs when the market risk premium is low. The cross section thus absorbs more high-beta stocks and beta dispersion increases when risk premiums are low.[21] As a result, we expect the cross-sectional dispersion in betas to be positively related to IPO.

C.2. Firm Investment

Investment opportunities can influence a firm's exposure to systematic risk, and we predict that greater heterogeneity in investment opportunities across firms produces more cross-sectional dispersion in firm betas. The ratio of book value of equity to market value of equity is a commonly used proxy for investment opportunities, so we empirically measure this heterogeneity using the cross-sectional standard deviation of firm-level log book-to-market ratios (σ_{BM}). High book-to-market can be a summary indicator that firm exposure to systematic risk is high because existing assets are relatively high risk and low value (Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2003)) or because a firm has a high mix of existing assets relative to growth options (Berk, Green, and Naik (1999)). Carlson, Fisher, and Giammarino (2004) show that high book-to-market may also signal high operating leverage, which increases exposure to systematic risk. In the presence of additional investment frictions such as costly adjustment, high book-to-market firms can have higher exposures to systematic risk because they cannot easily scale back on operations in bad times (Zhang (2005)) and can use their excess capacity to capitalize on positive economic shocks (Cooper (2006)). Based on the implications of these models, we expect the distribution of firm betas to be more disperse when σ_{BM} is high.

C.3. Leverage

Firm leverage also impacts equity betas through several mechanisms. We expect that the cross-sectional standard deviation of firm-level book leverage (σ_{LEV}) is positively related to the dispersion in betas across firms. Under the assumption that capital structure does not affect investment or firm

[21] Our model implications with respect to the timing and risk of IPOs are comparable to those of Pástor and Veronesi (2005), who develop a model that produces IPO volumes that vary based on expected market returns, expected aggregate profitability, and uncertainty about IPO firm profitability.

risk, equity beta is increasing in leverage in a Modigliani-Miller (1958) framework (Hamada (1972) and Rubinstein (1973)) or when equity is viewed as an option-like claim on the value of the firm (Galai and Masulis (1976)). Further, O'Doherty (2012) demonstrates that equity betas of levered firms decrease in an option pricing framework when unpriced information risk rises. Finally, Garlappi and Yan (2011) show that beta may have a hump-shaped relation with leverage if shareholders can strategically renegotiate debt contracts in times of distress.

The endogeneity of the capital structure decision can also impact the observed relation between beta and leverage. George and Hwang (2010) argue that firms with high systematic risk exposure may optimally choose lower leverage in the presence of distress costs. Further, joint financing and investment decisions could reinforce a positive beta-leverage relation, as leverage reduces the flexibility of financially constrained firms (Livdan, Sapriza, and Zhang (2009)), or produce a negative relation between beta and leverage, if debt is used to finance investments that lower the firm's asset beta (Gomes and Schmid (2010), Choi (2013)). To the extent firm leverage affects beta, the cross-sectional distribution of betas may be more disperse when σ_{LEV} is large.

C.4. Idiosyncratic Risk

Several studies show that, although idiosyncratic risk is unpriced under the CAPM, a stock's beta can be influenced by firm-specific shocks. Based on the theoretical literature, we predict that the cross-sectional average of firm-level idiosyncratic volatility ($IVOL$) is positively related to the systematic risk of the high-low beta portfolio. Brennan (1973), Bossaerts and Green (1989), and Babenko, Boguth, and Tserlukevich (2015) develop frameworks in which past idiosyncratic cash flow shocks affect a firm's current exposure to systematic risk. Intuitively, firms may have multiple components that are relatively more exposed to firm-specific or systematic risks. A positive (negative) idiosyncratic shock increases the importance of the idiosyncratic (systematic) component of firm value, leading to a decrease (increase) in firm beta. Babenko, Boguth, and Tserlukevich (2015) show that this result holds except in the special case in which the systematic and idiosyncratic components of cash flow risk are multiplicative. Thus, beta dispersion should be positively related to $IVOL$, given that larger firm-specific shocks have a greater impact on beta.

C.5. Funding Liquidity Conditions

Our final proposed driver of changes in the beta distribution is based on economy-wide funding liquidity. Following Frazzini and Pedersen (2014), we measure aggregate funding conditions as the standard deviation of daily Treasury-Eurodollar (TED) spread innovations ($\sigma_{\Delta TED}$). Frazzini and Pedersen (2014) consider a setting with constraints on investors' ability to borrow in the spirit of Black (1972). They derive equilibrium relations in a dynamic economy in which funding liquidity conditions vary over time. These shifts in funding liquidity produce time-series variation in the cross-sectional distribution of betas, as an increase (decrease) in the mutual exposure of all firms to these shocks produces a more compressed (diffuse) cross-sectional distribution of betas. From this model, the cross-sectional dispersion of betas should be negatively related to $\sigma_{\Delta TED}$.

D. Empirical Tests of Beta Determinants

We now empirically investigate the proposed explanations from Sections III.B and III.C for time variation in portfolio betas. Each state variable introduced above is available at a quarterly frequency over the period July 1971 to December 2012. We evaluate the abilities of the theory-based state variables to explain variation in portfolio betas over this period. We also relate the variables to the beta distribution and valuation components of portfolio betas in equation (13) to investigate the channels through which these predictors are related to portfolio betas. Finally, we use the theoretically motivated state variables to test the conditional CAPM in an IV framework.

In Table VIII, we regress conditional portfolio betas as well as their valuation and beta distribution components on each of the state variables. The conditional beta regressions follow equation (7) and use contemporaneous portfolio betas, $\hat{\beta}_\tau$, estimated from daily data during quarter τ. The average beta component is the simple average of firm-level betas for constituent firms in quarter τ (i.e., $\frac{1}{N_\tau}\sum_{n=1}^{N_\tau}\hat{\beta}_{n,\tau}$), and the valuation component is the difference between the conditional beta estimate and the average beta component. The coefficient estimates for the beta distribution and valuation components sum to equal the coefficient for the portfolio beta, so this approach also serves to decompose the overall effect of a given state variable on portfolio beta into its effects on the two components. Based on theoretical predictions in Section III.B, we expect $\hat{R}_m$ to have a negative impact on portfolio betas, particularly for the high-beta portfolio, with the effect working through the valuation component. The five explanations from Section III.C, in contrast, are expected to work primarily through the beta distribution channel. The IPO, σ_{BM}, σ_{LEV}, and $IVOL$ variables should be positively (negatively) associated with the beta of the high-beta (low-beta) portfolio, whereas $\sigma_{\Delta TED}$ is expected to have a negative (positive) relation with the high-beta (low-beta) portfolio beta.

Panel A of Table VIII contains univariate regression results for the high-beta portfolio. All six state variables show significant predictive ability for the beta of this portfolio in the theoretically predicted direction with regression R^2s ranging from 2.8% ($\sigma_{\Delta TED}$) to 10.0% ($IVOL$). Further, the fitted market risk premium primarily affects the portfolio beta by forecasting the valuation component (coefficient of -0.21 compared to the total effect of -0.32), which is consistent with predictions. The beta distribution variables σ_{BM}, σ_{LEV}, and $IVOL$ also largely affect the portfolio beta through the predicted channel of average beta. The IPO state variable, on the other hand, is more closely related to the valuation component compared to the average beta component. As

Table VIII

Beta Component Regressions, July 1971 to December 2012

The table reports results from univariate time-series regressions of portfolio betas and components of portfolio betas on lagged state variables. Panel A (Panel B) presents results for the high-beta (low-beta) decile. The portfolio beta regressions are given by $\hat{\beta}_{i,\tau} = \delta_{i,0} + \delta'_{i,1} Z_{i,\tau-1} + e_{i,\tau}$, where $\hat{\beta}_{i,\tau}$ is the contemporaneous portfolio beta estimated from daily portfolio excess returns during quarter τ. The instruments $Z_{i,\tau-1}$ include the fitted market risk premium ($\hat{R}_m$), the number of IPOs in the prior five years divided by the total number of sample firms (IPO), the cross-sectional standard deviation of firm-level log book-to-market ratios (σ_{BM}), the cross-sectional standard deviation of firm-level book leverage (σ_{LEV}), the cross-sectional average of firm-level idiosyncratic volatility computed from daily returns over the prior 12 months ($IVOL$), and the standard deviation of daily TED spread innovations over the prior three months ($\sigma_{\Delta TED}$). The fitted excess market return is estimated from a regression of quarterly excess market returns on the log dividend yield (DY), the default spread (DS), the term premium (TS), and the short-term interest rate (TB) using data from the period July 1930 to December 2012. The average beta component for a given portfolio, $\bar{\beta}_{n,\tau}$, is the equally weighted average of firm-level betas for constituent firms during quarter τ. The valuation component, $N_\tau \mathrm{Cov}(w_{n,\tau}, \beta_{n,\tau})$, for a given portfolio is the difference between the corresponding contemporaneous portfolio beta and the average beta component. For each regression, the table reports an adjusted R^2 value ($\bar{R}^2$), and the numbers in parentheses are t-statistics. The coefficient on the intercept is not reported.

		Portfolio Beta β_τ			Average Beta Component $\bar{\beta}_{n,\tau}$			Valuation Component $N_\tau \mathrm{Cov}(w_{n,\tau}, \beta_{n,\tau})$	
Case	State Variable	δ_1	$\bar{R}^2$	=	δ_1	$\bar{R}^2$	+	δ_1	$\bar{R}^2$
		Panel A: Regressions for High-Beta Portfolio							
1	$\hat{R}_m$	−0.32 (−3.86)	7.8		−0.11 (−1.19)	0.3		−0.21 (−3.11)	5.0
2	IPO	1.59 (4.28)	9.5		0.39 (0.92)	−0.1		1.20 (4.05)	8.5
3	σ_{BM}	1.40 (4.37)	9.9		1.13 (3.14)	5.1		0.27 (1.01)	0.0
4	σ_{LEV}	0.69 (3.19)	5.3		0.61 (2.55)	3.2		0.08 (0.45)	−0.5
5	$IVOL$	0.19 (4.40)	10.0		0.11 (2.35)	2.7		0.07 (2.08)	2.0
6	$\sigma_{\Delta TED}$	−0.75 (−2.41)	2.8		−0.51 (−1.49)	0.7		−0.24 (−0.95)	−0.1
		Panel B: Regressions for Low-Beta Portfolio							
1	$\hat{R}_m$	0.01 (0.24)	−0.6		−0.03 (−0.82)	−0.2		0.04 (0.96)	0.0
2	IPO	−0.17 (−0.71)	−0.3		0.12 (0.69)	−0.3		−0.29 (−1.40)	0.6
3	σ_{BM}	−0.36 (−1.81)	1.4		−0.18 (−1.22)	0.3		−0.18 (−1.03)	0.0
4	σ_{LEV}	0.14 (1.03)	0.0		0.09 (0.93)	−0.1		0.05 (0.39)	−0.5
5	$IVOL$	−0.04 (−1.64)	1.0		−0.01 (−0.30)	−0.6		−0.04 (−1.62)	1.0
6	$\sigma_{\Delta TED}$	−0.05 (−0.25)	−0.6		−0.15 (−1.06)	0.1		0.10 (0.60)	−0.4

discussed in Section III.C.1, IPO decisions of firms may be related to overall valuation levels, which could explain this effect. Finally, $\sigma_{\Delta TED}$ is not a significant predictor of either component individually but is negatively related to the portfolio beta as expected.

Table VIII, Panel B, presents results from regressing the low-beta portfolio beta and its components on the state variables. The σ_{BM} variable is significantly negatively related to the beta of this portfolio at the 10% level. All other coefficients are insignificant, and the regression R^2s are 1.4% or below. These results suggest that the proposed state variables are generally less informative in characterizing the dynamics of the low-beta strategy.

We now investigate the theory-based variables in an IV setting. The purpose of this analysis is twofold. First, although Table VIII contains univariate tests of the relations between portfolio betas and the state variables, we investigate a multivariate model using the IV2 method to distinguish different theoretical explanations. Second, the IV framework allows us to examine the extent to which the conditioning variables are associated with systematic trends in conditional betas that ultimately impact measured portfolio performance.

Table IX presents IV2 results over the July 1971 to December 2012 sample period covered by the state variables. Case 1 corresponds to the unconditional CAPM. The estimated unconditional alpha for the high-low portfolio over the sample period is -0.60% per month, which is significant at the 10% level. The six theory-based instruments are included in case 2. The $\hat{R}_m$, σ_{BM}, σ_{LEV}, and $IVOL$ state variables all have significant predictive ability for the beta of the high-beta portfolio, and each of these four coefficients has the predicted sign. The IPO and $\sigma_{\Delta TED}$ variables are insignificantly related to beta after controlling for the additional instruments. The first-stage regression R^2 is 20.0% for the high-beta portfolio, indicating that the state variables are capturing a substantial proportion of the time variation in the portfolio beta. In contrast, none of the variables are significantly related to the beta of the low-beta portfolio, and the adjusted R^2 of the first-stage beta regression is -0.3%. The estimated alpha for case 2 is insignificant at -0.39%, which indicates that the theory-based instruments are capturing systematic variation in portfolio betas.

Case 3 in Table IX includes the short-term and long-term LC betas as additional instruments. The $\hat{R}_m$ and $IVOL$ instruments retain significance for the high-beta portfolio after including the β^{LC3} and β^{LC36} variables. We interpret the coefficient estimates for the instruments with some caution after including LC betas, however, as these empirically motivated variables may be influenced by the underlying theory-based instruments. The first-stage R^2s for the high-beta and low-beta portfolios increase substantially after adding β^{LC3} and β^{LC36}, which likely suggests that additional determinants of portfolio betas exist. Finally, the conditional alpha estimate is -0.33%, which is significantly larger than the unconditional alpha at the 10% significance level.

Overall, the results in this section provide support for several of the proposed theoretical determinants of portfolio betas. The market risk premium negatively impacts the beta of the high-beta portfolio through the predicted valuation channel. In contrast, cross-sectional patterns in firm investment

Table IX

Two-Stage Instrumental Variables Regressions: Explaining Trends in Portfolio Betas, July 1971 to December 2012

The table reports two-stage IV regression results for decile portfolios formed on past market beta. "H" refers to the high-beta portfolio, "L" refers to the low-beta portfolio, and "HL" refers to their difference. The formation-period betas are estimated using 12 months of daily data as described in Section I.B.1, and the portfolios are rebalanced at the beginning of each July using all listed firms for the break points. The first-stage results are for a regression of contemporaneous portfolio beta on lagged state variables, $\hat{\beta}_{i,\tau} = \delta_{i,0} + \delta'_{i,1} Z_{i,\tau-1} + e_{i,\tau}$. The instruments $Z_{i,\tau-1}$ for a given portfolio include the fitted market risk premium ($\hat{R}_m$), the number of IPOs in the prior five years divided by the total number of sample firms (IPO), the cross-sectional standard deviation of firm-level log book-to-market ratios (σ_{BM}), the cross-sectional standard deviation of firm-level book leverage (σ_{LEV}), the cross-sectional average of firm-level idiosyncratic volatility computed from daily returns over the prior 12 months ($IVOL$), the standard deviation of daily TED spread innovations over the prior three months ($\sigma_{\Delta TED}$), and the three-month and 36-month LC betas (β^{LC3} and β^{LC36}). The fitted excess market return is estimated from a regression of quarterly excess market returns on the log dividend yield (DY), the default spread (DS), the term premium (TS), and the short-term interest rate (TB) using data from the period July 1930 to December 2012. The second-stage results are for the regression $R_{i,\tau} = \alpha_i^{IV2} + (\phi_{i,0} + \phi_{i,1}\tilde{\beta}_{i,\tau})R_{m,\tau} + v_{i,\tau}$. For each regression, R^2 is the adjusted R^2 value. The numbers in parentheses are t-statistics. The estimates of α_i^{IV2} are reported in percentage per month, and the second-stage t-statistics are computed using the Newey-West (1987) correction with a lag length equal to three. For each conditional model (i.e., cases 2 and 3), the table also reports a p-value ($p(\alpha_i \le \alpha_i^U)$) for the one-sided test that the conditional HL alpha is less than or equal to the corresponding unconditional alpha from case 1.

		Stage 1 Beta Regression										Stage 2 Return Regression				
Case		δ_0	$\hat{R}_m$	IPO	σ_{BM}	σ_{LEV}	$IVOL$	$\sigma_{\Delta TED}$	β^{LC3}	β^{LC36}	R^2	α_i^{IV2}	ϕ_0	ϕ_1	R^2	$p(\alpha_i \le \alpha_i^U)$
1	L	0.53										0.00		1.15	43.2	
		(24)										(0.0)		(8.2)		
	H	1.66										−0.60		1.11	77.3	
		(45)										(−2.4)		(14)		
	HL											−0.60				n/a
												(−1.7)				
2	L	0.85	0.02	0.19	−0.33	0.13	−0.03	−0.08			−0.3	−0.07	−1.63	4.32	47.3	
		(4.1)	(0.4)	(0.5)	(−1.1)	(1.0)	(−0.7)	(−0.4)				(−0.5)	(−2.4)	(3.2)		
	H	0.49	−0.30	−0.32	0.81	0.66	0.12	0.26			20.0	−0.47	−1.04	1.73	81.2	
		(1.6)	(−3.2)	(−0.5)	(1.9)	(3.1)	(1.8)	(0.8)				(−2.2)	(−1.3)	(3.5)		
	HL											−0.39				0.126
												(−1.3)				
3	L	0.27	0.03	−0.17	−0.31	0.29	0.02	0.06	0.16	0.51	14.6	−0.08	−0.05	1.39	46.0	
		(1.2)	(0.4)	(−0.4)	(−1.1)	(2.1)	(0.4)	(0.3)	(1.9)	(3.8)		(−0.5)	(−0.2)	(3.0)		
	H	−0.08	−0.25	−0.49	0.40	0.26	0.15	0.24	0.24	0.33	31.6	−0.41	−0.52	1.40	82.1	
		(−0.3)	(−2.8)	(−0.9)	(1.0)	(1.3)	(2.4)	(0.8)	(3.4)	(2.6)		(−1.9)	(−1.2)	(4.9)		
	HL											−0.33				0.096
												(−1.1)				

opportunities, leverage, and idiosyncratic risk positively forecast the high-beta portfolio beta due to their effects on the distribution of firm betas. The evidence also suggests that these factors produce much of the systematic variation in portfolio betas underlying the apparent underperformance of high-beta stocks found in prior literature.

IV. Conclusion

Our analysis suggests that the historical record of success for betting-against-beta strategies should be viewed with caution. In particular, the statistically significant differences in risk-adjusted performance for high-beta and low-beta portfolios found in prior studies are largely attributable to biases in unconditional performance measures. We show that the differences in conditional alphas across beta portfolios are substantially smaller in economic magnitude and are statistically insignificant. The key innovation is properly accounting for predictable time-series variation in market exposure for the strategies of interest.

We further establish that these results are an artifact of two complementary effects: (i) systematic trends in the association between market weights and firm-level betas and (ii) time-varying dispersion in the beta distribution. The first effect is largely mechanical. In a CAPM economy, the market weights of high-beta stocks will decline in response to a positive shock to the equity premium. These systematic valuation adjustments are then reflected in the conditional risk of beta-sorted trading strategies. We also find support for theoretical drivers of the second effect. In particular, we link changes in investment opportunities, leverage, and idiosyncratic risk to shifts in the cross-sectional distribution of firm-level betas.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.