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Beta Active Hedge Fund Management

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Abstract

We reconsider whether hedge funds' time-varying risk factor exposures are predictive of superior performance. We construct an overall measure (BA) of fund managers and present evidence that top beta active managers deliver superior long-term out-of-sample performance compared to top alpha active managers. BA captures the time-varying nature of beta exposures and can be interpreted as a common factor of both systematic risk (SR) and $(1 - R^2)$ measures. BA also compares favorably to extant measures of market timing, capturing the explanatory power of such measures of hedge fund performance.

I. Introduction

Hedge funds are considered the apex of professionally actively managed investment funds. Hedge fund researchers commonly consider alpha, the constant in a regression specified by an asset pricing model, as a proxy for fund performance due to active portfolio management. In essence, alpha is the performance of a fund that cannot be explained by the model; therefore, positive alpha is a proxy for superior performance relative to the factor returns. Alpha is firmly entrenched in the common investment lexicon as a sophisticated measure of performance; fund managers, investment advisors, and investors all are "seeking alpha."

It is questionable, however, whether alpha reliably encompasses all relevant information about hedge fund performance. Extant literature documents that relatively few funds produce significant alpha. Rather, funds exhibit exposure to systematic risk (SR) factors such that returns are driven by beta activity (BA).[1] However, there is no consensus in the literature as to the efficacy of BA on a

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[1]For example, Fung, Hsieh, Naik, and Ramadorai (2008) document that 78% of the funds in their sample did not deliver alpha, instead exhibiting "beta-only" return patterns. Still, demand for hedge fund shares remains strong, with $2.9 trillion invested in hedge funds globally, according to Hedge Fund Research (HFR, Feb. 5, 2016 press release). If relatively few funds deliver persistent and

risk-adjusted basis. For example, Titman and Tiu (2011) argue that successful managers hedge away SR exposure and, thus, exhibit low R^2 in multifactor regressions. In contrast, Bali, Brown, and Caglayan (2012) find that hedge funds with greater exposure to SR demonstrate higher risk-adjusted performance. It is, therefore, important for investors to better understand the nature of beta management in addition to alpha production.

In this paper, we reconsider the question of whether beta-driven hedge fund performance is valuable and predictive of superior performance to address the seeming conflict between the findings of Bali et al. (2012) and Titman and Tiu (2011). We then compare out-of-sample performance of funds chosen on the basis of beta-centric and alpha-centric methodologies. Specifically, we consider two styles of active portfolio management: "alpha active" and "beta active." We define alpha activity as that which is not ultimately reflected in factor loadings. Alpha activity is traditionally identified by an alpha coefficient from a suitable factor model regression. If a manager is skilled, the alpha should be positive and significant, reflecting superior performance.[2] We define BA as taking directional positions correlated with macroeconomic risk factors. Beta active managers' time-varying bets are revealed by changing factor loadings (beta coefficients) over time. Even in the absence of short-term alpha production, it is possible for beta active managers to deliver superior returns if they execute strategies that are correlated with the most profitable factors. We construct a measure of overall BA that captures both contemporaneous managerial success and dynamic changes in factor loadings. Like Bali et al. (2012), we do not attempt to capture timing with respect to any specific factor, instead focusing on overall activity. That is, instead of attempting to improve model specifications along any particular factor, we construct an aggregate measure of activity across all factors in an unconditional asset pricing model.[3]

We employ a modified Fung and Hsieh (2004) 8-factor model to compare consecutive short-term beta estimates.[4] We evaluate betas for nonoverlapping 2-year periods to construct variables capturing the contemporaneous success of BA, dynamic changes in beta exposures, and a combination of these into an overall measure of beta activity (BA). We find BA to be strongly predictive of long-term

significant alpha, then, arguably, investors reap some benefit from funds whose returns are driven by betas.

[2]Many hedge funds portray themselves as "pure alpha" investment vehicles that deliver returns uncorrelated with broad macroeconomic factors, which implies a low R^2 from a factor model regression. For example, equity market neutral, merger arbitrage, convertible arbitrage, and distressed securities managers would likely have a low R^2, as the variance in factor returns is less likely to explain fund returns. However, it is possible for a fund to display both high alpha, implying alpha activity, and a relatively high R^2, dependent upon model specification and fund strategy, inclusive of leverage. For example, hedge fund managers in directional strategies, such as global macro and emerging markets, would likely have considerable exposure to macroeconomic factors and a relatively high R^2.

[3]This is most relevant in the context of hedge fund investing due to the multitude of investment opportunities available to hedge fund managers. In contrast to comparatively constrained mutual fund managers, hedge fund managers implement global time-varying strategies across myriad asset classes potentially correlated with a multitude of risk factors.

[4]While Fung and Hsieh (2004) specify the 7-factor model, the updated specification on David Hsieh's Web site at http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm includes 8 factors. Other papers utilizing the Fung and Hsieh model include Kosowski, Naik, and Teo (2007), Fung et al. (2008), Jagannathan, Malakhov, and Novikov (2010), and Avramov, Kosowski, Naik, and Teo (2011), among others.

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out-of-sample performance. We compare portfolios of hedge funds based upon BA as well as traditional measures of alpha activity: alpha and alpha t-statistic. In out-of-sample tests of long-term portfolio performance we find beta portfolios significantly outperform alpha portfolios. Our combined measure of BA outperforms alpha portfolios while also delivering a Fung and Hsieh (2004) alpha of over 5% per annum.

We investigate the relationship between BA and other measures of fund exposure to SR, namely, those of SR per Bali et al. (2012) and $(1 - R^2)$ as considered by Titman and Tiu (2011). Unsurprisingly, there is considerable overlap in portfolios selected upon the basis of fund BA, SR, and $(1 - R^2)$. Excluding funds from the BA portfolio that would also be present in SR or $(1 - R^2)$ portfolios, we find that the remaining BA funds deliver superior and statistically significant out-of-sample performance. We conjecture that BA successfully captures the time-varying nature of beta exposures not fully captured by either SR or $(1 - R^2)$. The converse is not true, however; when we exclude funds from the SR portfolio that would also be in the BA portfolio, the SR portfolio loses much of its predictive power. The $(1 - R^2)$ portfolio does partially retain its risk-adjusted performance after excluding the funds common to the BA portfolio. This suggests that BA could be interpreted as a common factor behind the long-term out-of-sample predictive power of both SR and $(1 - R^2)$, well explaining the long-term predictive significance of SR and partially explaining the long-term significance of $(1 - R^2)$.

Finally, we demonstrate that our BA measure captures previously unexplored aspects of beta active portfolio management by comparing BA to existing measures of market, volatility, and liquidity timing. Specifically, we calculate the timing measures of Henriksson and Merton (1981), Chen and Liang (2007), and Cao, Chen, Liang, and Lo (2013) and a measure of the timing of SR implied by Bali et al. (2012). We find that BA fully or partially explains each measure, broadening our understanding of factor timing.

It is conceptually important to emphasize that BA in no way implies a "passive" investment style. Overall, identifying BA broadens the discussion of active portfolio management and is a complement to existing methodologies in the identification of superior managerial skill.

II. Related Literature

Alpha activity, traditionally referred to as "active management," is typically identified by the low R^2 from an asset pricing model regression (see, e.g., Jensen (1968), Sharpe (1992), and Amihud and Goyenko (2013)). If a manager is skilled, the alpha should be positive and significant, reflecting superior returns as compared to passively holding factor-mimicking portfolios. However, alpha is only a relative measure of the fund performance as it is sensitive to benchmark factor specifications (see, e.g., Roll (1978)). Furthermore, alpha provides a biased evaluation of the success of market-timing strategies (see, e.g., Jensen (1972)). These shortcomings have led to the development of alternative approaches used to identify managerial activity and evaluate performance.

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Our methodology extends three strands of literature. In identifying the differences between alpha and beta activity, we conceptually borrow from the performance attribution literature that attempts to separate security selection from market-timing activity (see, e.g., Fama (1972), Brinson, Hood, and Beebower (1986), and Daniel, Grinblatt, Titman, and Wermers (1997)). Our focus on BA echoes the market-timing literature as recognizing the importance of fund activity reflected in factor exposures. Finally, we test the power of BA metrics to predict future hedge fund performance, thereby contributing to the recent literature seeking to develop alternative methodologies that are predictive of future performance (see, e.g., Grinblatt and Titman (1993), Kacperczyk, Sialm, and Zheng (2008), Cremers and Petajisto (2009), Jagannathan et al. (2010), Titman and Tiu (2011), Avramov et al. (2011), Bali, Brown, and Caglayan (2011), Sun, Wang, and Zheng (2012), and Amihud and Goyenko (2013)).

Our attempt to identify and quantify overall alpha and beta activity is conceptually similar to identifying "security selection" and "market timing" as in the performance attribution and market-timing literatures, though we point to three significant differences. First, hedge funds do not report positions; thus, it is impossible to compare fund portfolio holdings against a benchmark to measure managers' security selections.[5] Second, rather than exploring timing with regard to a *single* factor, we quantify aggregate timing across *all* factors.[6] Finally, time-varying beta exposures may be driven by levered positions and those with option-like payoffs, as demonstrated by Jagannathan and Korajczyk (1986).[7] In sum, within the context of hedge funds, it is impossible to definitively conclude that security selection is reflected in alphas while market timing is reflected in betas. We, thus, concentrate on studying overall "alpha activity" and "beta activity" as we can better identify and quantify these processes.

From the perspective of performance attribution, our paper is closest to Daniel et al. (1997) who use return attribution analysis with respect to stock characteristic–based benchmark portfolios. The authors separate and capture the effects of managers' security selection and market timing relative to benchmark portfolios by employing average style (AS), characteristic timing (CT), and characteristic selectivity (CS) measures. While the CT measure quantifies market-timing activity in a way that is conceptually similar to the forward difference in beta returns (FDBR) measure in this paper, it relies on portfolio asset weights and style benchmarks matched to specific mutual fund asset holdings. In contrast, FDBR is constructed of time-varying beta coefficients on benchmark portfolios that reflect hedge fund investment opportunity sets.

[5]Hedge funds are under no obligation to report portfolio positions, with the exception of long positions in equity securities on Form 13F, if the total equity position under management is valued at least $100 million, per U.S. Securities and Exchange Commission requirements.

[6]This is conceptually similar to the approach in Bali et al. (2012) considering that overall SR is a proxy for overall time-varying directional activity, that is BA in our terminology.

[7]Notice that even the conceptual difference between security selection and market timing becomes less clear in the context of the hedge fund activity. For example, a prescient hedge fund manager decides to synthetically short mortgage-backed securities and purchase credit default swaps in 2007. Is that security selection or market timing?

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There are numerous studies dedicated to market timing with regard to mutual funds and more recently, as data became available, among hedge funds.[8,9] Most mutual fund studies conclude that there is little evidence of successful market timing by mutual fund managers. Hedge fund managers, on the other hand, are shown to enjoy considerable market-timing success made possible by the broad and dynamic strategies available to them.[10] However, these strategies involve significant factor risk, as documented in Fung and Hsieh (1997), (2001), (2004), Asness, Krail, and Liew (2001), Agarwal and Naik (2000), (2004), Patton (2009), and Bali et al. (2011), (2012). For example, Bali et al. (2012) conclude that SR is a powerful predictor of hedge fund returns, a finding consistent with managerial skill in BA. Our finding that overall BA is strongly predictive of hedge fund performance is consistent with the conclusions of Bali et al. (2012).

Finally, there is a realization that the success of active portfolio management may derive from a wide variety of strategies that defy simple categorization. A growing literature develops alternative methodologies to capture various aspects of managerial activity and skill. Grinblatt and Titman (1993) measure informed managerial activity apart from Jensen's alpha without reliance upon an exogenous benchmark. The authors construct a portfolio change measure that compares past fund holdings to current fund holdings. Using quarterly holdings of a sample of mutual funds, the authors document evidence of managerial skill, especially in aggressive growth mutual funds. While Grinblatt and Titman's portfolio change measure is computationally similar to the FDBR measure employed in this paper, there are conceptual differences in the two measures and their interpretations. The portfolio change measure uses past portfolio asset weights as benchmarks, thus combining the effects of alpha and beta active management, while FDBR accounts solely for beta active management by using past factor loadings as benchmarks. Also, FDBR measures the success of BA with respect to exogenously stipulated factor portfolios, unlike the portfolio change measure, which does not rely on any external benchmark.

Amihud and Goyenko (2013) consider $(1 - R^2)$ as a measure of the active management in a mutual fund, demonstrating that lower R^2 indicates greater security selectivity and predicts better performance. Kacperczyk et al. (2008) create a measure that quantifies "hidden" activity by mutual fund managers, that is, trades and other actions taken between disclosure periods. Specifically, the authors find that the "return gap," the difference between actual period fund returns and a synthetic return that would have been realized had managers held previously disclosed positions through the current period, is persistently predictive of future returns. Using a similar sample of mutual funds as that of Kacperczyk et al. Cremers and Petajisto (2009) create a measurement of active management that

[8]For mutual funds, see, for example, Treynor and Mazuy (1966), Henriksson and Merton (1981), Jagannathan and Korajczyk (1986), Grinblatt and Titman (1989), Ferson and Schadt (1996), Bollen and Busse (2001), Jiang, Yao, and Yu (2007), and Mamaysky, Spiegel, and Zhang (2008).

[9]For hedge funds, see, for example, Aragon (2002), Fung, Xu, and Yau (2002), Chen (2007), Chen and Liang (2007), Bollen and Whaley (2009), Cai and Liang (2012a), (2012b), and Cao et al. (2013).

[10]An exception is Aragon (2002), who did not find evidence of successful timing across different hedge fund styles in funds-of-funds, attributing this to the liquidity constraints imposed by individual hedge funds on funds-of-funds investors.

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they dub "active share," which is most easily defined as the degree to which a fund's portfolio differs from its closest benchmark in composition and securities weighting. Cremers and Petajisto find that the highest active share mutual funds exhibit some skill in stock picking, outperforming their benchmarks.

Conceptually similar to the Amihud and Goyenko (2013), Kacperczyk et al. (2008), and Cremers and Petajisto (2009) studies of mutual funds, several recent hedge fund studies rely on return patterns and factor models to create alternative measures to predict future performance.[11] Sun et al. (2012) create a "strategy distinctiveness index" (SDI) measuring the difference between the variance in returns of any particular hedge fund and its statistically determined closest peer group. The authors' clustering methodology overcomes the weaknesses inherent in relying upon self-declared style information. The authors find that funds with higher SDI, those with more distinct strategies, outperform funds with more common strategies in terms of out-of-sample Sharpe ratios, appraisal ratios, alphas, and manipulation-proof performance measures.[12] Jagannathan et al. (2010) also utilize peer benchmarks as they identify superior funds by considering alphas that are calculated relative to best fitting fund peer benchmark factors from HFR indices. Their approach allows them to identify superior funds that are able to persistently deliver alpha as measured by the Fung and Hsieh (2004) model.

Titman and Tiu (2011) test whether hedge funds with less exposure to identifiable factor portfolios are better performers. Utilizing both stepwise regression analysis with a broad set of risk factors and the Fung and Hsieh (2004) 7-factor model, the authors find that funds with lower R^2s are better performers on both a relative and risk-adjusted basis.[13] On the other hand, Bali et al. (2012) find that hedge funds taking higher (SR), defined as the difference of the total fund risk minus the idiosyncratic risk from a factor regression, demonstrate superior risk-adjusted future performance. They conjecture that the predictive power of SR emanates from hedge funds' competence in detecting shifts in financial markets and their ability to timely adjust positions to those changes in financial and economic conditions. This is consistent with our finding that overall BA is strongly predictive of performance.

Avramov et al. (2011) and Avramov, Barras, and Kosowski (2013) explicitly include macroeconomic variables in hedge fund performance evaluation, finding strong evidence of return predictability conditional on economic conditions.[14] Overall, the authors address a broad and important question: How does one utilize macroeconomic variables in a way that identifies managers whose skills are valuable conditional on economic conditions? We ask a similar question, seeking to identify managers who are able to recognize and profit from changing economic

[11] There are also studies investigating other hedge fund characteristics that affect future performance, such as investor liquidity provisions (Aragon (2007), Agarwal, Daniel, and Naik (2009)), liquidity risk (Sadka (2010), (2012)), managerial incentives (Agarwal et al. (2009)), and fund age (Aggarwal and Jorion ((2010))).

[12] See Goetzmann, Ingersoll, Spiegel, and Welch (2007) for the description of the manipulation-proof performance measure.

[13] However, Bollen (2013) finds higher probability of failure for zero-R^2 funds.

[14] Avramov et al. (2011) use the credit spread and the VIX volatility index, while Avramov et al. (2013) use the default spread, the dividend yield, VIX, and aggregate capital flows into the hedge fund industry as proxies for general macroeconomic conditions.

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conditions, that is, those who alter their strategies in anticipation of changing opportunity sets, thus incorporating macroeconomic information into their decisions. Our BA variable measures these qualities independent of macroeconomic variables, providing additional insight into active portfolio management and performance.

III. Description of Data

In this study, we utilize hedge fund data from Bloomberg for the period 1994–2013. Bloomberg is the most common platform used by both hedge funds, who utilize news, analysis, research, and trading tools, and accredited investors, who use Bloomberg to research hedge funds, private equity firms, and other alternative investment vehicles. As such, Bloomberg is a leading provider of data on private investment firms, inclusive of fund and parent company descriptions, manager and contact information, fees, past performance, and self-declared investment styles. Hedge funds report data voluntarily; however, Bloomberg requires all reporting funds to report all performance since inception. To minimize survivorship bias, the sample includes all funds reporting from 1994 to 2013, including those that are acquired, liquidated, or chose to stop reporting. We drop all funds-of-hedge-funds. We partially offset the effects of backfill bias by eliminating the first 24 months of reported returns.[15] After the backfill bias adjustment, we have 11,769 unique hedge funds in our sample. Since we require 4 years of data to calculate the measure of BA, this further reduces the number of funds to 3,960. Finally, of the 3,960 funds, the sample includes 1,814 live and 2,146 defunct unique funds.

Panel A of Table 1 reports summary statistics of fund returns, fees, investor liquidity measures, and fund longevity. As medians are more descriptive of the typical fund in our database, we find that the representative fund has $73 million under management, a 1.5% management fee, a 20% incentive fee on all profits over an investor's high water mark, a $250,000 minimum initial investment, and a 30 day redemption period.[16] Unsurprisingly, live funds display higher monthly excess returns, assets under management, and greater longevity than defunct funds. Interestingly, however, defunct funds have longer redemption periods and lockup periods. Panels B and C of Table 1 report percentages of funds with certain characteristics and declared styles, respectively. 85% of all funds have a high water mark provision, though only 4% allow hurdle rates in addition to high water marks. 32% of funds are non-U.S. domiciled. The most common declared style is

[15]Bloomberg requires that all funds report all results since inception regardless of when the funds first report to Bloomberg. However, as we do not have the date upon which the fund first reported to Bloomberg (and, therefore, do not have the exact number of months of backfill), we eliminate the first 24 monthly observations for all funds. The 24-month backfill correction is in line with results in Jagannathan et al. (2010) and Titman and Tiu (2011), suggesting dropping the first 25 and 27 months of returns.

[16]High water marks are investor relevant; that is, an investor will not be charged incentive fees until profits accrue over a previous high, net of flows. Thus, not all investors are charged incentive fees in any given year; the fees are partially determined by when the investor capital was employed by the fund manager. An investor whose fund shares are worth more this year than last will be charged incentive fees. An investor who suffered a loss previously will not pay incentive fees until previous losses are regained.

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long-short equity, at 30% of all funds, while shareholder activist is the least common style, accounting for 0.2% of hedge funds.

IV. Methodology and Results

A. Baseline Model

The baseline model employed in our regression analysis is a modified Fung and Hsieh (2004) model with tradable portfolio factors such that

$$\begin{aligned}(\mathrm{M}) \quad r_i - r_f \;=\; & \alpha_i + \beta_{i1}\mathrm{SP500} + \beta_{i2}\mathrm{EM} + \beta_{i3}10_\mathrm{YEAR} + \beta_{i4}\mathrm{SIZE_SPREAD} \\ & + \beta_{i5}\mathrm{CREDIT_SPREAD} + \beta_{i6}\mathrm{BOND_TREND} \\ & + \beta_{i7}\mathrm{COM_TREND} + \beta_{i8}\mathrm{FX_TREND} + \varepsilon_i.\end{aligned}$$

r_i is the monthly return of fund i, and r_f is a risk-free rate proxied by the monthly return of the 30-day U.S. Treasury bill. SP500 is the market risk premium proxied

TABLE 1
Summary Statistics: 1994–2013
(reporting as of Mar. 31, 2015)

Table 1 presents summary statistics of all hedge funds 1994–2013 with the longevity to be included in this study. Panel A reports fund returns, fees, investor liquidity measures, and fund longevity. Panel B reports means of indicator variables for fund characteristics. Panel C reports self-declared fund styles.

	Mean	Median	P10	P90	Std. Dev.
Panel A. Fund Characteristics					
Full Sample (3,960 unique funds)					
Monthly excess return	0.48	0.46	−0.17	1.17	1.03
Assets (in $millions)	275.07	72.60	7.93	536.72	1,666.04
Min. invest (in $millions)	1.45	0.25	0.025	1	16.65
Mgmt. fee (%)	1.50	1.5	0.9	2	0.67
Performance fee (%)	17.63	20	5	20	6.79
Hurdle rate (%)	0.30	0	0	0	1.56
Lockup period (days)	88.06	0	0	360	214.95
Redemption notice (days)	11.83	0	0	45	24.98
Redemption period (days)	57.33	30	30	90	58.24
Total redemption (days)	69.61	40	30	135	67.05
Longevity (months)	96.36	85.5	54.5	156	40.84
Live Funds (1,814 unique funds)					
Monthly excess return	0.62	0.61	0.05	1.32	0.74
Assets (in $millions)	285.96	93.86	12.46	722.58	625.79
Min. invest (in $millions)	1.37	0.25	0.025	1	13.15
Mgmt. fee (%)	1.49	1.5	1	2	0.61
Performance fee (%)	17.89	20	10	20	6.36
Hurdle rate (%)	0.34	0	0	0	1.59
Lockup period (days)	89.38	0	0	360	217.77
Redemption notice (days)	16.63	0	0	60	28.37
Redemption period (days)	53.58	30	30	90	55.68
Total redemption (days)	70.46	44	30	135	67.85
Longevity (months)	98.75	86	52	167	44.85
Defunct Funds (2,146 unique funds)					
Monthly excess return	0.36	0.33	−0.33	0.99	1.21
Assets (in $millions)	266.49	57.02	6.51	389.71	2,157.49
Min. invest (in $millions)	1.53	0.25	0.025	1	19.12
Mgmt. fee (%)	1.51	1.5	0.8	2	0.71
Performance fee (%)	17.40	20	0	20	7.14
Hurdle rate (%)	0.27	0	0	0	1.53
Lockup period (days)	86.89	0	0	360	212.49
Redemption notice (days)	7.77	0	0	30	20.87
Redemption period (days)	60.62	30	30	90	60.21
Total redemption (days)	68.87	35	30	120	66.35
Longevity (months)	94.34	84	57	150	37.00

(continued on next page)

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TABLE 1 (continued)
Summary Statistics: 1994–2013
(reporting as of Mar. 31, 2015)

	% of Funds		
	Full Sample	Live Funds	Defunct Funds
Panel B. Fund Characteristics and Indicator Variables			
High water mark	0.85	0.88	0.82
Hurdle rate	0.04	0.05	0.04
Offshore (non-U.S.)	0.32	0.35	0.29
Closed to new investors	0.06	0.06	0.06
Liquidated	0.24	0.00	0.45
Acquired	0.03	0.00	0.05

	% of Funds		
	Full Sample	Live Funds	Defunct Funds
Panel C. Fund Styles			
Activist	0.20%	0.17%	0.23%
Asset-backed securities	0.61%	1.05%	0.23%
Cap structure/credit arbitrage	1.44%	1.87%	1.07%
Convertible arbitrage	1.94%	1.49%	2.33%
Currency	0.91%	0.66%	1.12%
Discretionary	4.67%	3.47%	5.69%
Discretionary thematic	4.29%	4.74%	3.91%
Distressed securities	2.50%	1.93%	2.98%
Emerging market	3.51%	3.53%	3.49%
Emerging market debt	1.16%	0.72%	1.54%
Equity hedge diversified	1.19%	1.71%	0.75%
Event-driven diversified	1.87%	2.26%	1.54%
Fixed income arbitrage	2.40%	2.09%	2.66%
Fixed income diversified	3.36%	3.97%	2.84%
Long biased	5.88%	7.11%	4.85%
Long-short	29.67%	32.36%	27.40%
Macrodiversified	2.15%	0.94%	3.17%
Market neutral	6.54%	5.95%	7.04%
Merger arbitrage	1.39%	1.05%	1.68%
Mortgage backed	0.71%	0.72%	0.70%
Multistrategy	9.97%	9.32%	10.53%
Short biased	0.23%	0.06%	0.37%
Special situation	0.76%	1.16%	0.42%
Statistical arbitrage	1.69%	0.94%	2.33%
Systematic	5.45%	8.27%	3.08%
Systematic diversified	1.64%	2.32%	1.07%
Unknown/agnostic	3.86%	0.17%	6.99%

by the Standard & Poor's (S&P) 500 index return minus the risk-free rate. EM is the MSCI Emerging Market index return minus the risk-free rate. 10_YEAR is the monthly excess return of a 10-year U.S. treasury bond, proxied by the 10-year U.S. Treasury bond portfolio return from the Center for Research in Security Prices (CRSP), minus the risk-free rate. SIZE_SPREAD is an equity-based risk factor, the Russell 2000 index return minus the S&P 500 index return. CREDIT_SPREAD is a fixed income-based risk factor, calculated as the total return on the Citi BBB corporate bond index minus the total return on the Fama U.S. Treasury bond portfolio as per the CRSP. Both portfolios are comprised of bonds with maturities of 10 years or more. BOND_TREND, COM_TREND, and FX_TREND are excess returns on trend following factors constructed of look-back straddles on futures contracts of bonds, commodities, and currencies, respectively. All factors are, therefore, arbitrage (zero cost) portfolios. All returns and yields data are from Bloomberg and the CRSP, while trend-following risk

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factors are courtesy of David Hsieh's Web site (http://faculty.fuqua.duke.edu/~dah7/HFData.htm).

In order to quantify the dynamic nature of beta active management and identify beta active managers, we construct short-term rolling window regression metrics using model (M). We consider rolling 2-year windows, rolling them annually over the entire sample period between 1996 and 2013. We then run individual fund regressions (M) for every 2-year window. Short-term window estimates of alpha and beta coefficients, standard errors, adjusted-R^2, and $\text{SR}_i = \sigma_i^2 - \sigma_{\varepsilon,i}^2$ are then employed in the following sections to construct measures of BA.[17]

B. Measures of Beta Active Management

As previously discussed, beta active management is the attempt to take active positions that are correlated with factors yielding the highest absolute returns in the future. In other words, we want to identify managers that know *which* factor correlated levers to pull and *when* and *how hard* to pull them. The efficacy of beta active management, thus, depends upon the choices of factor betas, the timing of the positions, and the returns to those factors. First, we introduce two variables that capture different aspects of BA across all factors utilized in base model (M). Scaled beta success (SBS) measures contemporaneous success, and difference in beta returns (DBR) captures the dynamic effects of factor timing. We then introduce a combined measure of BA as an equal-weighted average of normalized individual variables SBS and DBR.

1. Scaled Beta Success

We create a measure of contemporaneous beta performance, SBS, which captures how well a manager's current factor loadings perform relative to the best and the worst performing factors. We first compute the fund's beta return, the weighted average of factor returns with observed factor loadings from equation (M). This is equivalent to the observed average excess return minus observed alpha from (M). We then benchmark fund i's composite beta return against the maximum and the minimum average factor returns over two preceding 24-month windows w and $w-1$:

$$(1)\quad \text{SBS}_{w,i} = \frac{1}{2}\frac{\beta'_{w,i}\overline{f}_w - \min_j\{\overline{f}_{w,j}\}}{\max_j\{\overline{f}_{w,j}\} - \min_j\{\overline{f}_{w,j}\}} + \frac{1}{2}\frac{\beta'_{w-1,i}\overline{f}_{w-1} - \min_j\{\overline{f}_{w-1,j}\}}{\max_j\{\overline{f}_{w-1,j}\} - \min_j\{\overline{f}_{w-1,j}\}},$$

where $\beta_{w,i}$ is the vector of factor loadings for fund i in window w; $\bar{f}_w$ is the vector of average factor returns in window w; and $\min_j\{\bar{f}_{w,j}\}$ and $\max_j\{\bar{f}_{w,j}\}$ are the lowest and the highest average monthly returns among the 8-factor portfolios for window w, respectively.

In other words, SBS allows us to measure how the manager's choice of factor-driven investment positions fared relative to the range between the best and worst performing factors in that time period. At first glance, a high SBS is good in that the fund is delivering strong contemporaneous performance; the

[17] Getmansky, Lo, and Makarov (2004) show that hedge funds exhibit serial correlation in returns due to fund positions in illiquid assets and/or due to deliberate smoothing by managers. We, therefore, apply an MA(2) smoothing correction in our baseline regressions (M).

manager's bets are paying off.[18] However, active managers change positions over time, and it is not clear that strong contemporaneous performance is necessarily indicative of skill or future strong performance. For example, a passive fund mirroring NASDAQ performance would have done very well in the late 1990s and poorly subsequently. The (hypothetical) fund's performance in the late 1990s arguably was not due to managerial skill. Brunnermeier and Nagel (2004) argue that informed fund managers over-weighted technology stocks in the run-up to the NASDAQ peak but transitioned away in time to avoid much of the crash.[19] The SBS of these managers would have been very high in the run-up as they are capturing the returns of the best performing factors, but low when managers transitioned away from tech stocks even as these continued to perform well. We are agnostic as to whether high or low SBS is a better predictor of future performance: Is it managers' ability to capture contemporary returns or their ability to forego these (i.e., be contrarian) that matters? It is likely both, as in the Brunnermeier and Nagel (2004) example. It is impossible for even the most prescient managers to precisely time a broad set of macroeconomic factors. In fact, once a manager takes a macro-factor-driven position, it may not be profitable for some time until macroeconomic conditions play out.[20] Hence, low contemporaneous SBS could be an indication of skillful risk-taking and high SBS indicative of skilled position taking and/or simple luck.

SBS is a measure of contemporaneous performance. We, therefore, need another means by which we are able to measure the dynamic nature of BA, that is, *changes* in positions, such that we are better able to distinguish skilled risk-taking from luck. We, therefore, introduce another variable, the DBR, to capture the dynamic aspect of beta active management.

2. Difference in Beta Returns

In order to measure the relative degree of active managers' success in making timely strategic changes in overall factor allocations, we compare 2-year window realized beta returns to forward and backward looking "what-if" synthetic beta returns. This allows us to quantify how well managers anticipate and react to changing economic conditions.

In the forward-looking scenario, we consider the difference between the realized beta return and the forward synthetic beta return, which is the beta return the manager *would* have realized if he had not changed strategies from the previous 2-year window. Specifically, we carry forward beta coefficients from the previous 2-year window and multiply them by the factor returns from the current window, finally averaging these to create a synthetic, what-if return. The "gap" between

[18]High SBS is a relative, beta-only performance, not total or excess return to an investor. A high SBS may still deliver a negative excess return to investors if factors are posting negative returns; a high SBS in this case is still performing well in that the total return is "less bad" than if the manager had held different positions.

[19]SBS is also correlated with leverage; the greater the leverage used capturing concurrently profitable factor returns, the higher the SBS should be. The use of leverage is itself a skill. Though we do not have leverage usage data, in subsequent analysis, we compare portfolios' Sharpe ratios, which are not sensitive to the use of leverage.

[20]For example, Michael Burry's bets against subprime mortgage-backed securities taken in 2005 were not profitable for 2 years until 2007 (see Lewis (2010)).

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realized and forward synthetic returns for fund i is FDBR, such that

$$\text{FDBR}_{w,i} = \beta'_{w,i}\overline{f}_w - \beta'_{w-1,i}\overline{f}_w, \tag{2}$$

where $\beta_{w,i}$ is the vector of factor loadings for fund i in window w and $\bar{f}_w$ is the vector of average factor returns in window w. Notice that the second term inside the summation in equation (2) utilizes the vector of beta coefficients from the previous window $(w-1)$ regression multiplied by the vector of the current window factor return averages in window w.

A positive FDBR may be indicative of manager skill if ex-ante the managers correctly anticipate changing macroeconomic opportunities; their beta returns are higher than they would have been had they not made changes to factor loadings. FDBR captures how well managers perform in relation to a "change nothing" strategy.[21] However, managers may also have a higher FDBR if they simply jump on the right bandwagon, adopting strategies correlated with the most successful factors from the previous period. If a trend continues into the next period, such strategy would result in a positive FDBR while not truly reflecting anticipatory managerial skill. Consider that economic conditions may persist for years (e.g., low interest rate environments or rising real estate prices). If we solely rely upon FDBR to identify skilled strategy changers, we would overestimate the skill of managers who are merely trend chasers.[22] We wish to find managers who anticipate changing economic conditions and make strategic changes to portfolio allocations regardless of past trends. We, therefore, also look backward to establish the relationship between current and past beta strategies with respect to past factor performance. We again create a synthetic return, this time in reverse, by carrying backward beta coefficients from the current 2-year window and multiplying these by the factor returns from the previous window, finally averaging these into a backward-looking what-if return. We calculate reverse difference in beta returns (RDBR), such that

$$\text{RDBR}_{w,i} = \beta'_{w-1,i}\overline{f}_{w-1} - \beta'_{w,i}\overline{f}_{w-1}, \tag{3}$$

where, as previously in equation (2), $\beta_{w,i}$ is the vector of factor loadings for fund i in window w and $\bar{f}_w$ is the vector of average factor returns in window w. RDBR measures the gap between the realized beta performance in the previous window and the synthetic past beta return. While FDBR shows improvement as compared to the change nothing strategy, RDBR simultaneously captures how well managers chose betas in the past and also whether they had the foresight to change betas in a way to deviate from previous trends, that is, not "copy today what worked yesterday." Indeed, if managers adopt betas that would have worked best

[21] "Change nothing" refers to only the beta active portion of the manager's portfolio, that is, the allocation of portfolio funds to strategies whose variance in returns is attributable to the variance in factor returns. Strategies not attributable to factors are captured by alpha, and these strategies may vary considerably. Finally, the manager's day-to-day real activity level may be quite high, especially with regard to options- and futures-based trend following strategies. Managers may be quite busy "changing nothing."

[22] Simple U.S. examples could be buying "dot-com" companies in 1998 or taking long positions in real estate in 2004. Both strategies were profitable prior to the years referenced, were profitable in the subsequent 2 years, and then were markedly unprofitable after that.

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in the past, this would result in the highest possible $\beta'_{w,i}\overline{f}_{w-1}$, lowering the value of RDBR. However, if managers chose betas in a prescient way, their contemporaneous beta return, $\beta'_{w-1,i}\overline{f}_{w-1}$, would have been high while the backward looking what-if return, $\beta'_{w,i}\overline{f}_{w-1}$, would be low, resulting in high values of RDBR.

Finally, as FDBR and RDBR capture complementary time-varying aspects of beta active management, we take an average of normalized FDBR and RDBR to create a combined forward- and backward-looking variable, DBR, such that

$$\text{DBR}_{w,i} = \frac{1}{2}\frac{\text{FDBR}_{w,i} - \min_i\{\text{FDBR}_{w,i}\}}{\max_i\{\text{FDBR}_{w,i}\} - \min_i\{\text{FDBR}_{w,i}\}} + \frac{1}{2}\frac{\text{RDBR}_{w,i} - \min_i\{\text{RDBR}_{w,i}\}}{\max_i\{\text{RDBR}_{w,i}\} - \min_i\{\text{RDBR}_{w,i}\}}. \tag{4}$$

We now have two variables of BA capturing the overall factor timing (DBR) and contemporaneous factor-driven performance (SBS).

C. Summary Statistics

We present summary statistics and pairwise correlations for SBS, FDBR, RDBR, and DBR in Table 2. Consistent with our interpretation of the variables capturing different aspects of overall BA, we observe relatively low correlations among the variables. The highest correlations are between FDBR and DBR (0.37) and between RDBR and DBR (0.28), which is not surprising given that FDBR and RDBR are the basis of DBR.

We explore the impact of individual variables and their interactions on hedge fund performance in the analysis that follows.

TABLE 2
Summary Statistics of Activity Metrics

Table 2 reports summary statistics and the pairwise correlation matrix of measures of hedge fund beta activity from 1998 to 2013. SBS is scaled beta success, the degree to which managers capture returns from the most profitable factors, contemporarily. FDBR is forward difference in beta returns and RDBR is reverse difference in beta returns, measures that capture the degree to which managers changed their investment strategies, resulting in different realized returns from what would have resulted absent these changes. DBR is the difference in beta returns, a combinatory measure of FDBR and RDBR.

Panel A. Summary Statistics

	Mean	Median	P10	P90	Std. Dev.
SBS	0.6605	0.6799	0.4317	0.8591	0.1705
FDBR	0.0021	0.0191	−1.1482	1.1307	1.1281
RDBR	0.0336	0.0443	−1.0697	1.1244	1.0920
DBR	0.5044	0.5009	0.3750	0.6198	0.0897

Panel B. Pairwise Correlations

	SBS	FDBR	RDBR	DBR
SBS	1.0000			
FDBR	0.2630	1.0000		
RDBR	0.1285	−0.2096	1.0000	
DBR	0.2558	0.3728	0.2838	1.0000

D. Out-of-Sample Portfolio Comparisons of Beta, Alpha, and SR Variables

We first consider the out-of-sample portfolio performance of the BA variables FDBR, RDBR, DBR, and SBS, comparing these to extant measures of

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alpha activity and SR exposure. We create portfolios based upon traditional measures of alpha active management, alpha and alpha t-statistic, because both alpha (Kosowski et al. (2007)) and alpha t-statistic (Jagannathan et al. (2010)) have been found to be predictive of future performance. We also calculate the SR (Bali et al. (2012)) and $(1 - R^2)$ (Titman and Tiu (2011)) variables of SR exposure as both are shown to be predictive of performance and related to BA. We concentrate our analysis on out-of-sample portfolio tests for several reasons. First, our FDBR, RDBR, DBR, and SBS metrics rely on imprecise estimates of beta coefficients from the baseline regression (M) and, hence, are measured with error.[23] We mitigate this problem by considering out-of-sample performance of portfolios of funds selected according to our variables of BA. Second, by considering all funds up until the moment of their disappearance from the database, we minimize any effects of survivorship bias. Third, out-of-sample portfolio comparisons allow us to evaluate beta, alpha, and SR variable performance over long periods of time and interpret results in terms of economic significance.[24] Finally, evaluating long-term portfolio performance provides a clear answer as to the efficacy of beta active management, since it is very unlikely for factor-driven investment styles to produce statistically significant alpha in the short term.

We form portfolios based upon top and bottom quartiles (25%) of past values of each variable.[25] Each "top" and "bottom" portfolio is initially formed on Dec. 31, 1999. We invest the same dollar amount into each fund within a portfolio in the beginning and follow its performance until Dec. 31, 2013, rebalancing each portfolio once a year based on updated rankings with respect to individual variables. When a portfolio fund disappears from the database, we redistribute the remaining capital in the fund equally among surviving portfolio funds.[26] This procedure produces a time series of 168 monthly returns for each portfolio, allowing us to evaluate long-term portfolio performance across various economic conditions, including the global financial crisis of 2008–2009. We then calculate end dollar values based upon a $1 initial investment, mean excess monthly returns, Sharpe ratios, Fung and Hsieh (2004) alphas, information ratios, and average annual attrition rates for each time series of monthly portfolio returns from Jan. 2000 to Dec. 2013.[27] Finally, we create top minus bottom arbitrage portfolios

[23] Notice that, in addition to measurement errors, there is also a model misspecification error, as the baseline model (M) assumes constant beta coefficients over 2-year windows.

[24] Annual rebalancing reflects real life investor experience, as it is not feasible for hedge fund investors, inclusive of funds-of-funds, to rebalance more frequently due to hedge fund lockup and redemption notice restrictions.

[25] FDBR, RDBR, DBR, SBS, and subsequently BA (introduced in the following subsection) rankings are based on the preceding two 2-year windows, while alpha, alpha t-statistic, SR, and $(1 - R^2)$ calculations only require a single 2-year window. Portfolio results reported herein compare our beta variables (requiring 4 years) to alpha, alpha t-statistic, SR, and $(1 - R^2)$ measures of one window (2 years). In robustness, we also rank portfolios based upon 4-year alpha, alpha t-statistic, SR, and $(1 - R^2)$; results are qualitatively and quantitatively very similar.

[26] This is somewhat conservative as it is possible that a fund simply chooses to stop reporting to the database, which is likely for well-performing funds that are no longer accepting new investor flows. However, without returns data, we obviously cannot keep the fund in the portfolio.

[27] A drawback of relying on a single long-term time series for each portfolio is that we can calculate t-statistic and evaluate statistical significance only for mean monthly returns and long-term Fung and Hsieh (2004) alphas.

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for each variable equivalent to taking a long position in the top 25% portfolio and a short position in the bottom 25% portfolio.

Table 3 reports out-of-sample performance results. While the difference between top and bottom portfolios is not statistically significant for most variables, we do observe a pattern of top portfolios doing better than bottom portfolios in RDBR, DBR, alpha, alpha *t*-statistic, and *SR* portfolios. Importantly, the top DBR portfolio delivers higher returns, alpha, Sharpe ratio, and information ratio, than either of the top FDBR or top RDBR portfolios, which is consistent with our interpretation of FDBR and RDBR as capturing complementary aspects of dynamic factor timing activity by hedge fund managers. On the other hand, we find that the bottom SBS portfolio delivers better performance than the top SBS portfolio,

TABLE 3
Out-of-Sample Performance of Single Variable Portfolios: 2000–2013

Table 3 reports out-of-sample performance of portfolios constructed of single variables inclusive of beta, alpha, and SR metrics. Top (Bottom) is a portfolio of funds comprised of the highest (lowest) quartile of funds with regard to each metric. Top − Bottom portfolios are equivalent to taking a long position in the top quartile and a short position in the bottom quartile of funds. FDBR is forward difference in beta returns and RDBR is reverse difference in beta returns, measures that capture the degree to which managers changed their investment strategies, resulting in different realized returns from what would have resulted absent these changes. DBR is difference in beta returns, a combinatory measure of FDBR and RDBR. SBS is scaled beta success, the degree to which managers capture returns from the most profitable factors, contemporarily. SR is systematic risk per Bali et al. (2012). $(1-R^2)$ is per Titman and Tiu (2011). Portfolios are created as of Dec. 31, 1999 and rebalanced annually. The End Value is the dollar value of the initial $1 investment as of Dec. 31, 2013. Excess Return and alpha are mean monthly figures. *t*-statistics are reported in parentheses; we report the Jobson and Korkie (1981) measure of statistical significance for Sharpe ratios. Info Ratio is the information ratio. Attrition Rate is the average annual rate at which funds stop reporting. When funds stop reporting, we assume the fund is defunct and equally invest resultant capital in the remaining portfolio funds. *, **, and *** designate statistical significance at the better than 10%, 5%, and 1% levels, respectively.

	End Value	Excess Return	Sharpe Ratio	α	Info Ratio	Attrition Rate
Panel A. Beta Activity						
FDBR						
Top	3.18	0.56***	0.22***	0.23**	0.18	8.74%
		(2.90)	(2.87)	(2.18)		
Bottom	3.21	0.57***	0.21***	0.24*	0.15	8.87%
		(2.68)	(2.66)	(1.89)		
Top − Bottom	0.96	−0.01	−0.01	−0.01	−0.01	—
		(−0.11)	(−0.11)	(−0.10)		
RDBR						
Top	3.55	0.62***	0.25***	0.33**	0.21	8.54%
		(3.21)	(3.18)	(2.44)		
Bottom	2.85	0.50**	0.19**	0.18*	0.15	9.45%
		(2.45)	(2.43)	(1.82)		
Top − Bottom	1.22	0.13	0.09	0.15	0.12	—
		(1.11)	(1.11)	(1.35)		
DBR						
Top	3.71	0.65***	0.26***	0.36***	0.24	8.69%
		(3.41)	(3.35)	(2.84)		
Bottom	2.82	0.49**	0.18**	0.16	0.12	9.28%
		(2.38)	(2.37)	(1.54)		
Top − Bottom	1.29	0.16	0.11	0.20*	0.15	—
		(1.42)	(1.42)	(1.80)		
SBS						
Top	3.22	0.58**	0.19**	0.22*	0.13	8.42%
		(2.46)	(2.44)	(1.72)		
Bottom	3.64	0.64***	0.28***	0.39***	0.29	9.58%
		(3.66)	(3.59)	(3.48)		
Top − Bottom	0.88	−0.05	−0.03	−0.16	−0.10	—
		(−0.34)	(−0.34)	(−1.18)		

(continued on next page)

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TABLE 3 (continued)
Out-of-Sample Performance of Single Variable Portfolios: 2000–2013

	End Value	Excess Return	Sharpe Ratio	α	Info Ratio	Attrition Rate
Panel B. Alpha Activity						
Alpha						
Top	3.29	0.59*** (2.76)	0.21*** (2.73)	0.26** (2.05)	0.15	6.18%
Bottom	2.85	0.50** (2.42)	0.19** (2.40)	0.18 (1.32)	0.11	13.13%
Top − Bottom	1.12	0.09 (0.53)	0.04 (0.53)	0.08 (0.54)	0.04	—
Alpha t-Statistic						
Top	2.71	0.45*** (3.34)	0.26*** (3.29)	0.25*** (3.31)	0.25	6.49%
Bottom	2.66	0.45** (2.32)	0.18** (2.31)	0.15 (1.15)	0.10	13.16%
Top − Bottom	0.97	−0.00 (−0.03)	−0.00 (0.03)	0.10 (0.88)	0.07	—
Panel C. SR						
SR						
Top	4.49	0.81*** (2.67)	0.21*** (2.65)	0.33** (2.10)	0.18	8.58%
Bottom	2.13	0.30*** (4.30)	0.33*** (4.13)	0.19*** (3.80)	0.35	10.25%
Top − Bottom	2.17	0.52** (2.02)	0.16** (2.01)	0.14 (0.88)	0.08	—
R^2						
Top	3.13	0.57** (2.27)	0.18** (2.26)	0.19* (1.76)	0.15	8.75%
Bottom	2.51	0.40*** (3.60)	0.28*** (3.51)	0.22*** (2.93)	0.23	10.82%
Top − Bottom	1.28	0.17 (0.93)	0.07 (0.93)	−0.02 (−0.22)	−0.02	—

while delivering the highest alpha, Sharpe ratio, and information ratio across all portfolios. This is consistent with the argument that managers with lower SBS make factor-related bets that are less profitable contemporaneously but that become profitable in the future as economic conditions change.[28] Finally, we find that, in agreement with Bali et al. (2012) and Titman and Tiu (2011), SR and $(1 - R^2)$, respectively, are predictive of superior performance.

E. BA, a Combinatory Measure

We next explore whether, and the degree to which, FDBR and RDBR capture different aspects of BA, necessitating the need for the combined measure DBR, and whether (1 − SBS) and DBR do likewise.[29] We create portfolios meant to isolate the contribution of each variable in two ways. We create portfolios by

[28] Given that SBS is equivalent to the observed average excess return, less alpha, the superior performance of the bottom SBS portfolio could potentially be attributed to mean reversal of past hedge fund performance, measured by the average past excess return. We compare performance of portfolios selected on the basis of SBS and the average excess return in Appendix A and conclude that SBS captures a unique aspect of hedge fund BA consistent with long-term factor bets, which is not reflected in average past returns.

[29] This is expected given the low and negative correlations between FDBR and RBDR and between (1 − SBS) and DBR shown in Panel B of Table 2.

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sorting all funds based upon a single variable, keeping the subsample of funds that are in the top quartile. We then exclude any funds that are also in the top quartile of a second variable to create independent portfolios. Alternatively, we also re-rank the subsample according to the second variable, discarding the top quartile of the resultant subsample, thus double sorting the portfolio. For example, an independent "FDBR excluding RDBR" portfolio is comprised of funds that are in the top quartile of FDBR that are not also in the top quartile of RDBR. To create a "Top DBR × Non-top (1 − SBS)" double-sorted portfolio, we rank all funds by DBR, keeping the subset of funds in the top quartile of DBR. We then rank the subsample of top DBR funds by (1 − SBS), discarding the top quartile.

Table 4 reports out-of-sample performance of isolate portfolios of BA measures. We observe that, comparing isolate portfolios to FDBR and RDBR portfolios of Table 3, the isolate portfolios fully retain their nominal and risk-adjusted performance. We, therefore, conclude that both FDBR and RDBR capture distinct complementary aspects of BA. This is consistent with the fact that the combined measure, DBR, displays stronger predictive power of the top

TABLE 4
Single Beta Variable Isolate Portfolios: 2000–2013

Table 4 reports out-of-sample performance of portfolios comprised of the top quartile of funds in various metrics of beta activity. FDBR is forward difference in beta returns and RDBR is reverse difference in beta returns, measures that capture the degree to which managers changed their investment strategies, resulting in different realized returns from what would have resulted absent these changes. DBR is difference in beta returns, a combinatory measure of FDBR and RDBR. SBS is scaled beta success, the degree to which managers capture returns from the most profitable factors, contemporarily. Panels A and B report the performance of portfolios sorted by a single variable to the exclusion of other variables in order to isolate the contribution of a single variable to out-of-sample portfolio performance. For example, FDBR excl. RDBR is a portfolio of funds in the top quartile of FDBR excluding any funds that are also in the top quarter of RDBR. In sequential double-sorted portfolios, funds in the top quartile of a variable are selected and then ranked with regard to a second variable. The top quartile of funds in the second variable are then discarded from the subsample, resulting in the final portfolio. For example, sorting all funds by FDBR, we keep the top quartile of funds. We then rank the subsample with regard to RDBR, discarding the top quartile, resulting in the Top FDBR × Non-top RDBR portfolio. Portfolios are created as of Dec. 31, 1999 and rebalanced annually. The End Value is the dollar value of the initial $1 investment as of Dec. 31, 2013. Excess Return and alpha are mean monthly figures. *t*-statistics are reported in parentheses; we report the Jobson and Korkie (1981) measure of statistical significance for Sharpe ratios. Info Ratio is the information ratio. Attrition Rate is the average annual rate at which funds stop reporting. When funds stop reporting, we assume the fund is defunct and equally invest resultant capital in the remaining portfolio funds. *, **, and *** designate statistical significance at the better than 10%, 5%, and 1% levels, respectively.

	End Value	Excess Return	Sharpe Ratio	α	Info Ratio	Attrition Rate
Panel A. Independent Portfolio Sorts						
FDBR excl. RDBR	3.19	0.56*** (2.86)	0.22*** (2.82)	0.24** (2.28)	0.18	9.11%
RDBR excl. FDBR	3.52	0.62*** (3.10)	0.24*** (3.07)	0.33** (2.15)	0.18	8.80%
DBR excl. (1 − SBS)	3.40	0.60*** (2.99)	0.23*** (2.96)	0.29** (2.21)	0.19	8.38%
(1 − SBS) excl. DBR	3.51	0.61*** (3.49)	0.27*** (3.44)	0.35*** (3.35)	0.28	9.36%
Panel B. Sequential Double Sorts						
Top FDBR × Non-top RDBR	3.11	0.55*** (2.83)	0.22*** (2.80)	0.21** (2.15)	0.18	8.59%
Top RDBR × Non-top FDBR	3.41	0.60*** (3.02)	0.23*** (2.99)	0.30** (2.07)	0.18	8.82%
Top DBR × Non-top (1 − SBS)	3.63	0.65*** (3.07)	0.24*** (3.03)	0.32** (2.42)	0.20	8.79%
Top (1 − SBS) × Non-top DBR	3.16	0.55*** (3.12)	0.24*** (3.09)	0.30*** (2.74)	0.23	9.39%

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quartile portfolio in Table 3 than either FDBR or RDBR individually. Similarly, we observe that the DBR and (1 − SBS) isolate portfolios also retain their nominal and risk-adjusted performance. We again conclude that both DBR and (1 − SBS) capture distinct and complementary aspects of BA.

It is conceptually important to note that, though both SBS and DBR point to the possibility of successful beta management, each variable alone cannot be definitively interpreted as direct evidence of skill. Success predicted on the basis of either (1 − SBS) or DBR can be alternatively interpreted as evidence of skill or mere luck. Considering these variables in concert allows us to simultaneously capture different aspects of BA reflected in (1 − SBS) and DBR while reducing the likelihood of reflecting random luck, as it is unlikely for managers to be lucky in both variables. Hence, we define the overall measure of BA as the equal-weighted average of normalized DBR and (1 − SBS):

$$\text{BA}_{w,i} = \frac{1}{2}\frac{\text{DBR}_{w,i} - \min_i\{\text{DBR}_{w,i}\}}{\max_i\{\text{DBR}_{w,i}\} - \min_i\{\text{DBR}_{w,i}\}} + \frac{1}{2}\frac{\max_i\{\text{SBS}_{w,i}\} - \text{SBS}_{w,i}}{\max_i\{\text{SBS}_{w,i}\} - \min_i\{\text{SBS}_{w,i}\}}. \tag{5}$$

To summarize, BA is a more comprehensive measure of BA, as SBS and DBR capture different aspects of BA. SBS is a contemporaneous measure with external factors as benchmarks, while DBR captures the time-varying aspect of overall BA across all factors, benchmarking against its own past and present betas. We turn next to the performance of portfolios constructed on the basis of BA.

V. Comparisons of Beta and Alpha Activity

Panel A of Table 5 presents the results of out-of-sample performance for portfolios selected with respect to the combined measure of BA. We create portfolios of the top and bottom quartile of funds ranked according to BA. We observe that top beta active portfolios significantly outperform bottom portfolios while delivering superior long-term returns, alphas, and Sharpe and information ratios. The "Top − Bottom" arbitrage portfolio of BA retains an economically large and statistically significant alpha. For illustrative purposes, Appendix B provides a descriptive example of a hedge fund that was in the top BA quartile for the majority of the sample along with its annual returns and its annual BA, DBR, and SBS percentiles.

We first compare the out-of-sample performance of portfolios formed on the basis of BA, reported in Panel A, to the performance of portfolios formed upon traditional measures of alpha active management, alpha, and alpha t-statistic, reported in Panel B of Table 3. We observe that top beta active portfolios dominate both top alpha and alpha t-statistic portfolios in overall returns, Sharpe ratios, and Fung and Hsieh (2004) alphas, indicating the superior predictive power of measures of BA over alpha activity. For completeness, we also report the performance of long beta short alpha arbitrage portfolios in Panel B of Table 5; the end values for both the long BA short alpha and the long BA short alpha t-statistic out-of-sample portfolios are greater than one. Further, the excess return, Sharpe ratio,

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TABLE 5

Out-of-Sample Portfolio Performance of Top Beta Activity, Alpha, and Alpha *t*-Statistic Portfolios: 2000–2013

Table 5 reports results comparisons of out-of-sample performance of portfolios of funds ranked by metrics of beta and alpha activity. BA, DBR, and SBS are beta activity measures, while alpha and alpha *t*-statistic measure alpha activity. Panel A reports out-of-sample performance of portfolios comprised of the top and bottom quartiles of funds in BA. Beta activity (BA) is the equal-weighted average of normalized DBR and (1 − SBS), per equation (5). The Top BA − Bottom BA portfolio is long for the top BA portfolio and short for the bottom BA portfolio. Panel B reports the performance of long-short portfolios of top BA, alpha, and alpha *t*-statistic funds. BA minus alpha *t*-statistic, for example, is the equivalent to a long position in the BA portfolio and a short position in the alpha *t*-statistic portfolio. As BA is a composite measure of beta activity, panel C reports the performance of portfolios double sorted by beta and alpha single variable measures, while panel D reports the performance of double-sorted arbitrage portfolios taking long positions in beta variables and short positions in alpha measures. DBR is difference in beta returns, a measure that captures the degree to which managers changed their investment strategies, resulting in different realized returns from what would have resulted absent these changes. SBS is scaled beta success, the degree to which managers capture returns from the most profitable factors, contemporarily. Funds are double sorted such that all funds are ranked by the first variable and then a second time by the second variable, each pass keeping the top quartile of funds. For example, keeping only the top quartile of funds in terms of alpha, the subsample funds are then ranked a second time by alpha *t*-statistic, again keeping only the top quartile of the subsample. The resulting portfolio is the Alpha × Alpha *t*-statistic portfolio. The End Value is the dollar value of the initial $1 investment as of Dec. 31, 2013. Excess Return and alpha are mean monthly figures. *t*-statistics are reported in parentheses; we report the Jobson and Korkie (1981) measure of statistical significance for Sharpe ratios. Info Ratio is the information ratio. Attrition Rate is the average annual rate at which funds stop reporting. When funds stop reporting, we assume the fund is defunct and equally invest resultant capital in the remaining portfolio funds. *, **, and *** designate statistical significance at the better than 10%, 5%, and 1% levels, respectively.

	End Value	Excess Return	Sharpe Ratio	α	Info Ratio	Attrition Rate
Panel A. BA Portfolio						
Top BA	4.18	0.72*** (4.18)	0.32*** (4.07)	0.47*** (3.94)	0.32	9.73%
Bottom BA	2.69	0.48* (1.96)	0.15* (1.95)	0.11 (0.90)	0.07	8.47%
Top BA − Bottom BA	1.42	0.24 (1.33)	0.10 (1.32)	0.36** (2.46)	0.19	—
Panel B. BA versus Alpha Activity						
BA − Alpha	1.21	0.13 (0.94)	0.07 (0.94)	0.22* (1.77)	0.13	—
BA − Alpha *t*-stat.	1.54	0.27** (2.39)	0.18** (2.37)	0.23** (2.10)	0.16	—
Panel C. BA and Alpha Activity Double Sorts						
(1 − SBS) × DBR	5.31	0.87*** (4.42)	0.34*** (4.29)	0.65*** (3.98)	0.33	10.16%
DBR × (1 − SBS)	3.76	0.66*** (3.66)	0.28*** (3.57)	0.46*** (2.98)	0.24	8.41%
Alpha × Alpha *t*-stat.	3.00	0.52*** (3.20)	0.25*** (3.17)	0.29*** (2.97)	0.22	5.89%
Alpha *t*-stat. × Alpha	2.94	0.53** (2.18)	0.17** (2.17)	0.22 (1.29)	0.10	6.48%
Panel D. BA versus Alpha Activity Double Sorts						
(1 − SBS) × DBR − Alpha × AlphaT	1.73	0.35* (1.95)	0.15* (1.94)	0.36* (1.93)	0.16	—
(1 − SBS) × DBR − AlphaT × Alpha	1.66	0.34 (1.63)	0.13 (1.63)	0.43** (2.05)	0.17	—
DBR × (1 − SBS) − Alpha × AlphaT	1.21	0.14 (0.76)	0.06 (0.76)	0.17 (0.96)	0.07	—
DBR × (1 − SBS) − AlphaT × Alpha	1.15	0.13 (0.58)	0.04 (0.58)	0.24 (1.17)	0.09	—

and out-of-sample alpha are statistically significant for the BA Alpha *t*-statistic arbitrage portfolio.

We find the correlations between BA and alpha metrics to be very low, at 0.03 and 0.001 for alpha and alpha *t*-statistic, respectively, and that the return

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series for top alpha and beta portfolios are markedly different. This strongly suggests that BA captures a different element of hedge fund management relative to alpha production. Figure 1 illustrates the cumulative return of a dollar investment in top BA, alpha, and alpha t-statistic portfolios. Figure 2 illustrates the time-series difference in cumulative returns between the top quartile BA, alpha, and alpha t-statistic portfolios that correspond to the arbitrage portfolios of Panel B in Table 5. Notice that the BA portfolio underperformed the alpha portfolio from mid-2005 through mid-2007, which is the period prior to the most dramatic macroeconomic shift during the period of this study.[30] Given the timing, a plausible conjecture is that top beta active managers anticipated changing economic conditions prior to the financial crisis of 2008–2009, reallocating portfolios in anticipation of changes to come. Beta active portfolio performance, therefore, declined relative to the alpha portfolio prior to the actual change in conditions. Even the most skilled managers do not have perfectly accurate timing foresight; thus, relative beta performance may be low in anticipatory periods prior to changes in economic conditions. However, as conditions changed, the difference between beta and alpha cumulative portfolio performance increased significantly as top beta active manager bets became profitable. Similarly, the BA portfolio underperforms alpha portfolios from roughly 2011 to 2013, perhaps in anticipation of changing economic conditions and prevailing interest rates. Overall, we interpret this as evidence that top beta active funds deliver superior long-term performance over top alpha active funds and, frequently, compare favorably in short-term performance to top alpha active funds. The attrition rate is higher for beta active funds than for alpha active funds, however. A comparison of alpha and beta portfolio performance under different loss assumptions is provided in Appendix C.

In additional analysis, we consider an alternative approach of evaluating overall BA based on the combined effect of (1 − SBS) and DBR through double sorting of hedge funds based on both variables. This facilitates a nonparametric comparison of the overall alpha activity, quantified by both alpha and alpha t-statistic, and BA, quantified by both (1 − SBS) and DBR. Such an approach complements the parametric approach of combining (1 − SBS) and DBR into a single variable, BA. We construct alpha and beta portfolios by double sorting of hedge funds based on both variables of alpha and BA. Specifically, for alpha portfolios, we first select the funds in the top quartile with respect to alpha, then rank selected funds with respect to alpha t-statistic, and select the funds in the top quartile, forming the final portfolio. We then repeat the exercise by switching the order of the sorting, that is, first ranking funds with respect to alpha t-statistic, followed by ranking the selected funds with respect to alpha. Similarly, for the beta portfolio, we first select funds in the top quartile with respect to (1 − SBS), then rank selected funds with respect to DBR, and select the funds in the top quartile, forming the final portfolio. We then repeat the exercise by switching the order of

[30]This pattern is less pronounced in the comparison of the top BA and top alpha t-statistic portfolios, which is consistent with the fact that alpha t-statistic provides better out-of-sample risk-adjusted predictions, as measured by the Fung and Hsieh (2004) alpha, along with Sharpe and information ratios.

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FIGURE 1

Hedge Fund Portfolio Cumulative Wealth Comparisons: 2000–2013

Figure 1 represents the cumulative wealth in USD (in natural logarithmic scale) from a $1 investment in portfolios of funds in the top quartile of respective metrics from 2000 to 2013. Beta active funds are in the top 25% of beta activity (BA). Alpha and alpha *t*-statistics funds are in the top 25% of funds with regard to the previous 4 years' alpha and alpha *t*-statistic metrics. Initial portfolios are constructed as of Dec. 31, 1999 and rebalanced annually.

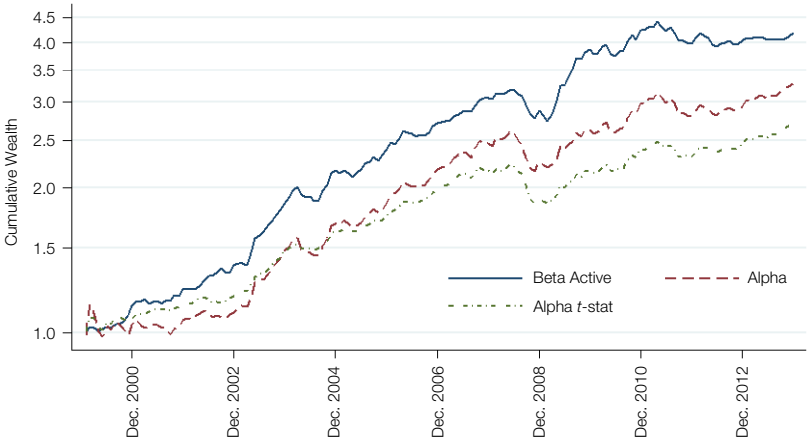
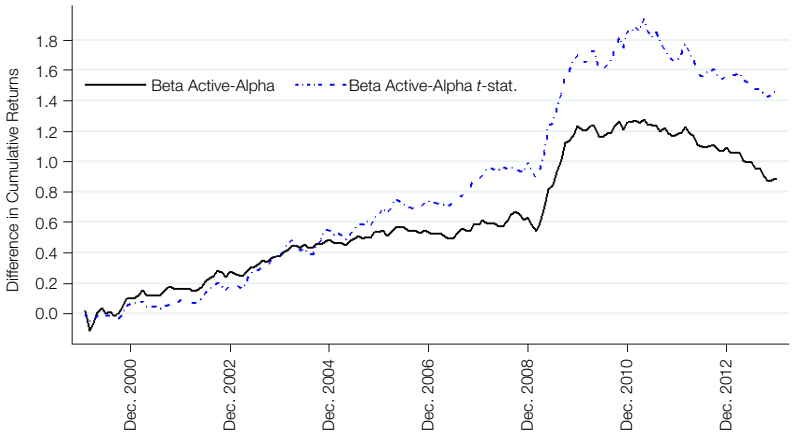


FIGURE 2

Cumulative Difference between BA and Alpha Portfolio Returns: 2000–2013

Beta active funds are in the top 25% of beta activity (BA) in Figure 2. Alpha and alpha *t*-statistic funds are in the top 25% of funds with regard to the previous 2 years' alpha and alpha *t*-statistic metrics. The lines represent the difference between the cumulative returns of the beta and alpha portfolios. This difference is equivalent to the return generated by an arbitrage portfolio long $1 in BA and short $1 in alpha and alpha *t*-statistic.



the sorting, that is, first ranking funds with respect to DBR, followed by ranking the selected funds with respect to (1 − SBS).

Panel C of Table 5 reports the performance of double-sorted beta and alpha portfolios, while Panel D reports the performance of long beta short alpha

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arbitrage portfolios. We find that both beta portfolios, (1 − SBS) × DBR and DBR × (1 − SBS), consistently deliver statistically significant performance, while one of the alpha portfolios, AlphaT × Alpha, fails to deliver statistically significant alpha. We also find that all arbitrage portfolios' end values are greater than one and that some portfolio statistics are marginally significant. The overall results are consistent with results of the parametric comparisons of beta and alpha portfolios in Panel B. Overall, beta portfolios compare favorably to alpha portfolios in all measures. It is, therefore, shown that identifying top beta active managers is a viable methodology by which to identify persistent superior performance. It is a complement to traditional alpha-centric methodologies.

Finally, we investigate whether top alpha and beta funds differ with regard to fund characteristics. We find evidence to suggest that top alpha funds are more likely than top beta funds to declare styles that require specialized information, such as activist, mortgage, and asset-backed securities, distressed securities, and special situation strategies. We find no difference in fee structures or high water mark provisions between alpha and beta funds. We do find, however, that top alpha funds have longer average lockup and redemption periods of 106.8 and 84.4 days, respectively, than top beta funds, at 84.6 and 71.8 days. The differences are statistically significant. A reasonable conjecture is that, since beta active positions are more reflective of broad macroeconomic factors, beta active managers may have less need of exotic securities with limited liquidity.

VI. BA and SR Measures

Extant literature does not provide a definitive conclusion about the contribution of BA to superior hedge fund performance. Titman and Tiu (2011) present evidence that higher $(1 - R^2)$ funds demonstrate better performance, yet Bali et al. (2012) show that higher SR is predictive of better subsequent performance. The evidence appears to be in conflict because SR is related to $(1 - R^2)$; in our data, $(1 - R^2)$ and SR are negatively correlated at −0.2952.

BA reflects both the magnitude and dynamic nature of BA, which includes the magnitude of timing across multiple factors, reflected in beta coefficients.[31] Hence, it is reasonable to assume that BA is to SR and R^2, since both measures depend on fund beta coefficients. Furthermore, Bali et al. (2012) argue that SR is a reflection of managers' market-timing abilities, which bears conceptual similarities to our interpretation of BA.

Here, we examine the relationship between BA, SR studied in Bali et al. (2012), and $(1 - R^2)$, considered in Titman and Tiu (2011). As discussed previously, all three variables relate to the concept of beta management and have been shown to have out-of-sample predictive power. Out-of-sample portfolio performance of top SR and $(1 - R^2)$ funds, per Bali et al. (2012) and Titman and Tiu (2011), respectively, are reported in Panel C of Table 3. As discussed previously, all three variables relate to the concept of beta management and exhibit out-of-sample predictive power.

[31] Notice that the magnitude of BA is inclusive of the dynamic use of leverage, which would be reflected in the magnitude of beta coefficients.

To better understand the contribution to out-of-sample performance of each measure, we create isolate portfolios following the procedure introduced in Section IV.E. The objective is to isolate the effect of each variable from the common effect that it could be sharing with other variables. In independent portfolio sorts, we rank all funds by one variable, keeping the subset of top quartile funds. We then exclude any fund that is also in the top quartile of a second variable. For example, "BA excluding SR" is the portfolio of top quartile BA funds excluding any fund that is also in the top quartile of SR that year. We also double-sort portfolios such that the subsample is ranked a second time by the second variable and the top quartile of the subsample is discarded. The "Top $(1-R^2)$ × Non-Top BA" portfolio is the result of an initial sort of all funds by $(1-R^2)$, keeping the top quartile. The subsample is then ranked by BA, and the top quartile is discarded. Panel A of Table 6 reports out-of-sample performance of independent portfolio sorts and Panel B reports the performance of double-sort portfolios.

When we consider the performance of both SR and BA portfolios after excluding the funds that are common to both portfolios, we observe that the top BA portfolio without the funds also present in the top SR portfolio delivers a statistically significant alpha, while the top SR portfolio excluding funds

TABLE 6

Out-of-Sample Performance of Beta Management Portfolios: 2000–2013

Table 6 reports comparisons of out-of-sample performance of portfolios of funds ranked by beta activity (BA) and extant measures of beta management. BA is the equal-weighted average of normalized DBR and (1 − SBS), per equation (5). SR is systematic risk, per Bali et al. (2012). $(1-R^2)$ is per Titman and Tiu (2011). Panel A reports the performance of portfolios sorted by a single variable to the exclusion of other variables in order to isolate the contribution of a single variable to out-of-sample portfolio performance. For example, BA excl. SR is a portfolio of funds in the top quartile of BA excluding any funds that are also in the top quarter of SR. Panel B reports the performance of double-sorted portfolios wherein funds in the top quartile of a variable are selected, then ranked with regard to a second variable. The top quartile of funds in the second variable are then discarded from the subsample, resulting in the final portfolio. For example, sorting all funds by BA, we keep the top quartile of funds. We then rank the subsample with regard to SR, discarding the top quartile, resulting in the Top BA × Non-top SR portfolio. Portfolios are created as of Dec. 31, 1999 and rebalanced annually. The End Value is the dollar value of the initial $1 investment as of Dec. 31, 2013. Excess Return and alpha are mean monthly figures. *t*-statistics are reported in parentheses; we report the Jobson and Korkie (1981) measure of statistical significance for Sharpe ratios. Info Ratio is the information ratio. Attrition Rate is the average annual rate at which funds stop reporting. When funds stop reporting, we assume the fund is defunct and equally invest resultant capital in the remaining portfolio funds. *, **, and *** designate statistical significance at the better than 10%, 5%, and 1% levels, respectively.

	End Value	Excess Return	Sharpe Ratio	α	Info Ratio	Attrition Rate
Panel A. Independent Portfolio Sorts						
BA excl. SR	3.12	0.53*** (4.09)	0.31*** (3.96)	0.34** (3.30)	0.29	9.47%
SR excl. BA	3.56	0.69** (2.06)	0.16** (2.05)	0.19 (1.14)	0.09	7.95%
BA excl. $(1-R^2)$	4.31	0.74*** (3.87)	0.30*** (3.79)	0.49*** (3.46)	0.29	9.26%
$(1-R^2)$ excl. BA	2.29	0.34*** (3.17)	0.24*** (3.13)	0.15** (2.09)	0.17	10.83%
Panel B. Sequential Double Sorts						
Top BA × Non-top SR	3.48	0.60*** (4.30)	0.33*** (4.16)	0.39*** (3.63)	0.31	9.26%
Top SR × Non-top BA	3.74	0.72** (2.15)	0.17** (2.14)	0.20 (1.22)	0.10	7.93%
Top BA × Non-top $(1-R^2)$	4.40	0.75*** (3.91)	0.30*** (3.83)	0.50*** (3.60)	0.29	9.48%
Top $(1-R^2)$ × Non-top BA	2.34	0.35*** (3.47)	0.27*** (3.41)	0.18*** (2.63)	0.21	10.96%

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common to the top BA portfolio fails to deliver a statistically significant alpha. We also observe that the portfolio of BA funds without SR funds largely retains its Sharpe and information ratios but that the portfolio of SR funds excluding BA funds displays considerably lower Sharpe and information ratios.

Similarly, we observe that the portfolio of top BA funds excluding top $(1-R^2)$ funds largely retains its single variable performance and dominates the portfolio of top $(1-R^2)$ funds excluding BA funds in all measures, delivering a higher end value, mean excess returns, alpha, Sharpe ratio, and information ratio. However, the top $(1-R^2)$ portfolio does partially retain its risk-adjusted performance after excluding top BA funds, as indicated by the noticeably diminished, but still statistically significant alpha.

These results provide evidence that BA could be interpreted as a common factor behind the long-term out-of-sample predictive power of both SR and $(1-R^2)$, completely explaining the long-term predictive significance of SR and partially explaining the long-term significance of $(1-R^2)$. Finally, as the top BA portfolio retains its long-term out-of-sample predictive power after excluding top SR and $(1-R^2)$ funds, we conjecture that BA successfully captures the time-varying nature of beta exposures that is not fully captured by either SR or $(1-R^2)$.[32]

In an effort to focus on individual roles of (1 − SBS) and DBR as drivers of the BA explanatory power, we further explore commonalities of (1 − SBS), DBR, SR, and $(1-R^2)$ in Appendix D. The results suggest qualitatively and quantitatively similar effects of either (1 − SBS) or DBR on explanatory power of SR and $(1-R^2)$. Hence, we conclude that (1 − SBS) and DBR capture different, but equally important dimensions of BA that drive the explanatory power of SR and $(1-R^2)$.

VII. BA and Market-Timing Measures

Here, we investigate the relationship between BA and extant measures of market-timing ability. As BA captures both contemporaneous managerial success and the effectiveness of dynamic factor loading changes, we compare BA and the extant measures of market timing in the ability to predict superior out-of-sample performance.

Henriksson and Merton (1981) construct a directional market return timing factor, $\text{Max}(0, r_m)$,[33] in order to measure the ability of fund managers to time the market. We calculate the exposure to the Henriksson and Merton stock market return timing factor by adding $\text{Max}(0, r_m)$ to base equation (M). The regression coefficient, HM, captures the stock market-timing ability of fund managers.

Chen and Liang (2007) construct a measure that jointly measures the ability of managers to time stock market returns and market volatility. We calculate the exposure to the Chen and Liang timing factor, $(r_m/\sigma_m)^2$, which jointly captures the degree to which managers are increasing market exposure when the expectation

[32] The fact that BA completely explains the predictive significance of the variation in systematic risk, proxied by DSR, reinforces the interpretation of BA as a common factor reflecting time-varying factor exposures. See Section VII.

[33] r_m is the excess return on a broad stock market index, less the risk-free rate. In our study, it is calculated as the excess return of the CRSP stock market value-weighted index over the monthly return of 30-day U.S. Treasury bills.

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of market returns is high and decreasing market exposure when the expectation of market volatility is high, by adding it to base equation (M). We follow Chen and Liang in constructing the measure, such that r_m is excess return of the CRSP stock market value-weighted index over the monthly return of 30-day U.S. Treasury bills and σ_m is the VIX implied volatility index per the Chicago Board Options Exchange. The regression coefficient, CLT, captures the joint timing ability of fund managers.

Cao et al. (2013) find that top market liquidity timing funds outperform low liquidity timing funds. Following Cao et al. (2013), we construct the liquidity-timing factor, $\text{SP500}_t(L_{m,t} - \bar{L}_{m,t-1})$, adding it to equation (M), where L_m is the Pastor–Stambaugh (2003) liquidity measure and LIQ is the regression coefficient representing liquidity timing. If LIQ is positive, the fund is increasing market exposure when liquidity is high and decreasing exposure when liquidity is poor, thus avoiding the potentially high cost of transacting large trades in poor liquidity states.

Finally, Bali et al. (2012) suggest that the predictive power of SR could be related to the time variation in SR, since the time variation in SR could be indicative of changes in overall factor exposures and, hence, factor timing. Following Bali et al. (2012), we capture the time variation in SR by calculating the difference in systematic risk (DSR):

$$\text{DSR}_{w,i} = |\text{SR}_{w,i} - \text{SR}_{w-1,i}|, \tag{6}$$

such that DSR is the absolute value of the difference between SR in the two preceding 2-year windows w and $w-1$. The regression coefficient on DSR, thus, should capture managers' ability to time SR.

We rank all funds to create portfolios of funds in the top quartile of HM, CLT, LIQ, and DSR to examine the out-of-sample performance of top market-timing funds. Panel A of Table 7 lends strong support to extant measures of timing ability. All four predict superior performance, though the HM and CLT measures do not deliver significant out-of-sample alphas.

As BA captures both contemporaneous managerial success and the effectiveness of dynamic factor loading changes, we consider the HM, CLT, LIQ, and DSR measures to be complementary to BA. To examine the commonality or heterogeneity of extant measures and BA, we again create out-of-sample isolate portfolios with respect to each measure and BA. Panel B of Table 7 reports performance of isolate portfolios such that the "HM excl. BA" is the portfolio of funds in the top quartile of HM excluding any funds that are also in the top quartile of BA. Complementarily, Panel C reports the performance of double-sorted portfolios. For example, the "Top HM × Non-top BA" is the portfolio of funds resultant from an initial sort on HM, keeping the top quartile of funds in HM, then resorted by BA, and the top quartile of BA funds discarded from the subsample. In each case, BA retains its economically large and statistically significant performance; all performance metrics are positive and significant at better than the 1% level. Conversely, HM and CLT portfolios lose all statistical significance. The DSR portfolio partially retains some of its predictive power, though it fails to deliver statistically significant alpha after excluding BA funds. Only the LIQ portfolio retains much of its predictive power after excluding BA funds, though all measures are diminished. We conclude that BA well explains the predictive

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power of HM and CLT, partially explains DSR, and is largely a complement to the Cao et al. (2013) measure of liquidity timing. Most importantly, we conclude that none of the HM, CLT, LIQ, and DSR measures drive the predictive power of BA.

VIII. Conclusion

We develop a methodology by which we comprehensively identify and quantify beta-driven active hedge fund management. Beta active management, which involves taking directional positions correlated with macroeconomic risk factors,

TABLE 7

Out-of-Sample Performance of Factor Timing Portfolios: 2000–2013

Table 7 reports comparisons of out-of-sample performance of portfolios of funds ranked by extant measures of factor timing and beta activity (BA). HM is the Henriksson–Merton (1981) market-timing measure. CLT is the Chen and Liang (2007) market liquidity timing measure. LIQ is the Cao et al. (2013) joint market and volatility timing measure. DSR is the difference in systematic risk, the absolute value of the difference in SR, as suggested by Bali et al. (2012). Beta activity is the equal-weighted average of normalized DBR and (1 − SBS) per equation (5). Panel A reports the performance of portfolios of funds in the top quarter of all funds as ranked by extant market-timing measures. Panel B reports the performance of portfolios sorted by a single variable to the exclusion of other variables in order to isolate the contribution of a single variable to out-of-sample portfolio performance. For example, BA excl. HM is a portfolio of funds in the top quartile of BA excluding any funds that are also in the top quarter of HM. Panel C reports the performance of double-sorted portfolios wherein funds in the top quartile of a variable are selected, then ranked with regard to a second variable. The top quartile of funds in the second variable are then discarded from the subsample, resulting in the final portfolio. For example, sorting all funds by BA, we keep the top quartile of funds. We then rank the subsample with regard to HM, discarding the top quartile, resulting in the Top BA × Non-top HM portfolio. Portfolios are created as of Dec. 31, 1999 and rebalanced annually. The End Value is the dollar value of the initial $1 investment as of Dec. 31, 2013. Excess Return and alpha are mean monthly figures. *t*-statistics are reported in parentheses; we report the Jobson and Korkie (1981) measure of statistical significance for Sharpe ratios. Info Ratio is the information ratio. Attrition Rate is the average annual rate at which funds stop reporting. When funds stop reporting, we assume the fund is defunct and equally invest resultant capital in the remaining portfolio funds. *, **, and *** designate statistical significance at the better than 10%, 5%, and 1% levels, respectively.

	End Value	Excess Return	Sharpe Ratio	α	Info Ratio	Attrition Rate
Panel A. Market-Timing Portfolios						
HM	2.71	0.47** (2.16)	0.17** (2.15)	0.13 (0.94)	0.08	8.92%
CLT	2.74	0.48** (2.22)	0.17** (2.20)	0.13 (0.84)	0.07	9.51%
LIQ	3.60	0.65*** (2.80)	0.22*** (2.79)	0.31*** (2.58)	0.21	8.16%
DSR	4.27	0.77*** (2.80)	0.22*** (2.77)	0.34** (2.51)	0.21	8.92%
Panel B. Independent Portfolio Sorts						
BA excl. HM	4.02	0.70*** (4.01)	0.31*** (3.92)	0.43*** (3.27)	0.28	9.23%
HM excl. BA	2.04	0.31 (1.30)	0.10 (1.30)	−0.08 (−0.59)	−0.05	8.11%
BA excl. CLT	4.42	0.75*** (4.38)	0.34*** (4.27)	0.49*** (4.29)	0.35	9.34%
CLT excl. BA	2.41	0.41* (1.71)	0.13* (1.71)	−0.00 (−0.02)	−0.00	9.05%
BA excl. LIQ	3.97	0.68*** (4.24)	0.33*** (4.12)	0.45*** (3.68)	0.30	9.98%
LIQ excl. BA	3.34	0.61** (2.52)	0.20** (2.51)	0.24** (2.02)	0.16	8.03%
BA excl. DSR	3.31	0.57*** (4.06)	0.31*** (3.93)	0.36*** (3.16)	0.27	9.26%
DSR excl. BA	3.45	0.65** (2.18)	0.17** (2.17)	0.21 (1.52)	0.12	8.30%

(continued on next page)

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TABLE 7 (continued)
Out-of-Sample Performance of Factor Timing Portfolios: 2000–2013

	End Value	Excess Return	Sharpe Ratio	α	Info Ratio	Attrition Rate
Panel C. Sequential Double Sorts						
Top BA × Non-top HM	4.06	0.70*** (4.11)	0.32*** (4.02)	0.43*** (3.59)	0.30	9.48%
Top HM × Non-top BA	2.15	0.34 (1.47)	0.11 (1.46)	−0.04 (−0.29)	−0.02	8.45%
Top BA × Non-top CLT	4.32	0.74*** (4.33)	0.33*** (4.22)	0.48*** (4.21)	0.34	9.41%
Top CLT × Non-top BA	2.41	0.41* (1.75)	0.13* (1.74)	0.01 (0.07)	0.01	9.28%
Top BA × Non-top LIQ	4.04	0.69*** (4.30)	0.33*** (4.18)	0.46*** (3.78)	0.31	9.95%
Top LIQ × Non-top BA	3.44	0.63*** (2.58)	0.20*** (2.57)	0.27** (2.21)	0.18	8.06%
Top BA × Non-top DSR	3.53	0.61*** (4.12)	0.32*** (4.00)	0.39*** (3.34)	0.28	9.36%
Top DSR × Non-top BA	3.62	0.68** (2.30)	0.18** (2.29)	0.22 (1.58)	0.13	8.10%

results in time-varying values of beta coefficients and is captured by the introduced measure of BA.

We report ample evidence that beta active managers deliver superior long-term risk-adjusted performance in terms of excess returns, Sharpe ratios, Fung and Hsieh (2004) alphas, and information ratios. Beta active portfolios outperform portfolios formulated upon traditional measures of alpha active performance (i.e., alpha and alpha t-statistic) as well as beta-centric measures extant in the literature, specifically SR and $(1-R^2)$. We find BA to be a stronger predictor of superior future fund performance than alpha activity.

We further conclude that our measure of BA captures a unique aspect of active portfolio management not captured by either SR or $(1-R^2)$. Furthermore, there is an indication that, over the long term, BA successfully captures the time-varying nature of beta exposures that can be interpreted as a common factor completely explaining the long-term predictive power of SR and partially explaining the long-term predictive power of $(1-R^2)$.

Finally, as BA is constructed in a manner that quantifies managers' ability to time economic factors, we provide evidence that BA fully or partially explains extant measures of market-timing ability.

Beta activity metrics expand our understanding of active portfolio management and managerial skill and are powerful complements to current alpha-centric, SR, and market-timing methodologies.

Appendix A. Scaled Beta Success versus Scaled Average Return Comparison

Given that scaled beta success (SBS) is equivalent to the observed average excess return, less alpha, the superior performance of the bottom SBS portfolio could potentially be attributed to mean reversal of past hedge fund performance, measured by the average past excess return. We define a new variable, scaled average return (SAR), in a similar way as we defined SBS, that is, benchmarking a fund i average return $\bar{r}_{w,i}$ against the

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maximum and the minimum of average returns across all funds over two preceding 24-month windows w and $w-1$:

$$\text{(A-1)} \quad \text{SAR}_i = \frac{1}{2}\frac{\bar{r}_{w,i} - \min_j\{\bar{r}_{w,j}\}}{\max_j\{\bar{r}_{w,j}\} - \min_j\{\bar{r}_{w,j}\}} + \frac{1}{2}\frac{\bar{r}_{w-1,i} - \min_j\{\bar{r}_{w-1,j}\}}{\max_j\{\bar{r}_{w-1,j}\} - \min_j\{\bar{r}_{w-1,j}\}},$$

where $\bar{r}_{w,i}$ is the average return for fund i in window w and $\min_j\{\bar{r}_{w,j}\}$ and $\max_j\{\bar{r}_{w,j}\}$ are the lowest and the highest average monthly returns, respectively, among all the hedge funds for window w.

We then compare the out-of-sample performance of the top and bottom quartile portfolios selected on the basis of SAR. We find that, as with SBS, the bottom SAR portfolio outperforms the top SAR portfolio in alpha, mean monthly excess return, Sharpe ratio, and information ratio.[34] This is not surprising given that SBS and SAR only differ in alpha and are positively correlated.[35] However, in a direct out-of-sample comparison between top quartile (1 − SBS) and (1 − SAR) portfolios, we observe that there is relatively little overlap in funds; only 37.84% of funds are common to both (1 − SBS) and (1 − SAR) portfolios. Table A1 reports results of out-of-sample performance of portfolios

TABLE A1

Out-of-Sample Portfolio Performance of SBS, SAR, and Isolate Portfolios: 2000–2013

Table A1 reports out-of-sample performance of portfolios of funds in the bottom quartile (25%) of SBS, SAR, and isolate portfolios. Panel A reports the performance of portfolios of the highest and lowest quartile of funds with regard to SAR. Top SAR − Bottom SAR is an arbitrage portfolio equivalent to taking a long position in the top quartile funds and a short position in the bottom quartile funds. Panel B reports the performance of funds sorted by a single variable to the exclusion of other variables in order to isolate the contribution of a single variable. For example, (1 − SBS) excl. (1 − SAR) is a portfolio of funds in the top quartile of (1 − SBS) excluding any funds that are also in the top quarter of (1 − SAR). Panel C reports the performance of double-sorted portfolios wherein funds in the top quartile of a variable are selected, then ranked with regard to a second variable. The top quartile of funds in the second variable are then discarded from the subsample, resulting in the final portfolio. For example, sorting all funds by (1 − SBS), we keep the top quartile of funds. We then rank the subsample with regard to (1 − SAR), discarding the top quartile, resulting in the Top (1 − SBS) × Non-Top (1 − SAR) portfolio. Portfolios are created as of Dec. 31, 1999 and rebalanced annually. The End Value is the dollar value of the initial $1 investment as of Dec. 31, 2013. Excess Return and alpha are mean monthly figures. t-statistics are reported in parentheses; we report the Jobson and Korkie (1981) measure of statistical significance for Sharpe ratios. Info Ratio is the information ratio. Attrition Rate is the average annual rate at which funds stop reporting. When funds stop reporting, we assume the fund is defunct and equally invest resultant capital in the remaining portfolio funds. *, **, and *** designate statistical significance at the better than 10%, 5%, and 1% levels, respectively.

	End Value	Excess Return	Sharpe Ratio	α	Info Ratio	Attrition Rate
Panel A. SAR Portfolio						
Top SAR	2.99	0.54** (2.25)	0.17	0.16 (1.21)	0.09	5.04%
Bottom SAR	3.15	0.55*** (3.28)	0.25*** (3.24)	0.30** (2.43)	0.21	15.38%
Top SAR − Bottom SAR	0.94	−0.01 (−0.04)	−0.00	−0.14 (−0.82)	−0.07	—
Panel B. Independent Portfolio Sorts						
(1 − SBS) excl. (1 − SAR)	3.55	0.62*** (3.38)	0.26*** (3.33)	0.38*** (3.61)	0.28	6.97%
(1 − SAR) excl. (1 − SBS)	2.74	0.46*** (2.82)	0.22*** (2.80)	0.21* (1.81)	0.16	16.26%
Panel C. Sequential Double Sorts						
Top (1 − SBS) × Non-Top (1 − SAR)	3.71	0.65*** (3.69)	0.29*** (3.63)	0.40*** (4.00)	0.32	7.57%
Top (1 − SAR) × Non-Top (1 − SBS)	2.73	0.46*** (2.82)	0.22*** (2.80)	0.20* (1.85)	0.16	15.75%

[34] Top versus bottom SAR portfolio comparisons are omitted for parsimony. The results are available from the authors.

[35] The correlation between SBS and SAR is 0.2342.

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of (1 − SBS), (1 − SAR), and variable-isolating ("isolate") portfolios. The (1 − SBS) portfolio outperforms the (1 − SAR) portfolio in all measures. Further, the performance and its statistical significance of the (1 − SBS) portfolio remain almost the same after excluding the funds that are also present in the (1 − SAR) portfolio, while the attrition rate is reduced by 2.61%. On the other hand, the (1 − SAR) portfolio after excluding funds common to the (1 − SBS) portfolio displays lower excess returns, lower statistical significance in alpha, and a 0.88% increase in the attrition rate.

We conclude that SBS captures a unique aspect of hedge fund management related to BA that is not captured by the average past return. The superior out-of-sample performance of the bottom SBS portfolio is consistent with the argument that managers with lower SBS are making long-term factor-related bets that are less profitable contemporaneously but that become profitable in the future as economic conditions change.

Appendix B. An Example of a Top BA Fund

Here, we apply our methodology to fund 4284 in our sample so that we may better understand the mechanics behind beta activity (BA) rankings and fund inclusion in the "top 25%" portfolio in the subsequent year in out-of-sample testing. As fund 4284 is currently a live fund, that is, it is still accepting investor flows, trading, and reporting performance to Bloomberg and other commercial databases, we do not disclose the fund's name or other identifying information as this is prohibited by law pertaining to alternative investments.

Fund 4284 is a fund with a self-declared style of "discretionary." It was founded prior to 1994 in the United States. The fund charges a 2% annual management fee of investor funds under management and 20% of annual profits over an investor-specific high water mark. The minimum initial investment in the fund is $500,000. To redeem funds, investors must give management at least a 15-day notice, and redemptions are made at the end of the month for a minimum total redemption period of 45 days.

Table B1 reports annual percentile rankings of fund 4284 in BA, DBR, SBS, and annual returns net of fees. The fund was included in the top BA portfolio in 2000 as the fund BA placed it in the 77th percentile, and thus in the top 25% BA portfolio. In 2000, the fund returned 12.94% after fees compared to the S&P 500's −9.10% return that year. The fund was not in the top BA portfolio again until 2005; the fund has been in the top BA portfolio for the remainder of our sample period.

TABLE B1

Annual Percentile Rankings of Fund 4284 in BA, DBR, and SBS: 2000–2013

Table B1 reports annual percentage rankings and annual investor returns (net of fees) of fund 4284, a U.S. domiciled discretionary hedge fund, with regard to beta activity (BA), difference in beta returns (DBR), and scaled beta success (SBS).

Year	BA	DBR	SBS	Return
2000	77.39	80.40	60.30	12.94
2001	58.97	44.69	30.04	14.59
2002	54.86	42.70	34.59	21.08
2003	27.93	21.11	30.49	20.82
2004	57.31	14.80	17.52	6.28
2005	93.02	90.01	68.95	−2.13
2006	78.52	68.09	41.29	8.38
2007	19.19	9.15	50.26	7.20
2008	94.05	61.89	3.60	34.82
2009	80.72	83.73	45.65	5.21
2010	79.41	65.73	34.78	−5.78
2011	96.17	94.25	54.06	2.06
2012	95.84	81.45	17.51	−19.91
2013	79.13	86.28	57.86	12.49

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Figure B1 illustrates the cumulative performance of fund 4284 from 2000 to 2013, the period encompassing the out-of-sample portfolio performance comparisons in this study. It is important to note that BA is a combined measure of DBR, a measure of factor-timing success, and (1 − SBS), a measure that indicates current market-timing efforts. From late 2004 to 2007, fund 4284 gave up contemporaneous returns by strategically moving positions away from the most profitable factors; the fund SBS was very low at the end of 2007, placing it in the 3rd percentile of SBS. The combination of a low SBS and a DBR in the 61st percentile (from previously successful timing) resulted in a BA in the 94th percentile, placing the fund in the portfolio of top BA funds for subsequent out-of-sample testing. Our conjecture is that fund management anticipated changing economic conditions prior to the financial crisis. The fund's return in 2008 was 34.82% after fees compared to the S&P 500's contemporaneous return of −37.00%.

FIGURE B1
Cumulative Performance of Fund 4284: 2000–2013

Figure B1 represents the cumulative wealth in USD (in natural logarithmic scale) from a $1 investment in Fund 4284, a U.S. domiciled discretionary hedge fund. The fund was in the top 25% beta activity (BA) portfolio in 2000 and from 2005 to 2013. The line represents the cumulative dollar value, after 2% annual management and 20% performance fees, of $1 invested in fund 4284 on Dec. 31, 1999.



Appendix C. Portfolio Performance and Loss Assumptions

Given the relatively higher attrition rate of top BA funds relative to top alpha funds, at 9.73%, 6.18%, and 6.49% for BA, alpha, and alpha t-statistic portfolios, respectively, we reconsider out-of-sample portfolio performance under different loss assumptions. Table C1 reports the long-term performance of individual variable and isolate portfolios in the top and bottom quartiles of BA, alpha, and alpha t-statistic. Panel A reports results under the assumption that, when a fund stops reporting, only 50% of the capital of the (presumed defunct) fund is available for equal reinvestment in surviving portfolio funds. Under a 50% loss assumption, our findings are unchanged; top BA portfolios continue to dominate alpha and alpha t-statistic portfolios in economic and statistical significance in all measures.

TABLE C1

Out-of-Sample Performance with Loss Assumptions: 2000–2013

Table C1 reports results of out-of-sample comparisons of portfolios comprised of funds in the top and bottom quartiles of beta active (BA), alpha, and alpha t-statistic. Top BA − Bottom BA is an arbitrage portfolio equivalent to taking a long position in top quartile funds and a short position in bottom quartile funds. When funds stop reporting, we assume the fund is defunct. Panel A reports performance under a 50% loss assumption wherein only 50% of capital from defunct funds is available for equal reinvestment in remaining portfolio funds. Panel B reports performance under a 100% loss assumption. Portfolios are created as of Dec. 31, 1999 and rebalanced annually. The End Value is the dollar value of the initial $1 investment as of Dec. 31, 2013. Excess Return and alpha are mean monthly figures. t-statistics are reported in parentheses; we report the Jobson and Korkie (1981) measure of statistical significance for Sharpe ratios. Info Ratio is the information ratio. Attrition Rate is the average annual rate at which funds stop reporting. When funds stop reporting, we assume the fund is defunct and equally invest resultant capital in the remaining portfolio funds. *, **, and *** designate statistical significance at the better than 10%, 5%, and 1% levels, respectively.

	End Value	Excess Return	Sharpe Ratio	α	Info Ratio	Attrition Rate
Panel A. 50% Loss BA, Alpha Activity, and BA versus Alpha Activity						
Top BA	2.29	0.36**	0.16*	0.11	0.07	9.73%
		(2.02)	(2.01)	(0.91)		
Bottom BA	1.55	0.15	0.05	−0.24*	−0.14	8.47%
		(0.61)	(0.61)	(−1.86)		
Top BA − Bottom BA	1.35	0.21	0.09	0.36**	0.18	—
		(1.14)	(1.14)	(2.34)		
Top alpha	2.23	0.36	0.13	0.02	0.01	6.18%
		(1.64)	(1.64)	(0.13)		
Top alpha t-stat.	1.80	0.21	0.11	−0.01	−0.01	6.49%
		(1.48)	(1.47)	(−0.07)		
Top BA − Top alpha	0.98	0.00	0.00	0.10	0.06	—
		(0.03)	(0.03)	(0.77)		
Top BA − Top alpha t-stat.	1.27	0.15	0.10	0.12	0.08	—
		(1.31)	(1.31)	(1.08)		
Panel B. 100% Loss BA, Alpha Activity, and BA versus Alpha Activity						
Top BA	1.25	0.00	0.00	−0.25*	−0.13	9.73%
		(0.01)	(0.01)	(−1.70)		
Bottom BA	0.89	−0.18	−0.05	−0.59***	−0.31	8.47%
		(−0.69)	(−0.69)	(−4.00)		
Top BA − Bottom BA	1.28	0.18	0.07	0.35**	0.16	—
		(0.92)	(0.91)	(2.05)		
Top alpha	1.51	0.12	0.04	−0.22*	−0.12	6.18%
		(0.56)	(0.56)	(1.69)		
Top alpha t-stat.	1.19	−0.04	−0.02	−0.26***	−0.21	6.49%
		(−0.26)	(−0.25)	(−2.68)		
Top BA − Top alpha	0.79	−0.12	−0.06	−0.02	−0.01	—
		(−0.80)	(−0.80)	(−0.16)		
Top BA − Top alpha t-stat.	1.04	0.04	0.02	0.02	0.01	—
		(0.31)	(0.31)	(0.12)		

Only when we assume a 100% loss of capital, reported in Panel B, do the alpha portfolios perform slightly better than the BA portfolios, with an end value of 1.51 to 1.21, respectively. BA continues to outperform alpha t-statistic portfolios even under the 100% loss assumption.

Appendix D. Commonality of (1 − SBS), DBR, SR, and (1 − R^2) Measures

We explore the commonality of SR, (1 − R^2), SBS, and DBR in predicting portfolio performance by comparing the long-term performance of individual variable isolate portfolios in Table D1. Individual variable isolate portfolios are those that contain funds in the top 25% portfolio of one variable, excluding funds that also belong to the top 25% portfolio

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of another variable. For example, "(1 − SBS) excl. SR" reports the performance of funds in the top 25% of funds in (1 − SBS) excluding funds that are also in the top 25% of funds in SR. The results in Table D1 suggest qualitatively and quantitatively similar effects of either (1 − SBS) or DBR on the explanatory power of SR and $(1 - R^2)$. Hence, we conclude that (1 − SBS) and DBR capture different, but equally important dimensions of beta activity that drive the explanatory power of SR and $(1 - R^2)$.

TABLE D1

Out-of-Sample Performance of Single Variable Isolate Portfolios: 2000–2013

Table D1 reports results of out-of-sample comparisons of portfolios double sorted on beta measures. SBS is scaled beta success, the degree to which managers capture returns from the most profitable factors, contemporarily. DBR is the difference in beta returns, a combinatory measure of FDBR and RDBR. SR is systematic risk per Bali et al. (2012). $(1 - R^2)$ is per Titman and Tiu (2011). For example, (1 − SBS) excl. SR is the portfolio of funds in the top quartile (25%) of (1 − SBS), again excluding any funds also in the top quartile of SR. Portfolios are created as of Dec. 31, 1999 and rebalanced annually. The End Value is the dollar value of the initial $1 investment as of Dec. 31, 2013. Excess Return and alpha are mean monthly figures. *t*-statistics are reported in parentheses; we report the Jobson and Korkie (1981) measure of statistical significance for Sharpe ratios. Info Ratio is the information ratio. Attrition Rate is the average annual rate at which funds stop reporting. When funds stop reporting, we assume the fund is defunct and equally invest resultant capital in the remaining portfolio funds. *, **, and *** designate statistical significance at the better than 10%, 5%, and 1% levels, respectively.

	End Value	Excess Return	Sharpe Ratio	α	Info Ratio	Attrition Rate
(1 − SBS) excl. SR	2.80	0.47*** (3.65)	0.28*** (3.57)	0.28*** (3.52)	0.27	9.58%
SR excl. (1 − SBS)	3.91	0.74** (2.30)	0.18** (2.29)	0.22 (1.27)	0.10	8.05%
(1 − SBS) excl. $(1 - R^2)$	3.72	0.66*** (3.32)	0.26*** (3.28)	0.39*** (3.15)	0.27	9.18%
$(1 - R^2)$ excl. (1 − SBS)	2.34	0.36*** (3.14)	0.24*** (3.09)	0.18** (2.20)	0.18	11.33%
DBR excl. $(1 - R^2)$	3.91	0.69*** (3.24)	0.25*** (3.19)	0.36** (2.52)	0.22	8.22%
$(1 - R^2)$ excl. DBR	2.35	0.36*** (3.43)	0.26*** (3.34)	0.17** (2.49)	0.19	11.04%
DBR excl. SR	2.96	0.51*** (3.38)	0.26*** (3.31)	0.28** (2.36)	0.21	8.93%
SR excl. DBR	4.06	0.77** (2.29)	0.18** (2.28)	0.25 (1.51)	0.12	8.85%

References

Agarwal, V.; N. D. Daniel; and N. Y. Naik. "Role of Managerial Incentives and Discretion in Hedge Fund Performance." *Journal of Finance*, 64 (2009), 2221–2256.

Agarwal, V., and N. Y. Naik. "On Taking the Alternative Route: Risks, Rewards, and Performance Persistence of Hedge Funds." *Journal of Alternative Investments*, 2 (2000), 6–23.

Agarwal, V., and N. Y. Naik. "Risk and Portfolio Decisions Involving Hedge Funds." *Review of Financial Studies*, 17 (2004), 63–98.

Aggarwal, R. K., and P. Jorion. "The Performance of Emerging Hedge Funds and Managers." *Journal of Financial Economics*, 96 (2010), 238–256.

Amihud, Y., and R. Goyenko. "Mutual Fund's R^2 as Predictor of Performance." *Review of Financial Studies*, 26 (2013), 667–694.

Aragon, G. "Timing Multiple Markets: Theory and Evidence." Working Paper, Arizona State University, http://ssrn.com/abstract=415740 (2002).

Aragon, G. "Share Restriction and Asset Pricing: Evidence from the Hedge Fund Industry." *Journal of Financial Economics*, 83 (2007), 33–58.

Asness, C.; R. Krail; and J. Liew. "Do Hedge Funds Hedge?" *Journal of Portfolio Management*, 28 (2001), 6–19.

Avramov, D.; L. Barras; and R. Kosowski. "Hedge Fund Return Predictability under the Magnifying Glass." *Journal of Financial and Quantitative Analysis*, 48 (2013), 1057–1083.

https://doi.org/10.1017/S0022109018000388 Published online by Cambridge University Press

Avramov, D.; R. Kosowski; N. Y. Naik; and M. Teo. "Hedge Funds, Managerial Skill, and Macroeconomic Variables." *Journal of Financial Economics*, 99 (2011), 672–692.
Bali, T. G.; S. J. Brown; and M. O. Caglayan. "Do Hedge Funds' Exposures to Risk Factors Predict Their Future Returns?" *Journal of Financial Economics*, 101 (2011), 36–68.
Bali, T. G.; S. J. Brown; and M. O. Caglayan. "Systematic Risk and the Cross Section of Hedge Fund Returns." *Journal of Financial Economics*, 106 (2012), 114–131.
Bollen, N. P. B. "Zero-R^2 Hedge Funds and Market Neutrality." *Journal of Financial and Quantitative Analysis*, 48 (2013), 519–547.
Bollen, N. P. B., and J. A. Busse. "On the Timing Ability of Mutual Fund Managers." *Journal of Finance*, 56 (2001), 1075–1094.
Bollen, N. P. B., and R. E. Whaley. "Hedge Fund Risk Dynamics: Implications for Performance Appraisal." *Journal of Finance*, 64 (2009), 985–1035.
Brinson, G. P.; L. P. Hood; and G. L. Beebower. "Determinants of Portfolio Performance." *Financial Analysts Journal*, 42 (1986), 39–44.
Brunnermeier, M. K., and S. Nagel. "Hedge Funds and the Technology Bubble." *Journal of Finance*, 59 (2004), 2013–2040.
Cai, L., and B. Liang. "On the Dynamics of Hedge Fund Strategies." *Journal of Alternative Investments*, 14 (2012a), 51–68.
Cai, L., and B. Liang. "Asset Allocation Dynamics in the Hedge Fund Industry." *Journal of Investment Management*, 10 (2012b), 35–59.
Cao, C.; Y. Chen; B. Liang; and A. W. Lo. "Can Hedge Funds Time Market Liquidity?" *Journal of Financial Economics*, 109 (2013), 493–516.
Chen, Y. "Timing Ability in the Focus Market of Hedge Funds." *Journal of Investment Management*, 5 (2007), 66–98.
Chen, Y., and B. Liang. "Do Market Timing Hedge Funds Time the Market?" *Journal of Financial and Quantitative Analysis*, 42 (2007), 827–856.
Cremers, K. J. M., and A. Petajisto. "How Active Is Your Fund Manager? A New Measure That Predicts Performance." *Review of Financial Studies*, 22 (2009), 3329–3365.
Daniel, K.; M. Grinblatt; S. Titman; and R. Wermers. "Measuring Mutual Fund Performance with Characteristic-Based Benchmarks." *Journal of Finance*, 52 (1997), 1035–1058.
Fama, E. F. "Components of Investment Performance." *Journal of Finance*, 27 (1972), 551–567.
Ferson, W., and R. Schadt. "Measuring Fund Strategy and Performance in Changing Economic Conditions." *Journal of Finance*, 51 (1996), 425–460.
Fung, H. G.; X. E. Xu; and J. Yau. "Global Hedge Funds: Risk, Return, and Market Timing." *Financial Analysts Journal*, 58 (2002), 19–30.
Fung, W., and D. A. Hsieh. "Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds." *Review of Financial Studies*, 10 (1997), 275–302.
Fung, W., and D. A. Hsieh. "The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers." *Review of Financial Studies*, 14 (2001), 313–341.
Fung, W., and D. A. Hsieh. "Hedge Fund Benchmarks: A Risk-Based Approach." *Financial Analysts Journal*, 60 (2004), 65–80.
Fung, W.; D. A. Hsieh; N. Y. Naik; and T. Ramadorai. "Hedge Funds: Performance, Risk, and Capital Formation." *Journal of Finance*, 63 (2008), 1777–1803.
Getmansky, M.; A. W. Lo; and I. Makarov. "An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns." *Journal of Financial Economics*, 74 (2004), 529–609.
Goetzmann, W.; J. Ingersoll; M. Spiegel; and I. Welch. "Portfolio Performance Manipulation and Manipulation-Proof Performance Measures." *Review of Financial Studies*, 20 (2007), 1503–1546.
Grinblatt, M., and S. Titman. "Portfolio Performance Evaluation: Old Issues and New Insights." *Review of Financial Studies*, 2 (1989), 393–421.
Grinblatt, M., and S. Titman. "Performance Measurement without Benchmarks: An Examination of Mutual Fund Returns." *Journal of Business*, 66 (1993), 47–68.
Henriksson, R., and R. Merton. "On Market Timing and Investment Performance II: Statistical Procedures for Evaluating Forecasting Skills." *Journal of Business*, 54 (1981), 513–534.
Jagannathan, R., and R. A. Korajczyk. "Assessing the Market Timing Performance of Managed Portfolios." *Journal of Business*, 59 (1986), 217–235.
Jagannathan, R.; A. Malakhov; and D. Novikov. "Do Hot Hands Exist among Hedge Fund Managers? An Empirical Evaluation." *Journal of Finance*, 65 (2010), 217–255.
Jensen, M. "The Performance of Mutual Funds in the Period 1954–1964." *Journal of Finance*, 23 (1968), 389–416.
Jensen, M. "Optimal Utilization of Market Forecasts and the Evaluation of Investment Portfolio Performance." In *Mathematical Methods in Investment and Finance*, G. Szego and K. Shell, eds. Amsterdam: North-Holland (1972), 310–335.

https://doi.org/10.1017/S0022109018000388 Published online by Cambridge University Press

Jiang, G.; T. Yao; and T. Yu. "Do Mutual Funds Time the Market? Evidence from Portfolio Holdings." *Journal of Financial Economics*, 86 (2007), 724–758.
Jobson, J. D., and B. M. Korkie. "Performance Hypothesis Testing with the Sharpe and Treynor Measures." *Journal of Finance*, 36 (1981), 889–908.
Kacperczyk, M.; C. Sialm; and L. Zheng. "Unobserved Actions of Mutual Funds." *Review of Financial Studies*, 21 (2008), 2379–2416.
Kosowski, R.; N. Y. Naik; and M. Teo. "Do Hedge Funds Deliver Alpha? A Bayesian and Bootstrap Analysis." *Journal of Financial Economics*, 84 (2007), 229–264.
Lewis, M. *The Big Short: Inside the Doomsday Machine*. New York, NY: W. W. Norton & Company (2010).
Mamaysky, H.; M. Spiegel; and H. Zhang. "Estimating the Dynamics of Mutual Fund Alphas and Betas." *Review of Financial Studies*, 21 (2008), 233–264.
Pastor, L., and R. Stambaugh. "Liquidity Risk and Expected Stock Returns." *Journal of Political Economy*, 111 (2003), 642–685.
Patton, A. J. "Are 'Market Neutral' Hedge Funds Really Market Neutral?" *Review of Financial Studies*, 22 (2009), 2495–2530.
Roll, R. "Ambiguity When Performance Is Measured by the Securities Market Line." *Journal of Finance*, 33 (1978), 1051–1069.
Sadka, R. "Liquidity Risk and the Cross-Section of Hedge-Fund Returns." *Journal of Financial Economics*, 98 (2010), 54–71.
Sadka, R. "Hedge-Fund Performance and Liquidity Risk." *Journal of Investment Management*, 10 (2012), 60–72.
Sharpe, W. F. "Asset Allocation: Management Style and Performance Management." *Journal of Portfolio Management*, 18 (1992), 7–19.
Sun, Z.; A. Wang; and L. Zheng. "The Road Less Traveled: Strategy Distinctiveness and Hedge Fund Performance." *Review of Financial Studies*, 25 (2012), 96–143.
Titman, S., and C. Tiu. "Do the Best Hedge Funds Hedge?" *Review of Financial Studies*, 24 (2011), 123–168.
Treynor, J., and K. Mazuy. "Can Mutual Funds Outguess the Market?" *Harvard Business Review*, 44 (1966), 131–136.

https://doi.org/10.1017/S0022109018000388 Published online by Cambridge University Press