IIJ Institutional Investor Journals

The Journal of Portfolio Management

VOLUME 43 NUMBER 4 www.iijpm.com SUMMER 2017

The Bernstein Fabozzi Jacobs Levy Awards

Outstanding Article 2017

Man vs. Machine: *Comparing Discretionary and Systematic Hedge Fund Performance*

CAMPBELL R. HARVEY, SANDY RATTRAY, ANDREW SINCLAIR, AND OTTO VAN HEMERT

Man

Man

Man AHL employs diversified quantitative techniques to offer a range of strategies which encompass traditional momentum, non-traditional momentum, multi-strategy and sector-based approaches. Man AHL's strategies are primarily alternative and seek to gain potential predictive, alpha-generating insights through rigorous analysis of large data sets. Man AHL is a specialised engine, applying scientific rigour and advanced technology and execution to a diverse range of data in order to build systematic investment strategies, trading continuously over hundreds of global markets. The team of 150 investment professionals, including 110 researchers, is comprised of scientists, technologists and finance practitioners, driven by curiosity and intellectual honesty, and a passion for solving the complex problems presented by financial markets. The engine leverages Man Group's unique collaboration with the University of Oxford: the Oxford-Man Institute of Quantitative Finance (OMI). The OMI conducts field-leading academic research into machine learning and data analytics, which can be applied to quantitative investing. Founded in 1987, Man AHL's funds under management were $25.1 billion at 30 September 2018. Further information can be found at www.man.com/ahl.

Campbell R. Harvey, a leading financial economist, has been an Investment Strategy Advisor to Man Group since 2005 and has contributed to both research and product design at Man Group. He is a Professor of Finance at Duke University, and Research Associate at the National Bureau of Economic Research in Cambridge, Massachusetts. He served as Editor of The Journal of Finance from 2006 to 2012 and as the 2016 President of the American Finance Association. Campbell received the 2016 and 2015 Bernstein Fabozzi/Jacobs Levy Award for the Best Article from the Journal of Portfolio Management for his research on differentiating luck from skill. He has also received eight Graham and Dodd Awards/Scrolls for excellence in financial writing from the CFA Institute. He has published over 125 scholarly articles on topics spanning investment finance, emerging markets, corporate finance, behavioural finance, financial econometrics and computer science. For the last five years, Campbell has taught a course called Innovation and Cryptoventures that focuses on the mechanics and applications of blockchain technology. He has served on the faculty of the University of Chicago, Stockholm School of Economics and the Helsinki School of Economics. He has also been a visiting scholar at the Board of Governors of the Federal Reserve System. He was awarded an honorary doctorate from Svenska Handelshögskolan in Helsinki. He holds a PhD in Finance from the University of Chicago.

Sandy Rattray is CIO of Man Group and a member of the Man Group Executive Committee. He is also a member of the Man Group Responsible Investment Committee. He was previously CEO of Man AHL from 2013 to 2017 and CIO of Man Systematic Strategies from 2010 to 2013. Before joining Man Group in 2007, Sandy spent 15 years at Goldman Sachs where he was a Managing Director in charge of the Fundamental Strategy Group. He also ran Equity Derivatives Research at Goldman Sachs in London and New York. Sandy is a co-inventor of the VIX index and has served on the FTSE UK, FTSE World and Russell index committees. He sits on the MSCI Editorial Advisory Board and the Jesus College Cambridge investment committee. Sandy is a founding patron of the London Cycling Campaign. He holds a Master's Degree in Natural Sciences and Economics from the University of Cambridge and a Licence Spéciale from the Université Libre de Bruxelles.

Otto van Hemert is Head of Macro Research at Man AHL. Prior to joining Man AHL in 2015, Otto ran a systematic global macro fund at IMC for over three years. Before that he headed Fixed Income Arbitrage, Credit, and Volatility strategies at AQR, and was on the Finance Faculty at the New York University Stern School of Business where he published papers in leading academic finance journals. Otto holds a PhD in Economics and Masters Degrees in Mathematics and Economics.

Andrew Sinclair joined Man AHL in 1996, working on projects ranging from transaction cost analysis to portfolio construction to predictor development. He left Man Group in 2017. Andrew holds a BA in Mathematics from Trinity Hall, Cambridge, and an MSc in Applied Statistics from Oxford University.

Man vs. Machine: *Comparing Discretionary and Systematic Hedge Fund Performance*

CAMPBELL R. HARVEY, SANDY RATTRAY, ANDREW SINCLAIR, AND OTTO VAN HEMERT

CAMPBELL R. HARVEY
is a professor of finance at Duke University in Durham, NC, and an investment strategy advisor at Man Group in London, UK.
cam.harvey@duke.edu

SANDY RATTRAY
is the CIO of Man Group and CEO of AHL in London, UK.
sandy.rattray@man.com

ANDREW SINCLAIR
is a senior quantitative analyst at Realindex Investments, in Sydney, NSW, Australia.
andrewcsinclair@btinternet.com

OTTO VAN HEMERT
is the head of commodities at AHL in London, UK.
ovanhemert@ahl.com

Quantitative investing, which deploys machine learning and other algorithms to big data, is in vogue. Recently, the *Wall Street Journal* declared, "For decades, investors imagined a time when data-driven traders would dominate financial markets. That day has arrived."[1] In this context, it is useful to take a step back and compare the performance and risk exposures of discretionary and systematic managers. Discretionary managers rely on human skills to make day-to-day investment decisions. Systematic managers, on the other hand, use rules-based strategies that are implemented by a computer, with little or no daily human intervention.

In our experience, some allocators to hedge funds, including some of the largest in the world, either partially or entirely avoid allocating to systematic funds. We have heard various reasons for this, such as the following:

- systematic funds are homogeneous.
- systematic funds are hard to understand.
- the investing experience in systematic funds has been worse than in discretionary funds.
- systematic funds are less transparent than discretionary funds.
- systematic funds are bound to perform worse than discretionary funds because they only use data from the past.

These reasons seem to be consistent with a distrust of systems, or "algorithm aversion," as illustrated by a series of experiments in Dietvorst, Simmons, and Massey [2015]. In line with our experience and algorithm aversion, as of the end of 2014, 31% of hedge funds were systematic and they managed just 26% of the total of assets under management (AUM).

In this article, we compare the performance of systematic funds to their discretionary counterparts and show that, after adjusting for volatility and factor exposures, the lack of confidence in systematic funds is not justified. Our analysis covers over 9,000 funds from the Hedge Fund Research, Inc. (HFR) database over the period 1996–2014. We classify funds as either systematic or discretionary based on algorithmic text analysis of the fund descriptions, because the categories used by HFR do not provide an exact match for our research question. We consider both macro and equity funds.

We find that based on returns that are not adjusted for factor exposures, systematic macro funds outperform discretionary macro funds, whereas the reverse is true for equity funds. The (annualized) return for the four styles varies from 2.86% to 5.01%. Unadjusted returns are in excess of the local short-term interest rate, averaged across funds of a particular style (i.e., we form an index), and after transaction costs and fees.

For discretionary funds, more of the return can be attributed to factors than for their systematic counterparts. We consider three sets of risk factors: traditional factors (equity, bond, credit), dynamic factors (stock value, stock size, stock momentum, FX carry), and a volatility factor. The latter is defined as a strategy of buying one-month, at-the-money S&P 500 calls and puts (i.e., straddles) at month end and letting them expire at the next month's end. For all four styles, the return attributed to traditional factors is meaningful, as it ranges from 1.5% to 2.2%. The return attributed to dynamic factors is also positive in all cases, ranging from 0.2% to 1.3%. The return attributed to the volatility factor is negative for systematic and discretionary macro funds, at −3.2% and −1.3% respectively, and close to zero for equity funds. Macro funds on average have a long exposure to the volatility factor, which has negative returns over time. The negative risk premium for the long volatility factor makes sense, given that being long volatility can act as a hedge for holding risky assets in general. Correcting macro funds' returns for their long volatility exposure essentially gives them credit for this hedging characteristic.

In terms of the average risk-adjusted returns, systematic macro has an annualized return of 4.9% compared to 1.6% for discretionary macro. However, the systematic macro style has more than double the volatility (10.9% compared to 5.1%). The two approaches have much closer performance after adjusting for the volatility difference. For equity funds, discretionary has a 1.2% risk-adjusted return, whereas for systematic it is 1.1%. In contrast to macro, the volatilities are similar, with discretionary having 4.8% volatility and systematic 3.2% volatility. Again, adjusting for risk-adjusted volatility, the performance of these two approaches in the equity category is similar.

All in all, the above results show that the hedge fund styles we consider have historically realized positive alphas, which are determined (1) in excess of the short-term interest rate, (2) after transaction costs and fees, and (3) after correcting for any return attributed to risk factors. We note that the factors themselves (especially the dynamic factors) cannot be produced for zero cost, and so a manager simply implementing a portfolio of these factor exposures would show a negative alpha.

Our empirical analysis allows us to comment not only on performance statistics but also on the amount of return variation explained by the risk factors. We find that for systematic funds, a slightly smaller proportion of variance is explained by the factors (both for macro and equity funds). A much larger proportion of variance is explained by factors for equity funds than for macro funds. This is mostly driven by a long equity market exposure in equity funds. For an investor who already has a meaningful investment in equities outside of his or her hedge fund portfolio, it is important to take this into account.

Finally, we analyze the dispersion of manager returns (the results previously discussed were based on an index for each category). We establish that the dispersion in Sharpe and appraisal ratios across funds within a hedge fund style is similar (and large) for systematic and discretionary funds. This means that the common investor observation that systematic funds are more homogeneous does not appear to stand up to scrutiny. So, in addition to style selection, fund selection seems to be just as important in each category.

CLASSIFICATION OF HEDGE FUNDS

In this article, we use hedge fund data from the HFR database. We exclude backfilled returns from before the moment a fund was added, and include the graveyard database to mitigate selection and survivorship bias concerns respectively. We start our analysis in 1996 because of the widely held view that prior to the mid-1990s hedge fund databases suffer from measurement biases.[2] We exclude a limited number of funds that report less frequently than monthly, or for which the reported performance is not classified as "net of all fees." See the appendix for more details on the fund selection filters and the fund classification method, which we discuss next.

We use the two largest strategy types covered in the HFR database: Equity Hedge (6955 funds) and Macro (2182 funds). Within the HFR Macro category, the two main substrategies conveniently cover:

- Systematic Diversified: "…with little or no influence of individuals over the portfolio positioning." (HFR [2016]).
- Discretionary Thematic: "…interpreted by an individual or group of individuals who make decisions on portfolio positions" (HFR [2016]).

For Equity Hedge, however, the HFR-provided categorization is less tailored to our research question. None of the substrategy names contain the word "systematic" or "discretionary," and none of the HFR descriptions clearly specify whether the decision making is done by algorithms or by humans. Some Equity Hedge substrategy names and descriptions contain the word "quantitative," but most hedge funds will employ some form of quantitative analysis, which does not mean they take trading decisions without human overlay. To illustrate this, we find that the word "quantitative" occurs in the description of Systematic Diversified macro funds only 1.7 times more often than it does for Discretionary Thematic.

Given that the HFR categorization does not bifurcate equity funds into systematic and discretionary, we rely on text analysis of the fund descriptions. Following a formal method for picking the words used, which utilizes the HFR-provided split into systematic and discretionary macro funds as a learning set (see Appendix A), we arrive at the following classification rule:

- *Systematic*—the fund description contains any of the following as (part of) a word: "algorithm," "approx," "computer," "model," "statistical," "system"
- *Discretionary*—the fund description contains none of the systematic words described above.

For consistency, and because funds may be misclassified by HFR, we also use our classification for macro funds (instead of the HFR classification). Sampling the Macro Systematic Diversified funds that we classify as discretionary, we do not, in general, see a clear indication that the fund is in fact systematic. So we deem it probable that the fund is not purely systematic but rather partially systematic or quantitative, but not rules based.[3]

RISK FACTORS

We want to evaluate whether hedge funds add value over and above any performance that can be attributed to factors that (1) were well known by 1996, when our sample period starts, and (2) are easy to implement. In this section, we discuss three types of factors: traditional, dynamic, and a volatility factor. See Exhibit 1, Panel A, for the full list of factors included.

As traditional factors, we include the main large and easily investable asset classes: equities (S&P 500 Index), bonds (Barclays U.S. Treasury Index), and credit (Citigroup USBIG High-Grade Credit Index minus the Barclays U.S. Treasury Index). The data are from Bloomberg.[4]

The dynamic factors we include are the three Fama–French U.S. stock factors and an FX carry factor. The Fama–French factors are size (small-minus-big U.S. stocks), value (high-minus-low book value U.S. stocks), and momentum (winner-minus-loser U.S. stocks). These factors were well known by the mid-1990s, following papers by Fama and French [1993] on size and value and Jegadeesh and Titman [1993] on the cross-sectional momentum factor.[5] The returns for these three factors can be obtained from Kenneth French's website.[6] The FX carry factor is applied to the most liquid G10 currency pairs. The existence of an FX carry factor is a direct implication of the failing of the "uncovered interest rate parity" that has been extensively discussed in the academic finance literature, going back to Meese and Rogoff [1983] and Fama [1984]. The data for the FX carry factor are from Deutsche Bank.[7]

We do not include dynamic factors that only recently became better known and documented—which typically occurred after hedge funds had profitably exploited them and they had thus garnered widespread attention (macro trend following, for example). As Frazzini, Kabiller, and Pedersen show, with the benefit of hindsight, even "Buffett's performance can be largely explained by exposures to value, low-risk, and quality factors" together with "a leverage of about 1.6-to-1" (Frazzini, Kabiller, and Pedersen [2013], p. 2).

Although cross-sectional momentum strategies applied to U.S. stocks were well known before 1996, time-series momentum applied to futures has been documented only much more recently and is therefore not included (see Appendix B for further discussion).

Finally, we note that our research is focused on past performance, rather than advocating a strategy for the future. Although we are aware that an analysis starting at the time of this writing would most likely use a simple macro time-series momentum factor as well as fixed income and commodity carry, for example, our objective here is to explain returns using factors known at the inception of the strategies, rather than on an ex post basis. If these funds are to remain successful, they will need to innovate beyond currently known factors, as they have done before (see also the online appendix).

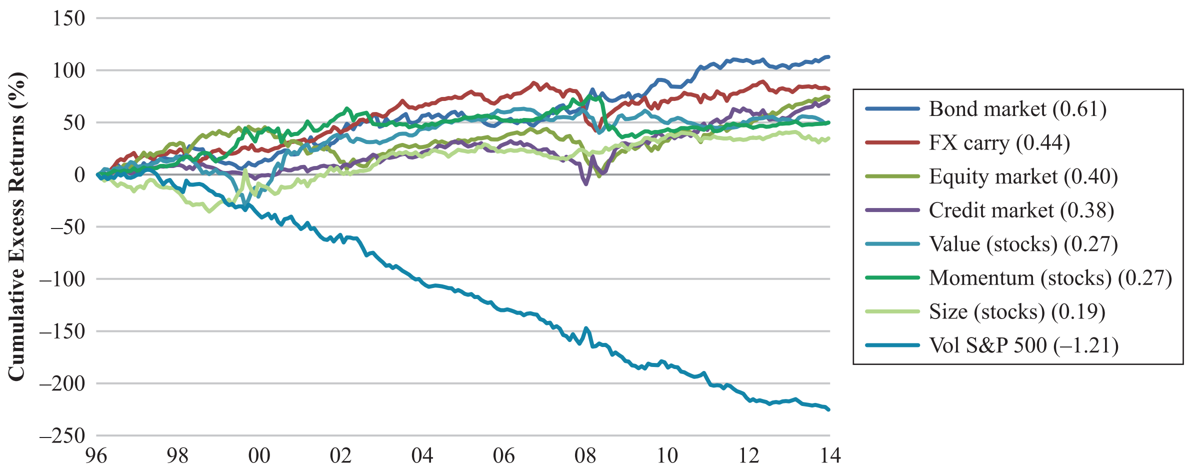
The volatility factor that we include is a long one-month, at-the-money S&P 500 straddle (call and put option) position, bought at month end and held to expiry. The data come from Goldman Sachs, which provided us with mid prices for OTC options.[8] Hedge funds may

Exhibit 1
Risk Factors, June 1996–December 2014

Panel A: Description Risk Factors

Category	Name	Instruments
Traditional	Equity market	S&P 500 Index
	Bond market	Barclays U.S. Treasury Index
	Credit market	Citigroup USBIG High-Grade Credit Index minus the Barclays U.S. Treasury Index
Dynamic	Size (stocks)	Small-minus-big U.S. stocks
	Value (stocks)	High-minus-low book value U.S. stocks
	Momentum (stocks)	Winner-minus-loser U.S. stocks
	FX carry	Deutsche Bank G10 currency carry index
Volatility	Vol S&P 500	Straddles for S&P 500 Index

Panel B: Cumulative Excess Returns of the Risk Factors, Scaled to 10% Volatility (Sharpe ratios added to legend)



Panel C: Correlation Risk Factor Returns

	Equity Market	Bond Market	Credit Market	Size (stocks)	Value (stocks)	Momentum (stocks)	FX carry	Vol S&P 500
Equity Market		–0.23	0.25	0.11	–0.16	–0.33	0.49	–0.13
Bond Market	–0.23		0.40	–0.16	0.04	0.15	–0.12	0.00
Credit Market	0.25	0.40		0.03	0.02	–0.13	0.27	–0.27
Size (stocks)	0.11	–0.16	0.03		–0.35	0.09	0.11	–0.18
Value (stocks)	–0.16	0.04	0.02	–0.35		–0.15	0.11	0.08
Momentum (stocks)	–0.33	0.15	–0.13	0.09	–0.15		–0.11	0.06
FX carry	0.49	–0.12	0.27	0.11	0.11	–0.11		–0.14
Vol S&P 500	–0.13	0.00	–0.27	–0.18	0.08	0.06	–0.14	

Notes: In Panel A, we list the risk factors considered in this article. Panel B shows the cumulative excess returns over the sample period, where we scale the annualized volatility (ex post) to 10% to facilitate comparison. The realized Sharpe ratio for each factor is reported in parentheses in the legend. In Panel C, we report the correlation between the monthly factor returns.

have an exposure to the volatility factor because of positions in nonlinear instruments, such as options. Hedge funds may also end up with an exposure to volatility because of the nature of their dynamic trading strategies; for example, Hamill, Rattray, and Van Hemert [2016] draw a parallel between a trend-following strategy and the dynamic replication of a straddle position. Finally, hedge funds may be exposed to the volatility factor if they trade in securities that are disproportionately hit at times of crisis, such as collateralized debt obligations.

Comparing the risk factors discussed above to what Bali, Brown, and Caglayan [2014] refer to as a set of "standard risk factors," we notice three main differences. First, instead of using the change in yield for the bond and credit factor, we believe it is important to express all factor returns as investment returns. Second, we augment the list of dynamic factors with an FX carry factor, as previously described. Third, we don't use the Fung and Hsieh [2001] volatility factors. The main reason for this is that these would, in our opinion, not be straightforward (or cheap) to implement.[9]

All factor returns are determined on an unfunded basis—which is done by using futures, a dollar-neutral long–short portfolio, or returns in excess of the three-month money market rate. We scale all factors to have 10% volatility (ex post). The alphas and risk-adjusted returns are not affected by this scaling. The scaling allows an easy comparison of betas to different factors: the larger the beta, the more variance is explained by the factor (in a multivariate sense). Exhibit 1, Panel B, shows the cumulative factor returns; we do not compound returns, so a straight line would correspond to constant performance over time. The Sharpe ratios of each factor are presented in parentheses in the legend and are calculated as the ratio of the mean to the standard deviation of the monthly excess returns, annualized by multiplying by the square root of 12. The traditional and dynamic factors have a positive risk premium; while the S&P 500 volatility factor carries a negative premium (that is, a long volatility strategy has a negative return on average) with a Sharpe ratio of −1.21. This is mostly driven by the put leg of the straddle, for which the price is bid up by the large demand to hedge against sudden equity market drawdowns.

In Exhibit 1, Panel C, we report the correlations between the different risk factors. The highest correlation (0.49) is between the equity and FX carry returns.

EMPIRICAL ANALYSIS: MACRO FUNDS

We select the subset of funds that we deem institutional-sized by applying an AUM cutoff of $100m in December 2014, and before that a value in proportion to the size of the overall hedge fund industry relative to December 2014 (i.e., $10m in December 1996). This size filter is implemented at the start of each calendar year, based on the median of the prior year's monthly AUMs.[10]

Also, we endeavor to remove funds which are repeats of each other. We identify repeats based on the similarity in fund name, taking into account that strings like "class A" and "LLP" tend to be uninformative about the underlying strategy and are more reflective of the particular structures. Having identified a group of repeated funds, we use the fund with the longest history as the representative of that group. Lastly, we sum AUMs across these groups of repeated funds, assigning the total AUM to the selected representative before applying the size screen mentioned above.

We conduct our performance analysis on hedge fund excess returns, so we deduct the short-term interest rate of the currency in which the returns are denominated. In 74% of cases, the funds are U.S. dollar denominated, and we deduct the three-month money market rate. Most of our empirical analysis is performed for the average returns of funds in a particular category, like systematic macro. We take the average at each point in time, using the then-available funds, hence forming an index return series. Later in this article, we will also provide some results based on individual fund returns.

In Exhibit 2, we report the results for the following regression:

$$R_t = \alpha + \sum_i \beta^i F_t^i + \varepsilon_t \qquad (1)$$

where R is the excess return, F represents factor excess returns, α and β are the regression coefficients, and ε is the error term.

In Panel A, we report the regression coefficients for systematic (left side) and discretionary (right side) macro funds. We indicate whether a coefficient is significant at the 10%, 5%, and 1% significance level with *, **, and ***, respectively (using a Newey–West adjustment with one lag).[11] In the left column, we only include a constant, in which case the alpha (which we annualize) simply equals the average unadjusted (annual) return.

Exhibit 2
Regression Analysis for Macro Funds, June 1996–December 2014

Systematic Macro

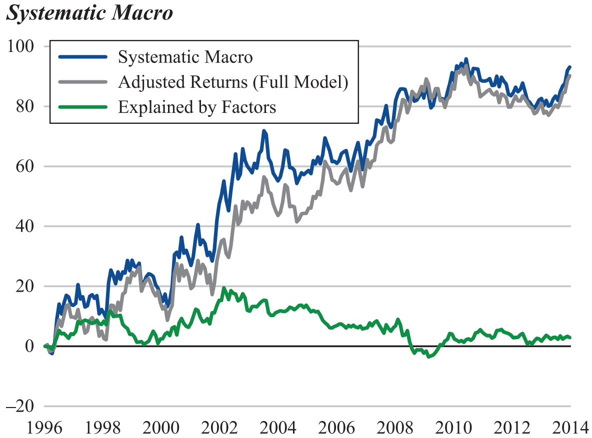
	None	Traditional	Traditional + Dynamic	Traditional + Dynamic + Vol S&P 500
Panel A: Regression Coefficients				
Alpha (annualized)	5.01%*	3.08%	1.85%	4.85%*
Equity		0.01	0.03	0.03
Bond		0.36***	0.36***	0.33***
Credit		–0.08	–0.09	–0.01
Size (stocks)			0.02	0.06
Value (stocks)			0.09	0.08
Momentum (stocks)			0.18**	0.18**
FX Carry			0.10	0.11
Vol S&P 500				0.26***
R^2	0%	8%	11%	16%
Panel B: Performance (annualized)				
Average Return	5.01%	5.01%	5.01%	5.01%
Attributed to Factors	0.00%	1.94%	3.17%	0.15%
Equity		0.04%	0.14%	0.11%
Bond		2.21%	2.16%	2.01%
Credit		–0.31%	–0.34%	–0.04%
Size (stocks)			0.04%	0.11%
Value (stocks)			0.25%	0.22%
Momentum (stocks)			0.49%	0.47%
FX Carry			0.43%	0.48%
Vol S&P 500				–3.21%
Avg. Adj. Return (alpha)	5.01%	3.08%	1.85%	4.85%
Adj. Return Volatility	11.71%	11.29%	11.19%	10.93%
Appraisal Ratio	0.43	0.27	0.17	0.44

Discretionary Macro

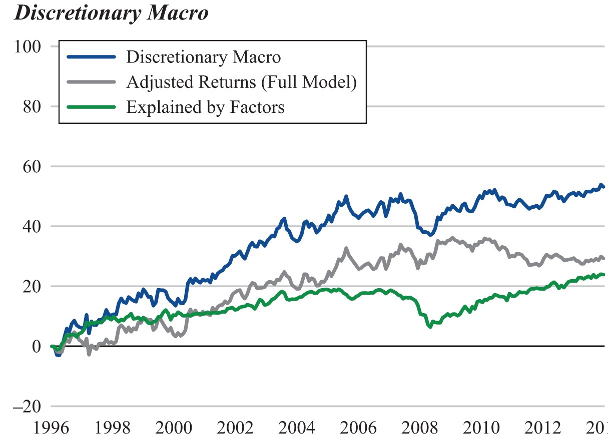
	None	Traditional	Traditional + Dynamic	Traditional + Dynamic + Vol S&P 500
Alpha (annualized)	2.86%**	1.24%	0.38%	1.57%
Equity		0.21***	0.19***	0.19***
Bond		0.12**	0.13***	0.12**
Credit		0.01	–0.01	0.02
Size (stocks)			0.06	0.07*
Value (stocks)			0.03	0.03
Momentum (stocks)			0.09*	0.09*
FX Carry			0.11**	0.12***
Vol S&P 500				0.11**
R^2	0%	15%	22%	25%
Average Return	2.86%	2.86%	2.86%	2.86%
Attributed to Factors	0.00%	1.62%	2.48%	1.28%
Equity		0.83%	0.75%	0.74%
Bond		0.73%	0.80%	0.74%
Credit		0.06%	–0.02%	0.10%
Size (stocks)			0.11%	0.14%
Value (stocks)			0.09%	0.08%
Momentum (stocks)			0.25%	0.24%
FX Carry			0.50%	0.52%
Vol S&P 500				–1.28%
Avg. Adj. Return (alpha)	2.86%	1.24%	0.38%	1.57%
Adj. Return Volatility	5.77%	5.37%	5.19%	5.10%
Appraisal Ratio	0.50	0.23	0.07	0.31

Panel C: Risk-Adjusted Returns (correcting for traditional, dynamic, and vol S&P 500 factor exposures)

Systematic Macro



Discretionary Macro



Notes: We run regressions of systematic macro (left side) and discretionary macro (right side) returns on different subsets of the risk factor returns. The factors are (ex post) scaled to 10% volatility to facilitate interpretation of the reported coefficients in Panel A. Panel B reports annualized performance statistics for the different subsets of risk factors considered, including the return attributed to factors, which is computed as the coefficient times the average factor return. Panel C shows the unadjusted (blue line), and risk-adjusted (gray line) cumulative excess returns, as well as the correction (green line). The risk-adjusted return is corrected for any variation explained by the exposure to traditional, dynamic, and vol S&P 500 factors (the fourth specification in Panels A and B). Funds are classified into systematic and discretionary using text analysis. We use monthly data from HFR.

*Notes: ***, **, and * represent the 1%, 5%, and 10% significance levels, respectively.*

In the second column of Panel A, we include traditional factors. For systematic macro managers, the long bond exposure (significant at the 1% significance level) stands out, which is intuitive given that many systematic macro managers employ trend signals, and bond prices have trended upwards over the 1996–2014 sample period. Discretionary macro managers have a meaningful long exposure to both equites and bonds.

In this third column, we also add dynamic factors. For systematic macro managers, there is a large exposure to U.S. stock momentum, which again can be understood from the prevalence of trend following in this category. Discretionary macro managers have a modest positive exposure to U.S. stock momentum, and also to FX carry.

In the fourth column, we add the long S&P options straddle (volatility) factor, which systematic macro managers have a (highly significant) positive exposure to. Hamill, Rattray, and Van Hemert [2016] argue that this is almost by construction for trend-following managers by showing that they would hold similar positions to what a straddle delta-replication strategy would imply. For discretionary macro funds, the coefficient on volatility is also positive, but less large and less significant.

Finally, Panel A of Exhibit 2 also reports the R^2 statistic—that is, the proportion of the return variance explained by the factors. For our baseline case (including traditional, dynamic, and vol S&P 500 factors), this is 16% for systematic macro managers and 25% for discretionary macro managers. So the majority of the return variation is, in fact, not explained by the well-known factors.

Panel B of Exhibit 2 reports annualized performance statistics, including the return attributed to factor exposures. The latter can be extracted from the regression analysis by taking the average over time of the left- and right-hand side of the above regression equation and recognizing that the average error is zero by construction:

$$Avg\{R\} = \alpha + \sum_i \beta^i Avg\{F^i\} \qquad (2)$$

Concretely, in Panel B we report the average annual return, $12 * Avg\{R\}$, in the first row. In the second row, we report the return attributed to factors—that is, $12 * \beta * Avg\{F\}$—aggregated over all factors. The attribution to individual factors is reported below that. Next, we report the annualized alpha, $12 * \alpha$, the annualized volatility of adjusted returns, $\sigma(\varepsilon)$ times square root 12, and the ratio of the two, which is known as the appraisal ratio and given by

$$\text{Appraisal Ratio} = \frac{\alpha}{\sigma(\varepsilon)}\sqrt{12} \qquad (3)$$

For systematic macro funds, the average unadjusted excess return is 5.01% (first row). Based on the baseline case specification (i.e., including traditional, dynamic, and the vol S&P 500 factors), 2.01% of that is attributed to the bond factor and −3.21% to the vol S&P 500 factor, leaving an alpha of 4.85% after taking into account the smaller effects of other factors as well. In regards to the risk adjustment for the vol S&P 500 exposure, notice that systematic macro funds have a long exposure to the volatility factor, which has negative returns over time. The negative risk premium for the volatility factor is intuitive, given that being long volatility can act as a hedge. Correcting systematic macro fund returns for the long volatility exposure essentially gives them credit for this hedging feature.

For discretionary macro funds, the average unadjusted return is 2.86%. In the baseline case specification, 0.74% of that is attributed to the equity factor and 0.74% to the bond exposure. The attribution to the vol S&P 500 factor is −1.28%, leaving an alpha of 1.57% after incorporating the smaller effects of other factors as well.

Looking at the appraisal ratio rather than the alpha, we see that the performance difference between systematic and discretionary macro funds is smaller—for example, for the baseline case we observe 0.44 and 0.31, respectively. The reason is that systematic macro returns are more volatile, both in terms of unadjusted returns and the unexplained returns (regression error term).

Finally, in Panel C of Exhibit 2, we plot the risk-adjusted returns, which are obtained by rearranging the regression equation:

$$R_t^{Adj} = R_t - \sum_i \beta^i F_t^i = \alpha + \varepsilon_t \qquad (4)$$

In this figure, we use the baseline case specification with the traditional, dynamic, and vol S&P 500 factors. We show the history of the unadjusted (blue line) and risk-adjusted (gray line) cumulative returns, where, as before in Exhibit 1, we do not compound returns. We also show the difference—that is, what is explained by the factors (green line). For systematic macro managers, the unadjusted and risk-adjusted cumulative returns are fairly close; adjustments for the various risk factors, notably the bond and volatility factors, are mostly off-setting. For discretionary macro managers, the risk-adjusted returns are well below unadjusted returns and the dip in unadjusted returns at the end of 2008 can largely be explained by factor exposures (particularly the long equity exposure).

We ran an additional regression with the difference between the systematic and discretionary macro return as the dependent variable, and all factor returns as explanatory variables. The alpha difference (captured by the constant) for the baseline case is 3.28% (annualized), which (of course) is identical to the difference between the alphas reported in Exhibit 2. More informative is the fact that the *t*-statistic on the alpha difference is only 1.66, failing to exceed two standard errors from zero.

At a minimum, our results suggest that systematic macro funds have performed at least as well as discretionary macro funds—a conclusion that is robust to using a number of performance metrics (average unadjusted return, average risk-adjusted return, and appraisal ratio).

EMPIRICAL ANALYSIS: EQUITY FUNDS

In Exhibit 3, we repeat our analysis for systematic equity (left panels) and discretionary equity (right panels) funds. In Panel A, the large (and significant) positive exposure to the equity market factor stands out, for both systematic and discretionary equity managers. Although many equity managers may advertise their funds as being market neutral, these results show that this does not hold up for the group in aggregate. The bond and credit factors are significant but have small coefficient values, which implies less economic meaning because the factors were scaled to equal volatility (as previously described).

Looking at the third column, traditional plus dynamic factors, we note that both systematic and discretionary equity managers have a sizable exposure to the stock size factor, suggesting a tendency to be long small-cap/short large-cap stocks on average. One possible explanation is that for the short side, it may be more feasible (and cheaper) to use the futures contract on a large-cap index, like the S&P 500 Index. Alternatively, it may just be easier for managers to find opportunities in small caps. For discretionary equity funds, there is also an important long exposure to the FX carry factor. A possible explanation is that discretionary equity funds find (long) investment opportunities in less liquid stocks, which (just like FX carry) may suffer when liquidity suddenly dries up.

The reported R^2 statistic in Exhibit 3, Panel A, is 73% for systematic equity managers and 77% for discretionary equity managers in the baseline case (i.e., including traditional, dynamic, and the vol S&P 500 factor). This is much higher than the 16% and 25% we reported previously for systematic and discretionary macro funds, respectively. The equity factor is the dominant driver of the R^2 statistic.

In Exhibit 3, Panel B, we report different performance statistics (for the method, see the discussion and formulas in the previous section). For systematic equity funds, the average unadjusted return is 2.88% (see first row). Based on the baseline case specification, 1.70% of that is attributed to the equity factor, leaving an alpha of 1.11% after taking into account the smaller effects of other factors as well.

For discretionary equity funds, the average unadjusted return is 4.09%. Based on the baseline case specification, 2.51% of that is attributed to the equity factor, leaving an alpha of 1.22% after taking into account the smaller effects of other factors as well. Hence, for the baseline case specification, the alpha for discretionary equity funds is slightly higher than it is for systematic equity funds. However, the appraisal ratio is slightly lower, with a value of 0.25 for discretionary equity funds versus 0.35 for systematic equity funds.

As we did for macro funds in the previous section, we plot in Panel C of Exhibit 3 the history of the unadjusted (blue line) and risk-adjusted (gray line) cumulative returns. Given the dominance of the equity risk factor, for both systematic and discretionary equity funds, the difference between the unadjusted and risk-adjusted returns (green line) follows closely the returns of the S&P 500 Index, with drawdowns when the tech bubble burst in 2000 and during the financial crisis in 2008.

We also ran an additional regression with the difference between the systematic and discretionary equity returns as dependent variable, and all factor returns as explanatory variables. The alpha difference for the baseline case is an insignificant −0.11% (annualized) with a *t*-statistic of −0.11.

In sum, although the average unadjusted return is higher for discretionary equity than for systematic

Exhibit 3

Regression Analysis for Equity Funds, June 1996–December 2014

Systematic Equity

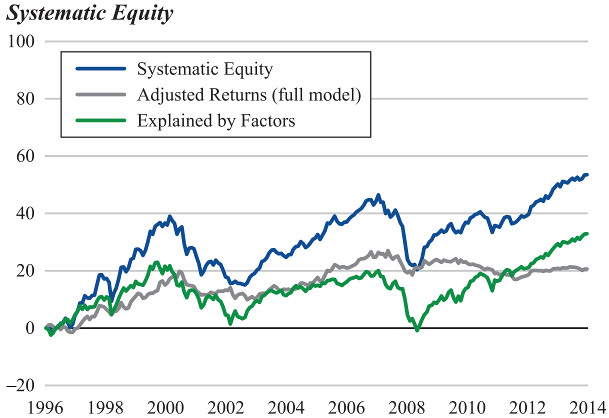
	None	Traditional	Traditional + Dynamic	Traditional + Dynamic + Vol S&P 500
Panel A: Regression Coefficients				
Alpha (annualized)	2.88%*	1.36%	1.17%	1.11%
Equity		0.45***	0.42***	0.42***
Bond		–0.08***	–0.07***	–0.07***
Credit		0.05	0.05	0.05
Size (stocks)			0.09***	0.09***
Value (stocks)			–0.09**	–0.09**
Momentum (stocks)			0.05*	0.05*
FX carry			0.04	0.04
Vol S&P 500				–0.01
R^2	0%	66%	73%	73%
Panel B: Performance (annualized)				
Average Return	2.88%	2.88%	2.88%	2.88%
Attributed to Factors	0.00%	1.51%	1.71%	1.77%
Equity		1.79%	1.70%	1.70%
Bond		–0.48%	–0.41%	–0.41%
Credit		0.20%	0.19%	0.18%
Size (stocks)			0.17%	0.17%
Value (stocks)			–0.23%	–0.23%
Momentum (stocks)			0.13%	0.13%
FX carry			0.16%	0.16%
Vol S&P 500				0.07%
Avg. Adj. Return (alpha)	2.88%	1.36%	1.17%	1.11%
Adj. Return Volatility	5.97%	3.53%	3.17%	3.18%
Appraisal Ratio	0.48	0.39	0.37	0.35

Discretionary Equity

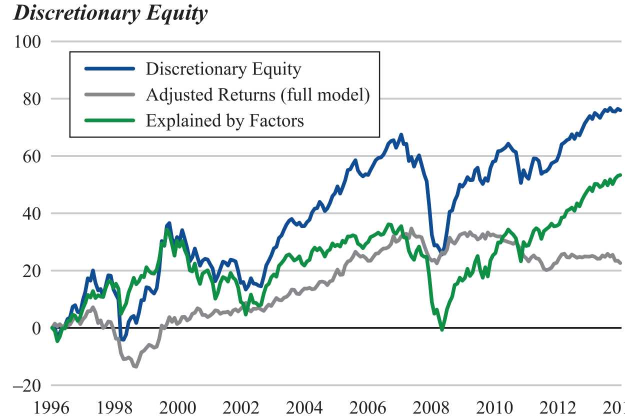
	None	Traditional	Traditional + Dynamic	Traditional + Dynamic + Vol S&P 500
Panel A: Regression Coefficients				
Alpha (annualized)	4.09%	1.80%	0.83%	1.22%
Equity		0.69***	0.62***	0.62***
Bond		–0.16***	–0.11***	–0.12***
Credit		0.13***	0.10**	0.11**
Size (stocks)			0.27***	0.28***
Value (stocks)			–0.10**	–0.10**
Momentum (stocks)			0.08*	0.08*
FX carry			0.14***	0.14***
Vol S&P 500				0.03
R^2	0%	63%	77%	77%
Panel B: Performance (annualized)				
Average Return	4.09%	4.09%	4.09%	4.09%
Attributed to Factors	0.00%	2.29%	3.25%	2.86%
Equity		2.78%	2.51%	2.51%
Bond		–1.00%	–0.70%	–0.72%
Credit		0.51%	0.36%	0.40%
Size (stocks)			0.51%	0.52%
Value (stocks)			–0.26%	–0.27%
Momentum (stocks)			0.22%	0.21%
FX carry			0.61%	0.62%
Vol S&P 500				–0.41%
Avg. Adj. Return (alpha)	4.09%	1.80%	0.83%	1.22%
Adj. Return Volatility	9.78%	5.96%	4.79%	4.79%
Appraisal Ratio	0.42	0.30	0.17	0.25

Panel C: Risk-adjusted returns (correcting for traditional, dynamic, and vol S&P 500 factor exposures)

Systematic Equity



Discretionary Equity



Notes: We run regressions of systematic equity (left side) and discretionary equity (right side) returns on different subsets of the risk factor returns. The factors are (ex post) scaled to 10% volatility to facilitate interpretation of the reported coefficients in Panel A. Panel B reports annualized performance statistics for the different subsets of risk factors considered, including the return attributed to factors, which is computed as the coefficient times the average factor return. Panel C shows the unadjusted (blue line) and risk-adjusted (gray line) cumulative excess returns, as well as the correction (green line). The risk-adjusted return is corrected for any variation explained by the exposure to traditional, dynamic, and vol S&P 500 factors (the fourth specification in Panels A and B). Funds are classified into systematic and discretionary using text analysis. We use monthly data from HFR.

*Notes: ***, **, and * represent the 1%, 5%, and 10% significance levels, respectively.*

EXHIBIT 4

Correlation between Different Hedge Fund Style Returns, June 1996–December 2014

	Unadjusted Returns			
	Macro		Equity	
	Systematic	Discretionary	Systematic	Discretionary
Macro				
Systematic		0.72	0.02	0.00
Discretionary	0.72		0.47	0.47
Equity				
Systematic	0.02	0.47		0.89
Discretionary	0.00	0.47	0.89	

	Risk-Adjusted Returns			
	Macro		Equity	
	Systematic	Discretionary	Systematic	Discretionary
Macro				
Systematic		0.77	0.22	0.16
Discretionary	0.77		0.44	0.41
Equity				
Systematic	0.22	0.44		0.63
Discretionary	0.16	0.41	0.63	

Notes: Correlations between the unadjusted excess returns (left side) and risk-adjusted returns (right side) of different categories using monthly data from HFR. The risk-adjusted return is corrected for any variation explained by the exposure to traditional, dynamic, and vol S&P 500 factors.

equity, when we control for risk factors, the performance is similar (both the alpha and appraisal ratios are similar).

DIVERSIFICATION POTENTIAL OF DIFFERENT HEDGE FUND STYLES

In Exhibit 4, we report the correlations between the different hedge fund styles using unadjusted returns (left side) and risk-adjusted returns (right side). Macro and equity fund returns historically have a low correlation with each other (in the 0.0 to 0.5 range), allowing for potentially substantial diversification benefits when combining both asset classes. However, discretionary and systematic funds within macro or equity are historically more highly correlated (in the 0.6 to 0.9 range). This suggests that discretionary and systematic managers' investment strategies are more similar than one might think.

So far, we have evaluated index returns by means of looking at returns averaged over all the funds in a particular category.[12] Next, we turn our attention to fund-level returns. In order to conduct a meaningful statistical analysis, we require that funds have a minimum of 36 months of data. This may create a survivorship bias, affecting the overall performance level. However, our main goal is to get a sense for the dispersion in performance, which is likely less affected by the selection method. It should also be noted that one cannot directly compare the fund-level results with the previous index-level results. For example, in the index-level results, funds with a longer history implicitly get more weight because they have been constituents for a longer period.

In Exhibit 5, we show the 25th, 50th, and 75th percentile of the average return and Sharpe ratio distribution for unadjusted fund returns (Panel A) and similarly the alpha and appraisal ratio for risk-adjusted returns (Panel B). The risk-adjusted returns are for the baseline case, which uses traditional, dynamic, and the vol S&P 500 factor. The analysis is performed on individual fund returns for each of the four different hedge fund styles. The spread between the 75th and 25th percentile average return ranges from 5.5% to 7.7% and the spread in alpha values is even larger, ranging from 5.9% to 10.5%. Dispersion between best and worst managers therefore is large for each of the hedge fund styles. Again, discretionary and systematic managers are historically more similar than some observers might think.

In Exhibit 5, we also report the 25th, 50th, and 75th percentile of the R^2 statistic of the regression underpinning the risk adjustment. Risk factors explain a slightly larger proportion of the return variance for equity funds than they do for macro funds. At the index level (Exhibits 2 and 3), where idiosyncratic risk is diversified, we found that the contrast is much bigger, with R^2 statistics of 16% and 25% for systematic and discretionary macro funds, and 73% and 77% for systematic and discretionary equity funds, respectively.

CONCLUSION

In this article, we used text analysis to categorize hedge funds as systematic (employing rules-based or algorithmic strategies) or discretionary (relying on human decision making). Our main focus is on risk-adjusted

EXHIBIT 5

Fund-Level Statistics, June 1996–December 2014

Panel A: No Factors (unadjusted returns)				
	Macro		Equity	
	Systematic	Discretionary	Systematic	Discretionary
Average Return (annualized)				
25th percentile	0.79%	0.82%	0.40%	1.42%
50th percentile	3.78%	3.27%	4.47%	5.40%
75th percentile	6.96%	6.36%	8.05%	9.02%
Spread 75th–25th	6.17%	5.54%	7.65%	7.60%
Sharpe Ratio (annualized)				
25th percentile	0.06	0.10	0.05	0.13
50th percentile	0.28	0.33	0.46	0.43
75th percentile	0.48	0.63	0.83	0.78
Spread 75th–25th	0.42	0.53	0.78	0.65

Panel B: Baseline Case Factors (risk-adjusted returns)				
	Macro		Equity	
	Systematic	Discretionay	Systematic	Discretionary
Alpha (annualized)				
25th percentile	–4.35%	–2.02%	–0.55%	–0.97%
50th percentile	1.67%	1.78%	2.03%	2.76%
75th percentile	6.10%	5.98%	5.31%	6.19%
Spread 75th–25th	10.45%	8.00%	5.86%	7.16%
Appraisal Ratio (annualized)				
25th percentile	–0.36	–0.19	–0.07	–0.12
50th percentile	0.13	0.20	0.29	0.33
75th percentile	0.47	0.72	0.75	0.70
Spread 75th–25th	0.83	0.91	0.82	0.82
R^2 Statistic				
25th percentile	15%	21%	24%	30%
50th percentile	24%	34%	39%	46%
75th percentile	34%	50%	57%	63%
Spread 75th–25th	19%	29%	33%	33%

Notes: In this exhibit, we report the 25th, 50th, and 75th percentile of the average return and Sharpe ratio distribution for unadjusted fund returns (Panel A) and, similarly, the alpha and appraisal ratio for risk-adjusted fund returns based on the baseline case with eight risk factors (Panel B). For the risk-adjusted returns, we also report the R^2 statistic. We only include funds with at least 36 months of return data.

returns. These are corrected for any variation in returns that is simply due to an exposure to risk factors that were already well known in 1996, when our empirical analysis starts. We found that for both equity and macro strategies, systematic and discretionary funds have historically had similar performance after adjusting for volatility and factor exposures. We do find some evidence that discretionary funds—in particular, discretionary equity funds—tend to have more exposure to well-known risk factors. Finally, we show that the dispersion of returns within the systematic and equity categories is similar.

Our analysis is conducted over the past 20 years. What about the future? Indeed, 20 years ago, advances such as neural networks were in vogue and they did not achieve much. We would argue that this time is different. The massive increase in computing power has enabled credible trading systems based on, for example, the modern day rebranding of neural networks, deep learning.

But what does this mean for the distinction between discretionary and systematic? One of the most interesting findings in our research is that the word "quant" is *not* part of our classification of systematic funds. The reason is simple: the word "quant" appears more often in descriptions of discretionary funds than in descriptions of systematic funds. Consistent with this finding, many discretionary funds are making investments in big data and machine learning. Hence, the distinction between systematic and discretionary is likely to blur in the future.

Our results show that an aversion to systematic managers, as displayed by some allocators, and in line with a more general "algorithm aversion" phenomenon, may be unjustified. However, these results should not be misconstrued to imply that systematic funds are intrinsically superior to discretionary. We believe it is likely that some market inefficiencies are more suitable for a systematic approach while others are better exploited by a discretionary approach. Also, most of our analysis was for hedge fund style index returns. The outlook for an investor who is skilled at selecting the best managers within a style may be quite different.

One could argue that the term "hedge fund" suggests hedged (or zero net) exposure to well-known risk factors. As a by-product of our risk-adjustment methodology, we mapped out the dominant risk factors for the different hedge fund styles. We find that in many cases the exposure is statistically significant and economically meaningful. We believe it is important for investors who allocate to hedge funds as part of a larger portfolio to be aware of the specific risk exposures of the different styles, because the non-hedge-fund investments may have a meaningful exposure to the same risk factors.

APPENDIX

FUND CLASSIFICATION METHOD

We use the HFR database on hedge funds, which classifies all hedge funds into four broad strategies: Equity Hedge, Event Driven, Macro, and Relative Value.[13] We focus on the Equity Hedge and Macro strategies, which are the largest and second-largest in terms of number of funds, respectively, and which naturally allow for both a discretionary and a systematic approach. For both strategies, we omit substrategies referred to as "multistrategy" because it would mostly likely be difficult to pinpoint the trading style and sector-specific substrategies, such as "Equity Technology/Healthcare" or "Macro Commodity-Agriculture." After doing so, we are left with the top four Equity Hedge and top two Macro substrategies in terms of fund count (see Exhibit A1).

Using Macro funds as a learning set, we search for "systematic words" defined as words that are more likely to occur in Macro Systematic Diversified than in Macro Discretionary Thematic fund descriptions. More precisely, we consider all strings of consecutive letters with a length of four or more and with the first letter coinciding with the start of a word. So the string "system" is counted not only if it occurs as standalone word, but also if "systems" or "systematic" occurs. We use three formal criteria that all need to be met:

1. **Material.** The difference between the percentage of systematic funds with the specified word and the percentage of discretionary funds with that word must be at least six percentage points.
2. **Polarizing.** The ratio of the percentage of systematic funds with the specified word and the percentage of discretionary funds with that word must be at least four times.
3. **Universal.** The ratio of the percentage of equity funds with the word and the percentage of macro funds with that word needs to be 0.21 times.[14]

By using the three criteria, we limit our selections to words that are material, polarizing, and universal in the sense that they are also relevant in an equity context. In Exhibit A1, we present the words that satisfy the three criteria (rows labelled as "this article"). The statistics associated with the three criteria are shown in the final three columns. Often, several similar words satisfy the criteria (e.g., "compute" and "computer"), in which case we typically select the longer word, unless it has a noticeably lower score on any of the three criteria used. The default choice for the longer word is to reduce the chance that the word is being used in an unexpected way in a different context (notably, the equity fund context).

A related paper by Chincarini [2014] compares performance and fees of quantitative and qualitative (as he calls it) funds. This is quite different from our study, as quantitative techniques are widely used (to a greater or lesser degree) by both systematic and discretionary funds. Also, Chincarini classifies Equity Market Neutral funds as quantitative by default. This is particularly problematic for comparing the equity market exposure (i.e., beta) of quantitative and qualitative funds: His finding that quantitative funds are more market neutral may be a direct result of the chosen categorization method. Comparing our words to those used by Chincarini [2014] (who partially relies on substrategy classifications as well) and referred to as such in Exhibit A1, one can see many differences. We pick up on "approx," "computer," and "system," which are highlighted in green for contrast. On the other hand, we don't use words such as "econometric" (which actually occurs more often in Discretionary Thematic descriptions) and "quantitative," which is quite common in Discretionary Thematic descriptions as well.[15]

Putting it all together, we classify funds for which the description contains at least one systematic word as *systematic* and all other funds are classified as *discretionary*. We considered using a list of discretionary words as well, but we found that it is harder to identify many words that are specific to discretionary managers, and thus, discretionary funds are best identified as not having any systematic words in their fund description. The fraction of funds classified as systematic for each HFR category is therefore given by the row "ANY" in the section labelled "This article" in Exhibit A1. For consistency, and because funds may be misclassified, we also use our classification for macro funds, rather than using the HFR classification. From Exhibit A1, Macro Systematic Diversified funds are classified as systematic in 68% of the cases, while for Macro Discretionary Thematic, this is only the case in 18%.

Looking through the Macro Systematic Diversified funds that we don't classify as systematic, there typically doesn't seem to be a clear indication that the fund is in fact systematic, and we deem it probable that the fund is rather partially systematic or quantitative, but not rules based. For equity funds, 49% of Equity Market Neutral, 41% of Quantitative Directional, 14% of Fundamental Growth, and 18% of Fundamental Value funds are classified as systematic.

In addition, we browsed through a number of descriptions for Equity Quantitative Directional funds *not* classified as systematic (i.e., classified as discretionary) and typically found no suggestions that the fund is actually systematic and,

EXHIBIT A1

HFR Category Names, Fund Count, Systematic Words Used

	HFR Substrategies						Criteria for "Systematic Words"		
	EQUITY Equity Market Neutral	EQUITY Quantitative Directional	EQUITY Fundamental Growth	EQUITY Fundamental Value	MACRO Systematic Diversified	MACRO Discretionary Thematic	%Systematic-%Discretionary (Cutoff: > 6.0%)	%Systematic/%Discretionary (Cutoff: > 4.0)	%EQUITY/%MACRO (Cutoff: > 0.21)
	Total Fund Count								
	1152	**689**	**2084**	**3030**	**1440**	**742**			
Word	Descriptions Containing Word (% of total)						**Material**	**Polarizing**	**Universal**
This Article									
algorithm	4.2%	8.3%	0.2%	0.3%	6.7%	0.3%	6.4%	24.7	0.37
approx	9.6%	6.2%	3.3%	4.0%	9.1%	1.8%	7.3%	5.2	0.75
computer	2.8%	5.4%	0.3%	0.5%	8.8%	0.5%	8.2%	16.2	0.22
model	28.5%	24.1%	7.2%	10.3%	30.8%	7.3%	23.5%	4.2	0.60
statistical	12.2%	5.8%	0.3%	1.1%	11.3%	1.9%	9.4%	6.0	0.39
system	18.8%	23.8%	4.8%	5.5%	54.0%	11.5%	42.6%	4.7	0.24
ANY	**48.8%**	**40.9%**	**14.0%**	**17.8%**	**68.4%**	**18.1%**	**50.3%**	**3.8**	**0.47**
Chincarini [2014]									
algorithm	4.2%	8.3%	0.2%	0.3%	6.7%	0.3%	6.4%	24.7	0.37
automate	2.1%	3.2%	0.0%	0.2%	3.9%	0.1%	3.8%	28.9	0.28
econometric	0.8%	0.7%	0.0%	0.0%	0.6%	1.1%	–0.5%	0.5	0.29
mathematical	2.0%	0.7%	0.2%	0.3%	4.9%	0.7%	4.3%	7.3	0.17
model	28.5%	24.1%	7.2%	10.3%	30.8%	7.3%	23.5%	4.2	0.60
quantitative	26.8%	21.2%	4.8%	8.2%	22.6%	13.2%	9.4%	1.7	0.59
statistic	12.3%	6.0%	0.5%	1.2%	11.6%	2.3%	9.3%	5.1	0.39
ANY	**45.9%**	**42.4%**	**11.3%**	**16.5%**	**47.7%**	**18.5%**	**29.2%**	**2.6**	**0.59**

Notes: For our six chosen HFR substrategies, we present the fund count and the percentage of fund descriptions containing a given word. In the last three columns, we also present the three criteria that all need to be met for a word to be deemed a "systematic word." We classify funds with at least one systematic word in their description as "systematic" and other funds as "discretionary" (see ANY row in the first block, labelled "This article"). For contrast, we also show the statistics for the words used in Chincarini [2014] in the second block, where we highlight in red words and statistics not satisfying our criteria. The other way around, we highlight in green words that we use and Chincarini [2014] does not.

in fact, often found language suggestive of a discretionary approach, such as "also opportunistically trades dislocations" or "identify investment opportunities through extensive meetings with company managements."

ENDNOTES

The authors would like to thank Chris Kennedy, Nick Granger, Shanta Puchtler, and Mark Refermat for their comments, as well as Goldman Sachs for providing option price data. Please direct correspondence to ovanhemert@ahl.com.

[1]See Wall Street Journal, May 21, 2017. https://www.wsj.com/articles/the-quants-run-wall-street-now-1495389108.

[2]For example, Fung and Hsieh [2002] mention that vendors started collecting hedge fund performance data in the early 1990s and that "post-1994 hedge fund data are less susceptible to measurement biases."

[3]That said, as a robustness check, we confirmed that the alpha and exposure to factors for systematic and discretionary macro funds (which we will discuss later in this article) is comparable when using the HFR classifications for Macro instead.

[4]Bloomberg tickers are SPX Index, LUATTRUU Index, and SBC2A10P Index for equity, bond, and credit, respectively.

[5]Carhart [1997] introduces the use of a momentum factor in relation to mutual fund performance.

[6]See mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[7]The Bloomberg ticker is DBHTG10U Index.

[8]Alternatively, one can use listed S&P 500 options, expiring on the third Friday of the month. We confirmed that the volatility factor we use has similar return and risk characteristics and is highly correlated to this alternative volatility factor. We prefer to use options expiring at the end of the month, because it is a more natural match to the monthly data used for hedge fund returns.

[9]The Fung and Hsieh [2001] PTFS risk factors require trading 26 pairs of straddles. The straddles are rolled to the new at-the-money contract whenever the underlying reaches a new high or low price, so as to replicate the behavior of a lookback straddle. Because several recent academic papers use the Fung and Hsieh volatility factors, we reran our regression analysis with them instead of the S&P 500 volatility factor and found that the risk-adjusted performance is similar for equity funds and slightly better for macro funds. To conserve space, we did not include these results in this article.

[10]The median is used here because it is robust to the occasional order-of-magnitude error we observe in the monthly AUM figures.

[11]The significance levels are only suggestive. Given that hundreds of factors have been tested, we are fully aware that a coefficient that is only two standard errors from zero is unlikely to be "significant" at the 5% level. See Harvey, Liu and Zhu [2016].

[12]The average-return approach essentially implies rebalancing fund weights to equal weights each month and, as such, is different from what a buy-and-hold position in each of the index constituents would give. See Granger et al. [2014] for a further discussion on this issue.

[13]See https://www.hedgefundresearch.com/hfr-hedge-fund-strategy-classification-system for an overview of strategy and substrategy names and descriptions (HFR [2016]).

[14]The cutoff values were chosen as the least-strict values for which only words that we consider germane to systematic strategies satisfy the criteria.

[15]Abis [2016] studies man versus machine performance in the context of mutual funds. Abis associates the word "quantitative" with her machine classification, like Chincarini [2014]. Again, we argue that many discretionary funds use quantitative inputs, which could lead to misclassification.

REFERENCES

Abis, S. "Man vs. Machine: Quantitative and Discretionary Equity Management." Working paper, 2016.

Bali, T., S. Brown, and M. Caglayan. "Macroeconomic Risk and Hedge Fund Returns." *Journal of Financial Economics*, Vol. 114, No. 1 (2014), pp. 1-19.

Carhart, M. "On Persistence in Mutual Fund Performance." *The Journal of Finance*, Vol. 52, No. 1 (1997), pp. 57-82.

Chincarini, L. "A Comparison of Quantitative and Qualitative Hedge Funds." *European Financial Management*, Vol. 20, No. 5 (2014), pp. 857-890.

Dietvorst, B., J. Simmons, and C. Massey. "Algorithm Aversion: People Erroneously Avoid Algorithms After Seeing Them Err." *Journal of Experimental Psychology: General*, Vol. 144, No. 1 (2015), pp. 114-126.

Fama, E. "Forward and Spot Exchange Rates." *Journal of Monetary Economics*, Vol. 14, No. 3 (1984), pp. 319-338.

Fama, E., and K. French. "Common Risk Factors in the Returns of Stocks and Bonds." *Journal of Financial Economics*, Vol. 33, No. 1 (1993), pp. 3-56.

Frazzini, A., D. Kabiller, and L. Pedersen. "Buffett's Alpha." Working paper, 2013.

Fung, W., and D. Hsieh. "The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers." *The Review of Financial Studies*, Vol. 14, No. 2 (2001), pp. 313-341.

——. "Benchmarks of Hedge Fund Performance: Information Content and Measurement Biases." *Financial Analyst Journal*, Vol. 58, No. 1 (2002), pp. 22-34.

Granger, N., D. Greenig, C.R. Harvey, S. Rattray, and D. Zou. "Rebalancing Risk." Working paper, 2014.

Hamill, C., S. Rattray, and O. Van Hemert. "Trend Following: Equity and Bond Crisis Alpha." Working paper, 2016.

Harvey, C.R., Y. Liu, and H. Zhu. "… and the Cross-Section of Expected Returns." *The Review of Financial Studies*, Vol. 29, No. 1 (2016), pp. 5-68.

Hedge Fund Research, Inc. (HFR). The website for HFR, headfundresearch.com, accessed June 14, 2016.

Jegadeesh, N., and S. Titman. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *The Journal of Finance*, Vol. 48, No. 1 (1993), pp. 65-91.

Meese, R., and K. Rogoff. "Empirical Exchange Rate Models of the Seventies: Do They Fit Out of Sample?" *Journal of International Economics*, 14 (1983), pp. 3-24.