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SUPERSTAR INVESTORS

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Superstar Investors

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“Ben Graham taught me 45 years ago that in investing it is not necessary to do extraordinary things to get extraordinary results.”

—Warren Buffett, 1994 Berkshire Hathaway
Annual Report

Many famous investors are outspoken about their investment philosophies, and carefully apply them to a select number of securities. In this article, we seek to apply their wisdom systematically to determine whether their philosophies applied broadly still generate alpha.^{1,2}

To do this, we apply one of the biggest so-called financial innovations of the

past few years: factor—or style—investing. Put simply, this type of investing typically follows well-known, time-tested principles in a rules-based manner (and thus hardly represents a true innovation). In this article we show how four very different, extraordinary track records—Berkshire Hathaway, PIMCO’s Total Return Fund in the Gross era, George Soros’s Quantum Fund, and Fidelity’s Magellan Fund under Peter Lynch—can be viewed as an expression of a handful of these systematic styles.^{3,4}

¹We are not the first to try to demystify successful investment strategies; see Siegel, Kroner, and Clifford (2001) for a range of public and private funds and institutions; Gergaud and Ziemba (2012) and Pedersen (2015) for hedge fund managers; Frazzini, Kabiller and Pedersen (2012) for a deeper treatment of Berkshire Hathaway; Hurst, Ooi, and Pedersen (2013) for trend-following strategies; and Chambers, Dimson, and Foo (2015) for Keynes. Additionally, see Asness et al. (2015) for more background on the styles underlying our analysis.

²Although our results may seem compelling, we have the clear benefit of hindsight—thus, any “alpha” that comes out of our analysis may be understated. These great investors “figured it out” first, had the ability to stick to their philosophies, and rightly deserve their reputations.

³Our focus is on performance, and not how much of it a specific portfolio manager was responsible for. In other words, we cannot say how much Berkshire Hathaway’s results reflect the contributions of Warren Buffett versus Charlie Munger, or how much of Quantum Fund’s results reflect decisions by George Soros versus Stanley Druckenmiller, or how much the many colleagues of Bill Gross and Peter Lynch at PIMCO and Fidelity contributed. Although these names are generally associated with these successful track records, we recognize that success is often the result of a team effort.

⁴An important caveat is that the factors used here are gross of fees, trading costs, and other real-world frictions and thus mechanically understate the “alpha” reported for these superstar track records. For an analysis of trading costs of factors such as those discussed here, refer to Frazzini, Israel, and Moskowitz (2012). Additionally, results of any regression analysis are sensitive to factor construction and specifications, which lead to either over- or understated alphas. For more on this point, we refer readers to Israel and Ross (2015).

But which styles should we test—and which should we not? Any analysis such as ours runs the risk of overfitting, or *p*-hacking—the bias that arises when you blindly include myriad inputs in the analysis, and then cherry-pick the ones that produce the best results in-sample (the kitchen sink approach).⁵ However, in our study, we can meaningfully reduce *p*-hacking bias by using the known styles pursued by our “superstars” (as demonstrated in their writings, their holdings, etc.) to first select a relevant list of inputs. For example, Buffett is a self-described value investor, so a natural style to test in Berkshire Hathaway’s returns is the value factor in equities. Buffett does not talk about momentum in his investment philosophy (nor does it seem relevant based on his average holding period), so we exclude the momentum factor in our analysis and thus reduce the likelihood of potentially spurious results. We follow this basic method throughout our study, regressing the returns associated with each “superstar” manager against the styles each manager uses to describe his investment philosophy.⁶

Our results suggest that idiosyncratic skill is not the only way to achieve long-run investment success. The takeaway for investors is to identify structural edges, such as the styles described here, and to commit to seeing them through inevitable periods of underperformance. As each of our superstars shows, “merely good” edges over time can compound to great long-term performance.

Two other effects are worth noting—and each influences alpha in the opposite direction. The first is that any study such as ours has some degree of unavoidable hindsight bias when choosing which factors to include. This results in some overfitting and “over-explanation” of these superstars’ track records, and thus will understate alpha. The second effect leads to alpha being overstated. How? This article picks four managers, out of thousands, who happened to do very, very well. Some readers may argue that we can’t be sure that these managers weren’t just very, very lucky, and that their true alpha is meaningfully smaller than what we estimate.

⁵ See, e.g., Harvey (2017) and Harvey, Liu, and Zhu (2016), and references therein.

⁶ A separate topic, but one that cannot be answered by this analysis, is whether these superstar investors skillfully harvested these styles or anomalies, or if they were merely lucky. Regardless, it’s likely they at least *knowingly* captured these anomalies, given each manager’s public writings on their investment styles, exemplified by the quotations we provide from each superstar.

BERKSHIRE HATHAWAY—VALUE, QUALITY, LOW-RISK (AND LEVERAGE)⁷

“Whether we’re talking about socks or stocks, I like buying quality merchandise when it is marked down.”

—Warren Buffett, 2008 Berkshire Hathaway Annual Report

1/1977– 5/2016 ⁸	Average Return	Volatility	Sharpe Ratio	Annual Outperformance	Information Ratio
Berkshire Hathaway	17.6%	23.6%	0.74	10.6%	0.49
US Equities ⁹	6.9%	15.5%	0.45	–	–

Sources: AQR, CRSP (for BRK data), Kenneth French Data Library (for Equities, which are CRSP cap-weighted returns; and risk-free rate, which is one-month Treasuries). For consistency, we’ve chosen the CRSP cap-weighted index to represent US Equities throughout this article. Returns are excess of cash throughout this article.

We start with Berkshire Hathaway (BRK) during the period from January 1977 to May 2016, following the methodology of Frazzini, Kabiller, and Pedersen (2012). We note that although BRK’s average annual return over this long period is much higher than that of the US stock market (excess of cash returns of 17.6% versus 6.9%), it also came with meaningfully higher volatility. Adjusting for volatility, BRK realized a Sharpe ratio of 0.74, compared with 0.45 for the broad US market.¹⁰

BRK has also produced significant alpha to traditional risk factors. However, we find that this alpha becomes statistically insignificant when controlling for some of the investment styles Buffett describes in his writings. Specifically, our “Buffett factors” for this analysis are:¹¹

- **Market:** the US equity market factor from Kenneth French’s data library
- **Value:** the HML factor from Kenneth French’s data library

⁷ For a more comprehensive analysis, including that of private holdings within Berkshire Hathaway, see Frazzini, Kabiller, and Pedersen (2012). One of their findings is that leveraging up low-risk, high-quality stocks (using insurance float and debt) has been a more important driver of Berkshire’s success than the better-known value tilt.

⁸ Returns in all exhibits are excess of cash, unless stated otherwise. Factor returns are all gross of fees and transaction costs.

⁹ US Equities throughout this article are the CRSP cap-weighted equity market factor from Kenneth French’s website.

¹⁰ Although a 0.74 Sharpe ratio might not seem stratospheric, it is higher than that of any other stock or mutual fund with a history of more than 30 years.

¹¹ See Appendix for details on factor construction.

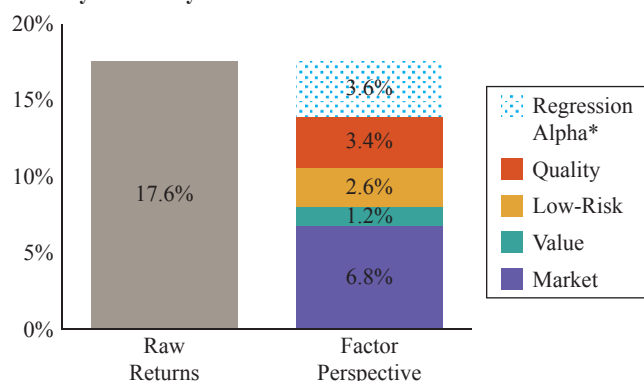
EXHIBIT 1

Berkshire Hathaway Stock, January 1977–May 2016 Regression Statistics

Panel A: Buffett's Factors

	Alpha (ann'l)	Market	Value	Low- Risk	Quality	R ²
Coefficient	3.6%	0.98	0.43	0.23	0.63	28%
T-Stat	1.03	12.41	3.60	2.64	4.64	

Panel B: Return Attributions Based on Regression Results,
January 1977–May 2016



Notes: Panel A: All variables here, and in subsequent exhibits, are excess of cash, unless stated otherwise. The market beta (0.98) is not statistically different than 1. The relatively low R² is due in part to high idiosyncratic volatility of Berkshire Hathaway stock compared with the broad factors used in the regression (as BRK includes not just public stocks but also wholly owned private companies). When separating Berkshire's portfolios into public stocks and private stocks, Frazzini, Kabiller, and Pedersen find higher R² values for the publics and lower for the privates.

Panel B: Contributions shown here are the product of the coefficients in the table and the average premium for each factor over the period January 1977–May 2016. *connotes estimates that are not statistically significant (i.e., t-stat less than 2).

- **Low-Risk:** the “Betting-Against-Beta” (BAB) factor¹² from AQR's data library
- **Quality:** the “Quality-Minus-Junk” (QMJ) factor¹³ from AQR's data library

Our regression results are presented in Panel A of Exhibit 1. Each of the “Buffett factors” used are statistically significant (i.e., the *t*-stats are all larger than 2), suggesting that each of these investment styles played a role in BRK's success. To provide a sense of magnitudes,

¹² As defined in Frazzini and Pedersen (2014).

¹³ As defined in Asness, Frazzini, and Pedersen (2014).

we also show an attribution (based on the regression results) in Panel B.¹⁴

One of the ways that Berkshire Hathaway was able to add so much return above that of the market was from access to cheap leverage via its insurance business, allowing it to harvest greater amounts of these style exposures than most traditional investors could.¹⁵ To get an idea of magnitude, for every dollar invested in BRK from 1977 through May 2016, investors on average got about \$1 exposure to the stock market (the market beta) and an additional \$1.3 dollars exposure to the other factor premiums shown in Exhibit 1 (the sum of the betas to the value, low-risk, and quality factors from the regression).

PIMCO'S TOTAL RETURN FUND—HIGH-YIELD CREDIT, SHORT MATURITY, SHORT VOLATILITY

“On a somewhat technical basis, my/our firm's tendency to sell volatility and earn ‘carry’ in a number of forms—outright through options and futures, in the mortgage market via prepayment risk, and on the curve via bullets and roll down as opposed to barbells with substandard carry—has been rewarded over long periods of time.”

—Bill Gross, *Investment Outlook*, April 2013¹⁶

1/1994– 9/2014 ¹⁷	Average Return	Volatility	Sharpe Ratio	Annual Outperformance	Information Ratio
PIMCO Total Return Fund	4.3%	4.1%	1.05	1.4%	0.83
Barclays US Aggregate	2.9%	3.6%	0.80	–	–

Sources: AQR, CRSP. Risk-free rate is one-month Treasury bills.

¹⁴ Return attributions are the factor coefficients multiplied by the average factor premium.

¹⁵ For more, see Frazzini, Kabiller, and Pedersen (2012). The authors use balance sheet data from Compustat/XpressFeed, hand-collected annual reports, holdings data for Berkshire Hathaway from Thomson Financial Institutional (13F) Holding Database (based on Berkshire's SEC filings), and the size and cost of the insurance float from hand-collected comments in Berkshire Hathaway's annual reports to estimate—among other characteristics—the leverage employed by Berkshire Hathaway, and the additional returns achieved via this leverage.

¹⁶ <https://www.pimco.com/insights/economic-and-market-commentary/investment-outlook/a-man-in-the-mirror>.

¹⁷ Our analysis starts in 1994 due to availability of factor data.

The PIMCO Total Return Fund (TRF) is arguably the best-known, and until recently the largest, bond fund in the world.¹⁸ Bill Gross was at the helm of TRF since its inception in 1987 until leaving PIMCO in 2014. Though Gross wasn't the sole portfolio manager, many of his well-read *Investment Outlooks* (including the one quoted above) described TRF's strategy to outperform the broader bond market.¹⁹

Gross's writings describe a long-run strategy of both harvesting many sources of returns, as well as trying to time them. For the former, many of these return sources were different forms of carry trades, summed up neatly by many bond managers as "own short-maturity BBBs," a well-known strategy for decades.²⁰ Although TRF's actual holdings were far broader (including mortgages, linkers and emerging market debt²¹), we find much of TRF's average excess return can be explained by exposure to shorter maturity names (using derivatives to achieve similar duration to the benchmark, the Barclay's US Aggregate), and picking up credit risk. Gross was also known to focus on another source of excess returns: short volatility. This was pursued in many ways, including exposure to mortgages, but we can express the same general idea of capturing the volatility risk premium by being short fixed income options.²²

Thus, to test if a "systematic Gross strategy" can explain the average returns of TRF, we use the following four factors:²³

- **Market:** Barclays US Aggregate Bond Index
- **Credit:** 5-year US High Yield CDX

¹⁸The PIMCO Total Return Fund hit a peak of \$292.9 billion in assets under management in April 2013, but was overtaken by Vanguard's Total Bond Market Index Fund in April 2015.

¹⁹Investment outlooks available at: <https://www.pimco.com/insights/economic-and-market-commentary>.

²⁰Of course, it didn't have to be BBB-rated debt, but the idea was that shorter-maturity, lower-rated debt was generally a "smart trade."

²¹Source: Morningstar.

²²The volatility risk premium is compensation paid by option buyers (i.e., insurance seekers) to sellers for bearing undesirable downside risk, and is typically measured by the difference between an option's implied volatility and its underlying asset's realized volatility. For more on this premium in multiple asset class contexts, see Israelov, Nielsen, and Villalon (2016).

²³See Appendix for details on factor construction.

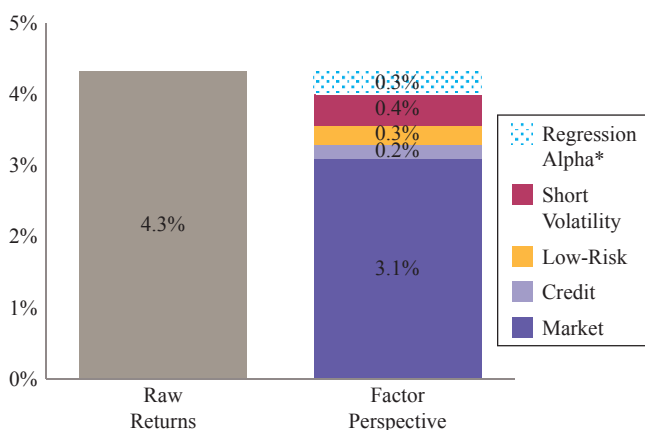
EXHIBIT 2

PIMCO Total Return Fund, January 1994–September 2014 Regression Statistics

Panel A: Gross Factors

	Alpha (ann'l)	Market	Credit	Low- Risk	Short Volatility	R ²
Coefficient	0.3%	1.06	0.06	0.07	0.04	88%
T-Stat	0.94	41.01	6.02	7.98	4.53	

Panel B: Return Attributions Based on Regression Results, January 1994–September 2014



Notes: Panel A: All data in this exhibit are gross of fees. Explanatory variables are gross of transactions costs. Market is the Barclays US Aggregate Bond Index, excess of cash, credit is 5-year US High Yield CDX, short maturity (rank-sorted portfolio of negative maturity on US 2/5/10/20-year bond futures), and short volatility (the returns from selling 1-month, 30-delta strangles on 10-year Treasury futures, delta-hedged). The "market beta" is statistically larger than 1.0 (with a t-stat of 2.32), suggesting that a portion of excess returns was also likely from taking more duration risk on average.

Panel B: *connotes estimates that are statistically insignificant.

- **Low-Risk:** duration neutral factor that is long 2- and 5-year, versus short 10- and 30-year US bond futures²⁴
- **Short Volatility:** selling 1-month, 30-delta strangles on 10-year Treasury futures²⁵

A regression against TRF shows that these factors can help explain much of the average returns, with statistically significant exposures on each factor (see Exhibit 2 for statistics and an illustrative return attribution).

²⁴More plainly, a factor that is long shorter duration bonds and short longer duration bonds (the "Betting Against Beta" [BAB] factor is the analogous concept in equities).

²⁵Delta-hedged.

THE QUANTUM FUND—EQUITIES, TREND (EVERYWHERE), AND FUNDAMENTAL CURRENCY TRADING

“We try to catch new trends early and in later stages we try to catch trend reversals. Therefore, we tend to stabilize rather than destabilize the market. We are not doing this as a public service. It is our style of making money.”

—George Soros²⁶

3/1985–5/2004 ²⁷	Average Return	Volatility	Sharpe Ratio
Quantum Fund	20.2%	23.1%	0.88
US Stock Market	7.8%	15.8%	0.49

Sources: AQR, HFR. Risk-free rate is 1-month Treasuries. For consistency, we’ve chosen the CRSP cap-weighted index to represent US Equities throughout this article.

George Soros is not only one of the first, but also arguably one of the most successful hedge fund managers of all time. He focuses on global macro strategies, and is particularly well known as a currency trader. Among his most successful funds is the Quantum Fund, perhaps best known for short-selling the British pound during the 1992 U.K. currency crisis (a trade attributed to Soros and Stanley Druckenmiller), which made around \$1B profit and led to Soros’s reputation as “the man who broke the Bank of England.”

Soros is known for developing a theory of boom/bust cycles and reflexivity, based on negative and positive feedback between prices and fundamentals (emphasizing the role of self-reinforcing positive feedback). Given his focuses on trends and currencies, our “Quantum factors” are:²⁸

- **Market:** the US equity market factor from Kenneth French’s data library
- **Trend**
 - In stocks, the UMD factor from Kenneth French’s data library²⁹

²⁶ As quoted in Bass (1999) “The Predictors,” Henry Hold and Company.

²⁷ Unfortunately, due to data availability we have “only” 20 years of data to analyze.

²⁸ See Appendix for details on factor construction.

²⁹ Though Soros did trade Japanese and European stocks, we use only a US equities momentum factor here, given his focus on US stocks.

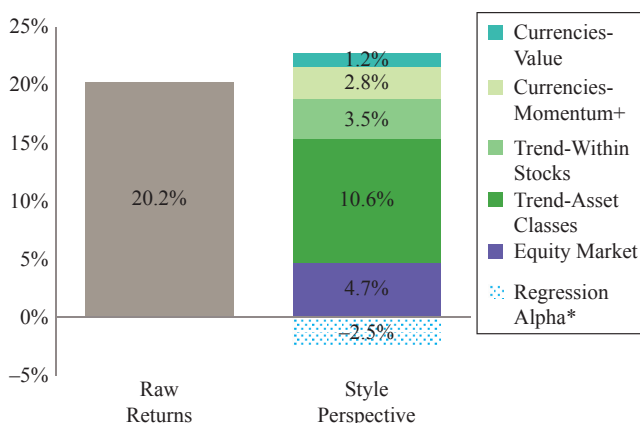
EXHIBIT 3

The Quantum Fund, March 1985–May 2004 Regression Statistics

Panel A: Soros Factors

	Alpha (Ann'l)	Market	Trend		Currencies		R ²
			Within Stocks	Asset Classes	Momentum	Value	
Coefficient	−2.5%	0.60	0.32	0.59	0.56	0.29	38%
T-Stat	−0.53	7.50	3.69	5.29	4.49	2.31	

Panel B: Return Attributions Based on Regression Results, March 1985–May 2004



Notes: Panel A: Quantum Fund returns are net of fees and only cover a portion of the full track record (due to data availability). Explanatory variables are gross of fees and transaction costs (which drives the alpha in the regression lower).

Panel B: + is used to highlight fundamental momentum, as opposed to traditional price-based momentum (see footnote 31).

*connotes estimates that are not statistically significant.

Source: HFR.

- In macro asset classes, the Time Series Momentum (TSMOM) factor³⁰ from AQR’s data library
- **Currencies**
 - Momentum: a “fundamental” measure using trailing 1-year equity market momentum, applied to G10 currencies³¹

³⁰ As defined in Hurst, Ooi, and Pedersen (2014).

³¹ As opposed to purely price-based momentum, “fundamental momentum” focuses on changes in non-price measures. For example in stocks, fundamental momentum may include earnings momentum, changes in profit margins, and changes in analysts’ forecasts. For more, see Novy-Marx (2015), Dahlquist and Hasseltoft (2016), and Brooks (2017).

- Value: purchasing power parity applied across G10 markets³²

Exhibit 3 shows results of our regression analysis (table) and a regression-based attribution of Quantum's average returns (bar chart). Not surprisingly, trend/momentum factors go a long way in explaining the average returns over the period.

MAGELLAN—SMALL STOCKS, MOMENTUM... AND A LOT OF ALPHA

Peter Lynch, 25 Years Later: It's Not Just 'Invest in What You Know' The one-time mutual-fund rock star says the famous advice isn't quite so simple

—Chana R. Schoenberger (2015) Wall Street Journal, Dec 6, 2015

5/1977– 5/1990	Average Return	Volatility	Sharpe Ratio	Annual Outperformance	Information Ratio
Magellan	20.8%	21.2%	0.98	13.7%	1.78
US Equities	7.1%	16.4%	0.43	—	—

Source: AQR, CRSP, Morningstar. Risk-free rate is 1-month Treasuries. For consistency, we've chosen the CRSP cap-weighted index to represent US Equities throughout this article.

Peter Lynch was at the helm of Fidelity's Magellan Fund from May 1977 to May 1990, over which time the mutual fund grew from approximately \$20M to \$14B (reflecting both returns and inflows), and posted an average excess of cash return of 21% (compared with the stock market's 7% excess return over the same period).³³

Like other superstars covered here, Lynch was public about his investment philosophy, having authored multiple books on the topic.³⁴ Yet Lynch's philosophy was arguably less parsimonious than that of the other superstars: he had various checklists for various categories of companies,³⁵ making the task of evaluating Magellan's track record via broad factors more difficult (and maybe less relevant).

Without a straightforward mapping from philosophy to well-known factors, we instead include some of

the most-used factors from academia.³⁶ Thus our "Lynch factors" are:³⁷

- **Market:** both the US equity market factor from Kenneth French's data library and the Barclays US Aggregate Bond Index³⁸
- **Size:** the SMB factor from Kenneth French's data library
- **Value:** the HML factor from Kenneth French's data library
- **Momentum:** the UMD factor from Kenneth French's data library
- **Quality:** the QMJ factor from AQR's data library
- **Low-Risk:** the BAB factor from AQR's data library

Our findings are presented in Exhibit 4. Part of Magellan's outperformance seems to be from taking more risk than the market,³⁹ and harvesting small cap and momentum premiums. We also find some exposure to the value premium, but smaller in magnitude. Although exposure to the quality premium is not statistically significant (i.e., the *t*-stat is below 2), we note that even when applied systematically, "quality" is among the most heterogeneous investment styles, and thus may be harder to measure. Finally, we note that Lynch's impressive performance appears to have been in spite of negative exposure to the low-risk premium (unlike for Buffett, who harvested it).

However, despite the plethora of factors examined here, the headline from this analysis might be that Magellan still posted more than 8% "alpha" on average each year for 13 years. Capping it off, Lynch is famous for the rare feat of having left at the top—his successors at Magellan have had a much more typical track record (in the 13 years following Lynch's departure, Magellan's alpha relative to the equity market factor has been indistinguishable from zero).⁴⁰

³⁶ We are fully cognizant of the risk of data-mining, given Lynch's investment philosophies don't map strongly to these standard factors. Note that these are all US factors, given Magellan's focus on US markets.

³⁷ See Appendix for details on factor construction.

³⁸ Magellan's investment policies permitted allocations to "so-called 'defensive securities,' including fixed-income securities of all types and US government obligations." For instance, corporate and treasury bonds represented 15% of Magellan's assets as of 9/30/1982.

³⁹ The beta of 1.16 is statistically higher than 1.0, with a *t*-stat of 3.91.

⁴⁰ Over the period May 1990–Dec 2012, using the same US Equities factor as in the previous analysis. Interestingly, the beta to

³² More specifically, PPP applied to G10 FX backtest (rank standardized portfolio, scaled to 10% ex post volatility).

³³ AUM figures from Morningstar.

³⁴ Including (subsequent to the period discussed here) in Lynch and Rothchild (1994, 2000).

³⁵ E.g., see Lynch and Rothchild (1994, chapter 15).

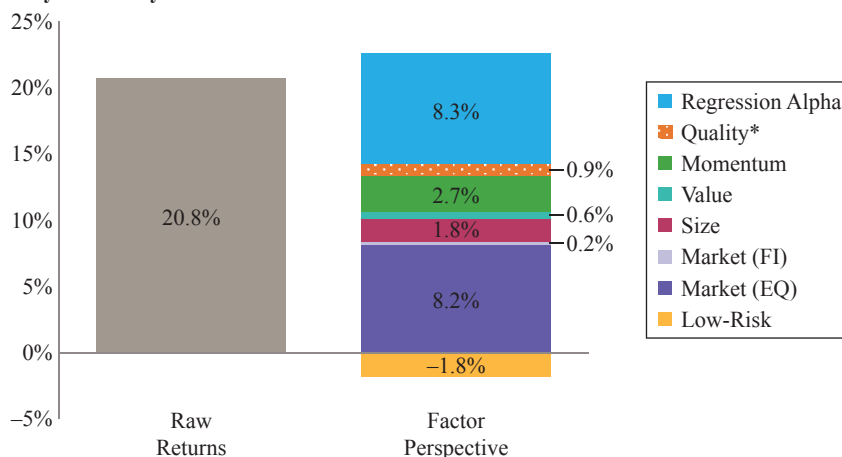
EXHIBIT 4

The Magellan Fund, May 1977–May 1990 Regression Statistics

Panel A: Lynch Factors

	Alpha (Ann'l)	Market (EQ)	Market (FI)	Size	Value	Momentum	Quality	Low-Risk	R ²
Coefficient	8.3%	1.16	0.14	0.64	0.17	0.26	0.15	−0.13	95%
T-Stat	4.53	28.18	2.39	10.00	2.18	5.17	1.48	−2.56	

Panel B: Return Attributions Based on Regression Results,
May 1977–May 1990



Notes: Panel A: All data in this exhibit are gross of fees. Explanatory variables are gross of transactions costs. Market (EQ) is the CRSP cap-weighted stock market index, excess of cash; Market (FI) is the Barclays US Aggregate Bond Index, excess of cash; Size and Value are the SMB and HML factors, respectively, as defined in Fama and French (1992); Momentum is the UMD momentum factor; Quality is the “Quality minus Junk” factor as defined in Asness, Frazzini, and Pedersen (2014); Low-Risk is the “Betting-Against-Beta” factor as defined in Frazzini and Pedersen (2014). Market beta is statistically different than 1.0.

Panel B: *connotes factor loadings that are statistically insignificant.

WHAT ABOUT MARKET TIMING?^{41,42}

Berkshire Hathaway

BRK’s equity market exposure, or beta, in general has fallen over 40 years (which means less returns from the equity risk premium). But this beta has varied meaningfully around its long-term decline, which leads to an interesting question: has tactical market exposure been an additional source of returns for BRK? One way to test this is to examine the “tactical beta” (which we define as the difference between the rolling 36-month

beta and the full-sample beta).⁴³ If this tactical beta was higher/lower when the market performed well/poorly, that would imply market timing skill.

The data shows no meaningful correlation between changes in market exposure and market returns, suggesting that market timing—whether intentional or not—has not been a source of “alpha” for BRK. In other words, BRK’s impressive long-term track record may be less about market timing

the equity market over this period is still above 1.0 (as it was during the Lynch era).

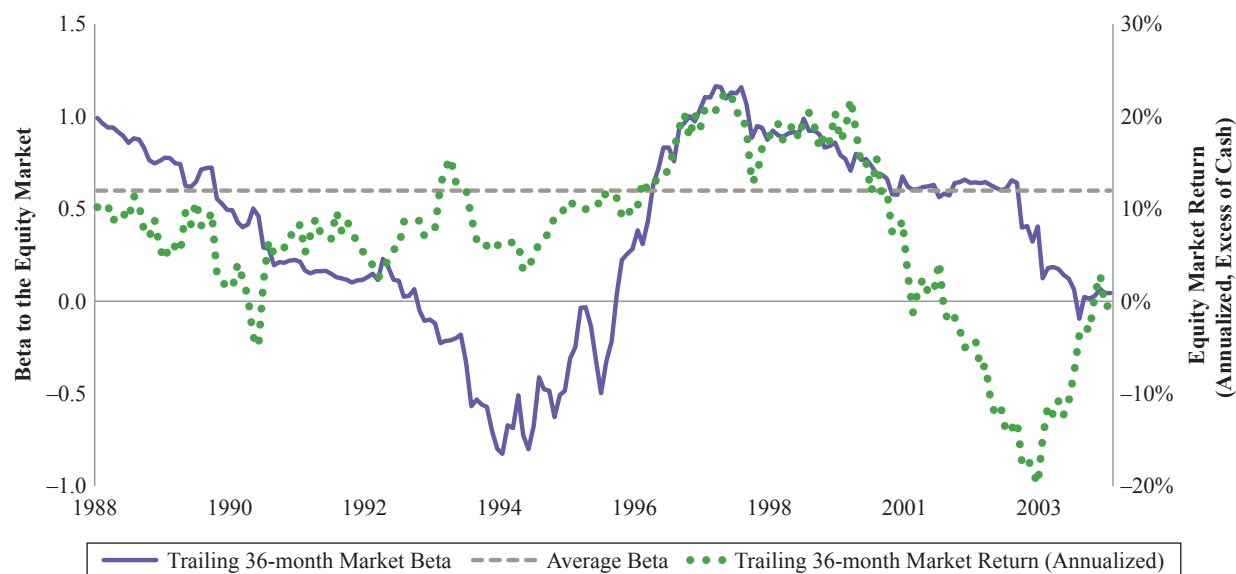
⁴¹For brevity, we do not include exhibits on timing (except for Quantum) and describe only high-level findings in this article.

⁴²We leave tests of factor, or style, timing for a separate article.

⁴³Specifically, for all track records, we look at the correlation between 36-month “tactical beta” and contemporaneous market return. “Tactical beta” is the difference between trailing 36-month beta and average (full sample) beta. We also analyzed tactical market exposures over a shorter horizon, using rolling 24-month observations, and find the same general results (though not shown here for brevity).

EXHIBIT 5

Quantum's 36-Month Rolling Beta to Equities vs. Market Returns, 1988–2003



Notes: The chart represents Quantum's 36-month rolling beta to equities (the CRSP cap-weighted equity factor) alongside market returns over the period 1988–2003. The average beta is from the full-sample regression, not the average of the 36-month market beta line.

Source: HFR, AQR.

and more about exposure to well-rewarded investment styles.⁴⁴

PIMCO Total Return Fund in the Gross Era

Our analysis of TRF did not include any time-variation in exposures, and thus already implies that tactical timing may have been less important to TRF's success than many investors assume. However, we know TRF timed markets, famously by tactically timing Treasury duration (and on occasion US dollar movements), and much of PIMCO's communication focused on secular and cyclical bets.

We find mixed success for “beta timing”: when it comes to timing exposure to the benchmark (in this case, duration timing), we find no correlation between market timing decisions and over/underperformance of the benchmark.⁴⁵

⁴⁴ Which is not surprising, given how much of BRK's average excess returns in Exhibit 1 could be attributed to these styles.

⁴⁵ The specific benchmark we use here is the Barclays US Aggregate.

In other words, duration timing—while certainly a feature of TRF—did not seem to add much value on average. In contrast, we find that credit timing may have added value.⁴⁶ Specifically, TRF increased its exposure to the credit premium following the financial crisis (a period over which credit performed well).

The Quantum Fund⁴⁷

Hedge fund managers as a group are long-equity biased,⁴⁸ and Soros seems to be no exception, with the Quantum Fund posting an average market beta of 0.6 over this 20-year period. However, the beta varies considerably around this average (see Exhibit 5)—over some

⁴⁶ More specifically, we find a 0.5 correlation between changes in 36-month rolling betas to contemporaneous 36-month high yield factor (5-year US High Yield CDX) returns, and a 0.3 correlation between changes in 24-month rolling betas to contemporaneous 24-month high yield factor returns.

⁴⁷ For brevity we address only time-varying equity market exposure.

⁴⁸ We've highlighted this going back at least 15 years—see, e.g., Asness, Krail, and Liew (2001).

three-year periods, the Quantum Fund had a beta in excess of 1, and in others, the beta was negative.

Did this market timing help? Exhibit 5 provides a simple way of approaching this question, by graphing Quantum's 36-month rolling beta to equities (purple line) alongside market returns (green dots) over those same periods. Visually, the decision to decrease market exposure in the early 1990s appears to have detracted value (as equity market returns were strongly positive over that period), and the decision to increase market exposure seems to have positively contributed in the late 1990s during the tech bubble. Over the 20-year sample, we find a positive correlation between his "tactical beta"⁴⁹ and returns, suggesting that Soros was able to add alpha via market timing.⁵⁰

Magellan in the Lynch Era

Given the magnitude of the alpha in the Magellan regression and attribution, it's natural to turn to market timing as a potential source of excess returns. However, our results suggest little (if any) timing benefit, suggesting that security selection was a much greater source of Magellan's success than was market timing.

CONCLUSION: LEARNING FROM THE MASTERS

"But let me admit something... All of us, even the old guys like Buffett, Soros, Fuss, yeah—me too, have cut our teeth during perhaps a most advantageous period of time, the most attractive epoch, that an investor could experience. Since the early 1970s ... an investor that took marginal risk, levered it wisely and was conveniently sheltered from periodic bouts of deleveraging

⁴⁹ Defined here as the difference between rolling 36-month beta and average beta.

⁵⁰ Our data extends only to 2004, and misses when Soros returned to the helm of Quantum to navigate through the financial crisis: "my coming out of retirement, or semiretirement, to take an active role in anticipation of the financial crisis of 2008 ... [Quantum] was a pretty large fund, where the positions tended to be on the long side so I opened a macro account where I hedged, basically, the positions of others and took positions that were net/net short" (Interview with George Soros in "Efficiently Inefficient" (2015)).

or asset withdrawals could, and in some cases, was rewarded with the crown of 'greatness.'"

—Bill Gross, Investment Outlook, April 2013

What can investors take away from this analysis? First, for many great investors success is not luck or chance, but reward for long-term exposure to styles that have historically produced excess returns. Second, the styles we analyzed have been successful in many contexts—from fixed income portfolios to global macro hedge funds.⁵¹ This has clear implications for manager selection, regardless of whether the manager is fundamental or quantitative, traditional or alternative: investors should understand which (if any) styles are part of a manager's process, and decide whether there are positive expected returns associated with those styles. Third, styles alone aren't sufficient for success; they also require patience, ability, and a long-horizon to stick with them.

So what about "alpha"? As Lynch shows, the onslaught of common (and some less common) factors still can't explain all of his outperformance—even with the benefit of hindsight. We are forced to conclude—at least for now—that part of Magellan's success was more than just compensation for style exposure. Namely, a meaningful portion of those excess returns was, and probably still is, "alpha."

What about for the other managers, the ones with no "alpha" in our regressions? They too had "alpha," but relative to what we knew about markets back when they were actually investing. Surely that should count.

Bigger picture, regardless of whether outperformance comes from alpha or style "betas," investors today face low expected returns across traditional asset classes.⁵² Given these headwinds, any additional non-market sources of returns may be especially valuable. While historically the main way to outperform was via alpha or simply taking more risk, investors now have access to a suite of other style premiums; potentially allowing for multiple paths to long-term success.

⁵¹ See Asness et al. (2015) for decades of evidence across multiple regions and asset classes.

⁵² See Asness and Iltanen (2012); also AQR Alternative Thinking 1Q2016 for more recent capital market assumptions; and, from a defined contribution perspective, Iltanen, Rauseo, and Truax (2016).

APPENDIX A

FACTOR DESCRIPTIONS

For Berkshire Hathaway

- Market (as described in Kenneth French's Data Library): $R_m - R_f$, the excess return on the market, value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 at the beginning of month, good shares and price data at the beginning of t , and good return data for t minus the one-month Treasury bill rate (from Ibbotson Associates). See Fama and French, 1993, "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics*, for a complete description of the factor returns.
- Value (as described in Kenneth French's Data Library): HML (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios, $HML = 1/2$ (Small Value + Big Value) $- 1/2$ (Small Growth + Big Growth). HML includes for July of year t to June of $t + 1$ all NYSE, AMEX, and NASDAQ stocks for which we have market equity data for December of $t - 1$ and June of t , and (positive) book equity data for $t - 1$.
- Low-Risk: the "Betting-Against-Beta" (BAB) factor from AQR's data library, as defined in Frazzini and Pedersen (2014). BAB factors are portfolios that are long low-beta securities and that short-sell high-beta. To construct each BAB factor, all securities in a country are ranked in ascending order on the basis of their estimated beta and the ranked securities are assigned to one of two portfolios: low-beta and high-beta. In each portfolio, securities are weighted by the ranked betas (lower-beta securities have larger weights in the low-beta portfolio and higher-beta securities have larger weights in the high-beta portfolio). The portfolios are rebalanced every calendar month. To construct the BAB factor, both portfolios are rescaled to have a beta of one at portfolio formation. The BAB is the self-financing zero-beta portfolio that is long the low-beta portfolio and that short-sells the high-beta portfolio.
- Quality: the "Quality-Minus-Junk" (QMJ) factor from AQR's data library, as defined in Asness, Frazzini, and Pedersen (2014). The Quality Score is the average of four aspects of quality: Profitability, Growth, Safety, and Payout. We use a broad set of measures to compute each of four aspects of quality; the score for each aspect is the average of the individual z-scores of the underlying measure. Each variable is converted each month

into ranks and standardized to obtain the z-score. 1) Profitability is measured by: Gross profits over assets, return on equity, return on assets, cash flow over assets, gross margin, and the fraction of earnings composed of cash. 2) Growth is measured by: The five-year prior growth in profitability, averaged across the measures of profitability. 3) Safety is defined as: Companies with low beta, low idiosyncratic volatility, low leverage, low bankruptcy risk, and low ROE volatility. 4) Payout is defined using: Equity and debt net issuance and total net payout over profits. QMJ factors are constructed as the intersection of six value-weighted portfolios formed on size and quality. At the end of each calendar month, we assign stocks to two size-sorted portfolios based on their market capitalization. For US securities, the size breakpoint is the median NYSE market equity. We use conditional sorts, first sorting on size, then on quality. Portfolios are value-weighted, refreshed every calendar month, and rebalanced every calendar month to maintain value weights. The QMJ factor return is the average return on the two high-quality portfolios minus the average return on the two low-quality (junk) portfolios.

For PIMCO Total Return

- Market: Barclays US Aggregate Bond Index minus 1-month Treasury bills (the risk-free rate used elsewhere in this article).
- Credit: 5-year US High Yield CDX.
- Short Maturity: We rank 2-year, 5-year, 10-year, and 20-year US bond futures by their respective durations. The portfolio goes long the futures whose durations are below average, and short the futures with durations above average. Finally, the positions are re-scaled to be duration-neutral.
- Short Volatility: The returns from selling a 1-month maturity, 30-delta strangle (i.e., selling a put and a call option), delta hedged option on US 10-year bond futures.

For Quantum:

- Market: same as used for the Berkshire Hathaway analysis.
- Trend.

In stocks: the UMD factor (as described in Kenneth French's Data Library): is constructed monthly, using the intersections of 2 portfolios formed on size (market equity,

ME) and 3 portfolios formed on prior (2–12) return. The monthly size breakpoint is the median NYSE market equity. The monthly prior (2–12) return breakpoints are the 30th and 70th NYSE percentiles.

In macro asset classes: the Time Series Momentum (TSMOM) factor from the AQR data library. We construct a return series for each of the underlying instruments as follows: Each day, we compute the daily excess return of the most liquid futures contract (typically the nearest or next nearest to delivery contract), and then compound the daily returns to a total return index from which we can compute returns at any horizon. We size each position (long or short) so that it has an ex ante annualized volatility of 40%. (Note: the choice of 40% is inconsequential, but it makes it easier to intuitively compare our portfolios to others in the literature, as it has an annualized volatility of about 12% per year over the sample period which is roughly the level of volatility exhibited by other factors such as those of Fama and French (1993) and Asness et al. (2013)). For more on this factor, see Moskowitz, Tobias J., Yao Hua Ooi and Lasse H. Pedersen, 2012, “Time Series Momentum,” *Journal of Financial Economics*, 104 (2), 228–250).

- Currencies

Momentum: a “fundamental” measure using trailing 1-year equity market momentum. We rank the 12-month equity returns for every country in our region (AU, BD, CN, JP, NW, NZ, SD, SW, UK, and US). The portfolio goes long the currency of any country whose equity return ranks above average, and goes short the below average countries. Finally, the positions are re-scaled to be dollar-neutral.

Value: purchasing power parity applied across G10 markets. We rank each country by their real exchange rate (spot rate divided by purchasing power parity). The portfolio goes long the currencies of the countries whose real exchange rates rank above average, and goes short the below average countries. Finally, the positions are re-scaled to be dollar-neutral.

For Magellan in the Lynch Era:

- Market:

Equities: the same as used for the Berkshire Hathaway analysis.

Fixed income: the same as used for the PIMCO Total Return analysis.

- Size: the SMB factor (as described in Kenneth French’s Data Library): is the average return on the three small

portfolios minus the average return on the three big portfolios: $SMB = 1/3$ (Small Value + Small Neutral + Small Growth) – $1/3$ (Big Value + Big Neutral + Big Growth). See Fama and French, 1993, “Common Risk Factors in the Returns on Stocks and Bonds,” *Journal of Financial Economics*, for a complete description of the factor returns.

- Value: the same as used for the Berkshire Hathaway analysis.
- Momentum: the same UMD factor as used in the Quantum analysis.
- Quality: the same as used for the Berkshire Hathaway analysis.
- Low-Risk: the same as used for the Berkshire Hathaway analysis.

REFERENCES

Asness, C., A. Frazzini, and L. H. Pedersen. 2014. “Quality Minus Junk.” AQR Working Paper.

Asness, C., and A. Ilmanen. 2012. “The Five Percent Solution.” *Institutional Investor*.

Asness, C., A. Ilmanen, R. Israel, and T. J. Moskowitz. 2015. “Investing with Style.” *Journal of Investment Management* 13 (1): 27–63.

Asness, C., R. Krail, and J. Liew. 2001. “Do Hedge Funds Hedge.” *The Journal of Portfolio Management* 28: 6–19.

Asness, C., T. J. Moskowitz, and L. H. Pedersen. 2013. “Value and Momentum Everywhere.” *The Journal of Finance* 68 (3).

Brooks, J. 2017. “A Half Century of Macro Momentum.” AQR Capital Management White Paper.

Chambers, D., E. Dimson, and J. Foo. 2015. “Keynes the Stock Market Investor.” *Journal of Financial and Quantitative Analysis* 50 (4): 843–868.

Dahlquist, M., and H. Hasseltoft. 2016. “Economic Momentum and Currency Returns.” Swedish House of Finance Research Paper No. 16–14.

Fama, E. F., and K. R. French. 1992. “The Cross-Section of Expected Stock Returns.” *The Journal of Finance* 47 (2): 427–465.

———. 1993. “Common Risk Factors in the Returns on Stocks and Bonds.” *The Journal of Financial Economics* 33: 3–56.

- Frazzini, A. R., Israel, and T. J. Moskowitz. 2012. "Trading Costs of Asset Pricing Anomalies." Fama-Miller Working Paper 14-05.
- Frazzini, A., D. Kabiller, and L. H. Pedersen. 2012. "Buffett's Alpha." NBER Working Paper No. 19681.
- Frazzini, A., and L. H. Pedersen. 2014. "Betting Against Beta." *The Journal of Financial Economics* 111: 1-25.
- Gergaud, O. and W. Ziemba. 2012. "Great Investors: Their Methods, Results, and Evaluation." *The Journal of Portfolio Management* 38: 128-147.
- Harvey, C. R. 2017. "The Scientific Outlook in Financial Economics." Duke I&E Research Paper No. 2017-05.
- Harvey, C. R., Y. Liu, Y., and H. Zhu. 2016. "... and the Cross-section of Expected Returns." *Review of Financial Studies* 29, 5-68.
- Hurst, B., Y. H. Ooi, and L. H. Pedersen. 2013. "A Century of Evidence on Trend-Following." AQR Working Paper.
- . 2014. "Time Series Momentum." *Journal of Financial Economics* 104 (2): 228-250.
- Ilmanen, A., M. Rauseo, and L. Truax. 2016. "How Much Should DC Savers Worry about Expected Returns?" *The Journal of Retirement* 4 (2): 44-53.
- Israel, R., and A. Ross. 2015. "Measuring Portfolio Factor Exposures: Uses and Abuses." AQR Working Paper.
- Israelov, R., L. N. Nielsen, and D. Villalon. 2016. "Embracing Downside Risk." *The Journal of Alternative Investments* 19 (3): 59-67.
- Lynch, P., and J. Rothchild. 1994. *Beating the Street*. New York: Simon & Schuster.
- . 2000. *One Up on Wall Street: How to Use What You Already Know to Make Money in the Market*. New York: Simon & Schuster.
- Novy-Marx, R. 2015. "Fundamentally, Momentum is Fundamental Momentum." NBER Working Paper No. 20984.
- Pedersen, L. H. 2015. *Efficiently Inefficient: How Smart Money Invests and Market Prices Are Determined*. Princeton, NJ: Princeton University Press.
- Siegel, L. B., K. F. Kroner, and S. W. Clifford. 2001. "The Greatest Return Stories Ever Told." *The Journal of Investing*, 10 (2): 91-102.

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