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DAVID BLITZ AND PIM VAN VLIET

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The Conservative Formula: *Quantitative Investing Made Easy*

David Blitz and Pim van Vliet

David Blitz
is the head of quantitative equity research at Robeco Asset Management in Rotterdam, the Netherlands.
d.c.blitz@robeco.nl

Pim van Vliet
is the founder and head of Conservative Equities at Robeco Asset Management in Rotterdam, the Netherlands.
p.van.vliet@robeco.nl

The early tests of the capital asset pricing model (CAPM) in the 1970s showed that the empirical risk–return relation is too flat. This low-risk effect is now regarded as one of the very first stock market anomalies. Many other anomalies have been documented since, such as the size, value, quality, and momentum effects. However, the "publish or perish" culture in academia may give a bias toward many false positive results. Harvey, Liu, and Zhu [2016] articulated this concern, documented the recent explosion in the number of factors, and suggested that thresholds for statistical significance be raised. Hou, Xue, and Zhang [2017] took a fresh look at the anomalies literature and found that many results cannot be replicated and are therefore likely the result of factor fishing. Moreover, the significance of many factors turns out to be critically dependent on methodological assumptions such as frictionless rebalancing, no leverage costs, and unlimited short-selling of micro caps.

Investors who want to profit from academic insights therefore have to be very careful. First, they should be highly critical as to which factors work and which do not because many results are spurious. The number of factors needs to be narrowed down to a subset that is persistent and robust. Second, translating multiple factors into one easily implementable investment strategy is not straightforward. Today, a good starting point for a limited set of persistent factors might be the ones identified by Fama and French [2015]. These factors are rigorously tested, complement each other, and require a limited amount of trading. To benefit, investors should tilt their portfolio toward small, attractively priced, profitable firms with low levels of investments. However, Fama and French did not create one integrated investment portfolio, but rather separate long–short portfolios for each factor, with many overlapping positions. This is of little use for investors looking for an easy and effective factor-based investment strategy. One could consider identifying stocks that score well on each of the Fama–French factors, but with such an approach the resulting number of stocks will be very low. For example, the expected number of stocks with a top quintile score on each of five independent factors is less than 1 in 3,000. Moreover, most investors face constraints on leverage and short selling. Therefore, an important practical question is how investors can obtain one liquid, easy to implement, long-only portfolio that gives access to multiple factors simultaneously.

These practical considerations are less relevant for academics. If a simple investment strategy is profitable but can be explained by exposures to a wide range of theoretical long–short factors, then from an academic point of view there is no relevant contribution to the existing literature, even if the control factors require the use of accounting data, rely on micro caps, require high-frequency trading, and assume full shorting opportunities. For practitioners, however, efficient exposure to multiple established factor premiums simultaneously is desirable—especially if this can be achieved in a single liquid portfolio that requires infrequent rebalancing, does not require expensive borrowing and/or shorting, and is not critically dependent on the inclusion of microcaps.

It comes as no surprise therefore that books that present simple investment formulas are very popular among investors. Value investing was popularized by the investment book *The Intelligent Investor* by Graham [2005], who presented an intrinsic value formula in the 1973 version of his book. In 1991, a strategy called the *Dogs of the Dow* was proposed, which selects stocks with the highest dividend yields from the Dow Jones Industrial Average Index (see O'Higgins and Downes [2000]). Greenblatt [2006] combines value (earnings to enterprise value) with a quality measure (return on capital) in his "Magic Formula," which helps investors identify the best 30 stocks.

More recently, Van Vliet and de Koning [2016] explained the concept of low-risk investing to investors and presented a new investment formula that selects 100 conservative stocks based on volatility, net payout yield (NPY), and momentum. The aim of this article is to rigorously test this easy-to-implement *Conservative Formula*, which aims to give investors full and efficient exposure to the strongest academic factor premiums. The formula relies on simple price data and dividend data only, which enables us to back test its persistency and robustness all the way back to 1929. The limited number of simple factors also reduces the risk of p-hacking or factor fishing. The formula is applied to the largest 1,000 U.S. stocks to ensure that the results are economically meaningful. Turnover is limited by rebalancing on a quarterly basis. Although the formula is based on three simple investment criteria, we evaluate it considering the most advanced asset pricing models that have been proposed in the recent literature. For robustness, we also test the conservative formula on U.S. midcaps (defined as the second largest 1,000 stocks) and international equity markets. Finally, we also test for sensitivity to different macroeconomic regimes and examine the impact of trading costs.

We find that a conservative portfolio consisting of 100 low-risk stocks with high NPY and positive price momentum returned 15.1% per year since 1929. The performance is persistent over time, with positive returns in every decade. It outperforms a portfolio of speculative stocks with the opposite characteristics (high risk, low NPY, and negative momentum) by 13.0% per year, with lower risk. For U.S. midcaps, Europe, Japan, and emerging markets (EM) we find similar results. The alphas are stable across different economic regimes and are robust for high levels of trading costs. This conservative investment strategy gives simultaneous positive exposures to the most profitable factor premiums and beats all Fama–French combinations of common investment strategies based on size, quality, value, and momentum.

The article is structured as follows. First we discuss the data and global results. Then we analyze the results through time and directly compare the conservative formula with single-sorted, double-sorted, and triple-sorted Fama–French portfolios. We next apply a battery of academic asset pricing tests to the formula and examine the robustness across economic regimes, size segments, and international markets. Finally, we analyze the impact of trading costs. The Appendix further examines the impact of compounding.

DATA AND GLOBAL RESULTS

We create a liquid universe of stocks by focusing on the largest 1,000 stocks at each point in time. Anomalies or price patterns that are only strong among small-cap or micro-cap stocks have little economic relevance, so we want to stay away from those. Restricting the universe to large-caps is a prudent approach, and results are likely to be more sustainable. We further reduce the risk of p-hacking by only using market data, so no accounting or other data are used. Specifically, our formula only uses dividends, shares outstanding, and returns as input data. For the United States we use the CRSP stock database, which offers data going back to 1926.[1] In addition, we also use international data, unlike many studies

[1] The series for the U.S. large stocks are also used in the book *High Return from Low Risk* by van Vliet and de Koning [2016] (www.paradoxinvesting.com). The U.S. midcap data and international data and the robustness analyses in this study are not included in the book.

in the anomalies literature that only consider U.S. data and report results that do not necessarily carry over to other markets. We focus on three broad regions: Europe, Japan, and EM. Although the United States makes up about half of the global stock market, ignoring the other half would be a significant loss of information. Therefore, we consider international samples consisting of the 1,000 largest European, 1,000 largest Japanese, and 1,000 largest EM stocks at each point in time. The data are sourced from Factset and start in 1986 for Europe and Japan and 1991 for EM. The European and Japanese sample is derived from FTSE World Developed or S&P World Developed index constituents, and the EM sample is derived from the S&P/IFC Global Emerging Markets index. Stocks that do not have at least 36 months of return data available are not eligible for inclusion in the various top 1,000 universes. We gather monthly gross stock returns in local currencies, as well as in U.S. dollars, taking into account dividends, stock splits, and other capital adjustments. Our stock return data sources are Interactive Data Exshare, MSCI, and S&P/IFS, in that order. Monthly returns are truncated at 500%. The free-float adjusted market capitalization data come from FTSE and S&P/IFC. Portfolio returns are in U.S. dollars. Stock-level volatility is calculated using returns in local currency. Finally, as a robustness check, we also test the formula on the second largest 1,000 U.S. stocks. This sample starts in 1970 because from that point in time onward the CRSP database contains more than 2,000 stocks in total.

At the end of each quarter the 1,000 largest stocks at that point in time are sorted into two groups, each consisting of 500 stocks, based on their historical 36-month stock return volatility (e.g., see Black [1993]; Blitz and Van Vliet [2007]; and Baker, Bradley, and Wurgler [2011]). Each stock is further ranked on its 12 – 1 month price momentum (Jegadeesh and Titman [1993]) and total NPY to shareholders (Boudoukh et al. [2007]). This shareholder yield consists of dividend yield and the net change in shares outstanding (calculated as the latest level divided by the 24-month average). The momentum and NPY ranks (1–500) are simply averaged and the top 100 of stocks are selected. To limit turnover this procedure is repeated on a quarterly basis. All factor scores are compared directly across sectors and (for Europe and EM) countries, and the 100 stocks in the final portfolio are equally weighted. We also create an opposite *speculative* portfolio by selecting from the 500 stocks with the highest volatility, those stocks with the weakest combined scores on momentum and NPY. This portfolio is used for comparing returns and for testing the formula in a long–short context. Exhibit 1 conceptually illustrates the selection mechanism of the conservative formula.

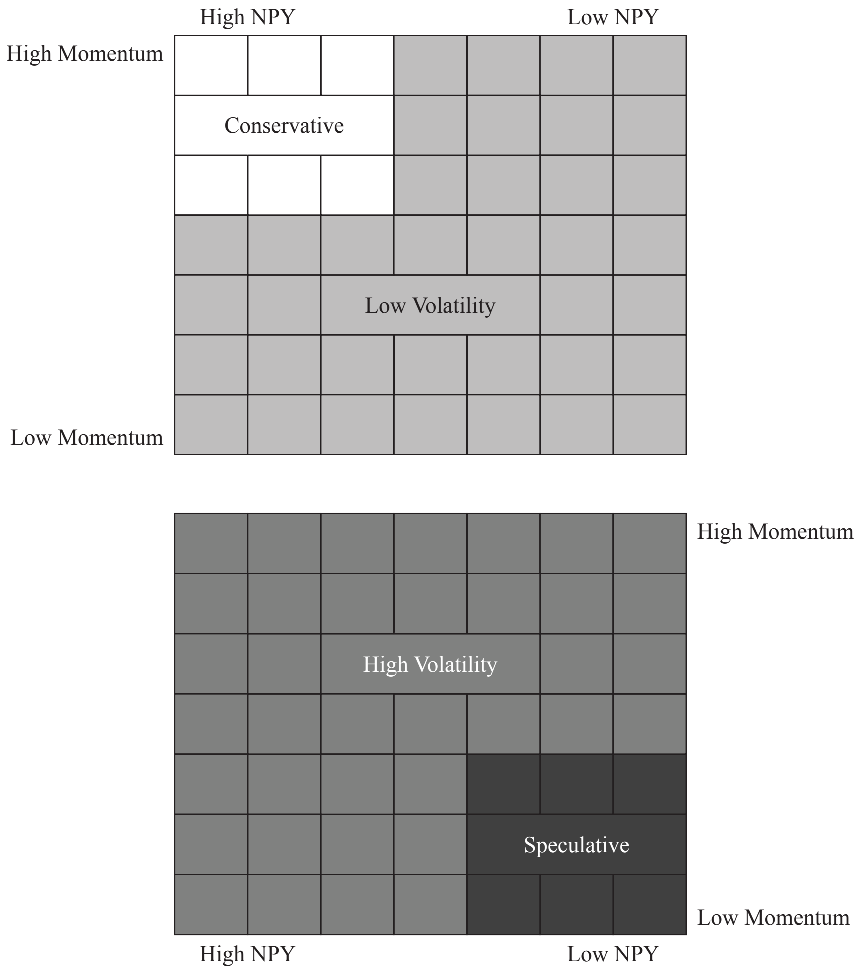
Exhibit 2 shows the main findings for the U.S. and international equity markets. For all regions, the conservative formula portfolio exhibits much lower risk than the speculative portfolio, yet much higher returns. The finding that ex post risk for the formula is consistently low implies that historical volatility is a good predictor of future risk, also on a portfolio level. The risk reduction varies from 50% for the United States and EM to about 35% in Europe and Japan. The return difference varies between 8.8% for Japan, 13.0% for the United States, 14.2% for Europe, and finally 17.2% for EM. This is a very large and internationally consistent return spread and shows the global potential of factor-based investing. In other words, the conservative formula offers a consistently high return-to-risk ratio across all markets. These results are based on the full samples and are not yet related to alternative factor-based strategies, nor tested for significance. We will proceed by taking a closer look at the U.S. stock market, for which the richest data history exists. After this, we further examine the results for the other markets.

RESULTS OVER TIME

A $100 investment in the 1929 U.S. equity market (CRSP value-weighted portfolio) would have grown to $246,000 dollars at the end of 2016. This translates into a compounded annualized nominal return on investment of 9.3% per year. Note that actual returns to investors tend to be lower as a result of taxes, implementation costs, and adverse market timing.[2] The conservative formula portfolio exhibits a terminal wealth that is almost a factor of 100 higher compared to the market, with a compounded return on investment of 15.1% per year. By contrast, the speculative portfolio shows a meager compounded return of only 2.1% per year. An inspection of

[2] Adverse market timing reduces average equity returns by 1.3% (Dichev [2007]), and implementation costs are often above 1%. Furthermore, real returns are 2.8% lower due to inflation over this sample period.

Exhibit 1
Visual Illustration of the Conservative Formula



Note: This exhibit visually illustrates the conservative formula.

Exhibit 3 shows that the dollar wealth development of the conservative formula portfolio is robust over time.

Exhibit 4 shows performance by decade. The average return for conservative stocks is remarkably stable, with positive (>8%) returns during each individual decade. The absence of negative 10-year investment results is important because most investors have relatively short investment horizons (e.g., Benartzi and Thaler [1995]). The return is also higher than the market average in 8 out of 9 decades, with the exception being the 1990s. The speculative portfolio shows consistently weak returns, falling short of the conservative portfolio during each decade.

COMPARISON WITH SINGLE-FACTOR PORTFOLIOS

Results look stable through time, but how does this compare to well-known alternative factor strategies such as size, value, and momentum? To this end we directly compare the conservative formula to other single-factor strategies using the same methodology: equally weighting 100 top stocks from the universe consisting of the largest 1,000 stocks. In the next section we compare the conservative formula with publicly available double-sorted and triple-sorted portfolios, and in the following section we control for factor exposures

Exhibit 2

Summary

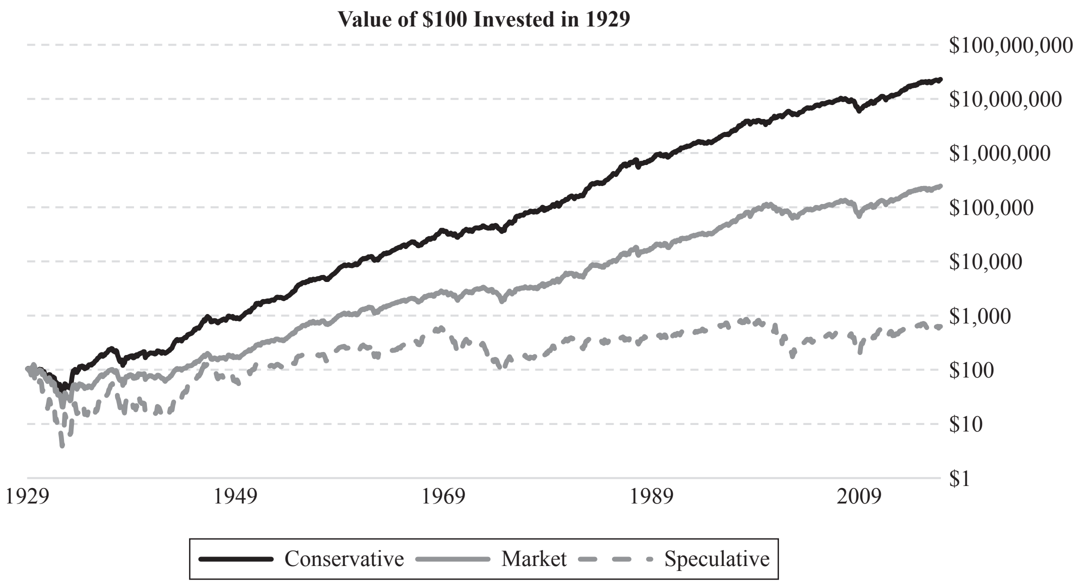
Notes: This exhibit shows the main results of this study. The total of largest 1,000 stocks are screened on historical three-year volatility. From the top 500 low-risk stocks the conservative formula selects the 100 stocks with the best combined 12 – 1 month momentum and NPY factor scores. The speculative portfolio consists of stocks with completely opposite characteristics. Portfolios are equally weighted and rebalanced on a quarterly frequency. The exhibit shows results for the United States, U.S. midcaps, Japan, Europe, and EM. The vertical axis denotes average compounded return, and the horizontal axis shows the full sample volatility. Note that the EM vertical axis is adjusted.

using various specifications of different multifactor asset pricing models.

Exhibit 5 shows that the conservative formula has a return similar to that of strategies based on size, value, momentum, and NPY, but with markedly lower risk. The simple return of small, value, and momentum strategies is a bit higher, but the compounded return shows a different ranking. Interestingly, the return gap between simple returns and compounded returns is only 0.4% for the formula. For most other factors this return gap

Exhibit 3

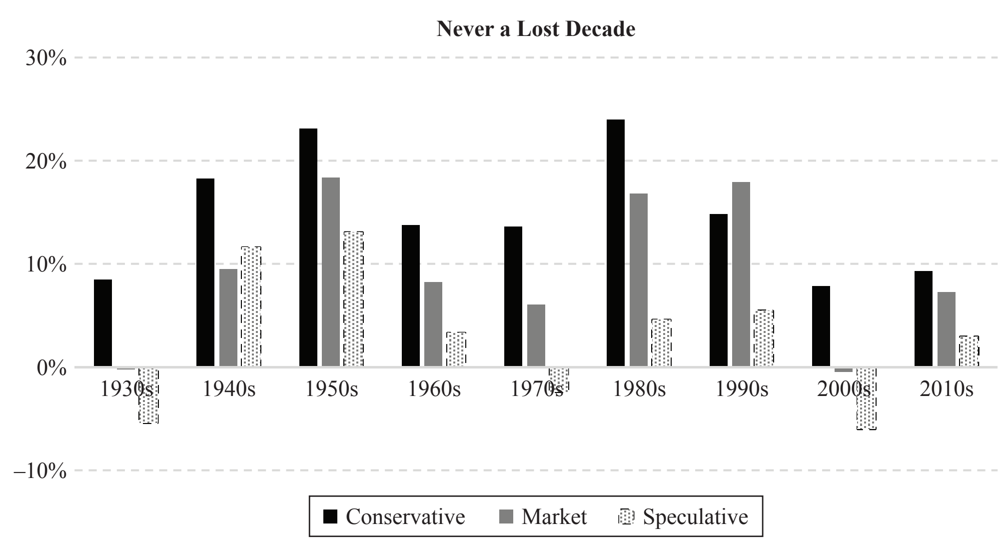
Development of Dollar Value over Time



Notes: This exhibit shows the dollar development over time for the conservative and speculative portfolios. The active portfolios each consist of 100 stocks and are equally weighted and rebalanced on a quarterly frequency. For comparison, we also show the U.S. stock market portfolio (CRSP value-weighted). The results are gross of implementation costs and before taxes.

Exhibit 4

Performance across Decades



Notes: This exhibit shows the average 10-year return of the conservative and speculative portfolios. The active portfolios each consist of 100 stocks and are equally weighted and rebalanced on a quarterly frequency. For comparison, we also show the U.S. stock market portfolio (CRSP value-weighted). The results are gross of implementation costs and before taxes.

EXHIBIT 5
Conservative Formula versus Other Factors

1929–2016	Formula	Market	Small	Value	Momentum	Low Vol	NPY
Return (simple) (%)	15.5	10.6	15.8	16.9	18.2	10.6	15.6
Return (compounded) (%)	15.1	9.3	12.0	13.1	15.9	10.2	14.5
Difference (Simple—Compounded) (%)	0.4	1.4	3.8	3.8	2.3	0.4	1.1
Volatility (%)	16.5	18.7	31.4	31.7	25.7	13.3	20.1
De-risking factor (%)	100	88	52	52	64	124	82
Sharpe ratio (simple)	0.94	0.57	0.50	0.53	0.71	0.80	0.78
Return same risk (%)	15.5	9.8	9.9	10.4	12.9	12.3	13.4

Notes: This exhibit shows the portfolio with 100 conservative stocks (formula) compared to other factors. These single-factor strategies equally weight the top 100 stocks based on market capitalization of equity (small), book-to-market ratio (value), 12 − 1 month return (momentum), three-year volatility (low vol), and NPY. Rebalancing is on a quarterly basis. Furthermore, the portfolios are scaled to the same volatility for a 1–1 comparison. The Sharpe ratio is calculated as the simple average excess return (minus U.S. 30-day T-bill) divided by the volatility. All figures are annualized. These results are gross of implementation costs and before taxes.

is above 1%, and in the case of small cap and value it even amounts to almost 4%. Asset pricing theory, such as the CAPM, does not specify the length of the investment horizon. Still, Exhibit 5 shows that the assumed investment horizon matters greatly. This horizon determines the average return and is for most investors longer than one month (simple return) but shorter than the full sample (compounded return). Some of the return drag is technical and driven by a higher volatility of the underlying strategy. To better compare strategies we de-risk all factors to the same volatility level as for the conservative formula (16.5%). For example, the de-risked market factor invests 88% in stocks and 12% in the risk-free asset to end up with the same risk as the formula. This approach converts Sharpe ratio differences into return differences.[3] The conservative formula has the highest return per unit of risk compared to all other factors. The formula, which consists of three factors, also has a higher return compared to each of its three components: low volatility, momentum, and NPY. On an equal-risk basis, the return differences amount to 2%–3% per year. Because the methodology is exactly the same—100 stocks with equal weighting and quarterly rebalancing—this difference can only be attributed to the integration and diversification benefits of combining multiple factors into one strategy.

COMPARISON WITH FAMA–FRENCH PORTFOLIOS

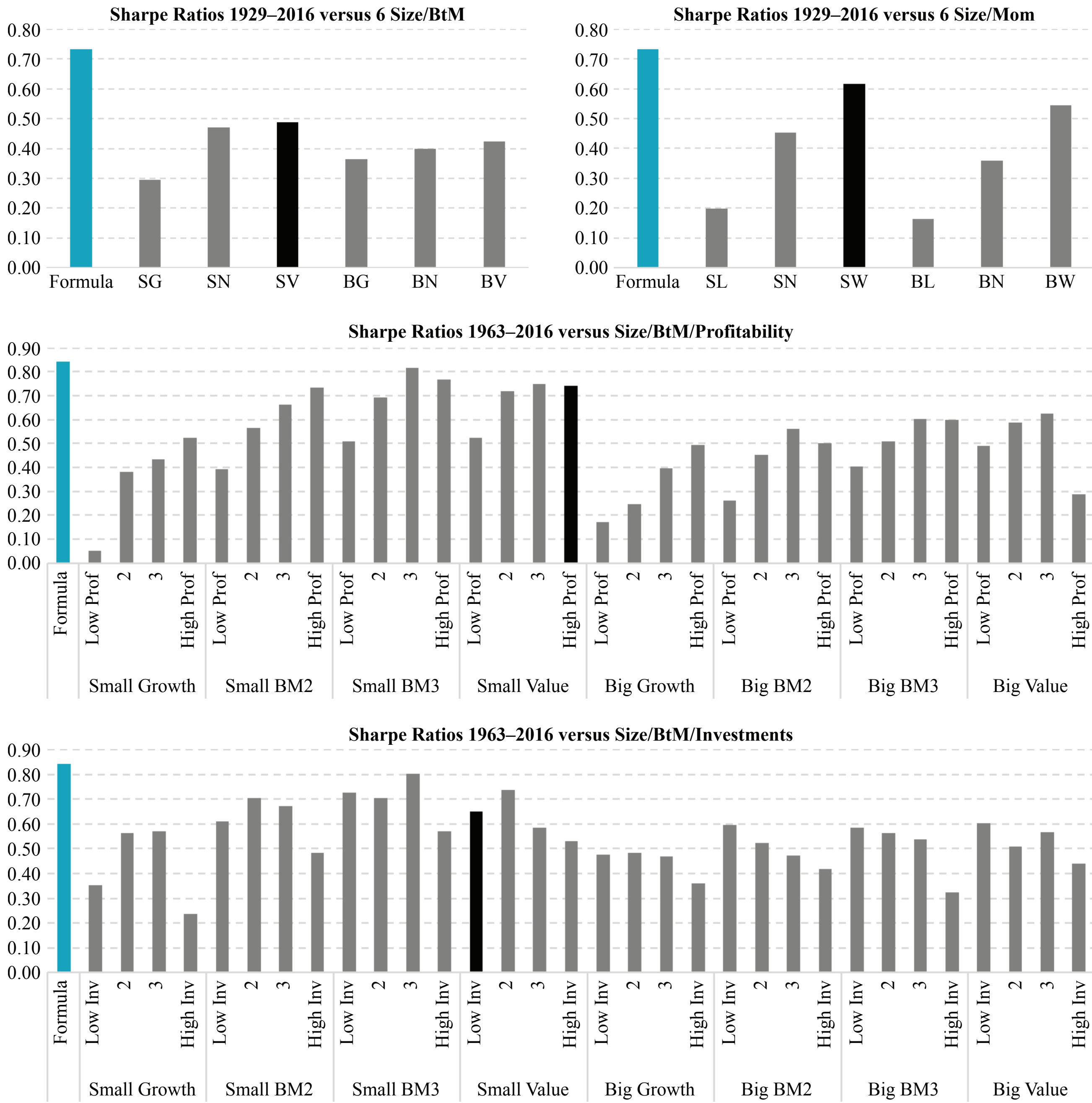
Because a large portion of the return can be attributed to integrating multiple factors, we also compare the conservative formula with other multifactor strategies (see Haugen and Baker [1996]). In particular, we consider the commonly used portfolios of Fama and French [1993, 2015]: double-sorted (2 × 3) portfolios based on size and book-to-market and based on size and momentum, and triple-sorted (2 × 4 × 4) portfolios on size, book-to-market, profitability, and investments.[4]

Exhibit 6 shows that the conservative formula has a higher Sharpe ratio compared to all other Fama–French factor-combination strategies. The small-winner (SW) and small-value (SV) strategies have the highest Sharpe ratios among the double-sorted portfolios, but still they all fall short of the conservative formula. The triple-sorted Fama–French portfolios offer more detailed insight. Because of limited data availability for profitability and investments, the sample for triple-sorted portfolios starts in July 1963. Small-value stocks with

[3] This de-risking explains most of the return drag resulting from compounding, but not all (see Exhibit A1).

[4] The Fama–French portfolios include all stocks available in the CRSP universe, but the universe is divided based on the NYSE median. The Fama–French small-cap portfolio (below median) grows from 227 stocks to 2,329 at the end of the sample. The large-cap portfolio (above median) grows from 251 to 856 at the end of the sample. To further limit the impact of micro caps or small caps driving results, the Fama–French portfolio returns are value weighted.

EXHIBIT 6
Conservative Formula versus Fama–French Portfolios



Notes: This exhibit shows the Sharpe ratios of the conservative formula with double-sorted and triple-sorted portfolios. The double-sorted portfolios are based on size (ME) and book-to-market ratio (BM) and size (ME) and momentum (12 – 1 month return). Profitability is defined as one-year operational profitability, and investment is defined as one-year change in total assets. The sample starts in January 1929 for the double-sorted portfolios and in July 1963 for the triple-sorted portfolios. Fama–French portfolios are value weighted and include all stocks in the CRSP database, including small and micro caps. The average number of included stocks is 2,569 stocks over the 1929–2016 period, of which 668 classify as above median NYSE. All figures are annualized. These results are gross of implementation costs and before taxes.

high profitability are among the best performing portfolios, with a Sharpe ratio of around 0.75. This comes close to the Sharpe ratio of 0.84 of the conservative formula over this sample period, but it still falls a bit short. Moreover, the Fama–French portfolio consists of only 26 stocks with an average market capitalization of $350 million as of December 2016. This specific portfolio may look attractive on paper, but it represents less than 0.05% of the total U.S. stock market, which means that large investors have limited opportunity to invest in this portfolio. By contrast, the conservative portfolio consists of 100 stocks with an average market capitalization of $35 billion as of December 2016. This makes up almost 20% of the total U.S. market. The lowest Sharpe ratios are earned by small growth firms with low profitability. We also observe that the positive relation between profitability and return is not consistent in the large-cap segment. Finally, small value stocks with low levels of investment earn high Sharpe ratios. Within the small-cap segment the relation between investment and risk-adjusted return is not linear. In the large-cap segment this relationship is more persistent, and the large value portfolio with low levels of investment earns a high Sharpe ratio. However, none of these triple-sorted portfolios is able to match the Sharpe ratio of the conservative formula.

CONTROL FOR FACTOR EXPOSURES

The return spread between the conservative portfolio and speculative portfolio is 13.0% per year. How much of this return spread can be attributed to exposure to the classic Fama–French long–short factors or exposure to newer factors? To answer this question we apply time-series spanning tests to the conservative minus speculative (CMS) portfolio. Some factors are available since 1929, whereas other factors only come available at a later date. Exhibit 7 shows various regression outcomes using the longest available data histories.

Panel A of Exhibit 7 shows that the CMS portfolio has a full-sample CAPM alpha of 13.9%. This goes along with a large negative exposure to the market factor, which is not surprising given that the formula is long low-volatility stocks and shorts high-volatility stocks. The 3-factor alpha is somewhat higher, mainly caused by a negative size (SMB) exposure. The positive exposure to large caps (and negative exposure to small caps) is caused by the inclusion of the low-volatility factor in the formula. In general, larger stocks tend to have lower volatility, and smaller stocks tend to have higher volatility. Over the long run, value stocks are more volatile and have higher betas than growth stocks (see Ang and Chen [2007]), and the formula loads negatively on the HML factor over the full sample period. Although NPY is a price-based measure that tilts the portfolio to value (book-to-price), this is countered by the fact that low volatility is strongly negatively exposed to HML in the earlier part of the sample (1930s) and to momentum most of the time. Therefore the formula exhibits a negative exposure to value over the full sample period. When momentum (MOM) is added, the 4-factor alpha drops to 8.8%, which is expected because momentum is one of the three building blocks of the formula. The alpha remains highly significant, however.

Panel B of Exhibit 7 shows that over the more recent (1963–2016) period the CAPM alpha of the formula remains similar, at 14.0%. During this period value stocks are less risky and volatile. At 13.0%, the 3-factor alpha is not much lower because the impact of a positive loading on the HML value factor is largely offset by a negative loading on the SMB size factor. Fama and French [2015] proposed to extend their classic 3-factor model to a 5-factor model by augmenting it with profitability (RMW) and investment (CMA) factors, for which data are available from 1963. Panel B shows that the conservative strategy has positive loadings on both these new factors, which reduces the alpha to 8.8%. When we additionally control for the momentum factor, we get another positive loading, and the 6-factor alpha is further reduced to 3.3%. In sum, the CMS strategy gives positive and significant exposure to the value (HML), momentum (MOM), profitability (RMW), and investment (CMA) factors at the same time. These are factor tilts most investors would like to see in their portfolio because all these factors are known to be associated with higher returns. After controlling for all these factors, a small but still statistically significant positive alpha remains. Unreported results show that this is mainly driven by the inclusion of NPY in the formula.

In Panel C of Exhibit 7 we subject the CMS portfolio to the recently proposed q-factor model of Hou, Xue, and Zhang [2015], who argued that this model is superior to the Fama–French models.[5] We find large positive loadings on the investment (IA) and profitability

[5] We thank Prof. Zhang for kindly providing the data.

EXHIBIT 7

Conservative Formula Dissected Using Multifactor Models

Panel A: Fama and French [1993]/Carhart [1997]

1929–2016	Alpha	Mkt-RF	SMB	HML	MOM
Coefficient	13.9%	–0.88			
t-value	7.07	–29.45			
Coefficient	16.5%	–0.65	–0.90	–0.38	
t-value	10.35	–24.66	–21.08	–9.96	
Coefficient	8.8%	–0.50	–0.89	–0.07	0.65
t-value	7.00	–23.98	–26.93	–2.27	27.03

Panel B: Fama and French [2015]

1963–2016	Alpha	Mkt-RF	SMB	HML	RMW	CMA	MOM
Coefficient	14.0%	–0.74					
t-value	6.93	–19.45					
Coefficient	13.0%	–0.55	–0.60	0.35			
t-value	7.29	–15.80	–12.12	6.48			
Coefficient	8.8%	–0.44	–0.46	0.03	0.59	0.75	
t-value	5.22	–12.67	–9.29	0.38	8.67	7.56	
Coefficient	3.3%	–0.36	–0.51	0.36	0.43	0.49	0.64
t-value	2.95	–15.62	–15.67	8.03	9.53	7.44	29.10

Panel C: Hou, Xue, and Zhang [2015]

1967–2016	Alpha	Mkt-RF	ME	IA	ROE
Coefficient	4.1%	–0.45	–0.30	0.98	0.8
t-value	2.39	–13.76	–6.52	13.00	14.67

Panel D: AQR

1963–2016	Alpha	Mkt-RF	SMB	HML	QMJ	BAB	MOM
Coefficient	4.7%	–0.40	–0.39	0.27	0.67	0.45	
t-value	3.21	–12.77	–8.65	5.78	9.83	11.45	
Coefficient	1.0%	–0.33	–0.45	0.52	0.51	0.27	0.58
t-value	0.97	–15.42	–14.71	15.96	11.12	9.95	29.49

Notes: This exhibit shows the conservative minus speculative (CMS) portfolio controlled for multiple factor models. All factors are from the online data library of Kenneth French. The sample for the three-factor and four-factor model starts in January 1926, whereas the five-factor and six-factor models start in July 1963; both end at December 2016.

(ROE) factors in the q-factor model, but after controlling for these exposures an alpha of 4.1% per annum remains. Thus, the formula is also attractive for investors looking for efficient exposure (and some more) to the factors in the q-factor model.

In the final spanning test we augment the Fama–French three-factor model and the Carhart [1997] four-factor model with the quality (QMJ) factor of Asness, Frazzini, and Pedersen [2013] and the betting-against-beta (BAB) factor of Frazzini and Pedersen [2014]. We call this the *AQR model*, as the authors of these two studies are employed at that firm. In Panel D of Exhibit 7 we observe large positive loadings on both the QMJ and BAB factors, implying that the formula also provides exposures toward these factor premiums. We also observe that only the combination of the classic value and momentum factors of Fama–French and the two new AQR factors is powerful enough to render the alpha of the CMS portfolio insignificant, although even in this case it does remain positive. It is good to keep in mind here, however, that the QMJ factor consists of over 20 underlying variables, which are aggregated into one combined quality score. The formula, on the other hand, only uses three variables, which do not even require

Exhibit 8
U.S. Midcap and International Results

Panel A: Factor Betas CMS

	Mkt-RF	SMB	HML	MOM	RMW	CMA
U.S. Large caps	–0.36	–0.47	0.41	0.66	0.46	0.36
U.S. Midcaps	–0.37	–0.59	0.43	0.58	0.71	0.29
Europe	–0.29	–0.18	0.01	0.56	0.60	0.58
Japan	–0.28	–0.28	0.34	0.57	0.03	0.09
EM	–0.52	–0.36	0.03	0.49	0.09	0.49

Panel B: Factor Premiums (%)

	Mkt-RF	SMB	HML	MOM	RMW	CMA
U.S. Large caps	6.35	1.87	4.76	7.60	3.20	4.32
U.S. Midcaps	6.35	1.87	4.76	7.60	3.20	4.32
Europe	7.43	–0.12	3.70	10.44	4.71	3.08
Japan	0.33	0.37	3.81	2.47	1.86	1.76
EM	6.29	1.69	4.66	7.07	3.74	3.41

Panel C: Alphas CMS (%)

	Premium	CAPM	3FM	4FM	5FM	6FM
U.S. Large caps	10.19**	15.00**	13.47**	5.96**	8.85**	3.40**
U.S. Midcaps	13.02**	17.99**	16.55**	9.83**	11.33**	6.54**
Europe	11.17**	14.62**	15.31**	6.60**	6.86**	2.75
Japan	6.50*	8.04**	7.64**	4.89**	6.72**	4.82**
EM	12.69**	17.25**	17.41**	11.97**	14.44**	10.93**

Notes: This exhibit shows the U.S. small- and midcap and international results for the conservative minus speculative (CMS) portfolio. The U.S. large-cap portfolio consists of the largest 1,000 stocks, and the U.S. midcap portfolio consists of the second largest 1,000 stocks. For each international market the largest 1,000 stocks are used to construct the two portfolios. The U.S. sample starts in January 1970, the European and Japanese samples start in January 1986, and the EM sample starts in January 1993. For Europe and Japan regional Fama–French control factors are used and backfilled prior to November 1990 with U.S. long–short factors. For EM, global long–short factors are used. Panel A shows the factor betas, Panel B shows the factor premiums, and Panel C shows the CMS premium and the factor-corrected alphas of the four regional strategies. The 3-factor model (3FM) consists of SMB and HML. The 4-factor model (4FM) adds momentum to the 3FM. The 5-factor model (5FM) consists of SMB, HML, RMW, and CMA. The 6-factor model (6FM) adds momentum to the 5FM.

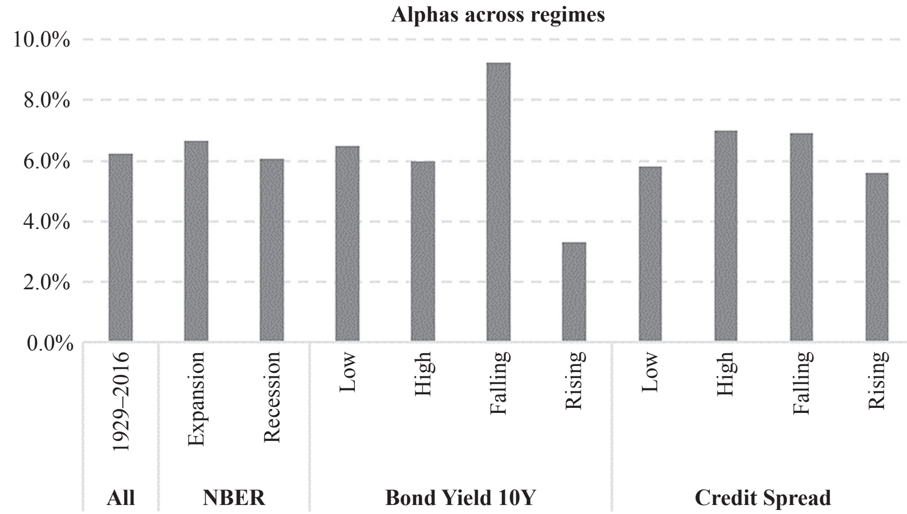
Asterisks are used to indicate significance at 5% (*) or 1% (**) level.

accounting data. Thus, the formula is able to match or outperform the most advanced asset pricing factors with much lighter data input requirements.

U.S. MIDCAP AND INTERNATIONAL RESULTS

The largest 1,000 stocks represent about 90% of total U.S. market capitalization at the end of 2016. The market capitalizations for the next 1,000 stocks range from $3.0 billion to $0.5 billion. Although this group of stocks represents less than 10% of total market capitalization, it provides an interesting robustness test for the conservative formula. The total number of stocks in CRSP exceeds 2,000 from 1970 onward, when AMEX stocks were added to the database, so for this analysis we consider the 1970–2016 sample period. For comparison purposes we also show the alphas of the conservative formula for the largest 1,000 stocks over this period. Exhibit 8 shows that the midcap conservative minus speculative portfolio exhibits factor betas that are very similar to those of the large-cap CMS portfolio. Exhibit 8 shows positive factor tilts toward the four factors with the highest premiums: HML, MOM, RMW, and CMA. The midcap CMS premium is 13.0%, which is about 3% higher than the CMS premium in the large-cap segment. The multifactor alphas are all statistically significant, ranging between 6% and 18% per annum.

EXHIBIT 9
Conservative Formula Alpha across Economic Regimes



Notes: This exhibit shows the conservative formula long-only CAPM alpha (6.2%) and the CAPM alphas across different regimes for the period 1929–2016. In total, 10 economic regimes are defined: NBER expansion and recession, low/high 10-year bond yields, falling/rising 10-year bond yields, low/high credit spreads (defined as Baa-Aaa), and falling/rising credits spreads.

The pattern in alphas is very similar compared to the results for the largest 1,000 U.S. stocks. Although returns are higher, expected implementation costs are also higher in this particular market segment, so after-cost return differences are likely to be smaller.

We also test for global robustness of the conservative formula by considering the European, Japanese, and emerging stock markets. To calculate multifactor alphas we use local factors provided in the Kenneth French data library for Europe and Japan and global factors for EM. As shown in Exhibit 2, the conservative portfolio consistently outperforms the speculative portfolio in all regions. Exhibit 8 shows the betas of the four regional CMS portfolios to the six different factors. For all regions we find a negative market beta exposure and a negative size (SMB) exposure, which is consistent with the U.S. results. We also find positive factor tilts to profitability (RMW), momentum (MOM), investment (CMA), and value (HML) for all regions, which is again consistent with the U.S. results. This is a desirable feature because each of these four factors carries a positive premium in each region. Panel B shows that the value premium is stable at around 4%, whereas the new Fama–French profitability and investment factors have premiums of around 3%. Momentum carries the highest premium of 7%, but this varies between very high in Europe (10%) and quite low in Japan (2%). The low momentum premium in Japan is a known phenomenon (see, e.g., Griffin, Ji, and Martin [2003]; Asness [2011]). Panel C shows the return spread and the single-factor and multifactor alphas for the regional strategies. The CAPM alphas are all posi-

EXHIBIT 10
After Trading Net Returns (%)

	U.S.	Europe	Japan	EM
Gross Return	15.24	16.18	9.63	20.93
Turnover Quarterly	32	33	32	30
Estimated Trading Costs—Low	0.26	0.26	0.26	0.48
Estimated Trading Costs—High	0.77	0.79	0.77	1.44
Trading Costs (high) as % of Return	5.0	4.9	8.0	6.9
Net Return (high trading costs)	14.47	15.39	8.86	19.49

Notes: This exhibit shows the impact of trading costs on the net returns of the conservative formula for the four regional strategies. The quarterly turnover is shown, which is calculated as single-counted. For transaction costs, a low level of 10 bps per dollar traded and a high level of 30 bps per dollar traded are assumed. For EM, these figures are 20 and 60 bps, respectively. Total trading costs include both market impact and broker costs. The net return assumes the conservative high estimate of transaction costs.

tive, with the highest alpha in EM and the lowest alpha in Japan. Most of the high returns can be explained by a positive exposure to the four factors that give the highest premiums: value, momentum, profitability, and investment. When the momentum factor is added to the Fama–French three-factor and five-factor models, we see the largest part of the alpha being explained. Interestingly, the momentum factor carries the highest premium, but it is also most difficult to implement in practice because it requires very high levels of turnover. That is one of the reasons why Fama and French prefer to not include this factor in their multifactor asset pricing models. The conservative formula offers positive and significant exposure to the momentum factor, but because momentum is integrated with other factors, it is able to achieve this with a relatively modest level of turnover. This lower turnover is a desirable feature for any practically implementable investment strategy.

MACRO RISK AND TRADING COSTS

It could be that systematically investing in stable stocks with high net payouts that are in a positive trend gives exposure to some form of macroeconomic risk. For example, one might be concerned that these stocks are sensitive to the economic cycle and underperform when the economy is in recession. Or they might be sensitive to interest rate changes or credit cycles.

Exhibit 9 shows that the conservative-formula long portfolio (100 stocks) has an average CAPM alpha of 6.2%, that this alpha is spread evenly across expansions and recessions, and that it is stable across high and low levels of interest rates. The alpha is sensitive to changes in interest rates, dropping to 3.3% when rates are rising. This rate sensitivity is a known feature of low-volatility stocks (see, e.g., Baker and Wurgler [2012]; De Franco, Monnier, and Rulik [2017]). Compared to a generic low-volatility approach, the formula does mitigate the sensitivity to interest rate changes by also including other factors, in particular momentum. In any case, the alpha remains significant, with all *t*-statistics being above 3.5. There is no clear relation with the credit cycle, as neither credit spread levels nor changes seem to have a large impact on results.

Finally, we estimate the impact of transaction costs on results. The formula is designed to suffer limited impact from transaction costs by assuming a quarterly (instead of monthly) rebalancing frequency. This reduces turnover, which is the most important driver of transaction costs (Novy-Marx and Velikov [2016]). Also, the focus is on the largest 1,000 U.S. stocks. Nevertheless, implementation costs could still be significant and negatively affect net results. Exhibit 10 shows for each of the regional strategies the amount of (single-counted) turnover needed to implement the conservative formula. The turnover levels are all very similar, at around 30% per quarter, which translates into an average stock holding period of slightly less than one year. The turnover can easily be brought down with more sophisticated trading rules—for instance, rules that do not immediately sell a stock if its rank drops to number 101 out of 1,000, but stay invested in such positions until they drop beyond a certain sell threshold. We will refrain from such sophistications here and work with the raw turnover levels to keep matters simple. Frazzini, Israel, and Moskowitz [2012] estimated transaction costs to be less than 20 bps for U.S. and international large-cap and midcap stocks. We show results for a low assumed transaction cost level of 10 bps (20 bps for EM) and a high assumed transaction cost level of 30 bps (60 bps for EM). For the most conservative estimate applied to EM we find that net returns go down up to 1.5% per year, which is not much compared to the raw return of the formula. In all cases, trading costs amount to less than 10% of the total return, so more than 90% of the returns remain for investors.

CONCLUSION

We propose a conservative formula that is designed to make quantitative investing easy for investors. Using three simple investment criteria, many different factor premiums can be captured with a single investment strategy consisting of 100 liquid stocks. The conservative formula uses past returns and NPY only, which means that no accounting or other data sources are needed. Despite its simplicity, the strategy gives simultaneous positive exposure to well-known factors such as low beta, value, quality, and momentum. The returns are consistent over time and across international stock markets and are present in U.S. small- and midcap stocks. In sum, this simple formula can be used by active investors as a way to profit directly from half a century of academic insights by applying one simple investment formula.

APPENDIX

EXHIBIT A1

Compounding Matters, Even When Strategies Have the Same Volatility

1929–2016	Formula	Market	Small	Value	Winner	Low Vol	NPY
% Leverage Factor	100%	88%	52%	52%	64%	124%	82%
Simple Return	15.5%	9.8%	9.9%	10.4%	12.9%	12.3%	13.4%
Compounded Return	15.1%	8.8%	9.0%	9.5%	12.1%	11.6%	12.7%
Total Return Drag	–0.4%	–1.0%	–0.9%	–0.9%	–0.7%	–0.8%	–0.6%
Caused by Volatility	–1.4%	–1.4%	–1.4%	–1.4%	–1.4%	–1.4%	–1.4%
Caused by Correlation	1.0%	0.3%	0.4%	0.5%	0.6%	0.6%	0.7%

Notes: This exhibit disentangles the difference between compounded returns and simple returns by splitting the return drag in volatility and correlation components. When all strategies are brought to the same risk level, differences between simple and compounded returns could remain but are solely caused by non-zero time-series correlation. Without time-series correlation, we expect a return difference of 0.5 × variance (0.5 × 16.5%^2) of 1.4% per annum. The conservative formula has a return drag of only −0.4%, which is caused by a favorable (negative) autocorrelation pattern. By contrast, small and value strategies have positive autocorrelation, which increases the return by about 2.5%.

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