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Factor-Based v. Industry-Based Asset Allocation: The Contest

Marie Brière and Ariane Szafarz

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JEL-Classification: G11, G01, C58, D92

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Factor-Based v. Industry-Based Asset Allocation:

The Contest*

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Abstract

Factor investing has emerged as the new paradigm for long-term investment. Applied to equities, factor investing is probably the most serious contender to the classical industry-based approach to asset allocation. By organizing a multi-trial contest opposing factor investing and sector investing, we address two questions: 1) Are the excess returns of factor investing offset by higher risks, and if so, are factor-specific risks eliminable by means of factor diversification? 2) How does factor investing perform during crisis times? Our results suggest that this form of investing is the best strategy when short sales are permitted. It also outperforms industry-based allocation during expansion and bull periods. In contrast, sector investing offers defensive opportunities to asset managers since it delivers better risk-return trade-offs for long-only portfolios during recessions and bear periods. Overall, factor investing keeps its promises, but it still has a long way to go before it can oust sector investing.

“In the beginning, there was chaos; practitioners thought one only needed to be clever to earn high returns. Then came the CAPM. Every clever strategy to deliver high average returns ended up delivering high market betas as well. Then anomalies erupted, and there was chaos again.” Cochrane (2011, p. 1058)

“The two most important words in investing are *bad times*.” Ang (2014, p. ix)

1. Introduction

Outside the Capital Asset Pricing Model (CAPM) academic comfort zone, asset pricing exhibits confusing diversity. As a result, investors—even the most rational ones—are left with various competing options to allocate assets. Due to a shortage of convincing theory, they face hard choices, and the risk of data mining is pervasive (Black, 1993; Harvey and Liu, 2014). In view of the numerous performance measures used in the literature, only extensive and robust empirical studies can assess the performance of asset allocation rules confidently.

Recently, factor investing has emerged from the banking world as the new paradigm for long-term investment. Cazalet and Roncalli (2014, p. 1) define the strategy as “an attempt to capture systematic risk premia.” Factor investing consists in holding assets with positive exposure to selected factors and, if possible, shorting those with negative exposure. Ang (2014) argues that this strategy is especially relevant in a long-term perspective because it acknowledges that bad times occur. According to Ilmanen and Kizer (2012), moving from traditional asset-class portfolio management to factor investing means shifting “from dollar allocations to risk allocations.” Applied to the equity market, factor investing is probably the most serious contender to the classical industry-based approach to asset allocation. This paper lays down a challenge to the newcomer by organizing a multi-trial contest pitting it against its well-established competitor.

The idea of identifying specific risk factors for investment purposes dates back at least to the arbitrage pricing theory proposed by Ross (1976), as well as to the three-factor model popularized by Fama and French (1992) and later generalized by Carhart (1997). By definition, each risk factor drives a specific risk premium. The best known of these is the market factor, which delivers the so-called market premium. According to the CAPM, the market premium is the only risk premium available to investors. However, a wealth of empirical work has uncovered additional factors, which entail significant risk premia. The most famous of these factors relate to size and value (Fama and French, 1992)[1] and momentum (Carhart, 1997).[2]

Factor-based asset allocation attracted fresh interest from investors after the public release of a report on active portfolio management produced by Ang *et al.* (2009) at the request of the Norwegian sovereign wealth fund. The debate among institutional investors centers on two core issues: the merits of active portfolio management, and the profitability of factor investing.

The literature amply documents that passive investing is a low-fee strategy (French, 2008), and that, on average, actively managed mutual funds underperform index investing (Gruber, 1996; Fama and French, 2010). On the other hand, practitioners keep arguing that dynamic asset allocations can be profitable to investors because they capture benefits driven both by market anomalies and by market timing. Recent evidence shows that, beyond the simple luck effect, the performance of some actively managed funds seriously challenges index funds. For instance, Del Guercio and Reuter (2014) underscore the performance of

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[1] The size factor, Small minus Big (SMB), is the return on an international portfolio of small stocks (bottom 10% in terms of market capitalization) minus that of a portfolio of big stocks (top 90% capitalization). The value factor, High minus Low (HML), is the return of a portfolio made of "value" stocks, i.e. those with a high (top 30%) book-to-market ratio (book value of common equity divided by the market equity) minus that of a portfolio of "growth" stocks (bottom 30% book-to-market ratio).

[2] The momentum factor, Winners minus Losers (WML), is the return of a portfolio of best-performing stocks (top 30%) minus that of a portfolio of worst-performing stocks (bottom 30%) over the previous year.

actively managed funds marketed directly to retail investors. According to Berk and van Binsbergen (2015), active mutual funds add value that can persist for 10 years. Overall, Pástor *et al.* (2015) confirm that the active management industry has become more skilled over time.

Among the many ways to actively manage funds, factor investing is an innovative method exploiting evidence on factors in asset pricing by means of systematic portfolio rebalancing. Basically, by buying assets with positive factor exposure and shorting those with negative exposure, investors capture the risk premia (or betas) of the chosen factors, and so benefit from excess returns (or alphas) with respect to the market portfolio, which serves as a benchmark for passive investing.

Longstanding criticisms of passive asset allocation methods have encouraged the emergence of innovative techniques. Traditionally, passive portfolio management is associated with class-based, industry-based, and country-based portfolio management (Eiling, et al., 2012). The main charge against the traditional segmentation of equities relates to their alleged lack of robustness in terms both of associated risks and of capital protection during crisis periods. Industry-based indices are meant to maximize diversification benefits for a limited number of classes. Logically, they do not capture any specific risk premium. Moreover, the way individual equities are grouped into sectors is debatable (Vermorken et al., 2010; Hoberg and Philipps, 2010 and 2015). More generally, in the wake of the recent financial crisis, investors feared that traditional asset allocations would offer insufficient protection against instable correlations (Chua et al., 2009). Changes in correlations are typically associated with market contagion and flight to quality during crises (Brière *et al.*, 2012). In addition, Ang and Chen (2002) show that correlations between U.S. stocks and the market are much greater for downside than for upside moves. According to Christoffersen et al. (2012), both developed and emerging markets have recently experienced increases in correlations, which mechanically reduce the expected benefits of diversification.

Factor investing has strong advocates among institutional investors.[3] But the claimed overall superiority of factor investing over traditional portfolio management techniques has yet to be proven, despite a few studies that provide partial evidence. Since factors are built to capture excess returns through betas, they could reasonably be expected to deliver higher returns than index investing, whether class-based, country-based or industry-based. If this is the case, two key questions need to be addressed. First, do excess returns entail higher risks, and if so, are excess risks eliminable by factor diversification? Combining factors optimally for investment purposes is still unchartered territory. Second, how does factor investing perform during crisis times? Ang (2014, p. 450) mentions that "while dynamic factors often beat the market over long periods of time, they can grossly underperform the market during certain periods—like the 2008-2009 financial crisis." This observation illustrates the instability of factor profitability, but the overall performance of factor investing in market downside and upside periods remains unknown.

Some recent papers address the characteristics of factor investing in specific investment universes: Ilmanen and Kizer (2012) explore asset classes, Eun et al. (2010) consider international capital markets, and Van Gelderen and Huij (2014) focus on U.S. equity mutual funds. Ilmanen and Kizer (2012) use long data series (1927-2010) to emphasize the high diversification potential of factor investing. For asset-class-diversified portfolios, the authors obtain a near-zero average pairwise factor correlation, which is remarkably low. Likewise, Eun et al. (2010) exploit international data during the period 1981–2008, and show that factor-based asset allocation outperforms country-based allocation. Using data on U.S. equity mutual funds over the period 1990 to 2010, Van Gelderen and Huij (2014) compare the

[3] See, for instance, the articles in the *Financial Times* by Stevenson (2014) and Authers (2015).

performances of factor-investing funds to those of other funds. The authors consider the following factors: 1) low-risk (Haugen and Baker, 1991), 2) small cap 3) value, 4) momentum (Jegadeesh and Titman, 1993), 5) short-term reversal (Lehmann, 1990), and 6) long-term reversal (De Bondt and Thaler, 1985). They find high value-added for strategies exploiting low-beta, small cap, and value, but the evidence is less convincing for the three other factors for which, they claim, “there is little documentation in the academic literature.” (p. 159). For instance, 96% of all short-term reversal funds underperform the market.[4]

Most studies draw conclusions on portfolio management with unrestricted short selling. This is a considerable limitation, since benchmark restrictions and implementation costs make long-short factor investing difficult to implement in practice (Huij et al., 2014). In the same vein, Idzorek and Kowara (2013) attribute most of the benefits of factor investing to the combination of long and short positions. From an extensive econometric analysis, Cocoma et al. (2015, p.21) conclude that “the case is yet to be made that investors should use factors as building blocks for forming portfolios rather than assets”.

Early asset pricing studies commonly used industry-based portfolios (Ferson and Harvey, 1991). However, to our knowledge, modern factor investing has not yet been contrasted with industry-based asset allocation. The contest promises to be fierce since industry-based allocation is known to be more resilient than its country-based counterpart to contagion during crises (Moerman, 2008). This paper fills a gap by comparing the financial performances of factor-based and industry-based asset allocations. The investment universe is composed of large and mid-cap U.S. equities. To compare the two investing styles, we organize a contest comprising three trials: the first compares efficient frontiers, the second is based on Jensen’s alphas, and the third relates to Sharpe ratios. Regarding alphas and Sharpe

[4] See Huij’s interview by Robecco on 6-1-2015: http://www.robeco.com/en/professionals/insights/quantitative-investing/factor-investing/2015/factor-investing-works.jsp

ratios, we oppose the performance of two groups: individual sectors against factors, and diversified portfolios made of sectors against diversified portfolios made of factors. Moreover, all tests are performed for asset allocations with and without short-selling restrictions. Each trial ends up with a winner (but with the possibility of a dead heat).

In sum, the results suggest that there is no overall winner, but we do find circumstantial evidence of superiority for each style. Factor investing is clearly the best strategy when short sales are permitted. It also outperforms industry-based allocation during expansion and bull periods. These results confirm that factors are more risky (Ang, 2014). In contrast, sector investing offers defensive opportunities for asset managers since it delivers better risk-return trade-offs for long-only portfolios during recessions and bear periods. In the end, it is up to each investor to reach their own conclusions, for instance by assigning weights to the criteria of interest. Broadly, one can conclude that factor investing keeps its promises, but it still has a long way to go before it can oust sector investing.

2. Data and Methods

2.1. Data

Our data are retrieved from Kenneth French's website,[5] the only source of publicly available long-period factor and sector returns coherently computed for the U.S. stock market. The data make it feasible to construct the long and short legs of each factor separately, allowing us to consider both situations–with short-selling restrictions ("long-only") and without them ("long-short")–separately. Our dataset includes monthly gross total returns (in USD) of ten industry-based and ten factor-based indices made up of U S. stocks listed on the NYSE, Amex and

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Nasdaq over the period July 1963 – November 2014. For this period, we also recorded the market index returns (value-weighted returns of all NYSE, Amex, or Nasdaq-listed U.S. firms)[6] and the risk-free interest rates (one-month Treasury bill rate from Ibbotson Associates) provided by French's website.

Each time series is examined over five different sample periods. The first period is the full sample. The second and third correspond to the recessions and expansions dated by the National Bureau of Economic Research (NBER) (visit their website for a precise definition).[7] The fourth and fifth periods are those associated with the bear and bull markets identified by Forbes Magazine.[8] Bear-market and recession periods exhibit significant differences with only partial overlap. Most NBER recession periods follow Forbes bear market times. Exceptions include the bear period due to the 1998 Asian crisis, which was not immediately followed by a recession.

Using French's database also imposes a set of working constraints. First, we have to rely on the Standard Industrial Classification (SIC), which is slightly different from the commonly-used Global Industry Classification Standard (GICS). The sector portfolios are constructed by assigning to each stock an industry portfolio based on its four-digit Standard Industrial Classification code at the end of June of each year. The ten sectors are: (1) non-durable consumer goods (food, tobacco, textile, apparel, leather, toys), (2) durable consumer goods (cars, TVs, furniture, household appliances), (3) manufacturing (machinery, trucks, planes, chemicals, office furniture, paper, commercial printing), (4) energy (oil, gas, and coal

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[6] The investment universe considered by Fama and French is made up of stocks with a CRSP share code and positive book equity data. Moreover, the data for year t are restricted to stocks for which market prices are available in June of year t and in December of year t-1.

[7] http://www.nber.org/cycles.html. NBER recession periods are: Dec 1969 to Nov 1970, Nov 1973 to Mar 1975, Jan to Jul 1980, Jul 1981 to Nov 1982, Jul 1990 to Mar 1991, Mar to Nov 2001, Dec 2007 to June 2009.

[8] Forbes bear market periods are: Feb to Oct 1966, Nov 1968 to Jun 1970, Jan 1973 to Sep 1974, Jan 1977 to Feb 1978, Dec 1980 to Jul 1982, Jul 1983 to Jul 1984, Sep 1987 to Nov 1987, June 1990 to Oct 1990, July 1998 to Oct 1998, Mar 2000 to Oct 2002, Oct 2007 to Feb 2009. They include i.a. the oil-shock-driven financial crises in the 1970s, the 1987 stock market crash, the 1998 Asian crisis, the2000 e-crash, and the recent subprime crisis.

extraction and products), (5) high tech (computers, software, and electronic equipment), (6) telecom (telephone and television transmission), (7) shops (wholesale, retail, and some services: laundries, repair shops), (8) health (healthcare, medical equipment, and drugs), (9) utilities, (10) other (mines, construction, building materials, transports, hotels, entertainment, finance, etc.).

Second, the factors we use are necessarily those fixed by Fama and French (1992, 2015) and Carhart (1997). French's website provides the so-called research factors, which denote long-short portfolios. In practice, however, most investors lack access to investments in such portfolios. Instead, they can trade factor-based mutual funds or exchange traded funds, which develop long-only investing strategies. The factors set forth by Fama and French (1992, 2014) and Carhart (1997) are thus barely investible by individual agents (Idzorek and Kowara, 2013; Cazalet and Roncalli, 2014; Huij et al., 2014). To allow fair comparisons with sector investing, we consider two situations. In the first, the investor is restricted to long-only positions; in the second, short-sales are authorized. This approach goes beyond Fama and French's original factors, which place opposite exposures on the two legs of the position (e.g., small minus big). In contrast, we let each leg have its own exposure (e.g., α small plus β big). In this way, portfolio optimization benefits from more degrees of freedom.[9] Arguably, the resulting factors closely mimic the investment practice suggested by the proponents of factor investing.

The five long-short portfolios available on French's website are: size, value, profitability, investment, and momentum.[10] We build long-only versions of these factors by

[9] In fact, any combination of factors is by definition suboptimal when compared to portfolios made of individual securities (Clarke et al., 2015).

[10] Fama and French (2015) do not include momentum in their latest 5-factor model. However, by means of Bayesian asset-pricing tests Barillas and Shanken (2015) show that factor models perform better when they contain momentum in addition to size, value, investment and profitability. Regarding the value factor, we stick

disentangling the long and short legs of each long-short portfolio. For this, we use the sub-portfolios provided on the site. For example, to derive the long-only "value" factor, we weigh equally the "small value" portfolio and the "big value" portfolio, both of which are long-only portfolios. The method, inspired by Huij et al. (2014), is detailed in Appendix A. We end up with ten long-only factors: (1) small; (2) big, (3) value, (4) growth, (5) robust profitability, (6) weak profitability, (7) conservative investment, (8) aggressive investment, (9) high momentum, (10) low momentum.

While working with widely used factors and sectors has undeniable advantages, the approach raises the issues of relevance and replicability. Regarding relevance, this approach draws heavily on Fama and French's findings. There is undoubtedly a literature consensus on the relevance of the "historic" size and value factors (Fama and French, 1992; Asness et al., 2013), as well as the momentum factor (Jegadeesh and Titman, 1993; Carhart, 1997). The two additional quality factors, profitability and investment, are useful for applications (Piotroski, 2000; Novy-Marx, 2013; 2014; Fama and French, 2015; Hou et al., 2015a and 2015b), but their theoretical foundations are controversial (Harvey et al., 2014; Pukthuanthong and Roll, 2014).[11] Finally, the replicability issue chiefly concerns short sales and investment in illiquid small caps. Ultimately, the success of new factors is crucially linked to their being available to investors.[12]

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to the classic Fama-French version as opposed to the recent version developed by Asness and Frazzini (2013) and heralded as more profitable.

[11] Evidence regarding the existence (and stability) of risk premia associated with the new factors is still lacking. According to Ang (2014), each factor refers to a specific set of bad times. Therefore, factors might underperform during a long period, which points to the need to diversify portfolios across factors. In this respect, the number of factors and their correlations are key.

[12] Factor investing is feasible through mutual funds, hedge funds, exchange traded funds, etc. Popular factors absent from our studies include the low-volatility factor (Haugen and Baker, 1991) and the betting-against-beta factor (Frazzini and Pedersen, 2014). Asness et al. (2015) provide compelling evidence to support the practical relevance of these two factors. In contrast, the liquidity factor introduced by Pástor and Stambaugh (2003) is still unexploited commercially.

2.2. Methods

We organize a multi-trial contest. The purpose is to examine the financial performance of factor and sector investing along several dimensions in order to cover the motivations behind style investing as comprehensively as possible. Our contest includes three trials, each devoted to a specific issue that matters (or ought to matter) to portfolio managers and is made up of a groups of tests. Every test is run on our five sub-samples of monthly returns to get a sense of performance in different types of period, i.e. during recession/expansion, and for bear/bull markets. In every case we compare the performance of factor investing to that of sector investing. To designate sector or factor indistinctly, we use the term “style”, which has become standard in the literature.

The first trial investigates the risk-return trade-off by drawing efficient frontiers for the ten portfolios (five subsamples with and five without short selling) of each style. Accordingly, we conduct ten comparisons of sector-based versus factor-based efficient frontiers. Unfortunately the literature proposes no formal test to run this type of comparison. Therefore, we rely on a rule of thumb, exploiting both the horizontal and vertical distances between two curves.

In the second and third trials, we address the performance of portfolio management with factors and sectors. The second trial tests the significance of the Jensen (1968) alpha for a collection of portfolios of each style with respect to the market portfolio. Jensen’s alpha (α) evaluates the abnormal return of a portfolio over its theoretical risk-adjusted expected return:

$$r - r_f = \alpha + \beta\left(r_M - r_f\right),$$

where r is the expected return of the portfolio under consideration, r_f is the risk-free rate, r_M is the expected return of the market, and $\beta\left(r_M - r_f\right)$ is the theoretical risk premium associated with the given portfolio following the CAPM. Here, we consider successively: one sector/factor portfolio, the portfolio maximizing the Sharpe ratio, the portfolio with minimum volatility, and the equally-weighted portfolio. In each case, we use the Wald test to assess the significance of their alphas (if positive).

In the last trial, we compare the ways risk is remunerated by the two investment styles. For this, we once again take the special portfolios (maximum Sharpe ratio, minimum volatility, equally-weighted) with and without short-selling restrictions. In each case we test the equality of the Sharpe (1966) ratios of the factor-based portfolio and the sector-based portfolio. The Sharpe ratio (SR) measures the excess return per unit of risk.

$$SR = \frac{r - r_f}{\sigma},$$

where σ is the volatility of the portfolio under consideration. The SR is a rough measure of performance (Modigliani and Modigliani, 1997), but, at the same time, it is free from any model-based premises. Moreover, we use the Ledoit and Wolf (2008) test, designed to acknowledge the possibility of non-normal returns.

3. Descriptive Statistics

3.1. Full-Sample Statistics

Panel A in Table 1 provides the figures for all ten sectors and for the market. The average annualized returns reveal that two sectors outperform all the others: non-durables (13.10%) and health (13.23%). The utilities, durables and telecom sectors are the worst performers (10.27%, 10.49% and 10.59% respectively). The risk levels differ substantially across sectors. Volatilities range from 13.97% (utilities) to 22.49% (high tech).[13] Skewness is negative for all but three sectors (durable, energy, health). Kurtosis is higher than three (between 4.13 and 7.88); and the Jarque-Bera test statistic confirms previous evidence on non-normal returns for all sectors (Harvey and Siddique, 2000). The Sharpe ratios range from 0.51 (high tech) to 0.85 (non-durables), showing that the risk-return performances of different sectors are dispersed.

Panel B in Table 1 gives the same information as Panel A, but for the ten factors. The returns have similar orders of magnitude for both styles. The factor annualized returns range from 8.42% (low momentum) to 15.19% (value). Volatilities lie between 15.02% (big) and 21.64% (low momentum). Skewness is negative for all factors, except low momentum. The highest absolute value of skewness (0.63) corresponds to high momentum. This is consistent with the evidence reported by Daniel and Moskowitz (2013) and Barroso and Santa-Clara (2015) that, despite attractive Sharpe ratios, momentum strategies can lead to severe losses, making them unappealing for investors sensitive to extreme risks. Kurtosis ranges between 4.92 and 6.48, and again the Jarque-Bera test detects non-normality. Sharpe ratios range from 0.37 (low momentum) to 0.88 (high momentum), showing a slightly higher performance

[13] In fact, t-tests fail to detect any significant differences among means, while some differences in variances are statistically significant.

dispersion than for sectors. Overall, Panels A and B in Table 1 show no clear financial outperformance of one style over the other.

Panels C and D in Table 1 report intra-group pairwise correlations for sectors and factors, respectively. The average correlation computed for factors (0.92) is much higher than the one obtained for sectors (0.66). This could be due to the fact that sectors are mutually exclusive (each stock belongs to a single sector), while factors can overlap. In any case, this tends to indicate that diversification benefits will be harder to capture with factors than with sectors. However, correlations among sectors exhibit substantial heterogeneity. High correlations (above 0.80) are found for durables, manufacturing, and the last sector ("other"), which includes finance. In contrast, the correlations between the returns of utilities and durables, and between the returns of energy and high tech are particularly low (around 0.40). The manufacturing sector is highly correlated with the market (0.94). Correlations between factors are far more homogeneous. They range from 0.74 (between low and high momentum) and 0.99 (between growth and aggressive investment). As expected, the highest correlation with the market is found for big stocks, which have the highest capitalization, and thus the largest share of the investment universe.

Table 1: Descriptive Statistics: Sectors and Factors, July 1963- Dec 2014

Panel A: Descriptive Statistics Sectors

	Non Dur	Durable	Manuf	Energy	Tech	Telecom	Shops	Health	Utilities	Other	Market
Mean	1.09%	0.87%	0.99%	1.05%	0.99%	0.88%	1.05%	1.10%	0.86%	0.95%	0.91%
Ann. Mean	13.10%	10.49%	11.83%	12.60%	11.93%	10.59%	12.56%	13.23%	10.27%	11.35%	10.98%
Median	1.13%	0.83%	1.23%	1.03%	1.02%	1.04%	1.09%	1.17%	0.92%	1.40%	1.26%
Maximum	18.88%	42.62%	17.51%	24.56%	20.75%	21.34%	25.85%	29.52%	18.84%	20.22%	16.61%
Minimum	-21.03%	-32.63%	-27.33%	-18.33%	-26.01%	-16.22%	-28.25%	-20.46%	-12.65%	-23.60%	-22.64%
Std. Dev.	4.29%	6.31%	4.93%	5.39%	6.49%	4.63%	5.20%	4.86%	4.03%	5.30%	4.44%
Volatility	14.85%	21.84%	17.08%	18.67%	22.49%	16.04%	18.00%	16.84%	13.97%	18.37%	15.39%
Skewness	-0.28	0.12	-0.49	0.02	-0.23	-0.21	-0.26	0.05	-0.10	-0.48	-0.52
Kurtosis	5.10	7.88	5.66	4.45	4.35	4.32	5.47	5.51	4.13	4.88	4.97
Sharpe Ratio	0.85	0.46	0.67	0.65	0.51	0.64	0.68	0.76	0.71	0.60	0.69
Jarque-Bera	121.95	613.66	206.84	54.28	52.04	49.34	163.54	162.76	33.76	115.15	127.23
Probability	0	0	0	0	0	0	0	0	0	0	0
Observations	618	618	618	618	618	618	618	618	618	618	618

Panel B: Descriptive Statistics Factors

	Small	Big	Value	Growth	Robust Profit	Weak Profit	Conserv Invest	Aggres Invest	High Mom	Low Mom
Mean	1.21%	0.94%	1.27%	0.90%	1.16%	0.91%	1.22%	0.90%	1.39%	0.70%
Ann. Mean	14.55%	11.29%	15.19%	10.84%	13.93%	10.95%	14.69%	10.81%	16.68%	8.42%
Median	1.62%	1.29%	1.77%	1.21%	1.49%	1.33%	1.53%	1.28%	1.85%	0.59%
Maximum	27.12%	16.66%	25.83%	17.79%	20.26%	21.21%	20.21%	21.09%	17.49%	40.27%
Minimum	-29.51%	-21.41%	-23.56%	-27.76%	-25.81%	-27.48%	-25.46%	-27.80%	-27.88%	-24.78%
Std. Dev.	5.83%	4.34%	4.92%	5.48%	4.92%	5.56%	4.94%	5.64%	5.34%	6.25%
Volatility	20.20%	15.02%	17.03%	18.99%	17.06%	19.25%	17.12%	19.55%	18.50%	21.64%
Skewness	-0.46	-0.43	-0.48	-0.46	-0.57	-0.49	-0.53	-0.51	-0.63	0.39
Kurtosis	5.47	4.92	6.48	4.68	5.39	4.92	5.25	4.76	5.29	7.20
Sharpe Ratio	0.70	0.72	0.87	0.55	0.79	0.55	0.83	0.53	0.88	0.37
Jarque-Bera	179.17	114.52	336.06	95.10	180.00	120.12	159.61	106.18	176.08	469.83
Probability	0	0	0	0	0	0	0	0	0	0
Observations	618	618	618	618	618	618	618	618	618	618

Panel C: Correlations Sectors

	Non Dur	Durable	Manuf	Energy	Tech	Telecom	Shops	Health	Utilities	Other	Market
Non Dur		0.66	0.82	0.49	0.58	0.61	0.83	0.76	0.61	0.83	0.83
Durable			0.84	0.47	0.67	0.59	0.75	0.52	0.43	0.79	0.80
Manuf				0.62	0.77	0.63	0.83	0.70	0.53	0.89	0.94
Energy					0.45	0.41	0.43	0.42	0.57	0.58	0.66
Tech						0.61	0.71	0.61	0.30	0.71	0.86
Telecom							0.63	0.53	0.50	0.67	0.75
Shops								0.67	0.46	0.83	0.86
Health									0.47	0.71	0.76
Utilities										0.58	0.59
Other											0.93

Panel D: Correlations Factors

	Small	Big	Value	Growth	Robust Profit	Weak Profit	Conserv Invest	Aggres Invest	High Mom	Low Mom	Market
Small		0.86	0.93	0.95	0.95	0.96	0.96	0.95	0.93	0.88	0.89
Big			0.90	0.92	0.95	0.91	0.93	0.93	0.89	0.86	0.99
Value				0.85	0.92	0.91	0.95	0.88	0.86	0.87	0.89
Growth					0.97	0.96	0.94	0.99	0.94	0.87	0.95
Robust Profit						0.92	0.95	0.97	0.94	0.88	0.96
Weak Profit							0.97	0.96	0.93	0.89	0.93
Conserv Invest								0.94	0.93	0.88	0.94
Aggres Invest									0.94	0.88	0.96
High Mom										0.74	0.92
Low Mom											0.87

3.2 Sub-sample Statistics

Table 2 summarizes the main statistics concerning sub-samples (see the full tables in Appendix B). As explained in Section 2, we are dealing with four sub-samples: bear market and bull market (as identified by Forbes Magazine), recessions, and expansions, as dated by the NBER. Table 2 is organized as follows. First, it gives the annualized means, volatilities, and correlations with the market for each sector over each sub-period (Panels A to D). Second, it reports the same information for each factor over each sub-period (Panels E to H).

Table 2: Descriptive Statistics for Sub-Samples

	Non Dur	Durable	Manuf	Energy	Tech	Telecom	Shops	Health	Utilities	Other	Market
Panel A: Bear Market											
Ann. Mean	-10.35%	-27.17%	-21.42%	-16.25%	-29.72%	-14.40%	-18.86%	-11.91%	-7.54%	-25.74%	-22.73%
Volatility	16.43%	23.54%	19.02%	21.51%	26.99%	19.97%	20.48%	17.90%	16.82%	21.40%	17.48%
Correlation with Market	0.81	0.81	0.92	0.64	0.86	0.73	0.85	0.75	0.54	0.90	1.00
Panel B: Bull Market											
Ann. Mean	21.15%	23.43%	23.25%	22.50%	26.24%	19.18%	23.35%	21.87%	16.39%	24.09%	22.55%
Volatility	13.52%	19.93%	15.02%	16.68%	19.07%	13.61%	15.94%	15.72%	12.38%	15.61%	13.04%
Correlation with Market	0.83	0.77	0.94	0.62	0.83	0.72	0.85	0.75	0.57	0.93	1.00
Panel C: Recessions											
Ann. Mean	4.70%	-4.27%	-6.03%	-3.32%	-3.73%	-2.20%	5.78%	3.60%	0.86%	-8.12%	-3.33%
Volatility	20.47%	33.29%	25.28%	25.85%	30.43%	19.33%	26.39%	22.62%	19.62%	28.12%	22.52%
Correlation with Market	0.91	0.84	0.97	0.71	0.90	0.80	0.90	0.79	0.76	0.95	1.00
Panel D: Expansions											
Ann. Mean	14.53%	13.01%	14.87%	15.31%	14.60%	12.77%	13.72%	14.88%	11.88%	14.67%	13.41%
Volatility	13.64%	19.18%	15.11%	17.06%	20.78%	15.34%	16.16%	15.62%	12.73%	15.97%	13.72%
Correlation with Market	0.80	0.79	0.92	0.63	0.84	0.73	0.85	0.75	0.51	0.92	1.00

	Small	Big	Value	Growth	Robust Profit	Weak Profit	Conserv Invest	Aggres Invest	High Mom	Low Mom
Panel E: Bear Market										
Ann. Mean	-23.36%	-20.63%	-14.37%	-29.34%	-20.71%	-29.02%	-18.43%	-31.49%	-20.50%	-32.26%
Volatility	22.95%	16.97%	19.11%	21.86%	19.17%	22.23%	19.03%	22.67%	20.28%	25.81%
Correlation with Market	0.89	0.99	0.87	0.95	0.95	0.93	0.94	0.96	0.91	0.88
Panel F: Bull Market										
Ann. Mean	27.57%	22.25%	25.35%	24.64%	25.83%	24.69%	26.07%	25.34%	29.46%	22.39%
Volatility	17.68%	12.87%	15.20%	16.09%	14.81%	16.35%	15.10%	16.41%	16.31%	18.38%
Correlation with Market	0.87	0.99	0.88	0.94	0.96	0.91	0.93	0.95	0.91	0.84
Panel G: Recessions										
Ann. Mean	-1.32%	-2.49%	1.97%	-4.64%	-0.81%	-4.78%	2.04%	-6.96%	0.16%	-5.31%
Volatility	29.11%	22.12%	25.88%	27.13%	25.39%	26.86%	24.34%	28.97%	23.54%	36.89%
Correlation with Market	0.92	1.00	0.92	0.97	0.97	0.96	0.96	0.97	0.95	0.89
Panel H: Expansions										
Ann. Mean	17.26%	13.63%	17.45%	13.48%	16.45%	13.64%	16.85%	13.84%	19.50%	10.76%
Volatility	18.17%	13.36%	14.95%	17.14%	15.11%	17.54%	15.50%	17.34%	17.39%	17.76%
Correlation with Market	0.87	0.99	0.88	0.95	0.96	0.92	0.93	0.95	0.91	0.86

The main lessons drawn from Table 2 relate to differences in sensitivity to crises and market downturns. During bear market periods, the average returns of all assets, be they sectors or factors, are negative. Apparently, factors suffer slightly more than sectors do. The average spread between the annualized returns of bull and bear markets is 40.92% (22.18% + 18.74%) for sectors and 48.99% (25.10% + 23.89%) for factors. The average spreads between expansions to recessions are less spectacular: 15.33% (13.87% + 1.46%) for sectors, and 17.44% (15.12% + 2.32%) for factors.

On an individual basis, the sectors that suffer the most during bear markets are high tech (-29.72%) and durables (-27.17%). Their losses are nevertheless smaller than those of the most exposed factors: low momentum (-32.26%), and aggressive investment (-31.49%).

Evidence on recessions is mixed: Some sectors deliver a negative return (“other:” -8.12%; manufacturing: -6.03%) while others perform positively (surprisingly, shops: 5.78%; non-durables: 4.70%; health: 3.60%). The returns of factors during recessions are less dispersed. The worst performers are: aggressive investment, low momentum, and weak profitability with annualized returns of-6.96%, -5.31%, and -4.78%, respectively, while only three resilient factors (conservative investment, value, and high momentum) exhibit modest but positive performances, with annualized returns of 2.04%, 1.97%, and 0.16%, respectively.

As expected, volatilities jump when the market turns from bull to bear. The spread is similar for the two styles, ranging from 15% to 20%. Likewise, volatilities are higher in recessions than in expansions, but the phenomenon is slightly more pronounced for factors than for sectors. On average, sector-wise volatility rises from 15.94% to 24.90%, and its factor-wise counterpart increases from 16.18% to 26.61%.

The figures suggest that crises have somewhat tougher consequences for factor investing than for sector investing. But these insights are mitigated by the fact that descriptive statistics are provided for individual sectors/factors, while investors are chiefly concerned with the performance of diversified portfolios, which rely heavily on correlations. In this respect Tables 1 and 2 concur in showing that correlations among factors are substantially higher than among sectors. Interestingly, the benefits of diversification seem to resist bear-market periods for both styles. Indeed the average correlation with the market stays between 0.62 and 0.64 for sectors, and remains idle at the fairly high value of 0.91 for factors. Surprisingly, the increase in correlations is stronger for the transition from expansions to recessions, particularly for sectors (from 0.62 to 0.73). For factors, the increase is smaller (from 0.91 to 0.94) because correlations are capped at one.

4. The Contest

4.1 First Trial: Efficient-Frontier Dominance

According to the Markowitz portfolio management principle, rational investors will always pick a portfolio lying on the efficient frontier of their investment universe. The efficient frontier is a curve in the risk/return plane. Each point on this frontier is a non-dominated portfolio in the fixed investment universe. By definition, portfolio P is dominated by portfolio Q if:

$$E[R_P] \leq E[R_Q] \text{ and } \sigma[R_P] \geq \sigma[R_Q], \tag{1}$$

with at least one strict inequality.

Here, we consider ten different period/short-sale scenarios. In each case, we determine two efficient frontiers, the first built from the ten sectors, and the second from the ten factors. The next step consists in deciding whether or not one frontier dominates the other. The rule of thumb we use to reach this goal generalizes the simple definition in Eq. (1) to two frontiers constructed from different investment universes. We rely on the following definition:

The efficient frontier F_U in universe U is dominated by the efficient frontier F_V in universe V if:

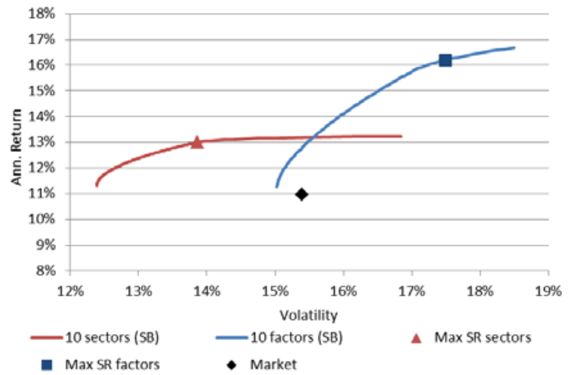
$$\forall P \in F_U : \exists Q \in F_V : E[R_P] \leq E[R_Q] \text{ and } \sigma[R_P] \geq \sigma[R_Q], \tag{2}$$

with at least one strict inequality. If neither frontier dominates the other, they will be considered a draw in our trial. The graphs featured in Figure 1 show, however, that a few cases are borderline. We will keep these visual considerations in mind for the conclusion.

Figure 1: Efficient Frontiers for Factors and Sectors

Short selling Banned (SB)

Fig 1a: Full Sample, SB



Short selling Authorized (SA)

Fig 1b: Full Sample, SA

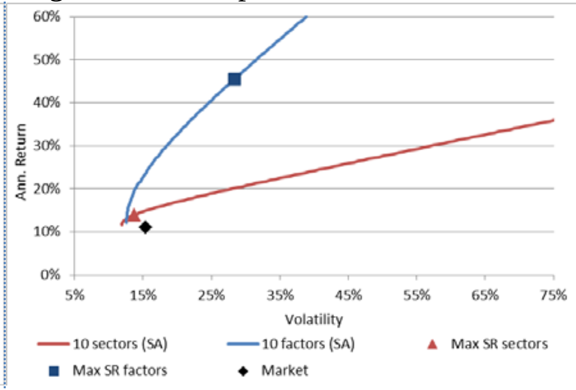


Fig 1c: Bear Market, SB

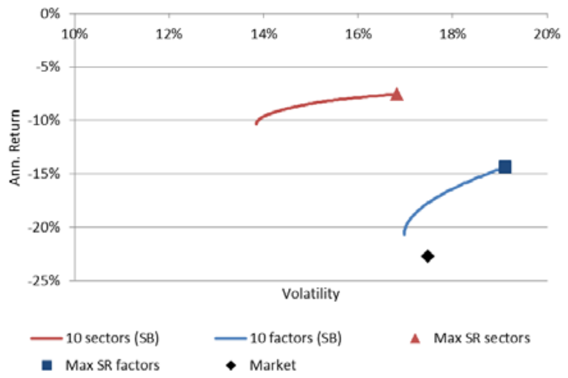


Fig 1d: Bear Market, SA

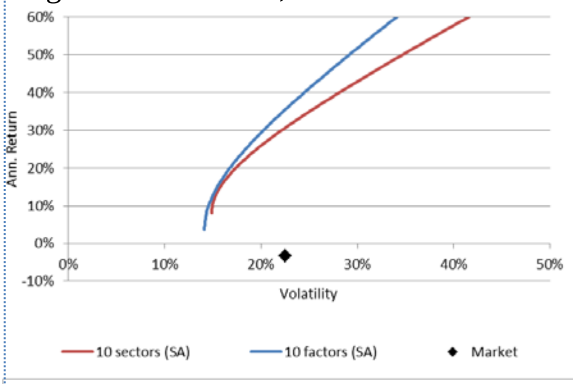


Fig 1e: Bull Market, SB

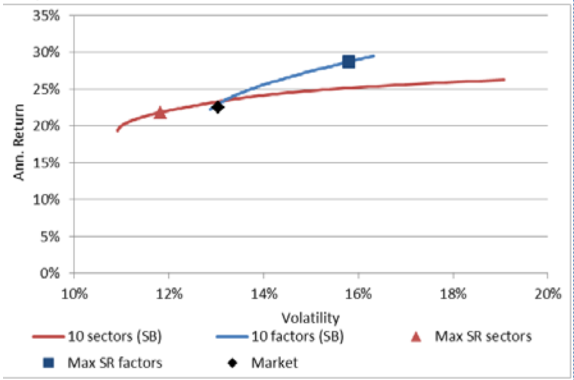


Fig 1f: Bull Market, SA

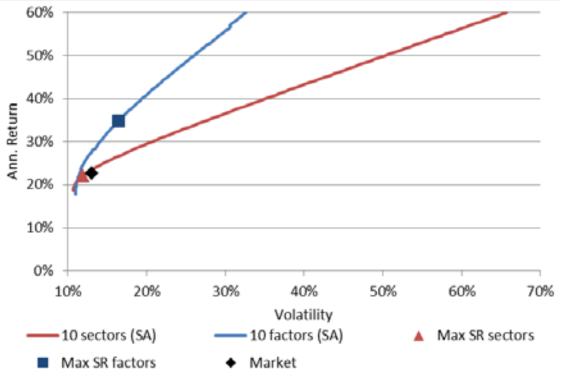


Fig 1g: Recessions, SB

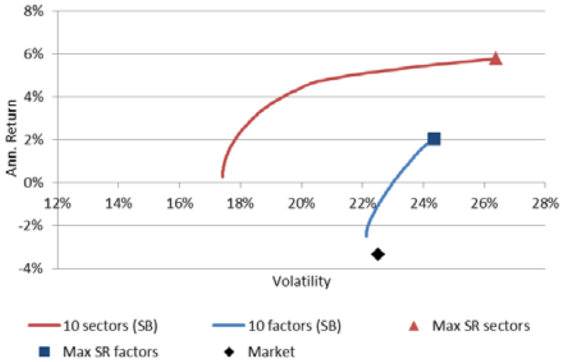


Fig 1h: Recessions, SA

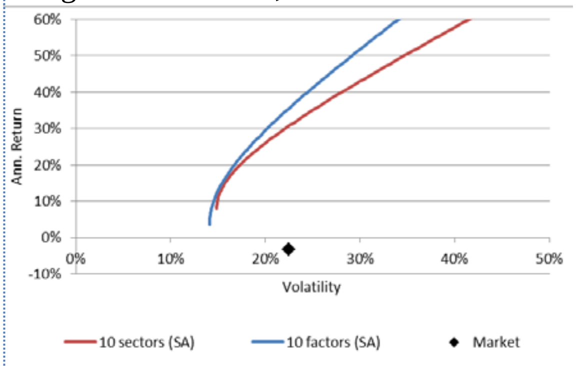


Fig 1i: Expansions, SB

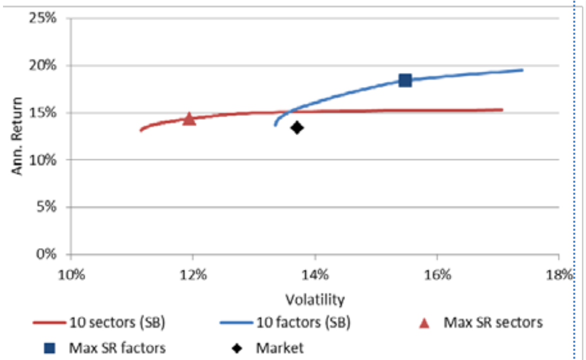


Fig 1j: Expansions, SA

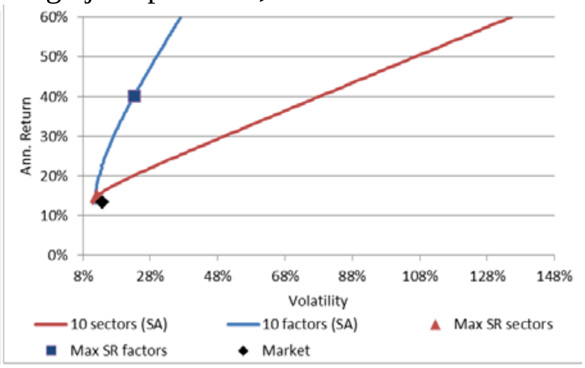


Table 3: Efficient Frontier Dominance

Sample Period	Winner
Panel A: Shortselling Banned	
Full sample	=
Bear Market	Sectors
Bull Market	=
Recessions	Sectors
Expansions	=
Panel B: Shortselling Authorized	
Full sample	=
Bear Market	Factors
Bull Market	=
Recessions	Factors
Expansions	=

Table 3 summarizes the information visible in Figure 1. First, the high prevalence of draws is partly attributable to the severity of criterion (2), which tolerates no exception to the dominance principle. That said, the results suggest that style matters most in hard times such as bear markets and recessions. More precisely, sector investing is better when short-sales are banned, while factor investing wins the trial when the portfolio is allowed to take short positions. Evidently, no overall winner emerges from trial 1.

4.2 Second Trial: Jensen's alphas

This trial checks whether a strategic asset allocation in sectors/factors outperforms well-diversified passive investment in the market portfolio. Put differently, we examine whether factor and sector investing both generate significant Jensen's alphas. Moreover, when this is the case, does either style generate a (significantly) higher value for alpha and should therefore be preferred by investors?

Academics and practitioners use various alternative measures of alpha. Most of these alphas are derived from the Fama-French factor model (Ang et al., 2009; Government Pension Fund Global, 2014). However, we cannot use such a benchmark model here because we are comparing two investment styles, one of which built from the Fama-French factors. Instead, we use the market as an unarguable benchmark for judging the performance of two competing investment styles.[14]

To run the test, we need to particularize portfolios and regress their returns on the market return. We consider two options for singling out a portfolio. In the first, the investor picks one sector/factor randomly.[15] In the second, which is more a likely option for rational investors, the portfolio is chosen for its intrinsic diversification qualities. In this respect, three special portfolios stand out in the literature: the efficient portfolio maximizing SR, the efficient minimum volatility portfolio, and the equally-weighted portfolio.[16] The first two make sense with and without short-selling restrictions, while the last is long-only by construction. As a result, we end up with five composite portfolios. Finally, in all cases we assume that the investor rebalances her portfolio monthly, in order to keep the asset weights constant over the investment period.

For the whole sample period, Table 4 shows that random picking delivers, on average, larger alphas for factors than for sectors. Sectors alone seldom deliver significant alphas, which is hardly surprising. In contrast, the performances of our five composite portfolios are much better overall. However, the Wald test for equal alphas across regressions detects a single case of significant difference in alphas at the 5% level. This is for the long-short portfolio maximizing SR, where factor investing outperforms sector investing.

[14]. We however discuss the limitations of this benchmark in sub-section 4.4.

[15] Picking one sector/factor is generally a sub-optimal investment strategy. Some investors, however, do the expedient thing and invest only in the expectedly best rewarded factor/sector. The “style rotation” investment strategy follows the same logic. It consists in investing in a single factor/sector at a time, chosen according to market conditions (Bala et al., 2007).

[16] Equal weighting significantly departs from the original spirit of Fama and French (1993) who impose opposite signs to the two legs of their factor components.

Table 4: Jensen's Alphas, Full Sample

Panel A reports the monthly alphas obtained from regressions of sector (left side of the table) and factor (right side) excess returns on market excess return. Panel B reports the alphas of specific portfolios (maximum Sharpe ratio, minimum volatility, equally weighted) made of sectors (left) and factors (right). SEE is the standard error of estimate; R2 is the R-squared of the regression; SB (resp. SA) means that short selling is banned (resp. authorized). SR stands for the Sharpe ratio. The panel-A winner has the highest number of positive alphas at the 5% significance level. The panel-B winner has a significantly higher alpha (Wald test) at the 5% level. The sample period is the full sample between July 1963 and December 2014. ***, **, *: significant at the 1%, 5% and 10% respectively.

Panel A: Individual Sectors and Factors											
	α(%)	T-stat	SEE	R2		α(%)	T-stat	SEE	R2	Number of positive alphas	Winner
Non Dur	0.28***	2.89	0.02	0.69	Small	0.21**	1.97	0.03	0.79		
Durable	-0.11	-0.74	0.04	0.65	Big	0.04**	2.02	0.01	0.99		
Manuf	0.05	0.72	0.02	0.88	Value	0.36***	3.96	0.02	0.79		
Energy	0.24	1.44	0.04	0.43	Growth	-0.10	-1.49	0.02	0.91		
Tech	-0.05	-0.36	0.03	0.74	Robust Profit	0.21***	3.91	0.01	0.93		
Telecom	0.08	0.66	0.03	0.56	Weak Profit	-0.09	-1.05	0.02	0.87		
Shops	0.13	1.20	0.03	0.74	Conserv Invest	0.29***	4.11	0.02	0.88		
Health	0.27**	2.14	0.03	0.58	Aggres Invest	-0.12*	-1.86	0.02	0.92		
Utilities	0.18	1.35	0.03	0.34	High Mom	0.42***	4.96	0.02	0.84		
Other	-0.02	-0.29	0.02	0.86	Low Mom	-0.33***	-2.59	0.03	0.75		
Sectors/Factors										2/6	Factors
Panel B: Special Portfolios											
	α(%)	T-stat	SEE	R2		α(%)	T-stat	SEE	R2	Wald test	Winner
Max SR Sectors (SB)	0.27***	3.72	0.02	0.80	Max SR Factors (SB)	0.4***	5.65	0.02	0.88		=
Min Vol Sectors (SB)	0.19**	2.47	0.02	0.73	Min Vol Factors (SB)	0.04**	2.02	0.01	0.99	*	=
Equal Weight Sectors	0.1***	3.44	0.01	0.97	Equal Weight Factors	0.09*	1.64	0.01	0.93		=
Max SR Sectors (SA)	0.45***	3.82	0.03	0.46	Max SR Factors (SA)	3.13***	9.81	0.08	0.07	***	Factors
Min Vol Sectors (SA)	0.27***	3.03	0.02	0.59	Min Vol Factors (SA)	0.27***	3.08	0.02	0.64		=

The detailed results deliver interesting insights as well. Panel A in Table 4 shows that two sectors (non-durables and health) generate significantly positive alphas. Although sectors might be expected to have different exposures to market (betas), finding positive alphas is more surprising because sectors alone are not meant to outperform the market. In contrast, six out of the ten factors generate positive alphas. Unsurprisingly, the five long legs of the Fama and French factors (small, value, robust profit, conservative investment, and high momentum) have positive alphas since they were built for that specific purpose. But more surprisingly, the "big" factor, traditionally considered as a short leg, also exhibits a significantly positive alpha.

Panel B in Table 4 concerns a collection of notable portfolios (maximum SR, minimum volatility, and equally-weighted). To counteract the impact of price fluctuations, all portfolios are rebalanced monthly to keep the asset weights constant over the full sample period. Almost all portfolios outperform the market at the 5% level. The only exception is the equally-weighted factor portfolio, which has a significant alpha but only at the 10% level. But ultimately, the Wald test detects few significant differences in the alphas generated by the two investment styles. The only situation without a tie corresponds to the long-short maximum SR portfolios: the factor-based portfolio exhibits an exceptional monthly outperformance of 313 basis points (bps)[17] while the alpha of the sector-based portfolio is a modest 27 bps. Overall, the factor allocation wins the full-sample trial.

Panel A in Table 5 shows that no sector outperforms the market during bear periods, which is somewhat reassuring for the proponents of passive investment. By contrast, two factors–value and conservative investment– produce positive alphas at the 5% level. Note that the long-only maximum SR portfolio made with factors outperforms the market by 57 bps. On the other hand, when short selling is authorized, the maximum SR portfolio does not exist, because the slope of the efficient frontier is such that the tangency point is located at infinity. Overall, the alphas of the specific sector-made portfolios are not significantly different for those of sector-made portfolios. Although equal weighting departs from the spirit of factor investing, the actual performances of equally-weighted factor portfolios are very close to those of equally-weighted sector portfolios. The figures lead to a tied result.

[17] This would be considerably lower if transaction costs were accounted for.

Table 5: Jensen's Alphas, Sub-Samples

This table reports the number of significantly positive (at the 5% level) monthly alphas obtained from the regression of sector and factor excess returns on market excess return, as well as the alphas of specific portfolios (maximum SR, minimum volatility, equally weighted) made of either sectors (left side) or factors (right side), with t-stats; SB (resp. SA) means that short selling is banned (resp. authorized). SR stands for the Sharpe ratio. For individual sectors/factors, the winner has the highest number of positive alphas at the 5% significance level. For the specific portfolios, the winner has a significantly higher alpha (Wald test) at the 5% level. The full sample covers the period July 1963 and December 2014. The sub-samples are characterized by: bear market (panel A), bull market (panel B), recession (panel C) and expansion (panel D). ***, **, *: significant at the 1%, 5% and 10% respectively.

	α(%)	T-stat		α(%)	T-stat	Wald test	Number of positive alphas	Winner
Panel A: Bear Market								
Individual Sectors/Factors							0/2	Factors
Max SR Sectors (SB)	0.09	0.26	Max SR Factors (SB)	0.57**	2.38			=
Min Vol Sectors (SB)	0.24	1.36	Min Vol Factors (SB)	0.08	1.21			=
Equal Weight Sectors	0.16*	1.76	Equal Weight Factors	0.16	1.24			=
Max SR Sectors (SA)	-	-	Max SR Factors (SA)	-	-	-		-
Min Vol Sectors (SA)	0.38*	1.65	Min Vol Factors (SA)	0.41*	1.84			=
Panel B: Bull Market								
Individual Sectors/Factors							0/3	Factors
Max SR Sectors (SB)	0.13***	2.95	Max SR Factors (SB)	0.34***	3.83	**		Factors
Min Vol Sectors (SB)	0.15*	1.90	Min Vol Factors (SB)	0.00	0.20	*		=
Equal Weight Sectors	0.05	1.48	Equal Weight Factors	0.06	0.85			=
Max SR Sectors (SA)	0.16***	3.01	Max SR Factors (SA)	1.1***	7.06	***		Factors
Min Vol Sectors (SA)	0.19**	2.08	Min Vol Factors (SA)	0.06	0.71			=
Panel C: Recessions								
Individual Sectors/Factors							2/1	Sectors
Max SR Sectors (SB)	0.8**	2.25	Max SR Factors (SB)	0.48**	2.31			=
Min Vol Sectors (SB)	0.05	0.24	Min Vol Factors (SB)	0.05	1.11			=
Equal Weight Sectors	0.14*	1.84	Equal Weight Factors	0.21	1.15			=
Max SR Sectors (SA)	-	-	Max SR Factors (SA)	-	-	-		-
Min Vol Sectors (SA)	0.48	1.41	Min Vol Factors (SA)	0.08	0.24			=
Panel D: Expansions								
Individual Sectors/Factors							1/4	Factors
Max SR Sectors (SB)	0.25***	3.5	Max SR Factors (SB)	0.38***	5.15			=
Min Vol Sectors (SB)	0.21***	2.67	Min Vol Factors (SB)	0.05**	2.25	*		=
Equal Weight Sectors	0.11***	3.33	Equal Weight Factors	0.08	1.44			=
Max SR Sectors (SA)	0.32***	3.67	Max SR Factors (SA)	2.45***	9.07	***		Factors
Min Vol Sectors (SA)	0.24***	2.82	Min Vol Factors (SA)	0.18**	2.23			=

During bull periods (panel B), no sector meets the 5% level for the positivity of alpha, while three factors reach that threshold, namely robust profitability, conservative investment, and high momentum. The winner for individual portfolios in bull periods is factor investing. Among the composite portfolios, we find two out of five (long-only minimum SR, long-short minimum SR) for which the factor-based alpha dominates the sector-based one. In the three other cases, we obtain a draw.

Panel C in Table 5 indicates that recessions support the dominance of sector investing to a slight degree. However, this superiority is visible only for individual portfolios, where positive alphas are obtained for the non-durable sector and shops, as well as for a single factor, conservative investment. Last, the results for expansion periods (panel D) are similar to those obtained for bull market periods. Unsurprisingly in this case, the winner, if there is one, is factor investing. Altogether, Tables 4 and 5 argue in favor of factor investing, except during recessions. But the most frequent conclusion in the trial is still more or less a draw, meaning that differences are not significant enough to be used as a guide for asset allocation.

4.3 Third Trial: Sharpe Ratio Test

To compare the SR performances of portfolios made up of either sectors or factors, we turn to the test developed by Ledoit and Wolf (2008), based on bootstrap confidence intervals. The final results of this trial are set forth in Table 6. They happen to be fairly close to those obtained in the previous trial.[18] Although the measures of performance used in the two trials differ significantly, the fact that they deliver similar results is comforting. This makes our contest robust. In general, the portfolios made up of sectors and those built from factors have similar risk-adjusted performances when short-selling is banned, with a slight preference for sectors in bear markets. When short positions are authorized, the factor-based portfolios clearly outperform their sector-based counterparts.

[18] In fact, there are two minor differences between the results of the second and third trials. First, according to their performances on alphas, the maximum SR factor-based portfolios are better than their sector counterparts in bull markets, and this is no longer the case with the SR test. Second, the SR test concludes that the minimum volatility sector-based portfolios outperform their factor-based contenders in bear markets, while the Wald test on the alphas failed to reach such a conclusion.

Table 6: Sharpe Ratio Test, Full Sample and Sub-Samples

This table reports the SRs of sector-based and factor-based portfolios. The winner has a significantly higher SR than its rival, according to the Ledoit and Wolf test, at the 5% level. SB (resp. SA) means that short selling is banned (resp. authorized). SR stands for the Sharpe ratio. The full sample covers the period July 1963 and December 2014. The sub-samples are characterized by: bear market (panel A), bull market (panel B), recession (panel C) and expansion (panel D). ***, **, *: significant at the 1%, 5% and 10% respectively.

	SR Sector Portfolio	SR Factor Portfolio	Winner
Panel A: Full Sample			
Max SR (SB)	0.58	0.65	=
Min Vol (SB)	0.52	0.42	=
Equal Weight	0.47	0.44	=
Max SR (SA)	0.66	1.43***	Factors
Min Vol (SA)	0.57	0.57	=
Panel B: Bear Market			
Max SR (SB)	-0.83	-1.09	=
Min Vol (SB)	-1.22**	-1.60	Sectors
Equal Weight	-1.51	-1.51	=
Max SR (SA)	-	-	-
Min Vol (SA)	-0.84	-0.98	=
Panel C: Bull Market			
Max SR (SB)	1.48	1.55	=
Min Vol (SB)	1.37	1.39	=
Equal Weight	1.42	1.38	=
Max SR (SA)	1.49	1.86***	Factors
Min Vol (SA)	1.35	1.22	=
Panel D: Recessions			
Max SR (SB)	-0.03	-0.19	=
Min Vol (SB)	-0.36	-0.41	=
Equal Weight	-0.36	-0.33	=
Max SR (SA)	-	-	-
Min Vol (SA)	0.10	-0.20	=
Panel E: Expansions			
Max SR (SB)	0.82	0.89	=
Min Vol (SB)	0.76	0.68	=
Equal Weight	0.73	0.68	=
Max SR (SA)	0.85	1.53***	Factors
Min Vol (SA)	0.77	0.72	=

4.4 *Discussion*

Table 7 summarizes the results of the three trials performed in the previous subsections. From there, we can draw some general conclusions. First, the most frequent outcome of the tests is a draw, testifying to a fierce contest. Second, among the cases with a clear winner, factor investing dominates. This is especially true for the tests performed on the full sample, where the outcomes include ten draws and three occurrences of winning factors. Third, with a single exception, the winning-sector cases are associated both with adverse market conditions (recession or bear market) and with banned short selling.

Our results rely on the factors we selected. In particular, the sole defensive factor in our analysis is the "large" factor. In contrast, several sectors are naturally defensive, such as utilities and health. Had we included the low-volatility factor (Haugen and Baker, 1991) or the betting-against-beta factor (Frazzini and Pedersen, 2014), it would probably have affected the outcomes of the contest, at least for recessions and bear market periods. Unfortunately, considering these two factors in our analysis is not feasible because neither their separate long and short legs nor the components necessary to reconstitute these legs are publicly available. Moreover, Cremers et al. (2013) point out that the Fama-French factors place disproportionate weight on small-value stocks and require high turnover. Ang et al. (2009) argue that some factor exposures might be difficult to replicate. Ferson and Lin (2014) mention that in incomplete markets, investors can have different marginal rates of substitution, and the alphas are investor-specific.

In addition, sector investing and factor investing rely on two different lines of reasoning, which is why we need multiple trials to compare their performances. Admittedly, the choice of trials will influence the conclusions. Some subjectivity is inevitable when designing such a contest, but it is partly mitigated by the multiplicity of trials.[19] This not only provides a global comparison of the two investment styles; it also corresponds to typical investors' objectives and constraints in practice.

The choice of the CAPM as a benchmark model is also questionable. One could argue that regressing factors and sectors on the market is a way to tilt performance in favor of factors, the rationale of which is precisely that the CAPM cannot explain them. But despite this limitation we find that some industry portfolios, such as the non-durable and health sectors, do exhibit positive and significant alphas.[20]

Overall, our results confirm that portfolios based on identified risk factors yield profitable investing opportunities. Apparently, systematic rebalancing is successful in capturing long-term risk premia. In this respect, however, it should be stressed that factor investing, which is transaction-intensive, probably benefits from neglecting transaction costs in the analysis. Evidence shows that including transaction costs can substantially hamper the financial performance of factor investing (Lesmond et al., 2004; Korajczyk and Sadka, 2004; Novy-Marx and Velikov, 2014). This is particularly relevant for factors that are subject to high turnover, such as momentum factors. The problem is that the magnitude of transaction costs is still controversial.

Factor and sector portfolios have very different transaction costs. Sector indices are made up of same-industry stocks weighted by their market capitalizations. Since the weights fluctuate in line with changes in capitalization, turnover is necessary only in exceptional circumstances such as a change of sector or a new entrant in the index. Hence, investing in a

[19] On the one hand, equal weighting is better suited to sector investing since some factors are designed to be sold short. On the other hand, accepting short sales when composing about half the portfolios considered will favor factor investing.

[20] Further robustness checks could for example regress factors on sectors, and sectors on factors. Although more symmetrical with respect to the two competing asset allocations, this approach is less theoretically sound than using the CAPM benchmark.

given sector is almost free of transaction costs. By contrast, factor indices rebalance individual stocks according to characteristics that change constantly. As a matter of fact, the amplitude of the changes varies with the type of factor. Factors such as value, size, profitability and investment are defined by means of stock characteristics with little variability, while momentum stocks change frequently. As a consequence, the rebalancing frequency adopted by Fama and French is yearly for the first group of factors (end of June) but monthly for the momentum portfolios.

Intuitively, estimating transaction cost involves computing turnover at some point. In practice, however, the notion of turnover itself is not clear-cut. Some authors determine it by taking the ratio of the market value of one-way transactions only[21] to total portfolio market value. Others add up the two sides of the market and define turnover as the sum of the market values of sales and purchases divided by total portfolio value. Considering a one-sided turnover resulting from averaging the values of purchased or sold assets, Novy-Marx and Velikov (2014) estimate that the turnover of the size and value long-short portfolios is around 2% per year and the associated transaction costs[22] are close to 5 bps per month, regardless of the size of the portfolio. For the momentum factor, the authors find a turnover of 25% per year and transaction costs of 50 bps per month. Asness et al. (2015) argue that HML's return might be overstated because the strategy involves shorting very small stocks. For the same reason Harvey (2015) suggests focusing on the market segment made of the top 1,000 or 1,500 stocks, where transaction costs are reasonable and trading problems infrequent. Although the transaction costs of investment and profitability factors are still unexplored, we

[21] Depending on the paper, "one-way transactions" is understood as the lesser of purchases or sales, total sales only, or the average of purchases and sales.

[22] The authors estimate round trip transaction costs related to bid-ask spreads, but do not account for the price impact of large trades (costs related to the change in price due to the trade).

conjecture that their turnover is close to that of their size and value counterparts, which are also rebalanced on a yearly basis.[23]

In addition, sophisticated transaction-cost models (Korajczyk and Sadka, 2004; Frazzini et al., 2014) consider the break-even capacity of each investment strategy in terms of portfolio size. By definition, break-even capacity is reached when the transaction costs are equal to the gross returns of the strategy. Using data on real-life trades, Frazzini et al. (2014) estimate that the break-even capacities of the Fama and French long-short size, value, and momentum factors are USD 103 billion, USD 83 billion, and USD 52 billion, respectively. These figures far exceed those computed by Chen et al. (2002), Lesmond et al. (2004), and Korajczyk and Sadka (2004), who all rely on simple microstructure models.

For portfolios involving short selling of individual securities, specific costs must also be taken into account. Whenever the short-selling position is open, the covered short seller has to pay the lender the dividends due, if any, and borrowing fees. In the equity loan market, the borrower usually gives cash as collateral, which earns interest at the so-called rebate rate, which is lower than the market rate (D’Avolio, 2002; Gruenewald et al., 2010; Bernal et al., 2014; Engelberg et al., 2014). Overall, the estimation of transaction costs is a contentious issue, and the literature seems to be still far from a consensus on this tricky, but fundamental, issue.

The outcomes of our trials are in line with previous results obtained by Idzorek and Kowara (2013) showing that short positions are useful to increase portfolio profitability. More specifically, our findings suggest that factor investing performs particularly well when short-selling is authorized. Table 7 shows that both the alphas (trial 2) and the Sharpe ratios (trial 3)

[23] At the portfolio level, transaction costs raise additional difficulties as purchases and sales of stocks can net out. However, we are not aware of any paper dealing with transaction costs at the factor portfolio level.

indicate that factor-based portfolios perform very well under the SA condition. In fact, the max SR portfolios do not exist in bad times (recessions and bear markets), but when they do exist (full sample, expansions, and bull markets), factor investing always produces significantly better performances. The efficient-frontier dominance (trial 1) confirms that the risk-return trade-off is excellent for factor-based optimal portfolios during bad times, provided that short positions are admissible. By contrast, sector investing is better in bad times when short sales are forbidden. The association between bad times and short-selling restrictions is far from benign, since crises are often associated with tougher regulation of shorting. This was especially the case during the 2008-2009 financial crisis (Bernal et al., 2014).

Table 7: Summary of the Results

This table reports the results of the three groups of tests run on our dataset. SB (resp. SA) means that short selling is banned (resp. authorized). SR stands for the Sharpe ratio. The full sample covers the period July 1963 and December 2014.

	Full sample	Recessions	Expansions	Bear Market	Bull Market	Winner
Trial 1: Efficient-Frontiers Dominance						
SB	=	Sectors	=	Sectors	=	Sectors
SA	=	Factors	=	Factors	=	Factors
Trial 2: Jensen's Alphas						
A. Individual Sectors / Factors						
	Factors	Factors	Factors	Factors	Sectors	Factors
B. Special Portfolios						
Max SR (SB)	=	=	=	=	Factors	Factors
Min Vol (SB)	=	=	=	=	=	=
Equal Weight	=	=	=	=	=	=
Max SR (SA)	Factors	-	Factors	-	Factors	Factors
Min Vol (SA)	=	=	=	=	=	=
Trial 3: Sharpe Ratio Tests						
Max SR (SB)	=	=	=	=	=	=
Min Vol (SB)	=	=	=	Sectors	=	Sectors
Equal Weight	=	=	=	=	=	=
Max SR (SA)	Factors	-	Factors	-	Factors	Factors
Min Vol (SA)	=	=	=	=	=	=

The association of strongly-performing factors and good times is in line with the role of risk factors, namely to capture risk premia. One can indeed expect that the excess return delivered by factor investing will be matched by higher losses during crises. As a result, factor investing is typically more risky than the classic sector investing strategy. This is visible on Fig. 1, which draws the efficient frontiers under the various scenarios in our contest. Overall, factor investing is more rewarding to investors who can afford to take relatively high levels of risk.

5. Conclusion

A fierce debate is taking place about the merits of factor-based asset allocation. Factor investing is an innovative method that emerged as the byproduct of factor models of asset pricing. Contributing to the ongoing conversation, this paper organizes a contest based on classic and well-recognized criteria used to gauge investing styles in the restricted arena of U.S. stocks. By limiting the investment universe in terms of asset class and jurisdiction, we can concentrate on two other dimensions, namely economic/market conditions and the status of short-selling. The available knowledge points to these two dimensions as potential sources of impact on the performance of factor investing. To conduct a meaningful comparison, we oppose factor investing to sector investing, i.e. the classic style used to compose portfolios of same-country stocks.

We find that factor investing dominates sector investing in every aspect when short sales are unrestricted. To a lesser extent, our results suggest that factor investing is also more profitable during expansion times and bull periods, even if short selling is forbidden. However, sector investing delivers better—or less bad—performances for long-only portfolios during recessions and bear periods.

Our contest has limitations. Perhaps the most important is the choice and number of factors. By using the well-known factors proposed by Fama and French (1993, 2015) for asset pricing, we left unaddressed the nature of factors relevant for investment purposes (Pukthuanthong and Roll, 2014; Harvey and Liu, 2015).[24] While the literature proposes over 300 such factors, which are supposed to deliver excess returns, a key question is whether they represent a sustainable risk or rather temporary market anomalies that will disappear when discovered (McLean and Pontiff, 2015).

Another limitation comes from neglecting transaction costs. Presumably, this omission plays in favor of factor investing when opposed to the more passive style of sector investing. Transactions are especially numerous for rebalancing the two momentum factors. Further work could investigate whether our results are robust to incorporating transaction costs. Factor investing is not only a transaction-intensive style, it also a good performer when short selling is permitted. But short sales imply additional expenses, such as borrowing costs. Accounting for all the costs could actually make passive strategies more competitive.

In theory, nothing prevents investors from mixing different styles. Plausibly, combining factors and sectors can deliver higher performances than factor-only and sector-only portfolios do. However, to draw fair conclusions, the mixed portfolios should be compared with their counterparts built from universes including the same number of assets. A fruitful avenue for further research could be to check whether portfolios made up of, say, five sectors and five factors outperform those composed of ten sectors or ten factors. More generally, the optimal number of factors and sectors to be considered in asset allocation could be determined by using, for instance, the identification method proposed by Pukthuanthong and Roll (2014),

[24] Pukthuanthong and Roll (2014) relate factors to principal components of the return covariance matrix. Harvey and Liu (2015) propose a factor selection process based on bootstrap multiple testing.

who state that a true factor should be related to the principal components of a conditional covariance matrix of returns.

The results of this paper definitely have practical consequences for investors. Overall, we show that factor investing is worth attracting the attention of investors with low to moderate risk aversion. At the same time, it stresses that factor investing performs best when it takes full advantage of short sales, which can be tedious, if not impossible, for individual investors to implement. Nowadays, the emergence of dedicated indices and funds has made factor investing more accessible to those investors. However, not all identified factors are investable in this way, and the available factor investment vehicles concentrate on long-only portfolios. Therefore, a major challenge for the advocates of factor investing is the practical implementation of the investment rules they recommend.

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Appendix A: Building Long-Only Factors

French's website reports the monthly returns of all the so-called Fama and French long-short factor portfolios,[25] as well as the decomposition of each factor's return into its subcomponents. We replicate the method used by Fama and French (1993, 2015) to derive the returns of long-only factors. However, we build separately the long leg and the short leg of each factor portfolio.

For instance, to build the value minus growth (or HML) factor, Fama and French (1993, 2015) compute:

$$HML = 1/2(S\ High\ BM + B\ High\ BM) - 1/2(S\ Low\ BM + B\ Low\ BM)$$

where *Small (S) High* book-to-market *(BM)*, *S Low BM*, *Big (B) High BM*, and *B Low BM* are four among the six sub-portfolios formed on size and BM and available on French's website.[26] Likewise, we are able to isolate the returns of the long and short legs of the long-short original portfolios:

$$Value = 1/2(S\ High\ BM + B\ High\ BM)$$

$$Growth = 1/2(S\ Low\ BM + B\ Low\ BM)$$

Similarly, we build the six following factors:

$$Robust\ Profitability\ (P) = 1/2(S\ Robust\ P + B\ Robust\ P)$$

$$Weak\ P = 1/2(S\ Weak\ P + B\ Weak\ P)$$

[25] The universe is made up of all the stocks listed on the NYSE, Amex and Nasqaq.
[26] The missing ones are *S Neutral BM* and *B Neutral BM.* The breakpoint for the size (small or big) is the median NYSE market value at the end of June each year. For the BM criterion, the breakpoint corresponds to the 30th and 70th percentiles measured in December each year. For more details, see http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5_factors_2x3.html.

$$Conservative\ Investment\ (INV) = 1/2(S\ Conservative\ INV + BConservative\ INV)$$

$$Aggressive\ INV = 1/2(S\ Aggressive\ INV + B\ Aggressive\ INV)$$

$$High\ Momentum\ (MOM) = 1/2(S\ High\ MOM + B\ High\ MOM)$$

$$Low\ MOM = 1/2(S\ Low\ MOM + B\ Low\ MOM)$$

where *S Robust P, B Robust P, S Weak P, B Weak P* are four sub-portfolios formed on size and profitability; *S Conservative INV, B Conservative INV, S Aggressive INV, B Aggressive INV are* four sub-portfolios formed on size and investment; *S High MOM, B High MOM, S Low MOM, B Low MOM* are four sub-portfolios formed on size and momentum. These sub-portfolios are all available on French's website.

In order to neutralize the potential biases arising from exposure to other factors, Fama and French (2015) determine the long-only *S* and *B* factors with eighteen sub-portfolios instead of four. We mimic their procedure to disentangle the long and short legs of the original long-short factors, and obtain:

$$\begin{aligned} S = 1/9(&S\ High\ BM + S\ Neutral\ BM + S\ Low\ BM + \ S\ Robust\ P + SNeutral\ P \\ &+ S\ Weak\ P + S\ Conservative\ INV + S\ Neutral\ INV \\ &+ S\ Aggressive\ INV) \end{aligned}$$

$$\begin{aligned} B = 1/9(&B\ High\ BM + B\ Neutral\ BM + B\ Low\ BM + \ B\ Robust\ OP + B\ Neutral\ OP \\ &+ B\ Weak\ P + B\ Conservative\ INV + B\ Neutral\ INV \\ &+ B\ Aggressive\ INV) \end{aligned}$$

where *Neutral BM, S Neutral P, S Neutral INV, B Neutral BM, B Neutral P, B Neutral INV* are the neutral sub-portfolios retrieved from French's website.

Appendix B: Descriptive Statistics

Table B1: Descriptive Statistics and Correlations, Sector and Factor Indices, Bear Markets, July 1963- Dec 2014

Panel A: Descriprive Statistics Sectors

	Non Dur	Durable	Manuf	Energy	Tech	Telecom	Shops	Health	Utilities	Other	Market
Mean	-0.86%	-2.26%	-1.79%	-1.35%	-2.48%	-1.20%	-1.57%	-0.99%	-0.63%	-2.14%	-1.89%
Ann. Mean	-10.35%	-27.17%	-21.42%	-16.25%	-29.72%	-14.40%	-18.86%	-11.91%	-7.54%	-25.74%	-22.73%
Median	-0.52%	-1.92%	-1.26%	-2.03%	-2.46%	-0.77%	-1.87%	-0.80%	-0.57%	-1.80%	-1.46%
Maximum	10.71%	15.50%	11.22%	13.01%	19.41%	21.34%	13.32%	11.99%	11.72%	14.11%	8.33%
Minimum	-21.03%	-32.63%	-27.33%	-18.33%	-26.01%	-16.22%	-28.25%	-20.46%	-12.65%	-23.60%	-22.64%
Std. Dev.	4.74%	6.80%	5.49%	6.21%	7.79%	5.76%	5.91%	5.17%	4.86%	6.18%	5.05%
Volatility	16.43%	23.54%	19.02%	21.51%	26.99%	19.97%	20.48%	17.90%	16.82%	21.40%	17.48%
Skewness	-0.74	-0.92	-0.99	-0.02	-0.08	0.12	-0.56	-0.39	-0.08	-0.49	-0.58
Kurtosis	4.78	5.86	5.87	2.74	4.07	4.13	5.25	3.96	3.17	4.08	4.36
Sharpe Ratio	-0.66	-1.17	-1.15	-0.77	-1.12	-0.74	-0.94	-0.69	-0.47	-1.22	-1.32
Jarque-Bera	35.20	75.84	80.11	0.45	7.77	8.76	41.64	10.09	0.37	14.00	20.99
Probability	0.00	0.00	0.00	0.80	0.02	0.01	0.00	0.01	0.83	0.00	0.00
Observations	158	158	158	158	158	158	158	158	158	158	158

Panel B: Descriprive Statistics Factors

	Small	Big	Value	Growth	Robust Profit	Weak Profit	Conserv Invest	Aggres Invest	High Mom	Low Mom
Mean	-1.95%	-1.72%	-1.20%	-2.45%	-1.73%	-2.42%	-1.54%	-2.62%	-1.71%	-2.69%
Ann. Mean	-23.36%	-20.63%	-14.37%	-29.34%	-20.71%	-29.02%	-18.43%	-31.49%	-20.50%	-32.26%
Median	-1.65%	-1.52%	-0.43%	-2.69%	-1.59%	-2.04%	-1.02%	-2.82%	-1.49%	-2.26%
Maximum	12.47%	9.12%	9.45%	12.18%	10.33%	12.18%	9.33%	11.53%	14.52%	24.41%
Minimum	-29.51%	-21.41%	-23.56%	-27.76%	-25.81%	-27.48%	-25.46%	-27.80%	-27.88%	-24.78%
Std. Dev.	6.63%	4.90%	5.52%	6.31%	5.53%	6.42%	5.49%	6.54%	5.85%	7.45%
Volatility	22.95%	16.97%	19.11%	21.86%	19.17%	22.23%	19.03%	22.67%	20.28%	25.81%
Skewness	-0.65	-0.54	-1.09	-0.39	-0.78	-0.48	-0.74	-0.42	-0.67	0.14
Kurtosis	4.51	4.42	5.20	4.15	4.92	4.03	4.83	3.98	5.04	4.14
Sharpe Ratio	-1.04	-1.24	-0.77	-1.36	-1.10	-1.32	-0.99	-1.41	-1.03	-1.27
Jarque-Bera	26.10	21.04	63.02	12.73	40.37	13.23	36.44	11.01	39.27	9.10
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Observations	158	158	158	158	158	158	158	158	158	158

Panel C: Correlations Sectors

	Non Dur	Durable	Manuf	Energy	Tech	Telecom	Shops	Health	Utilities	Other	Market
Non Dur		0.71	0.85	0.50	0.52	0.50	0.86	0.77	0.55	0.83	0.81
Durable			0.84	0.40	0.65	0.59	0.82	0.55	0.44	0.80	0.81
Manuf				0.61	0.70	0.57	0.84	0.71	0.55	0.88	0.92
Energy					0.39	0.37	0.42	0.42	0.64	0.56	0.64
Tech						0.68	0.66	0.60	0.27	0.65	0.86
Telecom							0.58	0.47	0.32	0.61	0.73
Shops								0.70	0.44	0.84	0.85
Health									0.43	0.69	0.75
Utilities										0.55	0.54
Other											0.90

Panel D: Correlations Factors

	Small	Big	Value	Growth	Robust Profit	Weak Profit	Conserv Invest	Aggres Invest	High Mom	Low Mom	Market
Small		0.85	0.91	0.94	0.95	0.95	0.97	0.95	0.92	0.86	0.89
Big			0.89	0.91	0.94	0.90	0.92	0.92	0.88	0.87	0.99
Value				0.82	0.91	0.87	0.94	0.84	0.85	0.83	0.87
Growth					0.96	0.96	0.93	0.99	0.93	0.88	0.95
Robust Profit						0.90	0.95	0.96	0.92	0.87	0.95
Weak Profit							0.95	0.96	0.92	0.88	0.93
Conserv Invest								0.93	0.93	0.86	0.94
Aggres Invest									0.93	0.89	0.96
High Mom										0.72	0.91
Low Mom											0.88

Table B2: Descriptive Statistics and Correlations, Sector and Factor Indices, Bull Markets, July 1963- Dec 2014

Panel A: Descriprive Statistics Sectors

	Non Dur	Durable	Manuf	Energy	Tech	Telecom	Shops	Health	Utilities	Other	Market
Mean	1.76%	1.95%	1.94%	1.88%	2.19%	1.60%	1.95%	1.82%	1.37%	2.01%	1.88%
Ann. Mean	21.15%	23.43%	23.25%	22.50%	26.24%	19.18%	23.35%	21.87%	16.39%	24.09%	22.55%
Median	1.53%	1.68%	2.05%	1.69%	2.16%	1.43%	1.72%	1.68%	1.36%	2.16%	1.80%
Maximum	18.88%	42.62%	17.51%	24.56%	20.75%	14.35%	25.85%	29.52%	18.84%	20.22%	16.61%
Minimum	-11.57%	-14.11%	-11.68%	-17.79%	-13.03%	-13.40%	-14.07%	-12.84%	-9.09%	-14.07%	-11.69%
Std. Dev.	3.90%	5.75%	4.34%	4.82%	5.51%	3.93%	4.60%	4.54%	3.57%	4.51%	3.76%
Volatility	13.52%	19.93%	15.02%	16.68%	19.07%	13.61%	15.94%	15.72%	12.38%	15.61%	13.04%
Skewness	0.24	1.00	0.19	0.43	0.30	0.07	0.34	0.45	0.26	0.09	0.06
Kurtosis	4.40	8.43	3.95	5.44	3.30	3.43	4.53	6.10	4.26	4.17	4.11
Sharpe Ratio	1.53	1.16	1.52	1.32	1.35	1.38	1.44	1.37	1.29	1.52	1.70
Jarque-Bera	42.10	641.74	20.12	128.61	8.78	3.89	53.54	200.02	35.83	27.09	23.94
Probability	0.00	0.00	0.00	0.00	0.01	0.14	0.00	0.00	0.00	0.00	0.00
Observations	460	460	460	460	460	460	460	460	460	460	460

Panel B: Descriprive Statistics Factors

	Small	Big	Value	Growth	Robust Profit	Weak Profit	Conserv Invest	Aggres Invest	High Mom	Low Mom
Mean	2.30%	1.85%	2.11%	2.05%	2.15%	2.06%	2.17%	2.11%	2.45%	1.87%
Ann. Mean	27.57%	22.25%	25.35%	24.64%	25.83%	24.69%	26.07%	25.34%	29.46%	22.39%
Median	2.59%	1.82%	2.26%	1.97%	2.34%	2.23%	2.25%	2.16%	2.66%	1.42%
Maximum	27.12%	16.66%	25.83%	17.79%	20.26%	21.21%	20.21%	21.09%	17.49%	40.27%
Minimum	-20.25%	-10.80%	-15.19%	-16.51%	-15.70%	-15.95%	-15.84%	-16.90%	-20.07%	-11.68%
Std. Dev.	5.11%	3.72%	4.39%	4.64%	4.27%	4.72%	4.36%	4.74%	4.71%	5.31%
Volatility	17.68%	12.87%	15.20%	16.09%	14.81%	16.35%	15.10%	16.41%	16.31%	18.38%
Skewness	0.06	0.15	0.21	0.04	-0.03	0.06	-0.08	0.04	-0.35	1.44
Kurtosis	5.25	4.09	6.19	3.95	4.55	4.45	4.66	4.11	5.07	10.18
Sharpe Ratio	1.54	1.70	1.64	1.51	1.72	1.48	1.70	1.52	1.78	1.20
Jarque-Bera	97.50	24.42	198.42	17.40	45.91	40.56	53.56	23.87	91.37	1146.12
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	460	460	460	460	460	460	460	460	460	460

Panel C: Correlations Sectors

	Non Dur	Durable	Manuf	Energy	Tech	Telecom	Shops	Health	Utilities	Other	Market
Non Dur		0.59	0.78	0.42	0.56	0.63	0.80	0.73	0.62	0.80	0.83
Durable			0.81	0.44	0.64	0.54	0.69	0.45	0.37	0.75	0.77
Manuf				0.58	0.78	0.62	0.79	0.67	0.46	0.88	0.94
Energy					0.40	0.37	0.36	0.37	0.48	0.53	0.62
Tech						0.51	0.69	0.57	0.24	0.69	0.83
Telecom							0.61	0.52	0.58	0.66	0.72
Shops								0.62	0.42	0.80	0.85
Health									0.46	0.68	0.75
Utilities										0.56	0.57
Other											0.93

Panel D: Correlations Factors

	Small	Big	Value	Growth	Robust Profit	Weak Profit	Conserv Invest	Aggres Invest	High Mom	Low Mom	Market
Small		0.83	0.93	0.94	0.94	0.97	0.96	0.95	0.92	0.87	0.87
Big			0.89	0.91	0.94	0.89	0.91	0.92	0.87	0.83	0.99
Value				0.85	0.91	0.92	0.95	0.88	0.85	0.88	0.88
Growth					0.96	0.95	0.93	0.99	0.94	0.84	0.94
Robust Profit						0.92	0.94	0.97	0.93	0.86	0.96
Weak Profit							0.97	0.95	0.92	0.87	0.91
Conserv Invest								0.93	0.91	0.87	0.93
Aggres Invest									0.94	0.86	0.95
High Mom										0.71	0.91
Low Mom											0.84

Table B3: Descriptive Statistics and Correlations, Sector and Factor Indices, Recessions, July 1963- Dec 2014

Panel A: Descriprive Statistics Sectors

	Non Dur	Durable	Manuf	Energy	Tech	Telecom	Shops	Health	Utilities	Other	Market
Mean	0.39%	-0.36%	-0.50%	-0.28%	-0.31%	-0.18%	0.48%	0.30%	0.07%	-0.68%	-0.28%
Ann. Mean	4.70%	-4.27%	-6.03%	-3.32%	-3.73%	-2.20%	5.78%	3.60%	0.86%	-8.12%	-3.33%
Median	0.18%	-0.58%	-0.26%	-0.44%	-0.68%	-0.11%	0.17%	-0.30%	0.06%	-1.97%	-0.61%
Maximum	18.88%	42.62%	17.51%	20.97%	18.00%	11.10%	25.85%	29.52%	18.84%	20.22%	16.61%
Minimum	-14.31%	-32.63%	-20.75%	-17.79%	-18.96%	-16.22%	-18.70%	-15.55%	-12.65%	-20.05%	-17.15%
Std. Dev.	5.91%	9.61%	7.30%	7.46%	8.78%	5.58%	7.62%	6.53%	5.66%	8.12%	6.50%
Volatility	20.47%	33.29%	25.28%	25.85%	30.43%	19.33%	26.39%	22.62%	19.62%	28.12%	22.52%
Skewness	0.09	0.60	-0.04	0.03	0.16	-0.26	0.19	0.85	0.21	0.14	0.05
Kurtosis	3.59	7.31	3.04	2.87	2.48	3.06	3.45	6.51	3.91	2.83	2.74
Sharpe Ratio	0.21	-0.14	-0.25	-0.14	-0.14	-0.13	0.20	0.14	0.02	-0.30	-0.17
Jarque-Bera	1.44	75.02	0.03	0.08	1.40	1.00	1.28	57.07	3.74	0.42	0.30
Probability	0.49	0.00	0.99	0.96	0.50	0.61	0.53	0.00	0.15	0.81	0.86
Observations	90	90	90	90	90	90	90	90	90	90	90

Panel B: Descriprive Statistics Factors

	Small	Big	Value	Growth	Robust Profit	Weak Profit	Conserv Invest	Aggres Invest	High Mom	Low Mom
Mean	-0.11%	-0.21%	0.16%	-0.39%	-0.07%	-0.40%	0.17%	-0.58%	0.01%	-0.44%
Ann. Mean	-1.32%	-2.49%	1.97%	-4.64%	-0.81%	-4.78%	2.04%	-6.96%	0.16%	-5.31%
Median	-0.52%	-0.59%	0.03%	-0.92%	-0.47%	-0.34%	0.17%	-0.98%	0.27%	-2.30%
Maximum	27.12%	16.66%	25.83%	17.79%	20.26%	21.21%	20.21%	21.09%	14.90%	40.27%
Minimum	-20.58%	-17.50%	-21.44%	-18.44%	-17.55%	-21.71%	-18.30%	-20.18%	-18.86%	-24.78%
Std. Dev.	8.40%	6.39%	7.47%	7.83%	7.33%	7.75%	7.03%	8.36%	6.80%	10.65%
Volatility	29.11%	22.12%	25.88%	27.13%	25.39%	26.86%	24.34%	28.97%	23.54%	36.89%
Skewness	0.04	0.08	-0.05	0.00	-0.04	-0.05	-0.05	0.05	-0.35	0.70
Kurtosis	3.33	2.90	4.19	2.54	2.81	2.89	3.16	2.50	3.02	4.49
Sharpe Ratio	-0.06	-0.13	0.06	-0.19	-0.05	-0.19	0.07	-0.25	-0.01	-0.15
Jarque-Bera	0.45	0.12	5.34	0.81	0.16	0.09	0.13	0.95	1.81	15.62
Probability	0.80	0.94	0.07	0.67	0.92	0.96	0.93	0.62	0.40	0.00
Observations	90	90	90	90	90	90	90	90	90	90

Panel C: Correlations Sectors

	Non Dur	Durable	Manuf	Energy	Tech	Telecom	Shops	Health	Utilities	Other	Market
Non Dur		0.72	0.88	0.56	0.77	0.70	0.90	0.80	0.73	0.88	0.91
Durable			0.87	0.42	0.79	0.73	0.83	0.53	0.55	0.83	0.84
Manuf				0.66	0.89	0.76	0.88	0.76	0.71	0.92	0.97
Energy					0.52	0.51	0.44	0.48	0.70	0.59	0.71
Tech						0.67	0.83	0.72	0.58	0.82	0.90
Telecom							0.72	0.59	0.70	0.77	0.80
Shops								0.70	0.64	0.88	0.90
Health									0.51	0.73	0.79
Utilities										0.69	0.76
Other											0.95

Panel D: Correlations Factors

	Small	Big	Value	Growth	Robust Profit	Weak Profit	Conserv Invest	Aggres Invest	High Mom	Low Mom	Market
Small		0.91	0.96	0.96	0.97	0.97	0.97	0.97	0.93	0.92	0.92
Big			0.92	0.95	0.96	0.96	0.96	0.96	0.94	0.89	1.00
Value				0.89	0.93	0.95	0.97	0.92	0.90	0.90	0.92
Growth					0.99	0.96	0.95	0.99	0.94	0.90	0.97
Robust Profit						0.96	0.97	0.99	0.95	0.91	0.97
Weak Profit							0.98	0.97	0.94	0.92	0.96
Conserv Invest								0.96	0.95	0.91	0.96
Aggres Invest									0.94	0.93	0.97
High Mom										0.80	0.95
Low Mom											0.89

Table B4: Descriptive Statistics and Correlations, Sector and Factor Indices, Expansions, July 1963- Dec 2014

Panel A: Descripive Statistics Sectors

	Non Dur	Durable	Manuf	Energy	Tech	Telecom	Shops	Health	Utilities	Other	Market
Mean	1.21%	1.08%	1.24%	1.28%	1.22%	1.06%	1.14%	1.24%	0.99%	1.22%	1.12%
Ann. Mean	14.53%	13.01%	14.87%	15.31%	14.60%	12.77%	13.72%	14.88%	11.88%	14.67%	13.41%
Median	1.22%	0.95%	1.40%	1.12%	1.28%	1.16%	1.18%	1.31%	1.04%	1.55%	1.39%
Maximum	14.63%	23.21%	16.80%	24.56%	20.75%	21.34%	13.32%	16.47%	11.72%	14.11%	12.89%
Minimum	-21.03%	-26.93%	-27.33%	-18.33%	-26.01%	-15.58%	-28.25%	-20.46%	-12.30%	-23.60%	-22.64%
Std. Dev.	3.94%	5.54%	4.36%	4.93%	6.00%	4.43%	4.66%	4.51%	3.67%	4.61%	3.96%
Volatility	13.64%	19.18%	15.11%	17.06%	20.78%	15.34%	16.16%	15.62%	12.73%	15.97%	13.72%
Skewness	-0.36	-0.08	-0.49	0.20	-0.29	-0.13	-0.45	-0.26	-0.13	-0.61	-0.63
Kurtosis	5.34	4.74	6.55	4.75	5.09	4.58	5.82	4.19	3.34	5.38	5.79
Sharpe Ratio	1.03	0.66	0.96	0.87	0.68	0.81	0.82	0.93	0.90	0.89	0.95
Jarque-Bera	131.43	67.06	297.69	70.49	103.31	56.39	192.97	37.17	4.02	156.45	206.96
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.00
Observations	528	528	528	528	528	528	528	528	528	528	528

Panel B: Descripive Statistics Factors

	Small	Big	Value	Growth	Robust Profit	Weak Profit	Conserv Invest	Aggres Invest	High Mom	Low Mom
Mean	1.44%	1.14%	1.45%	1.12%	1.37%	1.14%	1.40%	1.15%	1.63%	0.90%
Ann. Mean	17.26%	13.63%	17.45%	13.48%	16.45%	13.64%	16.85%	13.84%	19.50%	10.76%
Median	1.75%	1.36%	1.84%	1.26%	1.63%	1.40%	1.58%	1.36%	1.94%	0.72%
Maximum	19.36%	13.01%	21.49%	14.70%	15.07%	18.66%	17.49%	15.12%	17.49%	24.41%
Minimum	-29.51%	-21.41%	-23.56%	-27.76%	-25.81%	-27.48%	-25.46%	-27.80%	-27.88%	-20.01%
Std. Dev.	5.25%	3.86%	4.32%	4.95%	4.36%	5.06%	4.48%	5.00%	5.02%	5.13%
Volatility	18.17%	13.36%	14.95%	17.14%	15.11%	17.54%	15.50%	17.34%	17.39%	17.76%
Skewness	-0.57	-0.51	-0.53	-0.53	-0.67	-0.55	-0.63	-0.62	-0.63	0.15
Kurtosis	6.05	5.48	6.32	5.50	6.36	5.58	5.85	5.65	6.03	5.29
Sharpe Ratio	0.93	0.99	1.14	0.76	1.06	0.75	1.06	0.77	1.10	0.58
Jarque-Bera	232.95	158.94	268.06	162.85	287.98	173.54	213.37	188.32	237.16	117.58
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	528	528	528	528	528	528	528	528	528	528

Panel C: Correlations Sectors

	Non Dur	Durable	Manuf	Energy	Tech	Telecom	Shops	Health	Utilities	Other	Market
Non Dur		0.63	0.79	0.46	0.51	0.58	0.80	0.75	0.57	0.80	0.80
Durable			0.82	0.49	0.62	0.54	0.72	0.51	0.37	0.77	0.79
Manuf				0.60	0.72	0.59	0.81	0.68	0.44	0.88	0.92
Energy					0.41	0.38	0.42	0.40	0.51	0.57	0.63
Tech						0.59	0.66	0.57	0.19	0.67	0.84
Telecom							0.60	0.51	0.44	0.63	0.73
Shops								0.66	0.38	0.81	0.85
Health									0.46	0.70	0.75
Utilities										0.53	0.51
Other											0.92

Panel D: Correlations Factors

	Small	Big	Value	Growth	Robust Profit	Weak Profit	Conserv Invest	Aggres Invest	High Mom	Low Mom	Market
Small		0.83	0.91	0.94	0.93	0.96	0.96	0.95	0.93	0.86	0.87
Big			0.89	0.91	0.94	0.89	0.91	0.91	0.87	0.85	0.99
Value				0.83	0.91	0.89	0.94	0.86	0.86	0.85	0.88
Growth					0.96	0.95	0.93	0.99	0.95	0.86	0.95
Robust Profit						0.91	0.94	0.96	0.94	0.87	0.96
Weak Profit							0.96	0.96	0.92	0.88	0.92
Conserv Invest								0.93	0.92	0.88	0.93
Aggres Invest									0.95	0.87	0.95
High Mom										0.74	0.91
Low Mom											0.86