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When it Rains, it Pours: Multifactor Asset Management in Good and Bad Times*

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Abstract

We examine the profitability of multifactor portfolios on the U.S. stock market. Using passive sector investing as the benchmark, we assess the performances of factor-based asset management strategies in good and bad times. When short selling is unrestricted, factor investing outperforms sector investing in all respects. For long-only portfolios, our results reveal a trade-off between the risk premia associated with factors and the diversification potential of sectors. Multifactor

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investing tends to be more profitable than the benchmark during good times but less attractive during bad times, when diversification is needed the most.

1. Introduction

Fama and French (F&F, 1992) developed multifactor asset pricing models and demonstrated empirically the existence of factor-based premia.[1] Nowadays, asset managers offer factor-based mutual funds that combine the original F&F factors with more recent ones. In the F&F spirit, factor investing means capturing factor-based premia by holding assets with positive exposure to the specific factor and shorting those with negative exposure. Yet the performance of portfolios that combine factors optimally is still unchartered territory. Recent evidence points to the redundancy and lack of diversification among factors (Clarke et al., 2016; Li, 2018). Since each factor delivers a risk-premium in expected returns, the worst-case scenario in combining them would be that the correlations between factors are high enough to resist diversification benefits and be particularly damaging during a crisis. Two questions motivate this paper. First, are the risks of individual factors diversified away by optimal factor investing? Second, how does this type of investment perform during good and bad times? This paper proposes a long-horizon (1963-2014) study reporting on the risk-return characteristics of portfolios made up of risk factors during both crises and quiet times. Analyzing portfolio

[1] There is a debate about whether the factors correspond to the remuneration of risk, and hence be called "risk factors", or alternatively result from abnormal stock pricing, and then be referred to as "anomalies" (McLean, and Pontiff, 2016). We do not take sides in the controversy.

performance over long periods is important since financial crises tend to have longer-lasting consequences.

The discovery of risk factors is chiefly evidence-based, since only the market risk is grounded in financial theory, specifically the Capital Asset Pricing Model. Questioning the performance of factor investing is a move toward assessing the relevance of the F&F factors for portfolio management theory. These factors include the size factor “small-minus-big” (SMB) and the value factor “high minus low” (HML). Carhart (1997) uncovered the momentum factor (MOM), revealed by Jegadeesh and Titman (1993). Later, Hou et al. (2015) and F&F (2015) recognized the importance of quality—investment and profitability—factors. All these factors are represented as “long-short” portfolios, combining a long position in stocks exposed to a specific risk (for example, small stocks) and a short position in those with the opposite exposure (for example, large stocks). In portfolio management theory, two types of rewards are sought from assets grouped for portfolio management purposes: diversification benefits (lower risks) and risk premia (higher returns). The trade-off resulting from the dual objective is the basis of mean-variance optimization techniques used in portfolio management. While the need for diversification benefits has long been identified in the literature, the possibility of grouping selected stocks in a way that captures risk premia has remained unexplored for a long time.

Our aim is to determine whether multifactor investing systematically beats well-diversified passive investment strategies, or, alternatively, if the benefits brought by factor premia are cancelled out by the potential loss resulting from poor diversification. Since the performances of asset management depend on the economic situation, and possibly on dramatic climate events (Lanfear et al., 2019), we draw comparisons over a

50-year sample period, as well as over good and bad times separately. Bad times correspond to market downturns and recessions, which are typically associated with contagion episodes driving asset recorrelation (Brière et al., 2012; Bekaert et al., 2014), and so challenge diversification.

We assess optimal multifactor investing on the U.S. stock market by comparing its performances with those of optimal portfolios made up of sector indices, a common benchmark in stock allocation (Ferson & Harvey, 1991). Although sector-based asset allocation is not directly derived from optimized groups of stocks, it is recognized not only as an efficient diversification technique (Roll, 1992; Heston & Rouwenhorst, 1994) but also as the unchallenged asset management principle for long-term investment in same-country stock portfolios (De Moor & Sercu, 2011). We use the full range of static and dynamic performance measures, including those based on utility functions that account for downside risks. We gain statistical robustness by combining in-sample and out-of-sample tests of dynamically rebalanced portfolios. Another novelty of our study is its fully agnostic perspective on short selling. We find that for long-short portfolios, factor investing is always preferable to sector investment. By contrast, long-only factor investing is more profitable than the sector benchmark during expansion times and bull periods, but less attractive during recessions and bear periods, i.e., in periods where diversification is needed the most.

2. Data and Methods

2.1 *Data*

Our data are retrieved from Kenneth French's website,[2] 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–long-only and 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 Nasdaq over the period July 1963 – December 2014. We also recorded the market index returns (value-weighted returns of all NYSE, Amex, or Nasdaq-listed U.S. firms) and the risk-free interest rates (one-month Treasury bill rate from Ibbotson Associates) provided by French's website.

Using French's database also imposes working constraints. First, we rely on the Standard Industrial Classification (SIC). The ten sector portfolios are based on four-digit SIC codes: (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 extraction and products), (5) high tech (computers, software, and electronic equipment), (6) telecom (telephone and television transmission),

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[2] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The investment universe considered by F&F 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) 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 are those fixed by F&F (1993, 2015) and Carhart (1997). The five long-short portfolios available on French's website are: size, value, profitability, investment, and momentum. In practice, these factors are not directly investible (Idzorek & Kowara, 2013), but investors can trade factor-based mutual funds or exchange traded funds. There is a literature consensus on the relevance of the "historic" size and value factors (F&F, 1992; Asness et al., 2013), as well as the momentum factor (Jegadeesh & Titman, 1993; Carhart, 1997). The two additional quality factors, profitability (Novy-Marx, 2013) and investment (Hou et al., 2015), are still debated (Franke et al., 2017).

Each time series is examined over five 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) (http://www.nber.org/cycles.html). The fourth and fifth periods are those associated with the bear and bull markets identified by Forbes Magazine. 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.

2.2 *Methods*

We examine financial performance along several dimensions. Consider the investment universe of style $s \in \{\text{sector, factor}\}$ (in short: universe s) and composed of N assets with stationary returns characterized by a N-dimensional vector R^s, with $E(R^s) = \mu^s$, and

$Cov(R^s) = \Sigma^s$. Given a sample of returns of size T denoted $(R_t^s)_{t=1\dots T}$ for the N assets, the empirical counterparts of parameters μ^s, and Σ^s are given respectively by:

$$\hat{\mu}^s = \frac{1}{T}\sum_{t=1}^{T} R_t^s \qquad (1)$$

$$\hat{\Sigma}^s = \frac{1}{T}\sum_{t=1}^{T} R_t^s (R_t^s)' - \hat{\mu}^s \hat{\mu}'^s \qquad (2)$$

The market portfolio is the same in both universes; its return is the value-weighted average of the returns of all NYSE, Amex, and Nasdaq-listed U.S. firms. The estimates of its expected return and variance are $\hat{\mu}_M$ and $\hat{\sigma}_M^2$, respectively. Any other portfolio is universe-specific and represented by its weights with respect to the N basic assets (vector return R^s in universe s). The return of the portfolio $P^{w,s}$ defined in universe s by weight vector $w = (w_i, i = 1, \dots, N)$, with $\sum_{i=1}^{N} w_i = 1$, is given by random variable $[w'R^s]$. Eqs. (1) and (2) can be used to estimate the two first moments of any portfolio in any universe. The expected return of $P^{w,s}$ is proxied by $\hat{\mu}^{w,s} = w'\hat{\mu}^s$ while its estimated variance is given by $(\hat{\sigma}^2)^{w,s} = w'\hat{\Sigma}^s w$.

Portfolio managers are aware of the difficulty of taking into account asset movements in crisis periods as opposed to normal times. We acknowledge this reality in two different yet complementary ways: We run estimation with sub-periods and perform in-sample and out-of-sample estimation with utility functions sensitive to extreme risk.

We use four performance measures. First, we investigate the ability of efficient frontiers to beat the market. Most tests of mean-variance efficiency are spanning tests, which focus on time-series regressions of asset returns on the market index (Gibbons, Ross & Shanken, 1989; Harvey & Zhou, 1990). Spanning tests are inappropriate in our case because they apply only to portfolios with unconstrained weights (Wang, 1998). Instead, we test whether the distance in the mean-variance plan between the market portfolio and the efficient frontier is significantly different from zero (Kandel et al., 1995; Ehling & Ramos, 2006) by computing distances in the mean-variance plan. The distance proposed by Basak et al. (2002) is the "horizontal distance" between a given efficient frontier and any portfolio whose composition is known. When the portfolio of interest is the market portfolio in universe *s*, the horizontal distance measures the volatility gap between the market portfolio *M* and its same-return ($\hat{\mu}_M$) counterpart efficient portfolio. The Basak et al. (2002) test checks whether this distance is significantly positive, which would mean that style *s* "beats the market" by offering same-return but lower-volatility opportunities. The estimated horizontal distance is the solution of the following program:

$$\hat{\lambda} = \begin{bmatrix} \min_w \left\{ w' \hat{\Sigma}^s w - \hat{\sigma}_M^2 \right\} \\ s.t. w' \hat{\mu}^s = \hat{\mu}_M \\ \sum_{i=1}^{N} w_i = 1, w_i \geq 0 \; for \; i = 1 \ldots N \end{bmatrix} \quad (3)$$

If the returns on the *N* original assets are jointly normal, then, under the null that portfolio *M* is mean-variance efficient, $\hat{\lambda}$ asymptotically follows a normal distribution: $\sqrt{T}(\hat{\lambda} - \lambda) \rightarrow N(0, \varepsilon^2)$ as $T \rightarrow \infty$. A second test introduced by Brière et al. (2013) is based on the "vertical distance" between a given portfolio and its same-return counterpart portfolio on the efficient frontier. The second approach circumvents the possible absence of an efficient portfolio with the same expected return as the market. The vertical test statistic is the distance between the expected return of *M* and the expected return of its same-variance ($\hat{\sigma}_M^2$) efficient counterpart. If the vertical distance is significantly different from zero, style *s* outperforms the market by entailing portfolios with above-market expected returns and same level of risk. The estimated vertical distance is the solution to the following program:

$$\hat{\theta} = \begin{bmatrix} \min_w \{w' \hat{\mu}^s - \hat{\mu}_M\} \\ s.t. w' \hat{\Sigma}^s w = \hat{\sigma}_M^2 \\ \sum_{i=1}^N w_i = 1, w_i \geq 0 \; for \; i = 1 \dots N \end{bmatrix} \quad (4)$$

Under the null that portfolio M is mean-variance efficient, $\hat{\theta}$ asymptotically follows a normal distribution: $\sqrt{T}(\hat{\theta} - \theta) \rightarrow N(0, \varepsilon^2)$ as $T \rightarrow \infty$. To check whether optimal portfolios made of either sectors or factors beat the market, we use both the horizontal and vertical distances. Both tests can be implemented with or without restrictions on short selling.

Next, in line with F&F (2018a) we consider the usual mean-variance performance measures, Jensen's (1968) alpha and Sharpe (1966) ratio of the two styles by comparing pairs of portfolios built with sectors and factors. We examine three special portfolios that stand out in the literature (Liu, 2016): the efficient portfolio maximizing SR (*maxSR*), the minimum volatility portfolio (*minvol*), and the equally weighted (or 1/N) portfolio (*equalweight*). The first two make sense with and without short selling restrictions, while the last is long-only by construction. We end up with five specific portfolios: long-only max-SR (*LOmaxSR*), long-only min-vol (*LOminvol*), *equalweight*, long-short max-SR (*LSmaxSR*), and long-short min-vol (*LSminvol*). Let P_k^s denote portfolio of type $k \in \{LOmaxSR, LOminvol, equalweight, LSmaxSR, LSminvol\}$ and style $s \in \{sector, factor\}$, let $w_k^s = \left(w_{k,i}^s, i = 1, \dots, N\right)$ be its composition and R_k^s its return:

$$R_k^s = (w_k^s)' R^s \qquad (5)$$

and:

$$P_{LOmaxSR}^s = \text{argmax}_{w=(w_i, i=1,\dots,N);\, \sum_{i=1}^N w_i = 1; w_i \geq 0} \; \frac{w' \hat{\mu}^s - r_f}{w' \hat{\Sigma}^s w} \quad (6)$$

$$P_{LOminvol}^s = \text{argmin}_{w=(w_i, i=1,\dots,N);\, \sum_{i=1}^N w_i = 1; w_i \geq 0} \; w' \hat{\Sigma}^s w \quad (7)$$

$$w_{i,equalweight}^{s} = \frac{1}{N}, i = 1, \ldots, N \qquad (8)$$

$$P_{LSmaxSR}^{s} = \text{argmax}_{w=(w_i, i=1,\ldots,N);\ \sum_{i=1}^{N} w_i = 1} \ \frac{w\prime\, \hat{\mu}^{s} - r_f}{w\prime \hat{\Sigma}^{s} w} \qquad (9)$$

$$P_{LSminvol}^{s} = \text{argmin}_{w=(w_i, i=1,\ldots,N);\ \sum_{i=1}^{N} w_i = 1} \ w' \hat{\Sigma}^{s} w \ (10)$$

We assess mean-variance performances across pairs of composite portfolios: $\left(P_k^{sector}, P_k^{factor}\right)$, $k \in \{LOmaxSR, LOminvol\ , equalweight, LSmaxSR, LSminvol\}$. Six of them ($k \in \{LOmaxSR, LOminvol\ , equalweight\}, s \in \{sector, factor\}$) belong to universes where short selling is banned (*SB*), while the other four ($k \in \{LSmaxSR, LSminvol\}, s \in \{sector, factor\}$) are defined in universes where short selling is authorized (*SA*).

Equal weighting in Eq. (8) significantly departs from the original spirit of F&F (1993), who impose opposite signs on the two legs of their factor components. Our approach is less restrictive and consistent with current practice, it allows the weights of the long and short legs to adjust separately. Edelen et al. (2016) mention that institutional investors often have a long position in the short legs of F&F's factors. Moreover, DeMiguel et al. (2009) recommend 1/N investing to minimize the risk inherent in estimating optimal weights out of sample.

For every comparison, we run both in-sample and out-of-sample tests. In both cases, we compare the performance of dynamic factor investing[3] with that of static sector investing. The in-sample tests are run on the full sample and the four sub-samples to get a sense of performance in different types of period, i.e. during recession/expansion, and for bear/bull markets. By contrast, out-of-sample exercises are meaningful in the full sample

[3] The composition of the factors in individual stocks is updated every year at the end of June, except for the momentum factor, which is rebalanced monthly.

only as, by nature, real-time investment cannot rely on crisis periods determined *ex post*. The out-of-sample analysis relies on a rolling sample approach using two different estimation windows (M = 60 months and M = 120 months). In each month, the optimized portfolio weights from parameters are estimated from the data in the previous M months, including the risk-free interest rate. In this way, we obtain monthly out-of-sample returns for each portfolio in each period. In the in-sample tests, the portfolio weights are assumed time-invariant to keep the factor/sector exposure equal to the investor's predetermined optimal exposure. The weights of the out-of-sample portfolios change dynamically. T-tests compare the alphas of portfolios of each style with respect to the market portfolio. Jensen's alpha (α) measures the abnormal return of a portfolio over its theoretical risk-adjusted expected return. The alpha of portfolio k in universe s (α_k^s) is estimated by means of the following regression:

$$R_{k,t}^s - r_{f,t} = \alpha_k^s + \beta_k^s\left(R_{M,t} - r_{f,t}\right) + \varepsilon_{k,t}^s, t = 1, \dots T \qquad (11)$$

where $R_{k,t}^s$ is the return of portfolio k in universe s at time t, $r_{f,t}$ is the risk-free rate at time t, $R_{M,t}$ is the market return at time t, and $\varepsilon_{k,t}^s$ the estimated error term, to which we apply the Newey-West correction. Choosing the market portfolio as a benchmark is questionable.[4] Alternative measures of alpha derived from the F&F factor model (Ang et al., 2009; Government Pension Fund Global, 2014) cannot be used because we are comparing two investment styles, one of which built from the F&F factors. We also use the Sharpe ratio (SR), which measures excess return per unit of risk. SR is a rough gauge of performance, but it is free from any model-based premises. The empirical counterpart

[4] 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 that CAPM cannot explain them. Yet, some industry portfolios, such as the non-durable and health sectors, do exhibit positive and significant alphas.

of the SR of portfolio k in universe s $\left(\widehat{SR}_k^s\right)$ is obtained by subtracting the average risk-free rate ($\hat{r}_f$) from the average return of the portfolio ($\hat{\mu}_k^s$), and dividing it by its estimated volatility ($\hat{\sigma}_k^s$).

$$\widehat{SR}_k^s = \frac{\hat{\mu}_k^s - \hat{r}_f}{\hat{\sigma}_k^s} \quad (12)$$

To test the equality between SRs—one with sector indices, the other with factors—we use the Ledoit and Wolf (2008) test procedure, which builds bootstrapped p-values by fitting a semi-parametric model.[5] The Ledoit and Wolf (2008) test is a first step toward acknowledging the non-normal probability distributions of financial returns.

Certainty equivalent returns (CERs) built from utility functions encompass moments of unlimited orders of return distributions are typically used in studies of extreme risks. The CER of a given utility function is the risk-free rate that makes the investor indifferent between holding the risky portfolio of interest and earning the CER over the given investment horizon. The constant relative risk aversion (CRRA) utility (Brandt et al., 2005; Kadan & Liu, 2014) and the constant absolute risk aversion (CARA) utility (Simaan, 1997; Gollier & Zeckhauser, 2002) have respective analytical forms:

$$u_{CRRA}(\omega) = \frac{1}{1-\gamma}\omega^{1-\gamma}, \qquad (13)$$

where γ is the relative risk aversion, ω denotes the investor's wealth, and:

$$u_{CARA}(\omega) = -exp(-a\omega) \qquad (14)$$

where a is the absolute risk aversion. Following Christoffersen and Langlois (2013), we use bootstrapped confidence intervals to test for equal CERs of two portfolios. For each

[5] This test improves on the predecessor proposed by Jobson and Korkie (1981) by accommodating return series with heavy tails. On the use of the Ledoit and Wolf (2008) test, see also Maio (2014) and De Miguel et al. (2014).

utility function, we estimate the CER of portfolio *k* in universe *s* with a sample of length *T* as follows:

$$\widehat{CER}_k^s(CRRA) = \left(\frac{1}{T}\sum_{t=1}^{T}\left(1+R_{k,t}^s\right)^{1-\gamma}\right)^{\frac{1}{\gamma-1}} - 1 \qquad (15)$$

$$\widehat{CER}_k^s(CARA) = -\frac{1}{a}\,ln\left(\frac{1}{T}\sum_{t=1}^{T}\exp\left[-a\left(1+R_{k,t}^s\right)\right]\right) - 1 \qquad (16)$$

The bootstrap *p*-values are computed in each case using 10,000 bootstrap replications. CERs deal with crises and normal times together, so that we compute performance measures on the full sample only. To concentrate on extreme risks, we take values of *a* and γ between 5 and 15. The value of 15 is high when compared with standard values used in the literature, which are concentrated between 2 and 10 (Mehra & Prescott, 1985; Bekaert, G., and M. Hoerova, 2016; Bollerslev et al, 2011; Sercu and Vanpée, 2008).

Finally, we check the robustness of our CER results by computing the manipulation-proof performance measure (MPPM) developed by Goetzmann et al. (2007):

$$\widehat{MPPM}_k^s = \frac{12}{(1-\gamma)}\,ln\left(\frac{1}{T}\sum_{t=1}^{T}\left[\frac{\left(1+R_{k,t}^S\right)}{\left(1+r_{f,t}^S\right)}\right]^{1-\gamma}\right) \qquad (17)$$

where γ is the coefficient of relative risk aversion. MPPM can be interpreted as the annualized continuously compounded excess return certainty-equivalent of the portfolio, derived from a power utility function. The motivation for using the MPPM relates to its ability to counteract on moral hazard (Goetzmann et al., 2007). While the MPPM measure is primarily designed for hedge funds, it can be applied to any market with potentially manipulative fund managers.

We duplicate all the tests for portfolios with short sales banned ("long-only"), on the one hand, and authorized ("long-short") on the other hand. Restrictions imposed on short selling for prudential reasons can constitute a major issue in portfolio management (Jones & Lamont, 2002). Yet, factor-based asset management typically exploits short selling. By buying assets with positive factor exposure and shorting those with negative exposure, investors capture the risk premia of the chosen factors, and benefit from excess returns relative to the market portfolio. We build the long-only and long-short versions of our five factors of interest by disentangling the long and short legs of each long-short portfolio available on French's website (see 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. Long-only portfolios have positive quantities of the ten long-only factors. In long-short portfolios investors can short any of these factors. Going beyond F&F's original approach, which places opposite exposures on the two legs of the long-short position (e.g., small minus big), we let each leg have its own optimized exposure (e.g., α small plus β big). In this way, asset allocation benefits from more degrees of freedom.[6] The same terminology holds for sector-based portfolios.

3. Descriptive Statistics

Panel A in Table 1 provides descriptive statistics 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 risk levels differ across sectors. The Sharpe ratios range from 0.51 (high tech) to 0.85 (non-durables), showing that the risk-return

[6] We define short positions with respect to factors rather than to individual stocks. A long-short portfolio has a negative loading of a given factor even though the negative exposure to all the stocks included in this factor would cancel out with their positive exposure associated with other factors. This approach mimics the investment practice marketed by several index providers, such as MSCI and Russell.

performances of different sectors are dispersed. Two sectors (non-durables and health) generate significantly positive alphas.

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 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. Overall, Panels A and B in Table 1 show no clear financial outperformance of one style over the other. Six out of the ten factors generate significantly positive alphas. The five long legs of the F&F 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. At first sight, positive alphas might seem surprising given the very large correlations observed between each factor and the market portfolio (see Table 2). They are however the main reason why factor investing has been so successful since several factors manage to significantly beat the market despite being highly correlated with it.

Panels A and B in Table 2 report intra-group pairwise correlations as well as correlations with the market, for sectors and factors, respectively. The average correlation computed for factors (0.92) is higher than the one obtained for sectors (0.66), signaling that diversification benefits will be harder to capture with factors than with sectors (Marks & Shang, 2019). In fact, sectors are mutually exclusive (each stock belongs to a single sector), while factors can overlap. Correlations among sectors exhibit substantial heterogeneity while correlations between factors are far more homogeneous. 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 (0.99). To avoid multicollinearity, the market is excluded from the set of factors.

Figs. I and II compare the efficient frontiers built from the ten sectors and the ten factors, for short selling banned (SB) and short selling authorized (SA), respectively. They also exhibit the market portfolio. In Fig. I, the two frontiers intersect, implying that, when short selling is excluded, no style dominates any other. While sector investing looks attractive to investors with high risk aversion, factor-based portfolios are more suitable for their more risk tolerant counterparts. When short sales are authorized (Fig. II), the efficient frontier composed of factors tends to dominate the one made up of sectors. The next section applies formal test procedures to assess the robustness of the preliminary findings.

4. Performance Compared

4.1 *Beating the Market*

We consider ten different period/short-sale scenarios. To test whether our style-based portfolios outperform the market, we use the Basak et al. (2002) test in Eq. (3) based on the horizontal distance between the market portfolio and its same-return counterpart efficient portfolio, and the Brière et al. (2013) test in Eq. (4) exploiting the vertical distance between the market portfolio and its same-variance counterpart efficient portfolio.

Table 3 reports whether the distances are significant when short selling is banned. Panel A shows that sector investing can improve expected returns by regard to the market during recessions, while factor investing systematically beats the market by increasing expected returns, except during recessions. The superiority of factor investing in terms of expected returns is not surprising since, by construction, factors deliver risk premia. Less expectedly, Panel B indicates that sector investing mitigates market risk in bull markets and expansions. Meanwhile, factor investing is of little help in reducing risk exposure with respect to the market, which suggests that the diversification potential of factor investing is limited.

When short sales are authorized, Panel A in Table 4 confirms the observations from Fig. 2 that factor investing improves the market return in every subsample; this supports the superiority of factors over sectors when short selling is unconstrained. Panel B indicates that factors and sectors share the same ability to reduce market risk. Long-short factor investing dominates long-short sector investing, which corroborates the results of Eun et al. (2010) on international stock markets. Yet, the figures in Table 4 underscore that the overall dominance of factors is chiefly attributable to excess expected returns, since both styles have similar risk-mitigating properties.

4.2 ***Mean-Variance Performance Measures***

This subsection compares mean-variance performance measures of sector-based and factor-based portfolios. In each universe (short selling banned/authorized; sector/factor), we compute the Jensen's alphas in Eq. (11) and the Sharpe ratios (SRs) in Eq. (12) for our special portfolios of interest in Eqs. (6) to (10). To compare alphas, we use the Wald test with the Newey-West corrected standard errors in order to reduce as much as possible the bias in performance associated with dynamic strategies (Goetzmann et al., 2007). For SRs, we use the test developed by Ledoit and Wolf (2008), designed to address non-normality of financial returns.

Table 5 reports the results for investments excluding short selling. The full-sample Wald test detects only two significant differences in the alphas. The first corresponds to the in-sample long-only min-vol portfolio, where sectors have an average monthly alpha of 19 basis points (bps), and outperforms its competitor with 4 bps. The second is the out-of-sample long-only max-SR portfolios with M = 120 months: the factor-based portfolio shows a monthly outperformance of 37 bps versus 3 bps for its sector-based competitor. The difference between the results for M = 60 months and M = 120 months could be due to long-to-medium term mean-reversion in factor dynamics (De Bondt & Thaler, 1989). For bear markets and recessions, the outcomes of the Wald tests show no significant differences between sector and factor investing. The results for the bull periods and expansions mimic those obtained in-sample for the full period, with sector portfolios showing a significantly higher alpha than factors do.

As far as SR performances are concerned, the results of the Ledoit and Wolf (2008) tests reported in Table 5 are close to those of the Wald test. A few differences stand out, and all relate to the long-only min-vol portfolio. On the one hand, the Wald test concludes that the sector-based portfolio has superior alpha in the full sample, in bull markets, and in expansions. On the other hand, the Ledoit and Wolf test concludes that the sector-based portfolio produces a higher SR in bear markets.[7] All in all, many differences are insignificant, and the results are mixed. One byproduct of Table 5 concerns the alphas generated by sector investing. Contradicting common wisdom, which considers passive strategies incapable of generating excess returns, our results show that sectors can

[7] Portfolios maximizing the SR typically target high conditional expected returns. As pointed out by De Miguel et al. (2009), this specific feature tends to magnify the estimation risk and put the corresponding portfolios at disadvantage with respect to naïve-diversification portfolios, such as the 1/N. Here, Table 5 shows no such problem for factor portfolios.

produce significant values of alpha. So far, this "hidden side" of sector investing has gone unnoticed. Exceptions include Kacperczyk et al. (2005), who show that fund managers can outperform the market by concentrating their portfolios on a few industries. A possible economic rationale is provided by DellaVigna and Pollet (2007), who argue that changes in demand for age-sensitive industries such as toys, life insurance, and computers become predictable once each cohort is born.

When short selling is authorized, the outcomes of the tests reported in Table 6 show a clear pattern: the long-short max-SR portfolios made up of factors dominate their sector-based counterparts. This happens for in- and out-of-sample portfolios over the full sample, but also during bull markets and expansions. In-sample, the factor-based long-short max-SR portfolio exhibits an exceptional monthly outperformance of 313 bps while the alpha of the sector-based portfolio is a more modest 45 bps. The discrepancy between the alphas of factors and sectors is even greater out-of-sample. For bear market and recessions periods, the long-short max-SR portfolio does not exist, because the tangency point of the efficient frontier is located at infinity. For long-short min-vol portfolios, the two approaches provide similar alphas and SRs. Despite their conceptual differences, the two tests lead to close results, which confer robustness to our results.

4.3 *Certainty Equivalent Returns*

The purpose of using the CER-based performance measures in Eq. (13) and (14) is to acknowledge that exceptional events such as speculative bubbles and financial crises do happen, and that investors duly recognize this when building their portfolio allocations. The utility functions with moments of orders higher than two are compatible with probability distributions reflecting the presence of extreme risks more adequately than the

Gaussian distribution does. In CER analysis, there is no need to isolate recessions/expansions and bear/bull markets.

Tables 7 and 8 present the CER estimates of our benchmark portfolios for both CRRA and CARA utility functions, as well as the results of the bootstrapped t-tests for equal CERs between sectors and factors, when short selling is banned or authorized respectively. For the CRRA utility function, we report the results for the coefficient γ of relative risk aversion between 5 and 15, but we checked that the test delivers the same conclusions for values of $\gamma<5$ as for $\gamma=5$. Values above 10 deliver negative CERs, which may not be realistic. Similarly, the values selected for a, the absolute risk aversion in the CARA function range from 5 to 15.

Two examples show how to read the tables. First, the in-sample measurements with CRRA utility and low relative risk-aversion ($\gamma = 5$) reported in Table 7 (first row, first-to-third columns), indicate that holding the long-only sector-based max-SR portfolio is equivalent to getting a monthly risk-free rate of 0.67%, whereas the factor-based counterpart of this portfolio is equivalent to a rate of 0.65%. Second, for an investor with CARA utility and medium absolute risk aversion (a = 10), the out-of-sample calculations performed over 120-month estimation windows (Table 7, last row, fourth-to-sixth columns) reveal that the equal-weight sector-based portfolio is equivalent to a monthly 0.01% riskless return, but the same investor would require a 0.46 % monthly compensation to hold the equal-weight sector-based portfolio. These numbers should not be taken literally since the estimation errors are far from negligible. The 0.01% and 0.46 % figures mentioned in the previous example are not even significantly different from each other. Even more so, Table 7 fails to detect any significant difference between sector-based and factor-based long-only portfolios.

By contrast, Table 8 exhibits a few significant differences relating to long-short portfolios, but only for the long-short max-SR portfolio. Table 8 fails to detect any CER-based distinctive features between long-short min-vol portfolios, be it with CRRA or CARA functions, and for any level of risk aversion. Confirming our earlier findings, the directions of dominance suggest that sectors are typically preferred by investors with high risk aversion, whereas the preference for factor investing requires a relatively low degree of risk aversion. For the high levels of risk aversion ($\gamma = 10$, $a = 10$), there is no significant difference between CERs.

The conclusions drawn from the CER investigations converge on those from our previous mean-variance performance assessments, which show that factors offer attractive asset management opportunities but that these are targeted mainly on sophisticated investors who understand the meaning and consequences of risk taking, including shorting. Cold-feet investors are more likely to prefer traditional sector investing. As a last assessment of the evidence, Appendix B uses the Goetzmann et al. (2007) manipulation-proof performance measure presented in Eq. (26). The results are in line with those of Tables 7 and 8.

4.4 *Discussion*

Sector investing and factor investing rely on two different lines of reasoning, which is why we need multiple trials to compare their performances. The evident advantage of factors lies in the risk premia they were built to deliver. Their prime purpose was asset pricing rather than diversification and asset management. By contrast, sector indices have proven to meet the investors' diversification needs, especially when geographic diversification is inexistent.[8] While the need for diversification has long been identified in the literature, the possibility of grouping selected stocks in a way that captures risk premia has remained unexplored.

The main takeaway of our exercise is that the optimality of factor investing depends on whether the investor can go short. Factor investing outperforms sector investing when short sales are permitted, a remarkable accomplishment since sector investing remained an unchallenged benchmark for more than 50 years (Hong et al., 2007). Yet, the dominance sometimes requires unrealistically short positions (Brière & Szafarz, 2017). By contrast, when short selling is forbidden, the findings are mixed.

The outcomes of our tests confirm the results of Eun et al. (2010) who use spanning tests to check whether factors help outperforming the optimal international portfolio made of country market indices. The authors show that three long-short factors—size, book-to-market, and momentum—are useful in increasing portfolio profitability. We consider stocks from a single country (the U.S.) and compare optimal portfolios made of ten factor legs and optimal portfolios made of ten sectors. The portfolios maximizing the Sharpe ratio do not always exist in bad times (recessions and bear markets), but when they do exist (full sample, expansions, and bull markets), the factor-based version outperforms its sector-based counterparts. The geometric tests ("beating the market") confirm that the risk-return trade-off is excellent for factor-based optimal portfolios during good 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

[8] Grouping individual stocks into industrial sectors also raises issues (Martin and Klemkosky, 1976; Vermorken et al., 2010).

crises are often associated with tougher regulation of shorting. When short selling is authorized, the association of strongly performing factors and good times is consistent with the role of factors, namely to capture risk premia. The CER tests, which consider moments of higher orders, suggest that the excess return delivered by factor investing will be matched by higher losses during crises. The efficient frontiers in Figs. 1 and 2 show visually that optimal factor investing is typically riskier than the classic sector investing strategy, but it is more rewarding for investors who can afford to take high levels of risk.

Our findings are consistent with those of papers pointing out that some factors exhibit redundancy (F&F, 2015; Clarke, 2015). Several explanations could help rationalize the facts. Factors are built from quantiles of given characteristics; they may involve less idiosyncratic risks sectors. Each factor alone combines more individual assets (30% of them) than each sector alone does (around 10% on average). There can be a considerable amount of overlap between factor compositions, while overlaps between sectors are impossible by construction.

Moreover, the out-of-sample performances of portfolios are known to be sensitive to the asset clustering method (Tola et al., 2008). In our universe made up of U.S. stocks the differences are illustrated by Figs. C1 to C6 and Table C1 (Appendix C), which report dynamic weights, and show that factor-based optimal portfolios include systematically less distinct factors than their sector-based counterparts include distinct sectors.[9] Christoffersen and Langlois (2013) reach the connected conclusion that factors exhibit large and positive extreme correlations. The sole defensive factor in our analysis is the

[9] In addition, Table C2 shows the average short exposures of sectors (resp. factors) in the dynamically rebalanced optimal sector-based (resp. factor-based) LSminvol portfolios. They confirm that even minvol factor portfolios can be unrealistic portfolios for traders who must comply to short-restricting regulations (Brière & Szafarz, 2017).

“large” factor. Several sectors are naturally defensive, such as utilities and health. Had we included the low-volatility factor or the betting-against-beta factor (Frazzini & Pedersen, 2014), it would probably have affected the outcomes, at least for recessions and bear market periods. Cremers et al. (2013) point out that the F&F 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. From a theoretical standpoint, considering that factors are often considered as market anomalies (Hirshleifer, 2001; F&F, 2008; McLean & Pontiff, 2016), our results emphasize the robustness of the tenets of diversification and index investing.

Our results confirm that systematic rebalancing is successful in capturing long-term risk premia. Factor investing is, however, transaction-intensive and therefore benefits from neglecting transaction costs. Actually, transaction costs include three types of specific costs: 1) the rebalancing costs associated with changes in asset composition that take place *within* the factors (and the sectors to a much lesser extent) we are using as basic assets in our analysis, 2) the rebalancing costs relating to our multifactor/multisector portfolios of interest, and 3) the costs stemming from short sales in long-short portfolios. Overall, evaluating the total costs of the portfolio management strategies discussed in this paper is highly challenging as even articles discussing less sophisticated factor-based strategies find it difficult to produce raw estimates of these costs. Evidence shows that including transaction costs can hamper the financial performance of factor investing (Lesmond et al., 2004; Korajczyk & Sadka, 2004; Novy-Marx & Velikov, 2016). This is particularly relevant for factors subject to high turnover, such as momentum, and for those involving short selling. Brière et al. (2019) show that the annual transaction costs paid by institutional investors in factor-based assets range from 16 bps to 31 bps for size, value and quality factors, and reach 222 bps for momentum. The costs associated with short sales is linked to the need to borrow the assets that are sold. 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). The fees charged vary across stocks, depending on loan supply and demand (Diether et al., 2009). Overall, the magnitude of transaction costs in equity markets is still controversial (Frazzini et al., 2014) but there is little doubt that accounting for transaction costs would reduce the outperformance of factor investing with respect to sector investing, because factors involve by definition a much higher stock turnover than passive sector strategies.

5. Conclusion

Factor investing is an innovative method that emerged as the byproduct of factor models of asset pricing, but at present its potential for diversification and risk reduction is barely known (Sayili et al., 2017). Contributing to the ongoing conversation, we gauge investing styles in the restricted arena of U.S. stocks, where the natural rival of factor investing is passive sector investing. Our results show that the diversification potential of sector investing is higher than that of factor investing. But, diversification is only one side of the coin, the other is expected return. Taking both aspects into consideration, we find that factor investing dominates sector investing in every aspect when short sales are unrestricted. This may be due to the fact that sectors deliver low alphas anyway, and the option of going short makes no significant difference. Our results suggest also that sector investing delivers better—or less bad—performances for long-only portfolios during recessions and bear periods, i.e., in periods where diversification is needed the most.

Given the current dispersion in the literature about asset grouping, it is necessary to take steps toward unifying purely statistical approaches and economically meaningful factors. Ultimately, the ambition could be to develop a theory of portfolio management that takes asset grouping explicitly into account. Factor investing and sector investing are possible avenues to achieving that aim. Investing styles that mix factor and sector characteristics are still to come, due to their identified connections (Brière and Szafarz, 2018). The optimal number of factors and sectors to be considered in asset allocation could also be determined by using a method like the factor identification proposed by Pukthuanthong et al. (2018).

From the theoretical perspective, our conclusions meet those of Berk and van Binsbergen (2016) who use mutual fund data to test asset pricing models. They find that the CAPM betas are reliable measures of risk but that the CAPM itself explains poorly the cross-sectional variations in expected returns. This puzzling evidence is in line with our finding that alternatives to CAPM, namely factor asset pricing models, fail to produce portfolio management strategies that systematically beat index investing. Berk and van Binsbergen (2016) call for further research to address the puzzle. By identifying both the market circumstances (quiet periods) and investors' characteristics (low risk aversion and access to short selling) that correspond to higher discrepancies, our contribution can be viewed as a first step in this direction.

Our results 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 investors to implement. Nowadays, the emergence of dedicated indices and funds has made factor investing more accessible to those investors. However, the existing investment vehicles are still insufficient to build the optimal portfolios designed in this study, mainly because not all identified factors are investable and the available multifactor 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.

Last but not least, our results emphasize that the performances of multifactor portfolios are more crisis-sensitive than those of passive portfolios. For that reason, access to a wide range of factor-based portfolios makes investors increasingly sensitive to crisis risk, and so exposes markets to a greater threat of self-fulfilling, and therefore destabilizing, expectations. In this perspective, our results suggest that the development of multifactor asset management strategies among institutional investors deserves to be closely monitored. A first step in this direction would consist in assessing properly, i.e. on relatively long periods, the overall risk of factor investing and releasing the information to individual investors. This is also a message conveyed by our 50-year-period analysis.

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List of Tables

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

This table reports in Panel A the descriptive statistics of the 10 sectors (non-durable, durable, manufacturing, energy, technology, telecom, shops, health, utilities) compared with the market and in panel B the descriptive statistics of the 10 factors (small, big, value, growth, robust profitability, weak profitability, conservative investment, aggressive investment, high momentum, low momentum). Alphas of sectors and factors relative to the market are provided with their significance level. The sample covers the period July 1963 to December 2014. ***, **, *: significant at the 1%, 5% and 10% levels, respectively.

Panel A: 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

Alpha	0.28***	-0.11	0.05	0.24	-0.05	0.08	0.13	0.27**	0.18	-0.02	0.00
Observations	618	618	618	618	618	618	618	618	618	618	618

Panel B: 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
Alpha	0.21**	0.04**	0.36***	-0.10	0.21***	-0.09	0.29***	-0.12*	0.42***	-0.33***
Observations	618	618	618	618	618	618	618	618	618	618

Table 2: Correlation Matrices, Sectors and Factors, July 1963- Dec 2014

Panel A reports correlations between sectors (non-durable, durable, manufacturing, energy, technology, telecom, shops, health, utilities) and with the market. Panel B provides correlations factors (small, big, value, growth, robust profitability, weak profitability, conservative investment, aggressive investment, high momentum, low momentum) and with the market. The sample covers the full period from July 1963 to December 2014.

Panel A: Sectors

	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	1.00	0.84	0.47	0.67	0.59	0.75	0.52	0.43	0.79	0.80
Manuf	0.84	1.00	0.62	0.77	0.63	0.83	0.70	0.53	0.89	0.94
Energy	0.47	0.62	1.00	0.45	0.41	0.43	0.42	0.57	0.58	0.66
Tech	0.67	0.77	0.45	1.00	0.61	0.71	0.61	0.30	0.71	0.86
Telecom	0.59	0.63	0.41	0.61	1.00	0.63	0.53	0.50	0.67	0.75
Shops	0.75	0.83	0.43	0.71	0.63	1.00	0.67	0.46	0.83	0.86
Health	0.52	0.70	0.42	0.61	0.53	0.67	1.00	0.47	0.71	0.76
Utilities	0.43	0.53	0.57	0.30	0.50	0.46	0.47	1.00	0.58	0.59
Other	0.79	0.89	0.58	0.71	0.67	0.83	0.71	0.58	1.00	0.93

Panel B: Factors

	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	1.00	0.90	0.92	0.95	0.91	0.93	0.93	0.89	0.86	0.99
Value	0.90	1.00	0.85	0.92	0.91	0.95	0.88	0.86	0.87	0.89
Growth	0.92	0.85	1.00	0.97	0.96	0.94	0.99	0.94	0.87	0.95
Robust profit	0.95	0.92	0.97	1.00	0.92	0.95	0.97	0.94	0.88	0.96
Weak profit	0.91	0.91	0.96	0.92	1.00	0.97	0.96	0.93	0.89	0.93
Conserv invest	0.93	0.95	0.94	0.95	0.97	1.00	0.94	0.93	0.88	0.94
Aggres invest	0.93	0.88	0.99	0.97	0.96	0.94	1.00	0.94	0.88	0.96
High mom	0.89	0.86	0.94	0.94	0.93	0.93	0.94	1.00	0.74	0.92

Low mom	0.86	0.87	0.87	0.88	0.89	0.88	0.88	0.74	1.00	0.87

Table 3: Distances between Market Portfolio and Efficient Frontiers, Short Selling Banned

Panel A (resp. B) shows the outcomes of significance tests for the vertical (resp. horizontal) distance between the market portfolio and the efficient frontier. ***, **, *: significant at the 1%, 5% and 10% levels, respectively. The absence of result ("-") means that the style lacks an efficient vertical/horizontal counterpart of the market portfolio.

Sample	Sectors	Factors
Panel A: Beating the market (return): Vertical distance (λ)		
Full sample	0.0017*	0.0014***
Bear markets	-	0.0394***
Bull markets	0.0006	0.0003*
Recessions	0.0069***	0.0017**
Expansions	0.0013	0.0017***
Panel B: Beating the market (volatility): Horizontal distance (θ)		
Full sample	-	-
Bear markets	-	-
Bull markets	0.0001***	0.0002*
Recessions	-	-
Expansions	0.0005***	0.0004

Table 4: Distances between Market Portfolio and Efficient Frontiers, Short Selling Authorized

Panel A (resp. B) shows the outcomes of significance tests for the vertical (resp. horizontal) distance between the market portfolio and the efficient frontier. ***, **, *: significant at the 1%, 5% and 10% levels, respectively. The winning style, if any, is the one that reaches at least 5% significance while its competitor does not. There is a tie ("=") either if both styles have distances significant at the 5% level, or if none does. The absence of result ("-") means that at least one style lacks an efficient vertical/horizontal counterpart of the market portfolio.

Sample	Sectors	Factors
Panel A: Vertical distance (λ)		
Full sample	0.0032**	0.0106***
Bear markets	0.0303	0.0272***
Bull markets	0.0007	0.0037***
Recessions	0.0282***	0.0323***
Expansions	0.0019*	0.0076***
Panel B: Horizontal distance (θ)		
Full sample	-	-
Bear markets	-	-
Bull markets	0.0001***	0.0003***
Recessions	-	-
Expansions	0.0005***	0.0004***

Table 5: Alphas and Sharpe Ratios, Short Selling Banned

This table reports the alphas and Sharpe ratios of sector-based and factor-based portfolios (long-only maximum Sharpe ratio, long-only minimum volatility, equally weighted). To compare alphas, we use the Wald test with Newey-West (1987) corrected standard errors. To compare Sharpe ratios, we use the Ledoit-Wolf test (2008). The full sample covers the period July 1963 to December 2014. Portfolios are constructed either in sample, or out of sample, where M is the length of the rolling-window estimation period. ***, **, *: significant at the 1%, 5% and 10% levels, respectively.

Portfolio	Alpha		Wald test statistic	Sharpe ratio		Ledoit and Wolf test statistic
	Sectors	Factors		Sectors	Factors	
Full sample (in-sample estimation)						
LOmaxSR	0.27	0.40	1.45	0.58	0.65	0.66
LOminvol	0.19	0.04	5.08**	0.52	0.42	1.24
Equalweight	0.10	0.09	0.04	0.47	0.44	0.71
Full sample (out-of-sample estimation M=60 months)						
LOmaxSR	0.09	0.29	2.06	0.37	0.54	1.49
LOminvol	0.22	0.12	0.93	0.51	0.45	0.59
Equalweight	0.10	0.09	0.04	0.45	0.39	1.31
Full sample (out-of-sample estimation M=120 months)						
LOmaxSR	0.03	0.37	5.07**	0.40	0.69	2.28**
LOminvol	0.26	0.16	1.19	0.63	0.56	0.58
Equalweight	0.10	0.09	0.05	0.45	0.39	0.67
Bear markets						
LOmaxSR	0.09	0.57	0.00	-0.83	-1.09	1.05
LOminvol	0.24	0.08	0.00	-1.22	-1.6	2.49**
Equalweight	0.16	0.16	0.00	-1.51	-1.51	0.02
Bull markets						
LOmaxSR	0.13	0.34	3.12*	1.48	1.55	0.72
LOminvol	0.15	0.00	4.16**	1.37	1.39	0.47
Equalweight	0.05	0.06	0.01	1.42	1.38	1.705
Recessions						
LOmaxSR	0.80	0.48	0.00	-0.03	-0.19	0.84
LOminvol	0.05	0.05	0.00	-0.36	-0.41	0.22
Equalweight	0.14	0.21	0.00	-0.36	-0.33	0.35
Expansions						
LOmaxSR	0.25	0.38	1.57	0.82	0.89	0.16
LOminvol	0.21	0.05	5.09**	0.76	0.68	0.92
Equalweight	0.11	0.08	0.14	0.73	0.68	0.98

Table 6: Alphas and Sharpe Ratios, Short Selling Authorized

This table reports the alphas and Sharpe ratios of sector-based and factor-based portfolios (long-short maximum Sharpe ratio, long-short minimum volatility), and uses the Wald test with Newey-West (1987) corrected standard errors to check whether a style has a significantly higher alpha than its rival. The full sample covers the period July 1963 to December 2014. Portfolios are constructed either in sample, or out of sample, where M is the length of the rolling window estimation period. ***, **, *: significant at the 1%, 5% and 10% levels, respectively.

Portfolio	Alpha		Wald test statistic	Sharpe ratio		Ledoit and Wolf test statistic
	Sectors	Factors		Sectors	Factors	

Full sample (in-sample estimation)						
LSmaxSR	0.45	3.13	43.3***	0.66	1.43	4.33***
LSminvol	0.27	0.27	0.00	0.57	0.57	0.00
Full sample (out-of-sample estimation, M=60 months)						
LSmaxSR	-0.12	3.79	15.8***	0.02	0.77	3.03**
LSminvol	0.34	0.48	0.99	0.55	0.67	0.95
Full sample (out-of-sample estimation, M=120 months)						
LSmaxSR	-0.87	4.25	25.8***	-0.08	1.11	3.84***
LSminvol	0.36	0.45	0.49	0.67	0.75	0.58
Bear markets						
LSmaxSR	-	-	-	-	-	-
LSminvol	0.38	0.41	0.00	-0.84	-0.98	0.75
Bull markets						
LSmaxSR	0.16	1.10	35.29***	1.49	1.86	2.81***
LSminvol	0.19	0.06	1.74	1.35	1.22	1.23
Recessions						
LSmaxSR	-	-	-	-	-	-
LSminvol	0.48	0.08	0.00	0.1	-0.2	1.05
Expansions						
LSmaxSR	0.32	2.45	30.69***	0.85	1.53	4.45***
LSminvol	0.24	0.18	0.41	0.77	0.72	0.51

Table 7: Certainty Equivalent Returns (CERs), Short Selling Banned

This table reports the CERs for CRRA and CARA utility functions, with risk aversion coefficients of 5, 10, and 15, of sector-based and factor-based portfolios (long-only maximum Sharpe ratio, long-only minimum volatility, equally weighted) and uses the Christoffersen and Langlois (2013) bootstrap method to test the equality between the CERs of sector-based and factor-based portfolios. Portfolios are constructed either in sample, or out of sample, where M is the length of the rolling window estimation period. ***, **, *: significant at the 1%, 5% and 10% levels, respectively.

Portfolio	Low risk aversion			High risk aversion		
	CER (CRRA) γ=5		Bootstrapped equality t-test	CER (CRRA) γ=10		Bootstrapped equality t-test
	Sectors	Factors		Sectors	Factors	
In-sample estimation						
LOmaxSR	0.67	0.65	0.05	0.20	-0.25	1.03
LOminvol	0.62	0.45	0.69	0.27	-0.13	1.33
Equalweight	0.52	0.36	0.53	-0.02	-0.52	1.18
Out-of-sample estimation, M=60 months						
LOmaxSR	0.36	0.51	-0.47	-0.28	-0.34	0.14
LOminvol	0.61	0.47	0.54	0.26	-0.18	1.26
Equalweight	0.48	0.26	0.67	-0.09	-0.66	1.26
Out-of-sample estimation, M=120 months						

LOmaxSR	0.33	0.66	-0.93	-0.39	-0.23	-0.33
LOminvol	0.70	0.56	0.50	0.35	-0.11	1.28
Equalweight	0.56	0.39	0.46	-0.03	-0.56	1.06
	CER (CARA) a=5		Bootstrapped equality t-test	CER (CARA) a=10		Bootstrapped equality t-test
	Sectors	Factors		Sectors	Factors	
LOmaxSR	0.67	0.67	0.01	0.22	-0.16	0.96
LOminvol	0.62	0.45	0.67	0.28	-0.09	1.30
Equalweight	0.53	0.37	0.51	0.01	-0.44	1.16
Out-of-sample estimation, M=60 months						
LOmaxSR	0.36	0.53	-0.50	-0.24	-0.27	0.05
LOminvol	0.61	0.48	0.51	0.26	-0.13	1.20
Equalweight	0.49	0.28	0.66	-0.05	-0.57	1.24
Out-of-sample estimation, M=120 months						
LOmaxSR	0.33	0.68	0.00	-0.34	-0.15	0.96
LOminvol	0.70	0.57	0.67	0.36	-0.06	1.30
Equalweight	0.56	0.41	0.52	0.01	-0.46	1.16

Table 8: Certainty Equivalent Returns (CERs), Short Selling Authorized

This table reports the CERs for CRRA and CARA utility functions, with risk aversion coefficients of 5, 10, and 15, of sector-based and factor-based portfolios ((long-short maximum Sharpe ratio, long-short minimum volatility), and uses the Christoffersen and Langlois (2013) bootstrap method to test the equality between the CERs of sector-based and factor-based portfolios. Portfolios are constructed either in sample, or out of sample, where M is the length of the rolling window estimation period. ***, **, *: significant at the 1%, 5% and 10% levels, respectively.

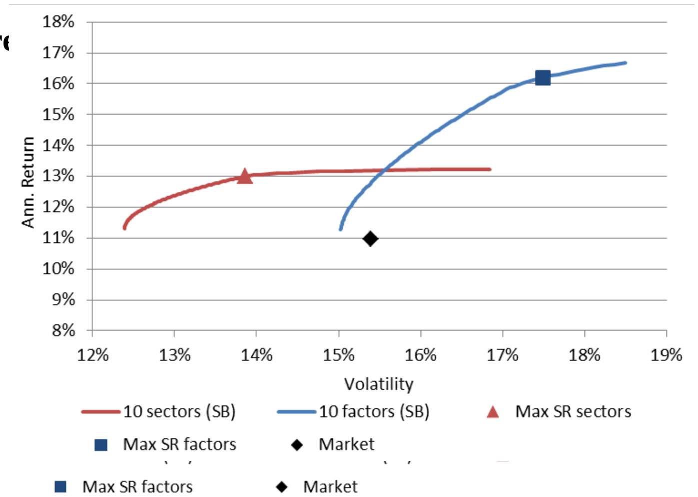
Portfolio	Low risk aversion			High risk aversion		
	CER (CRRA) γ=5		Bootstrapped equality t-test	CER (CRRA) γ=10		Bootstrapped equality t-test
	Sectors	Factors		Sectors	Factors	
In-sample estimation						
LSmaxSR	0,77	2.07	-3,09***	0,34	-0,16	0,71
LSminvol	0,68	0,67	0,05	0,36	0,28	0,32
Out-of-sample estimation, M=60 months						
LSmaxSR	-	-	-	-	-	-
LSminvol	0,66	0,78	-0,5	0,30	0,38	-0,3
Out-of-sample estimation, M=120 months						
LSmaxSR	-	-	-	-	-	-
LSminvol	0,75	0,82	-0,3	0,41	0,43	-0,0
	CER (CARA) a=5		Bootstrapped equality t-test	CER (CARA) a=10		Bootstrapped equality t-test
	Sectors	Factors		Sectors	Factors	
In-sample estimation						
LSmaxSR	0.77	2.09	-3.21***	0.35	-0.23	0.38
LSminvol	0.68	0.69	0.03	0.37	0.33	0.29

	Out-of-sample estimation, M=60 months					
LSmaxSR	-	-	-	-	-	-
LSminvol	0.66	0.78	-0.53	0.31	0.39	-0.34
	Out-of-sample estimation, M=120 months					
LSmaxSR	-	-	-	-	-	-
LSminvol	0.75	0.82	-0.04	0.41	0.44	0.17

List of Figures

Figure I: Efficient Frontiers, Short Selling Banned

Figur



Appendix A: Splitting apart the Long and Short Legs of the F&F Factors

French's website reports the monthly returns of all the so-called F&F long-short factor portfolios,[10] as well as the decomposition of each factor's return into its subcomponents. We replicate the method used by F&F (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, F&F (1993, 2015) compute:

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

[10] The universe is made up of all the stocks listed on the NYSE, Amex and Nasdaq.

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.[11] 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:

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

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

$Conservative\ Investment\ (INV)$

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

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

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

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

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.

To neutralize the potential biases arising from exposure to other factors, F&F (2015) determine the long-only *S* and *B* factors with eighteen sub-portfolios instead of four. We

[11] 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.

mimic their procedure to disentangle the long and short legs of the original long-short factors, and obtain:

$$S = 1/9(S\ High\ BM + S\ Neutral\ BM + S\ Low\ BM$$
$$+ S\ Robust\ P + SNeutral\ P + S\ Weak\ P$$
$$+S\ Conservative\ INV + S\ Neutral\ INV + S\ Aggressive\ INV)$$

$$B = 1/9(B\ High\ BM + B\ Neutral\ BM + B\ Low\ BM$$
$$+ B\ Robust\ OP + B\ Neutral\ OP + B\ Weak\ P$$
$$+B\ Conservative\ INV + B\ Neutral\ INV + B\ Aggressive\ INV)$$

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: Robustness Check: Manipulation-Proof Performance Measure

Table B1: Manipulation-proof Performance Measure Short Selling Banned

This table reports the Goetzmann et al. (2007) manipulation-proof performance measure (MPPM), with risk aversion coefficients of 5, 10, and 15, of sector-based and factor-based portfolios (long-only maximum Sharpe ratio, long-only minimum volatility, equally weighted), and uses the Christoffersen and Langlois (2013) bootstrap method to test the equality between the CERs of sector-based and factor-based portfolios. Portfolios are constructed either in sample, or out of sample, where M is the length of the rolling window estimation period. ***, **, *: significant at the 1%, 5% and 10% levels, respectively.

	Low risk aversion (γ=5)			High risk aversion (γ=10)		
	MPPM		Bootstrapped equality t-test	MPPM		Bootstrapped equality t-test
	Sector	Factor		Sector	Factor	
In-sample estimation						
LOmaxSR	3.09	2.89	0.05	-2.63	-7.99	1.05
LOminvol	2.50	0.45	0.70	-1.63	-6.45	1.35
Equalweight	1.32	-0.66	0.54	-5.17	-11.28	1.21
Out-of-sample estimation, M=60 months						
LOmaxSR	-0.74	1.14	-0.47	-8.52	-9.23	0.13
LOminvol	2.34	0.58	0.55	-1.92	-7.17	1.25
Equalweight	0.81	-1.86	0.68	-6.07	-13.02	1.25
Out-of-sample estimation, M=120 months						
LOmaxSR	-1.06	2.98	-0.93	-9.78	-7.82	-0.33
LOminvol	3.46	1.73	0.50	-0.71	-6.39	1.28
Equalweight	1.69	-0.29	0.46	-5.37	-11.76	1.06

Table B2: Manipulation-proof Performance Measure, Short Selling Authorized

This table reports the Goetzmann et al. (2007) manipulation-proof performance measure (MPPM), with risk aversion coefficients of 5, 10, and 15, of sector-based and factor-based portfolios (long-short maximum Sharpe ratio, long-short minimum volatility), and uses the Christoffersen and Langlois (2013) bootstrap method to test the equality between the CERs of sector-based and factor-based portfolios. Portfolios are constructed either in sample, or out of sample, where M is the length of the rolling window estimation period. ***, **, *: significant at the 1%, 5% and 10% levels, respectively.

	Low risk aversion (γ=5)			High risk aversion (γ=10)		
	MPPM		Bootstrapped equality t-test	MPPM		Bootstrapped equality t-test
	Sector	Factor		Sector	Factor	
			In-sample estimation			
LSmaxSR	4.29	19.53	-3.05***	-0.80	-13.45	0.72
LSminvol	3.25	3.34	0.05	-0.53	-1.16	0.33
			Out-of-sample estimation, M=60 months			
LSmaxSR	-	-	-	-	-	-
LSminvol	2.93	4.41	-0.52	-1.34	-0.35	-0.31
			Out-of-sample estimation, M=120 months			
LSmaxSR	-	-	-	-	-	-
LSminvol	3.99	4.86	-0.30	-0.07	0.20	-0.08

Appendix C: Dynamic Weights of Out-of-Sample Optimal Portfolios

The figures provide the dynamic weights of the out-of-sample sector portfolio maximizing the Sharpe ratio or minimizing the volatility. The optimized portfolio weights are computed monthly from the previous 60-month data.

Figure C1: Long-only Sector-Based Max-SR Portfolio

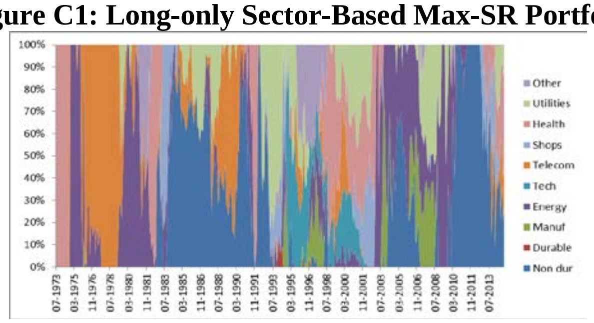


Figure C3: Long-only Sector-Based Min-Vol Portfolio

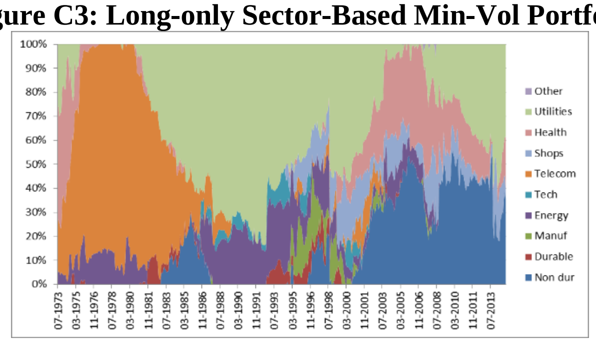


Figure C5: Long-short Sector-Based Min-Vol Portfolio

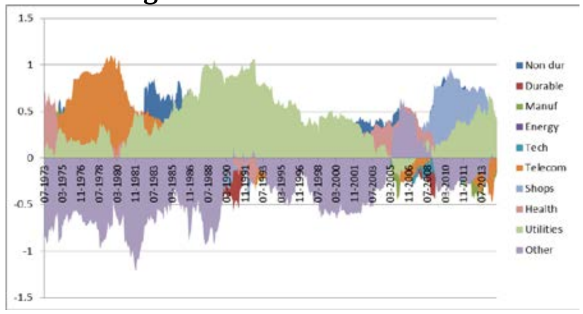


Figure C2: Long-only Factor-Based Max-SR Portfolio

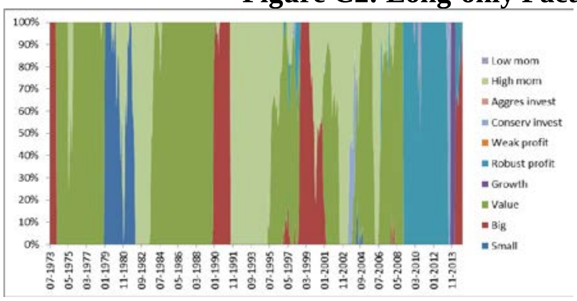


Figure C4: Long-only Factor-Based Min-Vol Portfolio

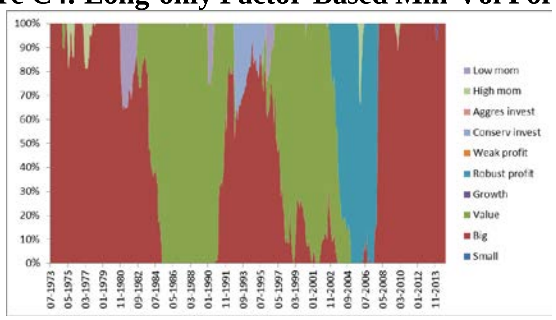


Figure C6: Long-short Factor-Based Min-Vol Portfolio

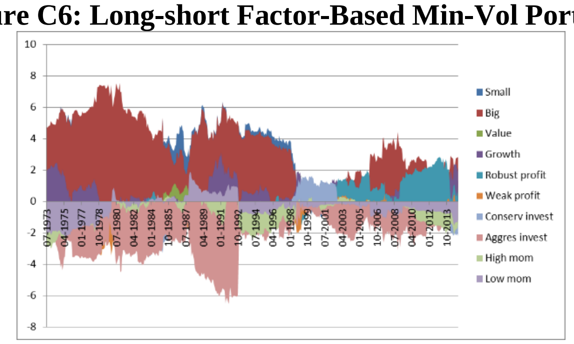


Table C1: Average Numbers of Sectors/Factors in Dynamic Out-of-Sample Portfolios

This table reports the average numbers of sectors (resp. factors) in the dynamically rebalanced optimal sector-based (resp. factor-based) portfolios, the estimation windows is 60 months.

Portfolio	Sectors M=60 months	Factors M=60 months
LOmaxSR	2.9	2.0
LOminvol	4.6	1.6
LSminvol	6.6	4.0

Table C2: Short exposure required in Dynamic Out-of-Sample Portfolios

This table reports the average short exposure of sectors (resp. factors) in the dynamically rebalanced optimal sector-based (resp. factor-based) LSminvol portfolios, the estimation windows is 60 months.

	min	p5	p25	mean	p50	p75	p95	max	sd	N
LSminvol: Sectors	-1.63	-1.43	-1.15	-0.88	-0.85	-0.60	-0.34	-0.18	0.34	498
LSminvol: Factors	-14.12	-12.92	-9.98	-7.73	-7.76	-5.45	-2.51	-1.75	3.14	498