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. This paper organizes a multi-trial contest opposing factor investing and sector investing. The results suggest that factor investing is the best strategy when short sales are permitted. When short-selling is forbidden, investors are typically better-off with the defensive opportunities of sector investing. The contest reveals that there is a trade-off between the risk premia associated with factors and the diversification potential of sectors. 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

According to the capital asset pricing model (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) and momentum (Carhart, 1997). Additional factors include so-called "quality factors" such as profitability and investment (Fama and French, 2015; Hou et al., 2015a). Factor investing consists in holding assets with positive exposure to selected risk factors and, if possible, shorting those with negative exposure. While factors are built to capture systematic risk premia, their diversification properties are still poorly understood. To fill the gap, we lay down a challenge to the novel approach of factor investing by organizing a multi-trial contest pitting it against a well-established competitor, the classical industry-based approach to asset allocation. For transparency, we opt for a well-defined market, namely the U.S. stock market, and use recognized performance measures computed from publicly available data.

In the early days of modern finance, authors realized that grouping assets *before* implementing portfolio optimization can be valuable in terms of both computational dimensionality and prediction accuracy (King, 1966; Elton and Gruber, 1973). Perhaps the most

natural way of grouping same-country stocks is based on companies' businesses (Sharpe, 1992; Heston and Rouwenhorst, 1994). This general idea on stock grouping shapes the definition of sectors, the creation of subsequent indices, and ultimately the now-classical industry-based portfolio allocation method. Alternatively, statistical methods based on principal components can deliver optimized groups of stocks, which nonetheless bear the risk of lacking economic interpretation. Moreover, the industry-based approach has the notable advantage of being stable over time, unlike purely statistical methods, which are inherently sample-dependent.

Grouping stocks conveniently is one thing; finding financial benefits in doing so is another. Two types of rewards are typically sought from assets grouped for portfolio management purposes: diversification benefits (lower risks) and risk premia (higher returns). 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. In fact, the discovery of risk premia, or risk factors, associated with specific groups of stocks was a milestone in the asset pricing literature. Strikingly, however, the risk factors popularized by Fama and French (1992) and others have long remained confined to asset pricing. Their potential for asset management attracted fresh interest only after the public release of a report by Ang et al. (2009), at the request of the Norwegian sovereign wealth fund. The report assesses the performance of active fund management, and emphasizes the benefits of factor investing.

Our paper aims to assess factor investing, which has recently emerged as the new paradigm for long-term asset management. 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. So far, more than 300 factors have been identified in the academic literature (Harvey and Liu, 2014). Factor investing has strong advocates among institutional investors. Since factors are built to

capture excess returns through betas, the argument goes, they could reasonably be expected to deliver higher returns than index investing, whether based on class, country or industry. But the claimed superiority of factor investing over traditional portfolio management techniques has yet to be proven. Two key questions motivate this paper. First, do excess returns entail higher risks; and if so, are excess risks diversified away by factor diversification? Combining factors optimally for investment purposes is still uncharted territory. Second, how does factor investing perform during crisis times? The overall performance of factor investing in market downside and upside periods remains unknown.

To assess factor investing, we compare its performances to those of sector investment, a benchmark in stock allocation. Although studies on financial markets commonly use industry-based portfolios (Ferson and Harvey, 1991), modern factor investing has not yet, to our knowledge, been contrasted with industry-based asset allocation. This paper fills a gap by comparing the financial performances of factor-based and sector-based asset allocations in the investment universe composed of U.S. equities. To compare the two investing styles, we organize a contest comprising four trials: the first compares efficient frontiers, the second is based on Jensen's alphas, the third relates to Sharpe ratios (SRs), and the fourth relies on certainty equivalent returns based on utility functions that account for downside risks. In each trial we combine in-sample and out-of-sample tests. We contrast the performance of diversified portfolios made up of sectors with diversified portfolios composed of factors. Each trial ends up with a winner (but with the possibility of a dead heat).

Another novelty of our study is its fully agnostic perspective on short-selling. We duplicate all the trials for portfolios with short sales banned ("long-only"), on the one hand, and authorized ("long-short") on the other hand. This is a key aspect since factor-based asset management

exploits 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 of the chosen factors, and so benefit from excess returns relative to the market portfolio. Idzorek and Kowara (2013) attribute most of the benefits of factor investing to the combination of long and short positions. In fact, legal restrictions and transaction costs can make long-short factor investing difficult in practice. This paper will remove this limitation by scrutinizing both long-short and long-only portfolios.

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. By contrast, when short-selling is forbidden, the more risk-averse investors will prefer industry-based allocation. 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. Interestingly, the sector-based portfolio with minimal volatility never loses to its factor-based competitor. More expectedly, the preferred maximal SR portfolio is made up of factors, except in the case of investors with high aversion to downside risk. 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,[1] 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 – 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) 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 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 extraction and products), (5) high tech (computers, software, and electronic equipment), (6) telecom (telephone and television

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

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 those fixed by Fama and French (1992, 2015) and Carhart (1997). The five long-short portfolios available on French's website are: size, value, profitability, investment, and momentum. 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, 2015) and Carhart (1997) are thus not directly investible (Idzorek and Kowara, 2013). 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 and leverage are authorized.

While working with widely used factors and sectors has undeniable advantages, this approach raises the issues of relevance and replicability. Regarding relevance, the 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; Hou et al., 2011). The two additional quality factors, profitability and investment, are useful for applications.[2] Finally,

[2] A wide variety of "quality" factors coexist, but there is a growing consensus regarding the use of profitability (Novy-Marx, 2013and 2014) and investment (Hou et al., 2015a and 2015b). Still, the theoretical foundations of these factors are controversial (Harvey et al., 2016), and the existence of risk premia associated with the new factors is 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.

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.[3]

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). 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. Long-Only and Long-Short Portfolios

A sizeable literature on portfolio management suggests that making short sales on a regular basis to rebalance portfolios is difficult. The obstacles stem both from legal barriers and from specific costs and risks associated with short-selling. First, some countries forbid short sales, which can be executed only off-exchange or offshore. In a comprehensive international comparison of short-selling restrictions, Bris et al. (2007) show that 35 countries (out of 47) permit the practice, but their tolerance is often coupled with temporary restrictions during specific periods, such as the 2007-2008 subprime crisis.

In fact, many market participants do not take full advantage of legal tolerance for short-selling, mostly because these sales typically require the borrowing of securities. For instance, U.S. mutual funds are forbidden to borrow money “unless authorized by the vote of a majority of its outstanding Voting Securities” (U.S. Investment Company Act, Section 13(a)). Europe's

[3] Factor investing is feasible through mutual funds, hedge funds, exchange traded funds, etc.

UCITS mutual funds are even more constrained, since they are prohibited from taking physical short positions,[4] and their borrowing is limited to 10% of net assets. In addition to regulatory constraints, restrictions can originate from funds' investment policies. Almanzan et al. (2004) find that 30% of a large sample of U.S. equity mutual funds have the option to sell short, but only 3% actually do so.

Second, covered and uncovered short sales entail specific costs and risks. Covered (or traditional) short-selling involves borrowing the security and returning it to the lender at a given future date.[5] The securities lending market is decentralized, so finding a lender involves a costly search. In addition, the exchanges where stocks are sold impose collateralization costs.[6] Short-selling also exposes the trader to the risk of liquidity shortage and short squeeze (Jones and Lamont, 2002). By contrast, uncovered short-selling is carried out without borrowing. Under U.S. rules, the seller has three days to deliver the security to the buyer. Past this deadline, the sale can be considered as "manipulative,"[7] putting the trader at risk of legal prosecution.

In sum, assuming that short-selling is always feasible at no extra cost might seem restrictive. However, the typical factor-investing strategies rely heavily on short sales, and the bulk of the empirical literature on risk factors disregards the additional constraints associated with shorting. We address this issue here by considering, on the one hand, the long-short sector-

[4] Routinely, US mutual funds borrow up to 33% of their total assets. The European Union Directive on Undertakings for Collective Investment in Transferable Securities (UCITS) covers around 75% of all collective investment by small investors in Europe (http://ec.europa.eu/finance/investment/ucits-directive/index_en.htm). Still, UCITS fund managers can take synthetic short positions through financial derivatives.

[5] Frazzini et al. (2014) find that selling short is more expensive than selling long by 3.7 basis points on average, but the difference is not statistically different. The authors, however, do not account for borrowing fees.

[6] The U.S. Federal Reserve Board's Regulation T governs credit extension by securities brokers and dealers and controls the margin requirements for stocks bought or sold. For instance, the NYSE requires that investors maintain 25% collateral for long positions and 30% for short positions. Collateral adjustments following price changes in the underlying asset are performed through margin calls (Mitchell et al., 2002).

[7] Section 10(b) of the U.S. Securities Exchange Act of 1934 prohibits the use of "any manipulative or deceptive device or contrivance in contravention of [SEC] rules." The 2008 SEC antifraud rule 10b-21 addresses "abusive naked short selling."

based and factor-based portfolios (short sales allowed) inspired from the Fama and French approach and, on the other hand, their long-only counterparts (short sales banned).

Practically, we build the long-only versions of our five factors of interest by disentangling the long and short legs of each long-short portfolio available on French's website. The method 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. Long-only portfolios are restricted by positive quantities of these ten long-only factors. In long-short portfolios investors can short any of these factors. Actually, this approach goes beyond Fama and French's original definitions, which place opposite exposures on the two legs of the long-short position (e.g., small minus big). Here, 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.[8] We have adopted the same terminology for sector-based portfolios.

2.3. The Trials

The purpose of our contest 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. Portfolio managers are well aware of the difficulty of taking into account the peculiarities of asset movements in crisis periods as opposed to normal times. We acknowledge this reality in two different yet complementary ways. First, we deal with five periods and restrict ourselves to using standard measures of portfolio performance. Second, we

[8] We simplify the presentation by defining short positions with respect to factors rather than to individual stocks. For instance, we would characterize as long-short a portfolio that 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. Arguably, our factors closely mimic the investment practice suggested by the proponents of factor investing and marketed by several index providers, such as MSCI and Russell.

consider the whole sample period only, but we gauge performance according to utility functions that are sensitive to extreme risk. Our contest includes four trials, each devoted to a specific issue that matters (or ought to matter) to portfolio managers and is made up of a group of tests.

The first trial uses tests of mean-variance efficiency of the market portfolio to investigate the ability of efficient frontiers to beat the market. Most empirical tests of mean-variance efficiency are spanning tests, which focus on time-series regressions of asset returns on the market index (Gibbons, Ross and Shanken, 1989; Harvey and Zhou, 1990). However, spanning tests are inappropriate in our case because they apply only to portfolios with unconstrained weights (Wang, 1998). Therefore, we follow another path and 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). For this, we compute two distances in the mean-variance plan, for which tests exist in the literature. First, Basak et al. (2002) exploit the "horizontal distance" between a portfolio and its same-return counterpart efficient portfolio to test whether this distance is significantly positive. Unfortunately, the market portfolio often does not have such a counterpart, which limits the applicability of the test. Second, Brière et al. (2013) introduce a test based on the "vertical distance" between a given portfolio and its same-return counterpart portfolio on the efficient frontier. The merit of the second approach is to circumvent the limitation of the Basak et al. (2002) test, due to the possible absence of an efficient portfolio with the same expected return as the market.

In the second and third trials, we address the performance of couples of same-type portfolios built with sectors and factors, respectively. We consider the three special portfolios that stand out in the literature (Liu, 2016): the efficient portfolio maximizing SR, the efficient minimum volatility portfolio, and the equally-weighted (or 1/N) portfolio. The first two make

sense with and without short-selling restrictions, while the last is long-only by construction. Actually, equal weighting significantly departs from the original spirit of Fama and French (1993), who impose opposite signs on the two legs of their factor components. Our approach is less restrictive since it allows the weights of the long and short legs to adjust separately. It is however consistent with current practice. In particular, Edelen et al. (2016) mention that institutional investors often have a long position in the short legs of Fama and French's factors. Moreover, the merits of 1/N investing are often underscored in the literature. For instance, DeMiguel et al. (2009) recommend this strategy to minimize the risk inherent in estimating optimal weights out of sample. In sum, we end up with three composite portfolios when short-selling is banned, and two of them when short-selling is authorized.

For every trial, we run both in-sample and out-of-sample tests. In all cases we assume that the investor rebalances her portfolio monthly, and we compare the performance of factor investing with that of 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 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, we determine the optimized portfolio weights from parameters 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 in order to keep the factor/sector exposure equal to the investor's

predetermined optimal exposure. On the contrary, the weights of the out-of-sample portfolios change dynamically.

The second trial uses t-tests to compare the Jensen (1968) 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:

$$r - r_f = \alpha + \beta(r_M - r_f), \tag{1}$$

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 $\beta(r_M - r_f)$ is the theoretical risk premium associated with the given portfolio following the CAPM. Choosing the CAPM as a benchmark model is questionable, as would any other choice. 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.[9] In fact, 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). 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. The influence of the CAPM on our conclusions is, however, mitigated by the tests, which rely on utility functions that account for higher moments, and so acknowledge the presence of asymmetric and extreme risks.

[9] But despite this limitation we find that some industry portfolios, such as the non-durable and health sectors, do exhibit positive and significant alphas.

In the third trial, we contrast the ways risk is remunerated by the two investment styles. For this, we test the equality of the Sharpe (1966) ratios of a factor-based portfolio and its sector-based counterpart. The Sharpe ratio (SR) measures the excess return per unit of risk.

$$SR = \frac{r - r_f}{\sigma}, \qquad (2)$$

where σ is the volatility of the portfolio under consideration. The SR is a rough measure of performance, but, at the same time, it is free from any model-based premises. To test the equality between the SRs of identically-constructed portfolios—one with sector indices, the other with factors—we use the test recently introduced by Ledoit and Wolf (2008), which acknowledges the possibility of non-normal returns. Based on bootstrapping, this test improves on the predecessor proposed by Jobson and Korkie (1981) by accommodating return series with heavy tails. Practically speaking, the Ledoit and Wolf (2008) test procedure builds bootstrapped p-values by fitting a semi-parametric model.[10]

The Ledoit and Wolf (2008) test is a first step toward acknowledging the non-standard probability distributions of financial returns. Still, all the performance indicators presented in the previous subsection are restricted to using moments of orders one and two of return distributions in one way or another. Going one step further and including higher order moments requires more sophisticated indicators, for which the literature offers various options. For instance, Agarwal and Naik (2004) propose modified SRs where the variance is replaced by a more comprehensive parameter combining moments of orders two (dispersion), three (skewness), and four (kurtosis). The problem is that these measures are barely used in practice; more importantly, there is no established test for comparing the performances of competing portfolios.

[10] On the use of the Ledoit and Wolf (2008) test, see also Maio (2014) and De Miguel et al. (2014).

Another route is provided by the certainty equivalent return (CER), which has the merits of being directly built from utility functions and encompassing moments of unlimited orders. By definition, CER 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. Studies of extreme risks (Brandt et al., 2005; Kadan and Liu, 2014) favor CERs obtained from Constant Relative Risk Aversion (CRRA) utility functions, which are sensitive to the third and fourth order moments:

$$u(w) = \frac{1}{1-\gamma} w^{1-\gamma}, \tag{3}$$

where γ is the coefficient of relative risk aversion.

The CER of utility u is then defined by:

$$u(CER) = E[u(r)] \tag{4}$$

Bootstrapped confidence intervals are used to test whether the CER is higher for portfolio A than for portfolio B. Here, we derive the standard deviations from 10,000 simulations and compute the extreme-risk performance measures on full samples only since, by nature, CERs are conceived to deal with crises and normal times together. To concentrate the exercise on extreme risks, we take values of γ between 5 and 15. The value of 15 is relatively high when compared with standard values used in the literature, which are concentrated mainly between 2 and 10 (Mehra and Prescott, 1985), but Brandt et al. (2005; 2009) emphasize that values up to 20 adequately represent the attitude of investors facing significant extreme risks.

Finally, the robustness checks provided in Appendix C compare our CRRA-based CER results with those obtained with three additional performance indicators: the CERs derived from

Constant Absolute Risk Aversion (CARA) utility functions, and the Goetzmann et al. (2007) manipulation-proof performance measure.

3. Descriptive 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).[11] 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. 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.

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,

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

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 dispersion than for sectors. 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. 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.[12]

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 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

[12] AppendixB provides the descriptive statistics concerning the sub-samples.

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

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 the correlation matrix between the market and the 10 sectors (non-durable, durable, manufacturing, energy, technology, telecom, shops, health, utilities). Panel B provides the correlation matrix between the market and the 10 factors (small, big, value, growth, robust profitability, weak profitability, conservative investment, aggressive investment, high momentum, low momentum). The sample covers the full period from July 1963 to December 2014.

Panel A: 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 B: 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

Tables B1 to B5 in Appendix B summarize the main statistics concerning our four sub-samples: bear markets and bull markets (as identified by Forbes Magazine), recessions, and expansions, as dated by the NBER. The main lessons drawn from Table B1 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% for sectors and 48.99% for factors; the average spreads between expansions to recessions

are less spectacular: 15.33% for sectors, and 17.44% for factors. 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. Tables B2 to B5 confirm that correlations among factors are 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. 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: Beating the Market?

We consider ten different period/short-sale scenarios. In each case, we determine two efficient frontiers, the first built from the ten sectors, the second from the ten factors (Fig. 1 for short-selling banned, Fig. 2 for short-selling authorized). The figures also help visualize the market portfolio. To test whether our style-based portfolios outperform the market, we use two different tests. First, the Basak et al. (2002) test computes the horizontal distance between the market portfolio and its same-return counterpart efficient portfolio (Table. 3 for short-selling banned, Table 4 for short-selling authorized). Second, the Brière et al. (2013) test exploits the vertical distance between the market portfolio and its same-variance counterpart efficient portfolio. In each case, there is a winner if a given style produces a significant distance whereas its competitor

delivers an insignificant one. Intuitively, the winning style is such that it beats the market when the other style fails to do so.

Figure 1: Efficient Frontiers, Short-Selling Banned

Fig 1a: Full sample

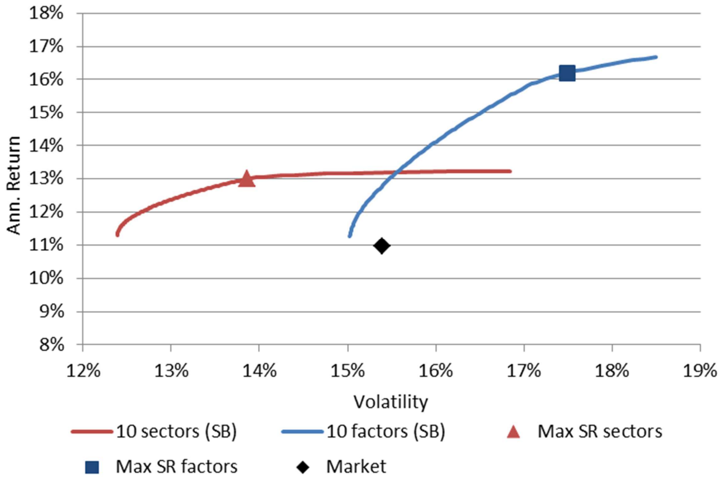


Fig 1b: Bear markets

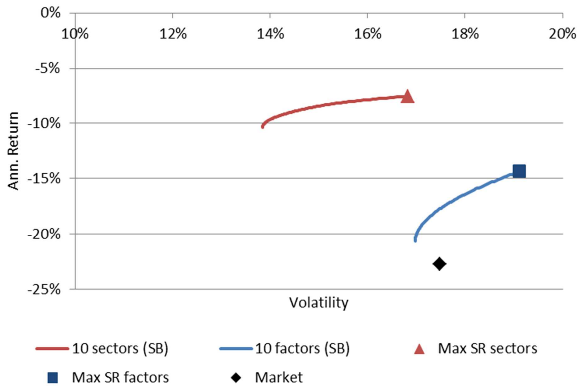


Fig 1c: Bull markets

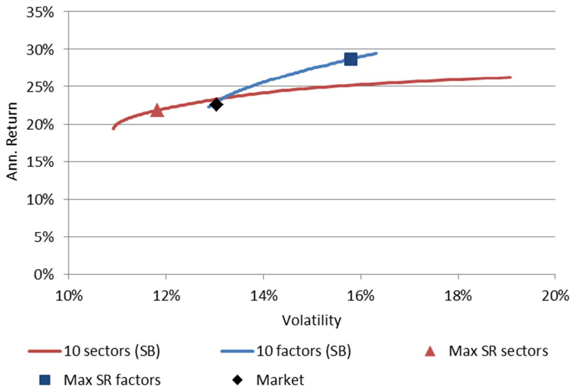


Fig 1d: Recessions

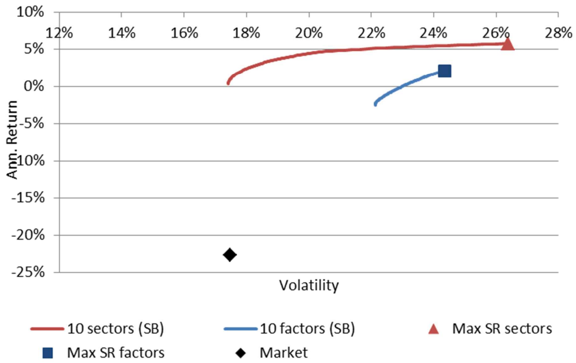
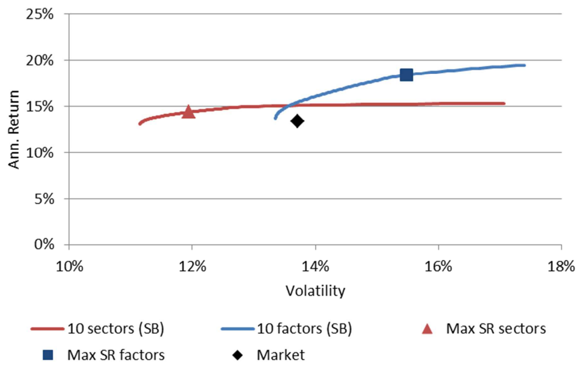


Fig 1e: Expansions



First, Figure 1 shows the efficient frontiers when short-selling is banned. Over the full sample, the efficient frontiers built from sectors and factors intersect. Therefore, no frontier dominates any other. The same evidence applies to bull markets and, lesser so, to expansion periods. While sector investing looks particularly attractive to investors with high risk aversion, factor-based portfolios are more suitable for their more risk tolerant counterparts. By contrast, in bear markets and recession periods, the efficient frontier composed of sectors is always above the one made up of factors. This is consistent with factor investing being a better strategy in troubled times, regardless of the investor's level of risk aversion.

Table 3 presents the test results corresponding to the graphs in Figure 1. They use geometric distances between the market portfolio and the efficient frontiers. The results in Panel A show that factor investing systematically beats the market by increasing expected returns. Precisely, all five winners of vertical-distance contests are factor-based. This is not surprising since, by construction, factors deliver risk premia. Less expectedly, Panel B indicates that sector investing manages to significantly mitigate market risk in bull markets and expansions. In sum, since factors and sectors win two tests each, the final result when short-selling is banned is a draw.

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 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 Period	Sectors	Factors	Winner
	Panel A: Vertical distance		
Full sample	*	***	Factors
Bear markets	-	***	-
Bull markets		*	=
Recessions	***	-	-
Expansions		***	Factors
	Panel B: Horizontal distance		
Full sample	-	-	-
Bear markets	-	-	-
Bull markets	***	*	Sectors
Recessions	-	-	-
Expansions	***		Sectors
Global			=

When short sales are authorized (Figure 2 and Table 4), the efficient frontier composed of factors tends to dominate the one made up of sectors. There is one exception, though: highly risk-averse investors prefer sectors to factors during bear markets. In the tests, factor investing wins because it manages to improve the market return in bear markets, bull markets and expansions. However, factors and sectors share the same ability (and inability) to reduce market risk in the five periods considered. Overall, the winning style for long-short portfolios is factor investment.

Figure 2: Efficient Frontiers, Short-Selling Authorized

Fig 2a: Full sample

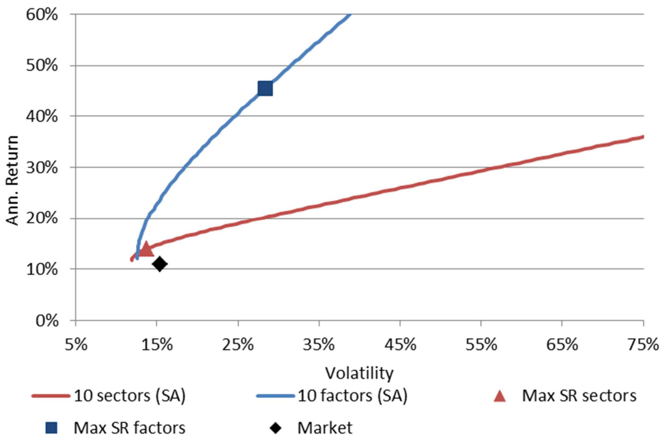


Fig 2b: Bear markets

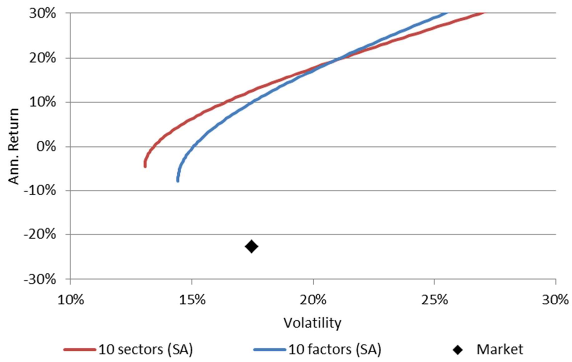


Fig 2c: Bull markets

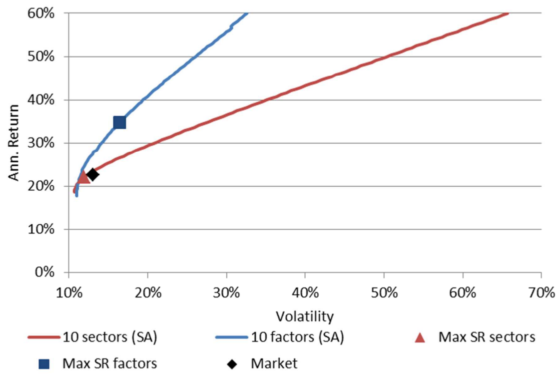


Fig 2d: Recessions

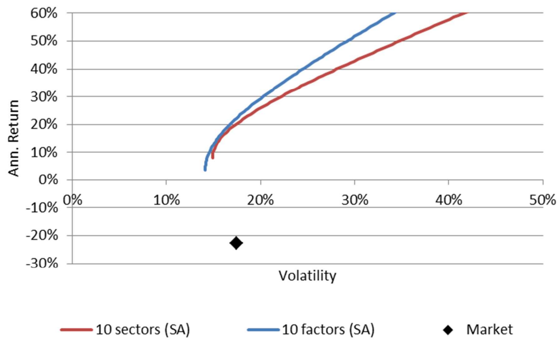


Fig 2e: Expansions

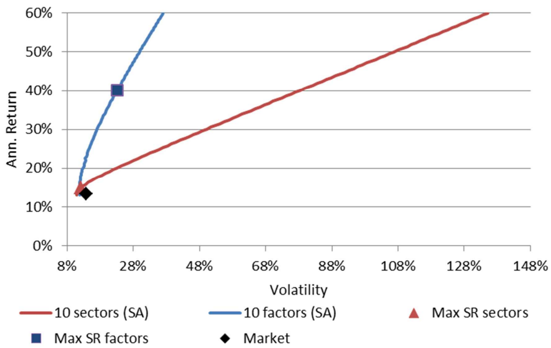


Table 4: Distances between Market Portfolio and Efficient Frontiers, Short-Selling Authorized

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 Period	Sectors	Factors	Winner
	Panel A: Vertical distance		
Full sample	**	***	=
Bear markets		***	Factors
Bull markets		***	Factors
Recessions	***	***	=
Expansions	*	***	Factors
	Panel B: Horizontal distance		
Full sample	-	-	-
Bear markets	-	-	-
Bull markets	***	***	=
Recessions	-	-	-
Expansions	***	***	=
Global			Factors

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? We consider the efficient portfolio maximizing SR, the efficient minimum volatility portfolio, and the equally-weighted portfolio. To determine the significance of their alphas, we use the Wald test with the Newey-West (1987)-corrected standard errors, which takes into account heteroskedasticity and autocorrelation in the residuals in order to reduce as much as possible the bias in portfolio performance typically associated with dynamic strategies

(Goetzmann et al., 2007). Tables 5 and 6 summarize the results of the tests when short-selling is banned and authorized, respectively.

For the whole sample period, Table 5 shows that the Wald test detects only two significant differences in the alphas generated by both investment styles. The first corresponds to the in-sample minimum volatility portfolio, where the sector-based investing style—with an average monthly alpha of 19 basis points (bps)—outperforms its competitor, with 4 bps. The second is the out-of-sample maximum SR portfolios for the case where M = 120 months: the factor-based portfolio shows a monthly outperformance of 37 bps versus 3 bps for its sector-based competitor. Apparently, when the optimization period shortens to 60 months, the SR portfolios based on factors tend to underperform those using a 120-month optimization period. This, however, is not the case for their sector-based counterpart. The difference could be due to long-to-medium term mean-reversion in factor dynamics (De Bondt and Thaler, 1989).

For bear markets and recessions, the figures in Table 5 show ties only. The results for the bull periods and expansions mimic those obtained in-sample for the full sample period, with sector portfolios showing a significantly higher alpha than factors do. All in all, the sector approach wins when short-selling is restricted. But the most frequent conclusion in the trial is still a draw, meaning that differences are not significant enough to be used as a guide for asset allocation.

When short-selling is authorized (Table 6), the maximum SR portfolios made up of factors win five times out of seven. 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 maximum SR

portfolio exhibits an exceptional monthly outperformance of 313 bps[13] while the alpha of the sector-based portfolio is a more modest 45 bps. The discrepancy between the performances of factor-based versus sector-based portfolios is even greater out-of-sample. Note that for bear market and recessions periods, 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. For minimum volatility portfolios, however, there is no winner, since the two approaches provide similar alphas. All in all, factors win when short-selling is permitted.

An interesting byproduct of this trial concerns the alphas generated by sector investing. Contradicting common wisdom that considers sector investing as purely passive, our results show that industry-based portfolio management can produce significant values of alpha. So far, this “hidden side” of sector investing has remained unnoticed by the literature. Exceptions include Kacperczyk et al. (2005), who show that fund managers can outperform the market by concentrating their portfolio in a few industries. A possible economic rationale for this striking outcome is provided by DellaVigna and Pollet (2007), who argue that the changes in demand for age-sensitive industries such as toys, life insurance, and computers become predictable once each cohort is born.

[13] Transaction costs might, however, substantially affect this performance.

Table 5: Second Trial: Jensen's Alphas, Short-Selling Banned

This table reports the alphas of specific portfolios (maximum SR, minimum volatility, equally weighted when short-selling is banned) made up of either sectors (left side) or factors (right side), with t-stats. We use Newey-West (1987) corrected standard errors. SR stands for the Sharpe ratio, Vol stands for volatility. The winner has a significantly higher alpha (Wald test) at the 5% level. The full sample covers the period July 1963 to December 2014. Portfolios are constructed either in-sample, or out-of-sample. M (= 60 months or 120 months) is the length of the rolling window estimation period for the parameters used in the dynamic optimization process for out-of-sample portfolios. For M = 60 months, the sample covers the period from July 1968 to December 2014; for M = 120 months, it covers the period from July 1973 to December 2014. The sub-samples are characterized by: bear markets, bull markets, recessions and expansions. ***, **, *: significant at the 1%, 5% and 10% levels respectively.

Portfolio	Sectors	Factors	Comparison	
	α (%)	α (%)	Wald test	Winner
Full sample (in-sample estimation)				
Max SR	0.27	0.40		=
Min vol	0.19	0.04	**	Sectors
Equal weights	0.10	0.09		=
Full sample (out-of-sample estimation M=60 months)				
Max SR	0.09	0.29		=
Min vol	0.22	0.12		=
Equal weights	0.10	0.09		=
Full sample (out-of-sample estimation M=120 months)				
Max SR	0.03	0.37	**	Factors
Min vol	0.26	0.16		=
Equal weights	0.10	0.09		=
Bear markets				
Max SR	0.09	0.57		=
Min vol	0.24	0.08		=
Equal weights	0.16	0.16		=
Bull markets				
Max SR	0.13	0.34	*	=
Min vol	0.15	0.00	**	Sectors
Equal weights	0.05	0.06		=
Recessions				
Max SR	0.80	0.48		=
Min vol	0.05	0.05		=
Equal weights	0.14	0.21		=
Expansions				
Max SR	0.25	0.38		=
Min vol	0.21	0.05	**	Sectors
Equal weights	0.11	0.08		=
Global				Sectors

Table 6: Second Trial: Jensen's Alphas, Short-Selling Authorized

This table reports the alphas of specific portfolios (maximum SR, minimum volatility when short-selling is authorized) made up of either sectors (left side) or factors (right side), with t-stats. We use Newey-West (1987) corrected standard errors. SR stands for the Sharpe ratio, Vol stands for volatility. The winner has a significantly higher alpha (Wald test) at the 5% level. The full sample covers the period July 1963 to December 2014. Portfolios are constructed either in sample, or out of sample. M (= 60 months or 120 months) is the length of the rolling window estimation period for the parameters used in the dynamic optimization process for out-of-sample portfolios. For M = 60 months, the sample covers the period July 1968 to December 2014; for M = 120 months, it covers the period July 1973 to December 2014. The sub-samples are characterized by: bear markets, bull markets, recessions and expansions. ***, **, *: significant at the 1%, 5% and 10% levels respectively.

Portfolio	Sectors	Factors	Comparison	
	α (%)	α (%)	Wald test	Winner
Full sample (in-sample estimation)				
Max SR	0.45	3.13	***	Factors
Min vol	0.27	0.27		=
Full sample (out-of-sample estimation, M=60 months)				
Max SR	-0.12	3.79	***	Factors
Min vol	0.34	0.48		=
Full sample (out-of-sample estimation, M=120 months)				
Max SR	-0.87	4.25	***	Factors
Min vol	0.36	0.45		=
Bear markets				
Max SR	-	-		-
Min vol	0.38	0.41		=
Bull markets				
Max SR	0.16	1.10	***	Factors
Min vol	0.19	0.06		=
Recessions				
Max SR	-	-		-
Min vol	0.48	0.08		=
Expansions				
Max SR	0.32	2.45	***	Factors
Min vol	0.24	0.18		=
Global				Factors

4.3. Third Trial: Sharpe Ratios

Tables 7 and 8 present the results of the test developed by Ledoit and Wolf (2008) to compare the SR performances of portfolios made up of either sectors or factors, when short sales are banned and authorized, respectively. The overall impression happens to be fairly close to that of the previous trial. In fact, the results of the second and third trials differ only in the performance of the long-only sector-based minimum volatility portfolio. On the one hand, the Wald test used in the second trial concludes that this portfolio is better than its factor counterpart in the full sample, both in bull markets and in expansions. On the other hand, the Ledoit and Wolf test used in the third trial concludes that the portfolio outperforms its factor-based contenders in bear markets. By contrast, in both the second and third trials, the portfolios made up of sectors and those built from factors have similar risk-adjusted performances when short-selling is banned, but with a slight preference for sectors. Last, when short positions are authorized, the factor-based maximum SR portfolio clearly outperforms its sector-based counterpart.

The main differences between the second and third trials appear when short-sales are banned. In the Sharpe-ratio trial, there are only two winners: the SR max factor portfolio for the full-sample with out-of-sample estimation (M = 120 months) and the in-sample minimum volatility sector portfolio during bear markets. The trial based on alphas identifies two additional situations with a declared winner (sectors, in both cases). When short-selling is authorized both trials lead to the same conclusions. Overall, despite their differences, the second and third trials lead to qualitatively close results, which confer robustness to the outcomes of our contest.

Table 7: Third Trial: Sharpe Ratios, Short-Selling Banned

This table reports the SRs of sector-based and factor-based portfolios maximum SR, minimum volatility, equally weighted) when short-selling is banned. The winner has a significantly higher SR than its rival, according to the Ledoit and Wolf (2008) test, at the 5% level. SB (resp. SA) means that short-selling is banned (resp. authorized). SR stands for the Sharpe ratio, Vol stands for volatility. The full sample covers the period July 1963 to December 2014. Portfolios are constructed either in sample, or out of sample. M (= 60 months or 120 months) is the length of the rolling window estimation period for the parameters used in the dynamic optimization process for out-of-sample portfolios. For M = 60 months, the sample covers the period July 1968 to December 2014; for M = 120 months, it covers the period July 1973 to December 2014. The sub-samples are characterized by: bear markets, bull markets, recessions and expansions. ***, **, *: significant at the 1%, 5% and 10% levels, respectively.

Portfolio	Sectors	Factors	Comparison	
	Sharpe ratio	Sharpe ratio	Ledoit and Wolf test	Winner
Full sample (in-sample estimation)				
Max SR	0.58	0.65		=
Min vol	0.52	0.42		=
Equal weights	0.47	0.44		=
Full sample (out-of-sample estimation, M=60 months)				
Max SR	0.37	0.54		=
Min vol	0.51	0.45		=
Equal weights	0.45	0.39		=
Full sample (out-of-sample estimation, M=120 months)				
Max SR	0.40	0.69	**	Factors
Min vol	0.63	0.56		=
Equal weights	0.45	0.39		=
Bear markets				
Max SR	-0.83	-1.09		=
Min vol	-1.22	-1.6	**	Sectors
Equal weights	-1.51	-1.51		=
Bull markets				
Max SR	1.48	1.55		=
Min vol	1.37	1.39		=
Equal weights	1.42	1.38		=
Recessions				
Max SR	-0.03	-0.19		=
Min vol	-0.36	-0.41		=
Equal weights	-0.36	-0.33		=
Expansions				
Max SR	0.82	0.89		=
Min vol	0.76	0.68		=
Equal weights	0.73	0.68		=
Global				=

Table 8: Third Trial: Sharpe Ratios, Short-Selling Authorized

This table reports the SRs of sector-based and factor-based portfolios maximum SR, minimum volatility) when short-selling is authorized. The winner has a significantly higher SR than its rival, according to the Ledoit and Wolf (2008) test, at the 5% level. SB (resp. SA) means that short-selling is banned (resp. authorized). SR stands for the Sharpe ratio, Vol stands for volatility. The full sample covers the period July 1963 to December 2014. Portfolios are constructed either in sample, or out of sample. M (= 60 months or 120 months) is the length of the rolling window estimation period for the parameters used in the dynamic optimization process for out-of-sample portfolios. For M = 60 months, the sample covers the period July 1968 to December 2014; for M = 120 months, it covers the period July 1973 to December 2014. The sub-samples are characterized by: bear markets, bull markets, recessions and expansions. ***, **, *: significant at the 1%, 5% and 10% levels, respectively.

Portfolio	Sectors	Factors	Comparison	
	Sharpe ratio	Sharpe ratio	Ledoit and Wolf test	Winner
Full sample (in-sample estimation)				
Max SR	0.66	1.43	***	Factors
Min vol	0.57	0.57		=
Full sample (out-of-sample estimation, M=60 months)				
Max SR	0.02	0.77	**	Factors
Min vol	0.55	0.67		=
Full sample (out-of-sample estimation, M=120 months)				
Max SR	-0.08	1.11	***	Factors
Min vol	0.67	0.75		=
Bear markets				
Max SR	-	-		-
Min vol	-0.84	-0.98		=
Bull markets				
Max SR	1.49	1.86	***	Factors
Min vol	1.35	1.22		=
Recessions				
Max SR	-	-		-
Min vol	0.1	-0.2		=
Expansions				
Max SR	0.85	1.53	***	Factors
Min vol	0.77	0.72		=
Global				Factors

4.4. Fourth Trial: Certainty Equivalent Returns

The CER approach is used to assess the higher-moment-sensitive performance of the portfolios under investigation. Tables 9 and 10 present the CRRA CERs of our benchmark portfolios and the results of the tests for the difference between the CER of each sector-based portfolio and its factor-based counterpart, when short-selling is banned or authorized respectively. The previous trials give the impression that factor portfolios are better in normal times, while a sector-based asset allocation can outperform in crisis periods. Intuitively, one would thus expect that factors, respectively sectors, behave better when the values of parameter γ is relatively low, respectively high. By allowing this parameter to take a wide range of values, we can check the validity of this intuition. Therefore, Tables 9 and 10 feature values of γ ranging between 5 and 15. In addition, we obtain the same conclusions for $\gamma < 5$ as for $\gamma = 5$. The tables reveal that, in line with the literature, values above 10 deliver negative CERs, which may not be realistic.

Table 9 suggests that, for an investor with CRRA utility and low risk-aversion (γ= 5), the sector-based maximum SR portfolio (short-selling banned) is equivalent to a risk-free 0.67% monthly return, whereas the factor-based counterpart of this portfolio is equivalent to a risk-free 0.65% monthly return. Moreover, the difference between the two is insignificant. This result holds true whatever the portfolio construction methodology (Maximum SR, minimum volatility, equally weighted), in- and out-of-sample and on all subsamples as well.

The only significant difference occurs for the maximum SR portfolio with short-selling permitted (Table 10), where the factor portfolio dominates with a monthly CER of 2.07% against 0.77% for its sector counterpart. For the moderate risk aversion (γ= 10), there is no significant difference between CERs of factor-based and sector-based portfolios. The first significant

advantage of sector investment appears at the fairly high value of γ= 15. However, at this level of risk aversion, almost all CERs are negative. When short sales are authorized, the investor dislikes the maximum SR factor portfolio (CER = -3.37%) even more than the sector one (CER = -0.13%). Interestingly, however, significant differences are observed for one type of portfolio only, the maximum SR portfolio with short-selling authorized. It is thus fair to say that in the common situation where the investor cannot (or does not want to) sell short, the two styles are equivalent. Note that when short-selling is authorized, Table 10 reports no result for out-of-sample CERs estimations corresponding to Maximum SR portfolios, be they sector-based or factor-based. This is because those portfolios are impracticable in several periods during which they would require unbounded short positions. Two groups of robustness checks are provided in Appendix C for the full sample. The first group uses CRRA-based CERs, and the second computes the Goetzmann et al. (2007) manipulation-proof performance measure. In both cases, the results are in line with those of the fourth trial.

Table 9: Fourth Trial: Certainty Equivalent Returns (CERs), Full Sample only, Short-Selling Banned

This table reports the CERs for CRRA utility, with risk aversion coefficients of 5, 10, and 15, of sector-based and factor-based portfolios maximum SR, minimum volatility, equally weighted) when short-selling is banned. The winning style has a CER significantly higher than its rival (sector v. factor) in the bootstrapped t-test for equal CER at the 5% level. SB (resp. SA) means that short-selling is banned (resp. authorized). The full sample covers the period July 1963 to December 2014. Portfolios are constructed either in sample, or out of sample. M (= 60 months or 120 months) is the length of the rolling window estimation period for the parameters used in the dynamic optimization process for out-of-sample portfolios. For M = 60 months, the sample covers the period July 1968 to December 2014; for M = 120 months, it covers the period July 1973 to December 2014. ***, **, *: significantly different at the 1%, 5% and 10% levels, respectively.

	Panel A: Low risk aversion (γ=5)			Panel B: Medium risk aversion (γ=10)			Panel C: High risk aversion (γ=15)		
Portfolio	Sector CER (%)	Factor CER (%)	Winner	Sector CER (%)	Factor CER (%)	Winner	Sector CER (%)	Factor CER (%)	Winner
In-sample estimation									
Max SR	0.67	0.65	=	0.20	-0.25	=	-0.38	-1.57	=
Min vol	0.62	0.45	=	0.27	-0.13	=	-0.10	-0.84*	=
Equal weights	0.52	0.36	=	-0.02	-0.52	=	-0.69	-1.74	=
Out-of-sample estimation, M=60 months									
Max SR	0.36	0.51	=	-0.28	-0.34	=	-1.04	-1.51	=
Min vol	0.61	0.47	=	0.26	-0.18	=	-0.13	-1.05*	=
Equal weights	0.48	0.26	=	-0.09	-0.66	=	-0.80	-1.93	=
Out-of-sample estimation, M=120 months									
Max SR	0.33	0.66	=	-0.39	-0.23	=	-1.26	-1.46	=
Min vol	0.70	0.56	=	0.35	-0.11	=	-0.02	-1.03*	=
Equal weights	0.56	0.39	=	-0.03	-0.56	=	-0.78	-1.91	=
Winner of the trial									=

Table 10: Fourth Trial: Certainty Equivalent Returns (CERs), Short-Selling Authorized

This table reports the CERs for CRRA utility, with risk aversion coefficients of 5, 10, and 15, of sector-based and factor-based portfolios maximum SR, minimum volatility) when short-selling is authorized. The winning style has a CER significantly higher than its rival (sector v. factor) in the bootstrapped t-test for equal CER at the 5% level. SB (resp. SA) means that short-selling is banned (resp. authorized). The full sample covers the period July 1963 to December 2014. Portfolios are constructed either in sample, or out of sample. M (= 60 months or 120 months) is the length of the rolling window estimation period for the parameters used in the dynamic optimization process for out-of-sample portfolios. For M = 60 months, the sample covers the period July 1968 to December 2014; for M = 120 months, it covers the period July 1973 to December 2014. ***, **, *: significant at the 1%, 5% and 10% levels, respectively.

	Panel A: Low risk aversion (γ=5)			Panel B: Medium risk aversion (γ=10)			Panel C: High risk aversion (γ=15)		
Portfolio	Sector CER (%)	Factor CER (%)	Winner	Sector CER (%)	Factor CER (%)	Winner	Sector CER (%)	Factor CER (%)	Winner
In-sample estimation									
Max SR	0.77	2.07***	Factors	0.34	-0.16	=	-0.13	-3.37***	Sectors
Min vol	0.68	0.67	=	0.36	0.28	=	0.02	-0.19	=
Out-of-sample estimation, M=60 months									
Max SR	-	-	-	-	-	-	-	-	-
Min vol	0.66	0.78	=	0.30	0.38	=	-0.08	-0.07	=
Out-of-sample estimation, M=120 months									
Max SR	-	-	-	-	-	-	-	-	-
Min vol	0.75	0.82	=	0.41	0.43	=	0.05	0.00	=
Winner of the trial									=

4.6. Discussion

Table 11 summarizes the results of the four trials performed in the previous sub-sections. The main takeaway from our contest is that the global winner depends crucially on whether the investor is able or willing to go short. In a universe where short-selling is banned, sector investing dominates. By contrast, when short sales are authorized, factor investing is preferable. Admittedly, the dominance of factors in an unconstrained investment universe is stronger than that of sectors in a long-only world. However, the optimal factor-based portfolios sometimes require unrealistically short positions. Moreover, a frequent outcome of the tests is a draw, testifying to a fierce contest.

Table 11: Summary of the Results

This table reports the results of the four trials according to the status of short-selling (banned or authorized). For each trial we report the winner, if any, and between parentheses the scores of factor investing and sector investing, respectively.

Short-selling	Trial 1: Beating the market	Trial 2: Alphas	Trial 3: Sharpe ratios	Trial 4: Certainty equivalent returns	Global winner
Short-Selling Banned	= (2/2)	Sectors (1/3)	= (1/1)	= (0/0)	Sectors
Short-Selling Authorized	Factors (3/0)	Factors (5/0)	Factors (5/0)	= (1/1)	Factors

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 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. 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. 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. First, the evident advantage of factors lies in the risk premia they were built to deliver. However, their prime purpose was asset pricing rather than diversification and asset management. Second, sector indices have proven to meet the investors' diversification needs, especially when geographic diversification is inexistent. 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.[14] This not only provides a global comparison of the two investment styles; it also corresponds to typical investors' objectives and constraints in practice.

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, 2016). 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

[14] 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.

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 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. Considering a one-sided turnover resulting from averaging the values of purchased or sold assets, Novy-Marx and Velikov (2016) estimate that the turnover of the size and value long-short portfolios is around 2% per year and the associated transaction costs[15] 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 and Liu (2015) suggests focusing on the market segment made up 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 conjecture that their turnover is close to that of their size and value counterparts, which are also rebalanced on a yearly basis.[16] In addition, sophisticated transaction-cost models

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[15] 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).

[16] 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.

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 Lesmond et al. (2004), and Korajczyk and Sadka (2004), who all rely on simple microstructure models.

For portfolios involving short-selling, 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; 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. In fact, the maximum 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 "beating the market" trial (trial 1) confirms 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 crises are often associated with tougher regulation of shorting. This was especially the case during the 2008-2009 financial crisis.

When short-selling is authorized, the association of strongly-performing factors and good times is in line with the role of risk factors, namely to capture risk premia. The fourth trial, which takes into account moments of higher orders, suggests 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.

4 Conclusion

A fierce debate is taking place about the merits of factor-based asset allocation (Eun et al., 2010). 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. Contributing to the ongoing conversation, this paper organizes a contest based on well-recognized criteria used to gauge investing styles in the restricted arena of U.S. stocks, where the natural rival of factor investing is sector investing. 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.

Surprisingly, our results suggest the diversification potential of sector investing is higher than that of factor investing. Several explanations could help rationalize the facts. In particular, factor-specific returns may involve more idiosyncratic risks than factor-specific returns. 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. Likewise, the sectors cover the whole investment universe of interest, while factors built from quantiles of given characteristics could leave some stocks aside. In short, unlike the situation of sectors, the way stocks are grouped into factors makes them depart from a partition of the investment universe. The out-of-sample performances of portfolios are known to be sensitive to the asset clustering method (Tola et al., 2008).[17] In our universe made up of U.S. stocks the differences are illustrated by Figures D1-D11 and Table D1 (Appendix D), which report dynamic weights and show that sector-based optimal portfolios do systematically include more distinct sectors than their factor-based counterparts include distinct factors. Interestingly, Christoffersen and Langlois (2013) reach the connected conclusion that factors exhibit large and positive extreme correlations, which induces a drastic reduction in the benefits of factor diversification. In sum, sector investing is better in delivering diversification benefits.

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 that factor investing tends to be more profitable during expansion times and bull periods, even if

[17] Grouping individual stocks into industrial sectors also raises issues (Martin and Klemkosky, 1976).

short-selling is forbidden. However, 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 (Brière et al., 2012; Bekaert et al., 2014). And in fact, sectors appear to provide significantly greater diversification benefits than factors do. On this issue, our findings are consistent with those of papers pointing out that some factors tend to exhibit redundancy (Fama and French, 2015; Clarke, 2015). 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).[18] While the literature proposes over 300 such factors, which are supposed to deliver excess returns, a key question is whether they represent long-term risk premia or rather temporary market anomalies that disappear when discovered (McLean and Pontiff, 2016). Likewise, our results are contingent on both the market (U.S. stock market) and the period (1963-2014) of investigation. Further work is needed to assess the robustness of our findings along these dimensions.

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. The rebalancing of the momentum factors, specifically, involves a large number of transactions. In addition, factor investing also performs well when short-selling is permitted, and short sales imply additional expenses, such as borrowing costs. Accounting for all the costs could actually make passive strategies more competitive. Further work could investigate whether our results are robust to incorporating transaction costs.

[18] 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.

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), 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,[19] 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.[20] 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:

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

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

[19] The universe is made up of all the stocks listed on the NYSE, Amex and Nasdaq.
[20] 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: Sub-sample Descriptive Statistics

Table B1: Descriptive Statistics for Sub-Samples

This table reports the annualized mean return, volatility, skewness, and kurtosis for the 10 sectors (non-durable, durable, manufacturing, energy, technology, telecom, shops, health, utilities) in bear markets (Panel A), bull markets (Panel B), recessions (Panel C) and expansions (Panel D) and for the 10 factors (small, big, value, growth, robust profitability, weak profitability, conservative investment, aggressive investment, high momentum, low momentum) in bear markets (Panel E), bull markets (Panel F), recessions (Panel G) and expansions (Panel H). The sample covers the period July 1963 to December 2014.

Sectors	Non dur	Durable	Manuf	Energy	Tech	Telecom	Shops	Health	Utilities	Other	Market
Panel A: Bear markets											
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
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
Panel B: Bull markets											
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
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
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
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
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
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

Factors	Small	Big	Value	Growth	Robust profit	Weak profit	Conserv invest	Aggres invest	High mom	Low mom
Panel E: Bear markets										
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
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
Panel F: Bull markets										
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
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
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
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
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
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

Table B2: Correlations in Bear Markets, July 1963 - Dec 2014

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

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 B3: Correlations in Bull Markets, July 1963 - Dec 2014

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

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 B4: Correlations in Recessions, July 1963- Dec 2014

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

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 B5: Correlations in Expansions, July 1963 - Dec 2014

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

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

Appendix C: Robustness Checks for Higher-Moment Performance Measures

To assess the robustness of our results using CRRA-based CERs, we introduce three additional performance indicators. First, we compute CERs derived from the Constant Absolute Risk Aversion (CARA) utility functions given by:

$$u(w) = -exp(-aw)$$

where a is the coefficient of absolute risk aversion. Table C1 (short-selling banned) and C2 (short-selling authorized) show that the results are identical to those featured in Table 9 and 10 for the CERs of CRRA utility functions.

Table C1: Certainty Equivalent Returns (CERs), CARA Utility, Full Sample, Short-Selling Banned

This table reports the CERs for CARA utility, with risk aversion coefficients of 5, 10, and 15, of sector-based and factor-based portfolios maximum SR, minimum volatility, equally weighted) when short-selling is banned. The winning style has a CER significantly higher than its rival (sector v. factor) in the bootstrapped t-test for equal CER at the 5% level. SB (resp. SA) means that short-selling is banned (resp. authorized). The full sample covers the period July 1963 to December 2014. Portfolios are constructed either in sample, or out of sample. M (= 60 months or 120 months) is the length of the rolling window estimation period for the parameters used in the dynamic optimization process for out-of-sample portfolios. For M = 60 months, the sample covers the period July 1968 to December 2014; for M = 120 months, it covers the period July 1973 to December 2014. ***, **, *: significant at the 1%, 5% and 10% levels, respectively.

	Panel A: Low risk aversion (γ=5)			Panel B: Medium risk aversion (γ=10)			Panel C: High risk aversion (γ=15)		
Portfolio	Sector CER (%)	Factor CER (%)	Winner	Sector CER (%)	Factor CER (%)	Winner	Sector CER (%)	Factor CER (%)	Winner
In-sample estimation									
Max SR	0.67	0.67	=	0.22	-0.16	=	-0.31	-1.24	=
Min vol	0.62	0.45	=	0.28	-0.09	=	-0.08	-0.73	=
Equal weights	0.53	0.37	=	0.01	-0.44	=	-0.60	-1.46	=
Out-of-sample estimation, M=60 months									
Max SR	0.36	0.53	=	-0.24	-0.27	=	-0.94	-1.27	=
Min vol	0.61	0.48	=	0.26	-0.13	=	-0.11	-0.88	=
Equal weights	0.49	0.28	=	-0.05	-0.57	=	-0.70	-1.63	=
Out-of-sample estimation, M=120 months									
Max SR	0.33	0.68	=	-0.34	-0.15	=	-1.13	-1.20	=
Min vol	0.70	0.57	=	0.36	-0.06	=	0.00	-0.85	=
Equal weights	0.56	0.41	=	0.01	-0.46	=	-0.66	-1.58	=
Winner of the trial									=

Table C2: Certainty Equivalent Returns (CERs), CARA Utility, Full Sample, Short-Selling Authorized

This table reports the CERs for CARA utility, with risk aversion coefficients of 5, 10, and 15, of sector-based and factor-based portfolios maximum SR, minimum volatility) when short-selling is authorized. The winning style has a CER significantly higher than its rival (sector v. factor) in the bootstrapped t-test for equal CER at the 5% level. SB (resp. SA) means that short-selling is banned (resp. authorized). The full sample covers the period July 1963 to December 2014. Portfolios are constructed either in sample, or out of sample. M (= 60 months or 120 months) is the length of the rolling window estimation period for the parameters used in the dynamic optimization process for out-of-sample portfolios. For M = 60 months, the sample covers the period July 1968 to December 2014; for M = 120 months, it covers the period July 1973 to December 2014. ***, **, *: significant at the 1%, 5% and 10% levels, respectively.

	Panel A: Low risk aversion (γ=5)			Panel B: Medium risk aversion (γ=10)			Panel C: High risk aversion (γ=15)		
Portfolio	Sector CER (%)	Factor CER (%)	Winner	Sector CER (%)	Factor CER (%)	Winner	Sector CER (%)	Factor CER (%)	Winner
In-sample estimation									
Max SR	0.77	2.09***	Factors	0.35	-0.23	=	-0.10	-3.26**	Sectors
Min vol	0.68	0.69	=	0.37	0.33	=	0.04	-0.09	=
Out-of-sample estimation, M=60 months									
Max SR	-	-	-	-	-	-	-	-	-
Min vol	0.66	0.78	=	0.31	0.39	=	-0.06	-0.04	=
Out-of-sample estimation, M=120 months									
Max SR	-	-	-	-	-	-	-	-	-
Min vol	0.75	0.82	=	0.41	0.44	=	0.06	0.02	=
Winner of the trial									=

Second, the manipulation-proof performance measure (MPPM) developed by Goetzmann et al. (2007) cannot be gamed by active fund managers, and it thus counteracts on moral hazard. The three manipulative strategies the authors have in mind cover: manipulating the underlying probability distribution, inducing time variations in order to game a stationarity-based measure, and derivative-based strategies that distort the evolution of the estimation errors. While MPPM is especially meaningful for hedge funds, it can be applied to any performance check since potentially manipulative fund managers can be active in any market segment.

Technically, MPPM is built as the average of a power utility function, calculated over the return history. Therefore, it incorporates moments of high orders. Parameter ρ in Table 3 is the relative risk aversion. MPPM can be interpreted as the annualized continuously compounded excess return (over the risk-free rate) CER of the portfolio for investors with CARA utility. The figures in Table C3 (short-selling banned) and C4 (short-selling authorized) confirm the findings of Tables 9 and 10 showing that, when the tie between styles is broken, factor investing is preferred to sector investing for low risk aversion, while sector investing is preferred by investors seeking safer options.

Table C3: Manipulation-proof Performance Measure, Full Sample, Short-Selling Banned

This table reports the Goetzmann et al. (2007) manipulation-proof performance measure (MPPM), with risk aversions of 5, 10, and 15, of sector-based and factor-based portfolios maximum SR, minimum volatility, equally weighted) when short-selling is banned. The winning style has a MPMM significantly higher than its rival (sector v. factor) in the bootstrapped t-test for equal MPMM at the 5% level. SB (resp. SA) means that short-selling is banned (resp. authorized). The full sample covers the period July 1963 and December 2014. Portfolios are constructed either in sample, or out of sample. M (= 60 months or 120 months) is the length of the rolling window estimation period for the parameters used in the dynamic optimization process for out-of-sample portfolios. For M = 60 months, the sample covers the period July 1968 to December 2014; for M = 120 months, it covers the period July 1973 to December 2014. ***, **, *: significant at the 1%, 5% and 10% levels, respectively.

	Panel A: Low risk aversion (γ=5)			Panel B: Medium risk aversion (γ=10)			Panel C: High risk aversion (γ=15)		
Portfolio	Sector CER (%)	Factor CER (%)	Winner	Sector CER (%)	Factor CER (%)	Winner	Sector CER (%)	Factor CER (%)	Winner
In-sample estimation									
Max SR	3.09	2.89	=	-2.63	-7.99	=	-9.67	-24.20	=
Min vol	2.50	0.45	=	-1.63	-6.45	=	-6.12	-15.13*	=
Equal weights	1.32	-0.66	=	-5.17	-11.28	=	-13.37	-26.21	=
Out-of-sample estimation, M=60 months									
Max SR	-0.74	1.14	=	-8.52	-9.23	=	-18.03	-23.60	=
Min vol	2.34	0.58	=	-1.92	-7.17	=	-6.51	-17.84*	=
Equal weights	0.81	-1.86	=	-6.07	-13.02	=	-14.75	-28.69	=
Out-of-sample estimation, M=120 months									
Max SR	-1.06	2.98	=	-9.78	-7.82	=	-20.61	-22.96	=
Min vol	3.46	1.73	=	-0.71	-6.39	=	-5.14	-17.49*	=
Equal weights	1.69	-0.29	=	-5.37	-11.76	=	-14.46	-28.35	=
Winner of the trial									=

Table C4: Manipulation-proof Performance Measure, Full Sample only, Short-Selling Authorized

This table reports the Goetzmann et al. (2007) manipulation-proof performance measure (MPPM), with risk aversions of 5, 10, and 15, of sector-based and factor-based portfolios maximum SR, minimum volatility, equally weighted) when short-selling is authorized. The winning style has a MPMM significantly higher than its rival (sector v. factor) in the bootstrapped t-test for equal MPMM at the 5% level. SB (resp. SA) means that short-selling is banned (resp. authorized). The full sample covers the period July 1963 to December 2014. Portfolios are constructed either in sample, or out of sample. M (= 60 months or 120 months) is the length of the rolling window estimation period for the parameters used in the dynamic optimization process for out-of-sample portfolios. For M = 60 months, the sample covers the period July 1968 to December 2014; for M = 120 months, it covers the period July 1973 to December 2014. ***, **, *: significant at the 1%, 5% and 10% levels, respectively.

	Panel A: Low risk aversion (γ=5)			Panel B: Medium risk aversion (γ=10)			Panel C: High risk aversion (γ=15)		
Portfolio	Sector CER (%)	Factor CER (%)	Winner	Sector CER (%)	Factor CER (%)	Winner	Sector CER (%)	Factor CER (%)	Winner
In-sample estimation									
Max SR	4.29	19.53***	Factors	-0.80	-13.45	=	-6.48	-66.66***	Sectors
Min vol	3.25	3.34	=	-0.53	-1.16	=	-4.60	-6.63	=
Out-of-sample estimation, M=60 months									
Max SR	-	-	-	-	-	-	-	-	-
Min vol	2.93	4.41	=	-1.34	-0.35	=	-5.90	-5.78	=
Out-of-sample estimation, M=120 months									
Max SR	-	-	-	-	-	-	-	-	-
Min vol	3.99	4.86	=	-0.07	0.20	=	-4.32	-4.98	=
Winner of the trial									=

Appendix D: Dynamic Weights of the Out-of-Sample Optimal Portfolios

Figure D1: Dynamic Weights of the Sector-Based Portfolio Maximizing the 60-Month Rolling Sharpe Ratio, Short-Selling Banned

This figure provides the dynamic weights of the out-of-sample sector portfolio maximizing the Sharpe ratio when short-selling is banned. The optimized portfolio weights are computed on a monthly basis from the previous 60-month data.

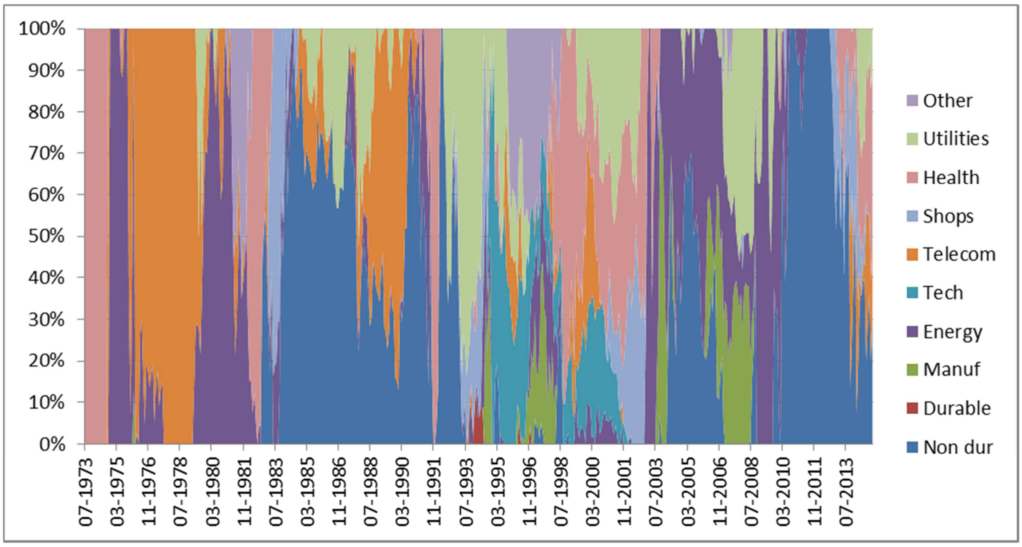

Figure D2: Dynamic Weights of the Factor-Based Portfolio Maximizing the 60-Month Rolling Sharpe Ratio, Short-Selling Banned

This figure provides the dynamic weights of the out-of-sample factor portfolio maximizing the Sharpe ratio when short-selling is banned. The optimized portfolio weights are computed on a monthly basis from the previous 60-month data.

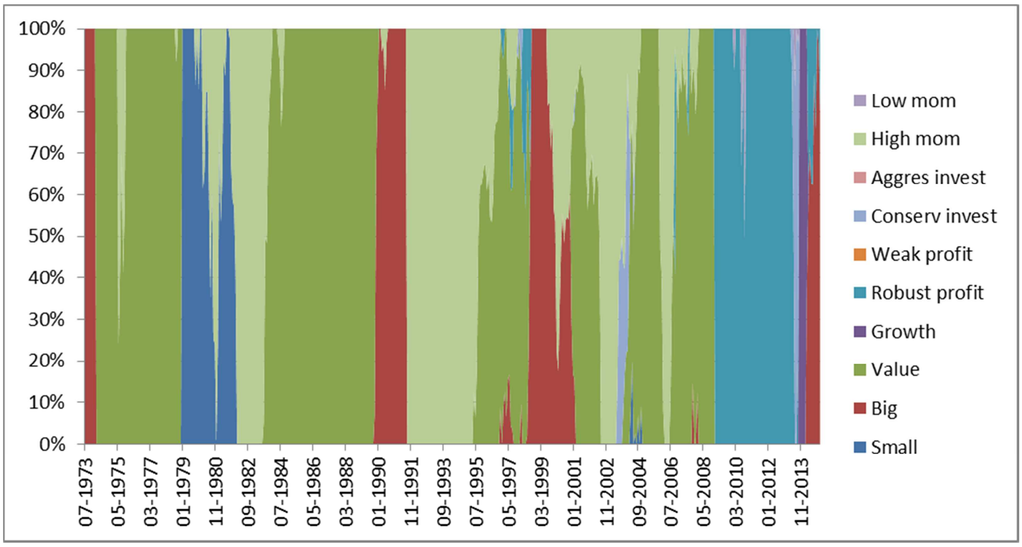

Figure D3: Dynamic Weights of the Sector-Based Portfolio Minimizing the 60-Month Rolling Volatility, Short-Selling Banned

This figure provides the dynamic weights of the out-of-sample sector portfolio minimizing the volatility when short-selling is banned. The optimized portfolio weights are computed on a monthly basis from the previous 60-month data.

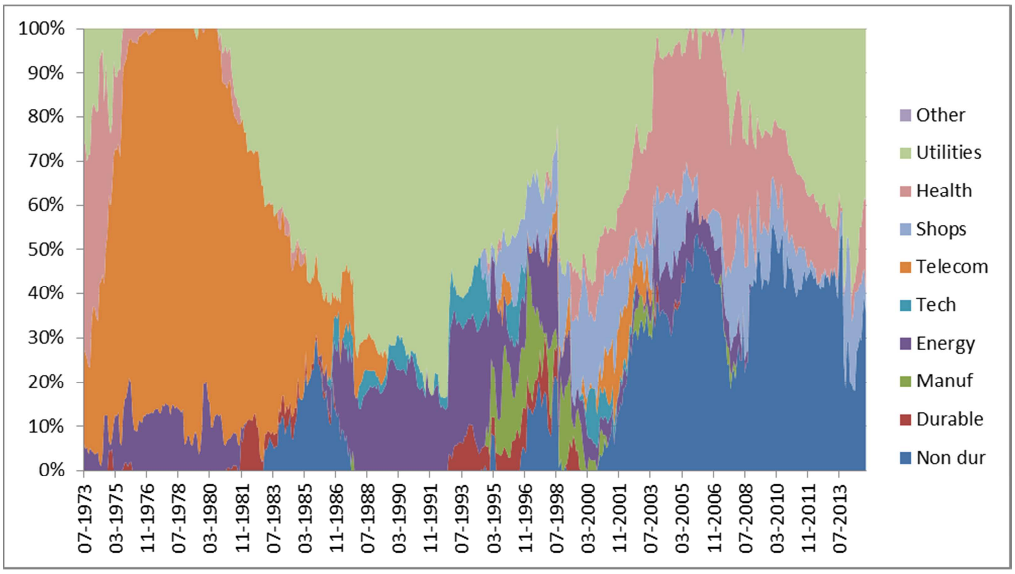

Figure D4: Dynamic Weights of the Factor-Based Portfolio Minimizing the 60-Month Rolling Volatility, Short-Selling Banned

This figure provides the dynamic weights of the out-of-sample factor portfolio minimizing the volatility when short-selling is banned. The optimized portfolio weights are computed on a monthly basis from the previous 60-month data.

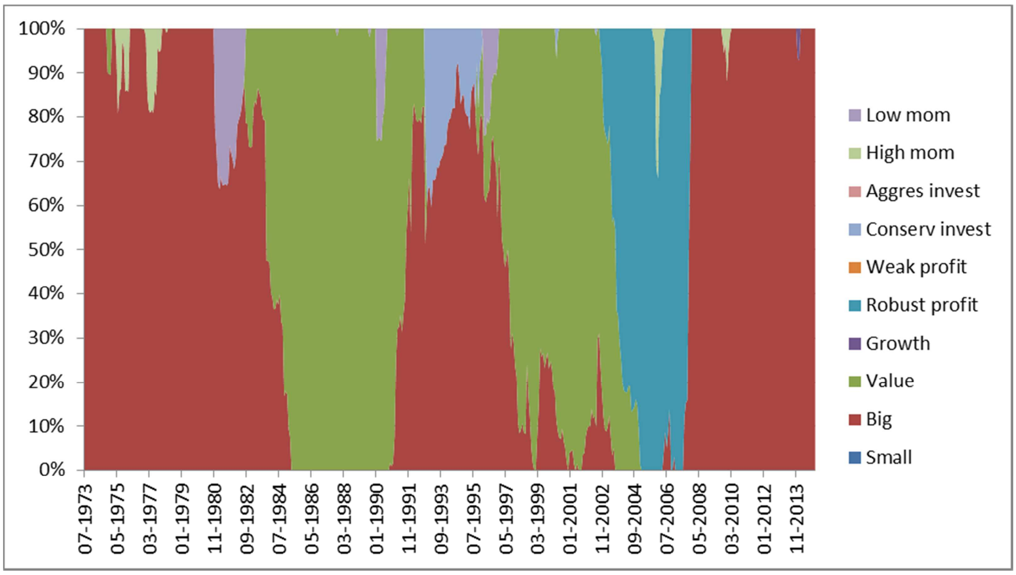

Figure D5: Dynamic Weights of the Sector-Based Portfolio Minimizing the 60-Month Rolling Volatility, Short-Selling Authorized

This figure provides the dynamic weights of the out-of-sample sector portfolio minimizing the volatility when short-selling is authorized. The optimized portfolio weights are computed on a monthly basis from the previous 60-month data.

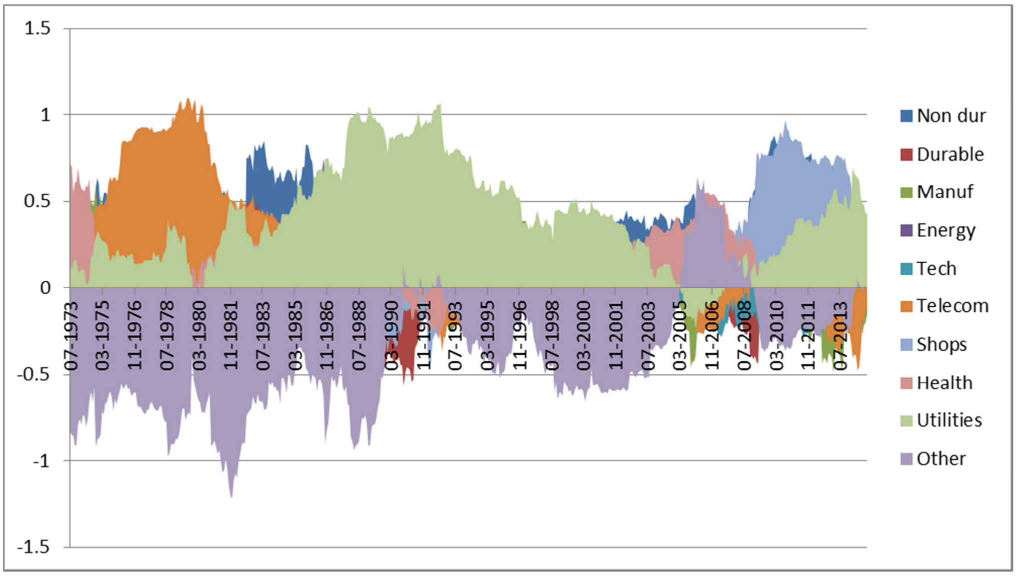

Figure D6: Dynamic Weights of the Factor-Based Portfolio Minimizing the 60-Month Rolling Volatility, Short-Selling Authorized

This figure provides the dynamic weights of the out-of-sample factor portfolio minimizing the volatility when short-selling is authorized. The optimized portfolio weights are computed on a monthly basis from the previous 60-month data.

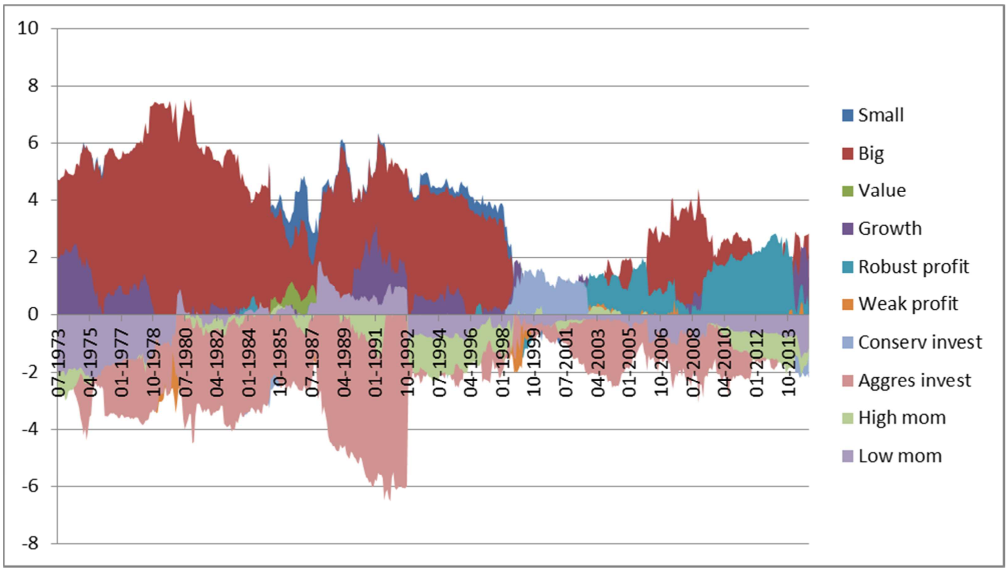

Figure D7: Dynamic Weights of the Sector-Based Portfolio Maximizing the 120-Month Rolling Sharpe Ratio, Short-Selling Banned

This figure provides the dynamic weights of the out-of-sample sector portfolio maximizing the Sharpe ratio when short-selling is banned. The optimized portfolio weights are computed on a monthly basis from the previous 120-month data.

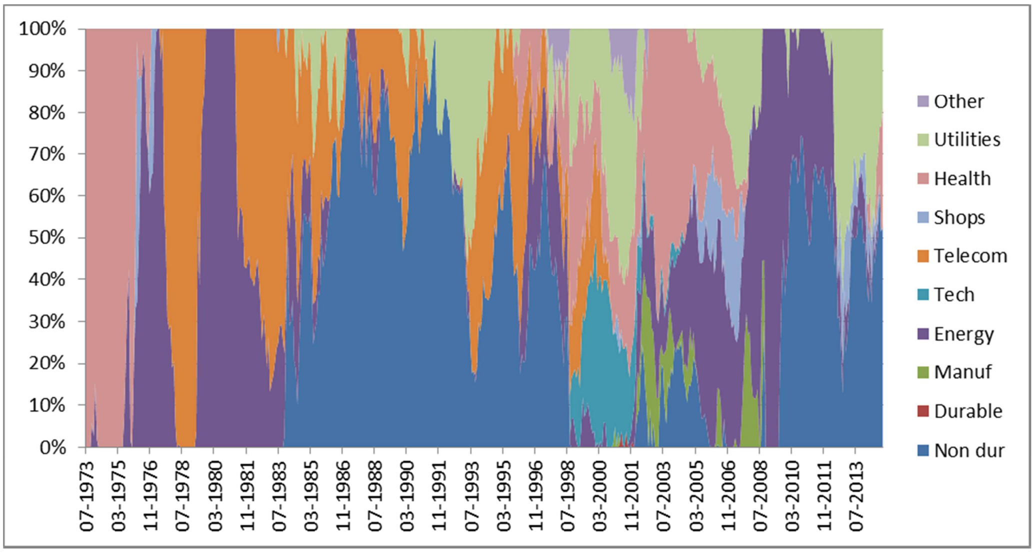

Figure D8: Dynamic Weights of the Factor-Based Portfolio Maximizing the 120-Month Rolling Sharpe Ratio, Short-Selling Banned

This figure provides the dynamic weights of the out-of-sample factor portfolio maximizing the Sharpe ratio when short-selling is banned. The optimized portfolio weights are computed on a monthly basis from the previous 120-month data.

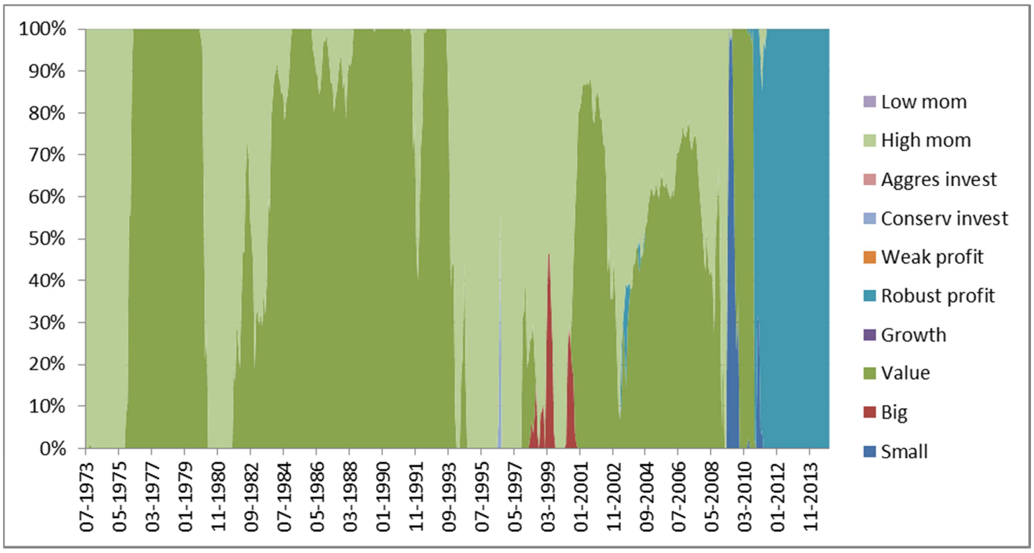

Figure D9: Dynamic Weights, Sector Portfolios Minimizing the 120-Month Rolling Volatility, Short-Selling Banned

This figure provides the dynamic weights of the out-of-sample sector portfolio minimizing the volatility when short-selling is banned. The optimized portfolio weights are computed on a monthly basis from the previous 120-month data.

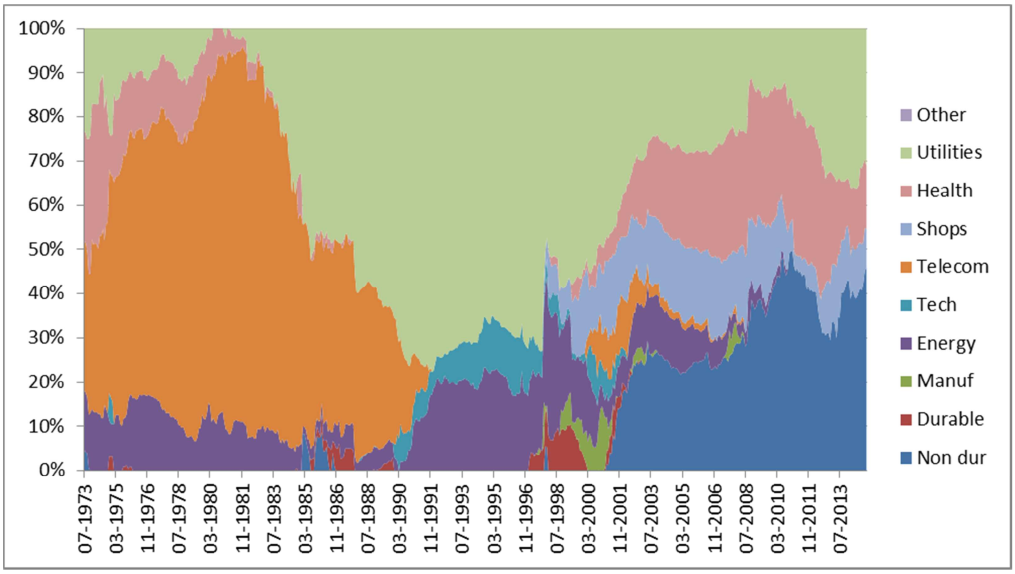

Figure D10: Dynamic Weights, Factor Portfolios Minimizing the 120-Month Rolling Volatility, Short-Selling Banned

This figure provides the dynamic weights of the out-of-sample factor portfolio minimizing the volatility when short-selling is banned. The optimized portfolio weights are computed on a monthly basis from the previous 120-month data.

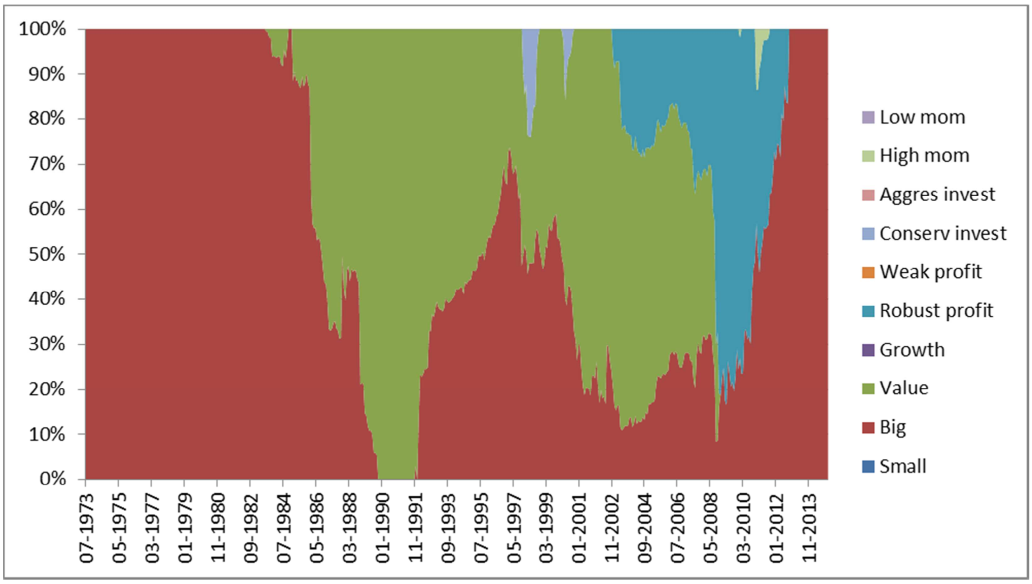

Figure D11: Dynamic Weights, Sector Portfolios Minimizing the 120-Month Rolling Volatility, Short-Selling Authorized

This figure provides the dynamic weights of the out-of-sample sector portfolio minimizing the volatility when short-selling is authorized. The optimized portfolio weights are computed on a monthly basis from the previous 120-month data.

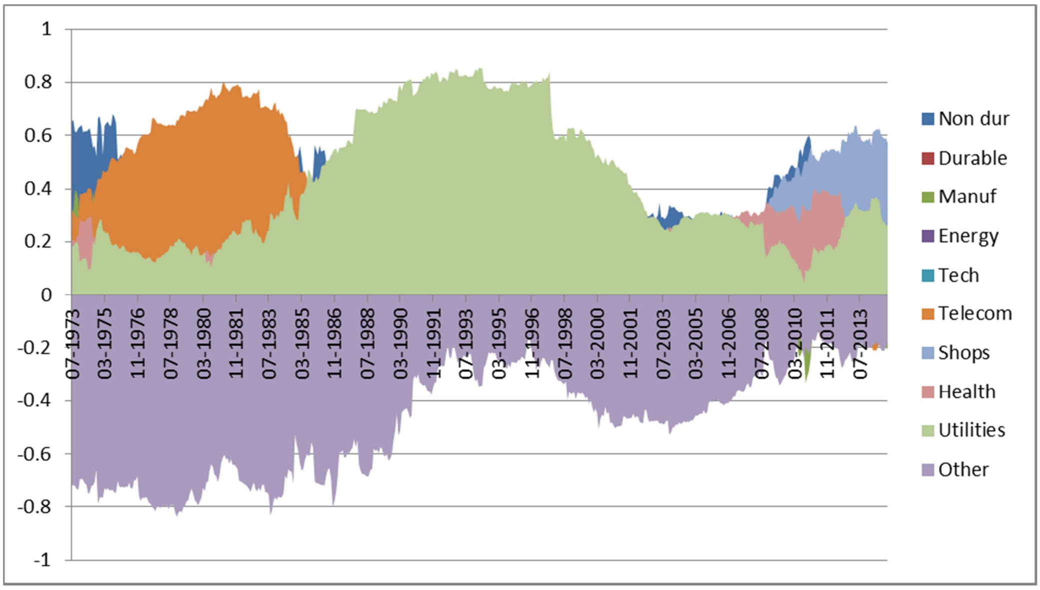

Figure D12: Dynamic Weights, Factor Portfolios Minimizing the 120-Month Rolling Volatility, Short-Selling Authorized

This figure provides the dynamic weights of the out-of-sample factor portfolio minimizing the volatility when short-selling is authorized. The optimized portfolio weights are computed on a monthly basis from the previous 120-month data.

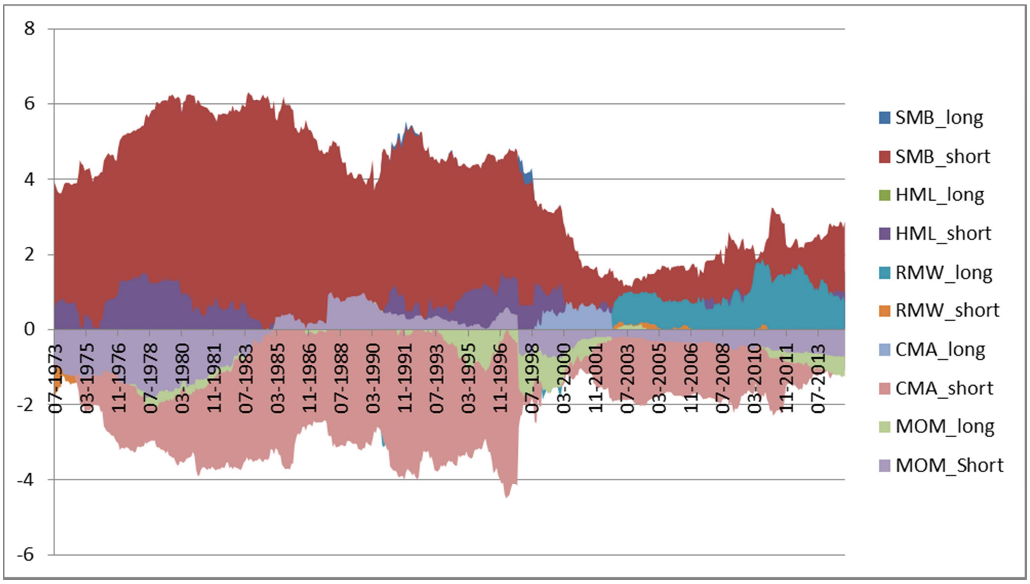

Table D1: Average Numbers of Sectors/Factors in Dynamic Out-of-Sample Portfolios

This table reports the average numbers of sectors (resp. factors) in the dynamically rebalanced optimal sector-based (resp. factor-based) portfolios, for the estimation windows of 60 months and 120 months successively.

Portfolio	Sectors M=60 months	Factors M=60 months	Sectors M=120 months	Factors M=120 months
Max SR (SB)	2.9	2.0	3.3	2.0
Min vol (SB)	4.6	1.6	4.7	1.8
Min vol (SA)	6.6	4.0	6.8	3.9