

Portfolio Construction Matters

Stefano Ciliberti and Stanislao Gualdi

Capital Fund Management

23 rue de l'Université,

75007 Paris, France

(Dated: October 22, 2018)

Abstract

The role of portfolio construction in the implementation of equity market neutral factors is often underestimated. Taking the classical momentum strategy as an example, we show that one can significantly improve the main strategy's features by properly taking care of this key step. More precisely, an optimized portfolio construction algorithm allows one to significantly improve the Sharpe Ratio, reduce sector exposures and volatility fluctuations, and mitigate the strategy's skewness and tail correlation with the market. These results are supported by long-term, world-wide simulations and will be shown to be universal. Our findings are quite general and hold true for a number of other "equity factors". Finally, we discuss the details of a more realistic set-up where we also deal with transaction costs.

I. INTRODUCTION

A portfolio manager in charge of the implementation of a systematic equity strategy faces a number of challenges ranging from alpha signal research, allocation, risk and cost management, and portfolio construction. In this paper, we assume that alpha signals are available (taken for instance from the large literature on equity factors), and that a certain weighting scheme has been chosen. We then study the role of portfolio construction: more precisely, we are interested in how the information contained in a factor (which we will equivalently refer to as a predictor or signal) is translated into physical trades and positions.

As is well known, this problem was first tackled in a quantitative way by Markowitz [17] in 1952 in what is considered to be the first brick of Modern Portfolio Theory (MPT) [30]. From a theoretical perspective, that paper set the scene for the research work of Sharpe [26], Treynor [27], Ross [23], Roll [11], Fama and French [10, 16], Chen [6] and many others [3, 18, 19], that led to the development of the Capital Asset Pricing Model and later on the Arbitrage Pricing Theory [22, 23] and factor modeling [5, 9].

For the financial practitioner, the interesting statistical observation put forward by Markowitz is that by combining assets whose correlation is less than 1, one can significantly reduce the risk of the total portfolio. In more mathematical terms, the problem of maximising the expected gain under a risk budget constraint translates into a mean-variance portfolio construction algorithm. When applied to real-world situations, though, the Markowitz solution often ends up loading on a relatively small number of (supposedly) weakly correlated stocks. In practice, the mathematical solution is a function of the inverse of the stocks' covariance matrix which is known to be very noisy, that is, strongly dependent on the measurement protocol. Although a number of techniques has been proposed to “clean” the covariance matrix and shown to be quite efficient (see e.g. [4] for a recent review), the lack of robustness of the naive Markowitz solution is probably the main reason why the equal-weighted “ $1/N$ ” approach has gained more popularity in the subsequent decades. As the story goes, Harry Markowitz himself would not apply the efficient frontier criterion to his personal portfolio, instead going for the simplest $1/N$ rule [29].

Since then, academic research has been more devoted to the definition and identification of equity factors than to portfolio construction. Broadly speaking, equity factors can be classified into three different categories:

- Macroeconomic (exogenous) factors like oil prices, industrial production, inflation or surprises in the yield curve [7];
- Statistical factors, which can be extracted from empirical covariance matrices through statistical techniques such as the Principal Component Analysis (PCA); and
- Microeconomic or Fundamental (endogenous) factors, built as long-short equity portfolios aimed at capturing features like fundamental ratios, price-based indicators, or even industry or country membership.

The latter factors are by far the most popular and we will concentrate exclusively on them. They include the well-known Value, Size, Momentum, Low-Volatility and Quality factors, among others (see e.g. [13, 25]).

In the first part of this paper we will pay particular attention to the Momentum factor [8, 14, 20, 24]. In a nutshell, a Momentum strategy consists in buying past winners and selling past losers. It is one of the oldest and most popular strategies in the financial market, and it has been proved to be successful across different asset classes, geographies, and time periods. The equity market-neutral Momentum strategy is implemented in the single-name equity space and it corresponds to a long-short relative value portfolio which takes no net exposure to the market as a whole. The signal is usually defined as the cumulative performance of a stock over the past 12 months, where the last month is taken away [5]. Put differently, the momentum signal needs to be lagged by (at least) one month in order to get rid of the mean-reversion effect which is quite strong on that time-scale and as such would deteriorate the trend following performance. As our focus is on the role of the portfolio construction, the precise definition of the signal is not important in our study and we will stick to the classical academic definition mentioned above.

Our main results can be shortly summarized as follows: In order to get statistically significant results, robustness across regions and epochs, and better performance profiles, the portfolio construction step plays a crucial role. The Markowitz solution, when the correlation cleaning is correctly taken care of, leads to better results for the main equity factors in almost all cases we considered.

II. SETTING THE STAGE: DATA, SIGNAL, RISK, AND METHODOLOGY

We will use daily stock data in the period 1996-2018 (sources: Bloomberg and Reuters) on the following geographical zones:

- US: the 1000 most liquid stocks in the Russell 3000 Index. More in detail, we compute the aggregated Average Daily (dollar) Volume over 3 months and take the 1000 most liquid stocks as our investment pool for the next quarter. This puts us in a realistic, causal set-up. The same liquidity-based procedure is applied to the below pools.
- Canada: we first collect quarterly data about company fundamentals from Bloomberg and select the 500 largest cap stocks from which we extract the 200 most liquid stocks.
- Europe: this zone includes the UK in addition to developed markets in continental Europe. Here too we first take the 2000 largest cap stocks and then select the 1000 most liquid stocks among them.
- Japan: the 500 most liquid stocks in the TOPIX index.
- Australia: we take the 500 largest cap stocks and then select the 200 most liquid stocks among them.

We also independently back-test our strategies on CRSP data, that is US daily data since 1927, in order to get a higher level of statistical significance. Here as well, we build a pool with the 1000 most liquid stocks (to note, there are less than 1000 stocks in the CRSP data base until about 1950, but this number is always larger than 1000 since then). The annualized volatility of the performance will be chosen as the risk metrics, but special attention will be devoted to tail events and tail correlation with the market. We will assume to have a normalized, ranked predictor p_i on stock i that is uniformly distributed in $[-1, +1]$ and will test the following (known) techniques.

FF: Following Fama and French (FF), we put on the buy-list the top 30% of the stocks, on the sell-list the bottom 30%, and take long or short positions accordingly. These positions are taken proportionally to market-cap.

Neutral: We take a position x_i on all the stocks i , proportionally to the predictor: $x_i \propto p_i$. The resulting portfolio is cash neutral by construction. This portfolio is supposed to be more diversified than FF, and positions evolve more continuously with time.

Beta: In the two previous examples, market neutrality is not necessarily ensured because the single-stocks' sensitivities to the market (i.e. the β 's) may be different. One simple way to deal with that is to compute the aggregate β of the long and short legs separately, and rescale them such that the overall β is zero. Here the β is computed from a simple 1-year statistical regression of a one-factor model, where the driving factor is identified with the market-cap weighted index.

Betaopt: Another way to implement the β neutrality while maximising the expected gain as defined by the predictor is to solve the following optimization problem:

$$\min_{\{\mathbf{x}\}} (\mathbf{p} - \mathbf{x})^T C (\mathbf{p} - \mathbf{x}) \quad \text{subject to} \quad \boldsymbol{\beta} \cdot \mathbf{x} = 0 \quad (1)$$

where C_{ij} is the covariance matrix of the stocks' returns and everything is in vectorial notation such that $(\mathbf{x})_i = x_i$. The rationale behind the optimization problem in (1) is that we are looking for a portfolio which is as close as possible to $x_i = p_i$ while respecting the Beta neutrality. The solution to the above problem is given by

$$\mathbf{x} = \mathbf{p} - \frac{\boldsymbol{\beta} \cdot \mathbf{p}}{\boldsymbol{\beta}^T C^{-1} \boldsymbol{\beta}} C^{-1} \boldsymbol{\beta} \quad (2)$$

which, by substituting $\boldsymbol{\beta} \propto C \mathbf{w}$ (where \mathbf{w} is the weight vector in the index), can be conveniently rewritten as

$$\mathbf{x} = \mathbf{p} - \frac{\mathbf{w}^T C \mathbf{p}}{\mathbf{w}^T C \mathbf{w}} \mathbf{w} \quad (3)$$

where no matrix inversion is needed [31]. Note that if $\boldsymbol{\beta}$ coincides with the first eigenvector of the covariance matrix C then the portfolio is simply built as a predictor whose projection to the $\boldsymbol{\beta}$ vector is removed.

Markowitz: The classical solution to the portfolio construction problem is (at least formally) given by the Markowitz solution, that is $x_i \propto C^{-1} p_i$. As already mentioned in the introduction, the empirical covariance matrix is extremely noisy and has to be "cleaned" before the inversion. Here, we only keep the k largest eigenvectors of the covariance matrix, which correspond to the so-called statistical factors.

The covariance matrix is computed empirically from individual stock returns, usually taking at least two years of historical close-to-close daily returns (see e.g. [4] for a discussion on how long the time series should be for a pool of stock of a certain size). That matrix is then

diagonalized and the top eigenvectors (that is, the eigenvectors corresponding to the top eigenvalues) are extracted: these are called “modes” or “statistical factors”. It is interesting to elaborate more on the role of the statistical factors in the development of the Markowitz solution. The $k = 1$ factor, also called the “market mode”, can be seen as a portfolio where most if not all stocks are aligned in the same direction (more or less so, depending on their sensitivity to a macroeconomic move, that is, their individual β 's). As a consequence, the corresponding Markowitz solution is close to the β -neutral cases above. The factors for $k > 1$ are less universal and are typically related to industry sectors, or to groups driving the local economy [21, 28]. For example, the $k = 2$ statistical factor of an Australian pool of stocks usually exhibits a large (say) positive exposure to Basic Materials and/or Energy stocks, and a negative exposure to Financial stocks. The $k = 2$ statistical factor on another pool is in general different (it could be UK vs continental stocks in Europe, for instance, or Consumer-Non-Cyclical vs Consumer-Cyclical in Japan). The idea behind the eigenvalue methodology is that one can let the covariance data speak and identify the main risk drivers on any pool of stocks, which themselves may change in time. The Markowitz solution will then automatically reduce the portfolio's exposure to these risk drivers accordingly. The choice of k can be optimized in different ways [4], but we will instead test a few values up to $k = 5$ in order to better understand its role in the present study.

In more formal terms, we will do the following approximation:

$$C_{ij} \simeq \sigma_i \sigma_j \left(\sum_{\alpha=1}^k \lambda^\alpha v_i^\alpha v_j^\alpha + \varepsilon^2 \delta_{ij} \right) \quad (4)$$

where σ_i is the volatility of stock i , λ^α , and \mathbf{v}^α are respectively eigenvalues and eigenvectors of the correlation matrix, and the diagonal variance term ε^2 is chosen such that the total variance of the portfolio is unchanged, i.e. $\text{Tr}C = \sum_i \sigma_i^2$.

In any of the above setups, the portfolio is rebalanced on a daily basis. The world-wide portfolio is built as a flat average of the various local portfolios [32]. In order to compare the different portfolio construction methods, each world-wide portfolio has been rescaled in order to have the same average risk over the total back-test period.

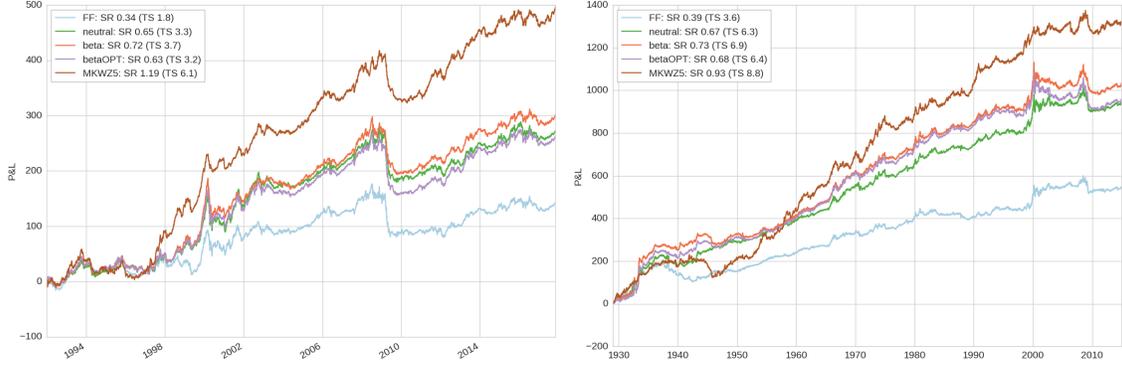


FIG. 1: Left: The world-wide performance of the momentum strategy with different portfolio construction techniques. Right: Same as in the left panel, but on the CRSP US pool since 1927.

III. RESULTS FOR THE MOMENTUM STRATEGY

In this section we analyze the results obtained for the Momentum strategy. The left panel of Fig. 1 shows the world-wide P&L corresponding to the different portfolio construction algorithms described in the previous section. The FF construction is the worst performing with a Sharpe Ratio of 0.34, while the Markowitz solution, with $k = 5$ statistical factors of the covariance matrix kept before matrix inversion, has the highest Sharpe Ratio (1.19). All the other schemes are in between these two extremes. In term of statistical significance, the t-stat of the P&L of the Markowitz solution is well above the usual acceptance threshold (i.e. t-stat larger than 3). The cash-neutral and β -neutral solutions are borderline significant, while the FF is below (t-stat=1.8). These summary numbers are very close to those found on a much longer back-test ranging from 1927 until 2016 (right-panel) where we use CRSP data for US stocks.

In order to get a better understanding of why the Markowitz solution works better than classical score-based approaches, we look into the details of the risk profile. The 1-year rolling volatility of the different P&Ls is shown in the left panel of Fig. 2. Fluctuations around the average (here set to 1) are quite large for all implementations, but the Markowitz one appears to be better controlled. Some more insight on the risk control can be deduced from the rolling correlation with a market-cap weighted index, as shown in the right panel of Fig. 2. Here, again, the FF approach results in very large fluctuations around zero, at odds with the other portfolio construction techniques.

From a risk-control perspective, the global and sector exposures are also interesting (see

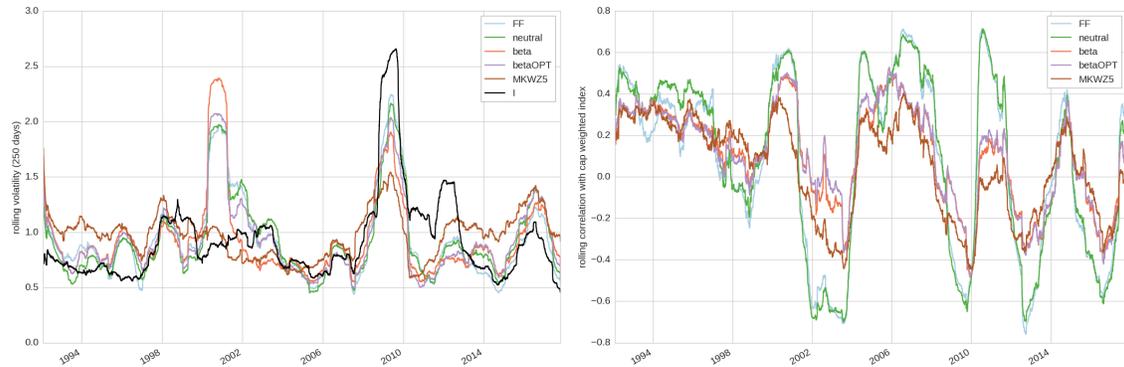


FIG. 2: Left panel: The 1-year rolling volatility of the different P&Ls in Fig. 1. The time-average is set to 1 for all and fluctuations are within a factor 2. Right panel: The 1-year rolling correlation between the performance and the market-cap weighted index. The time-average of these curves is always consistent with zero, but fluctuations can be pretty large over certain time periods.

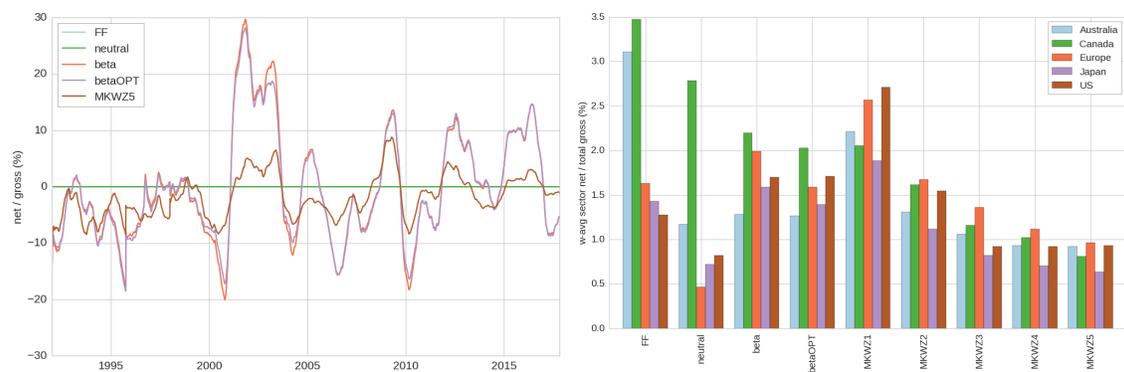


FIG. 3: The average net market value exposure (left: global; right: sector)

Fig. 3). The net-over-gross market value as a function of time is plotted in the left panel. The neutral solution has its net equal to zero by construction, while all the other exhibit fluctuations around zero. Once again, the fluctuations of the Markowitz portfolio are smaller on average. The right panel focuses on the average exposure on the classical industry sectors for the different portfolios. The results are shown by pool. While FF does not control at all these exposures, the neutral and Beta constructions manage to reduce them to some extent.

It is interesting to look at the behavior of the Markowitz solution as a function of the number of statistical factors kept in the optimization process (i.e. the parameter k in Eq. 4). The Markowitz $k = 1$ solution, as discussed above, is not very different from other β neutralisation recipes. As we retain more statistical factors, we manage to better

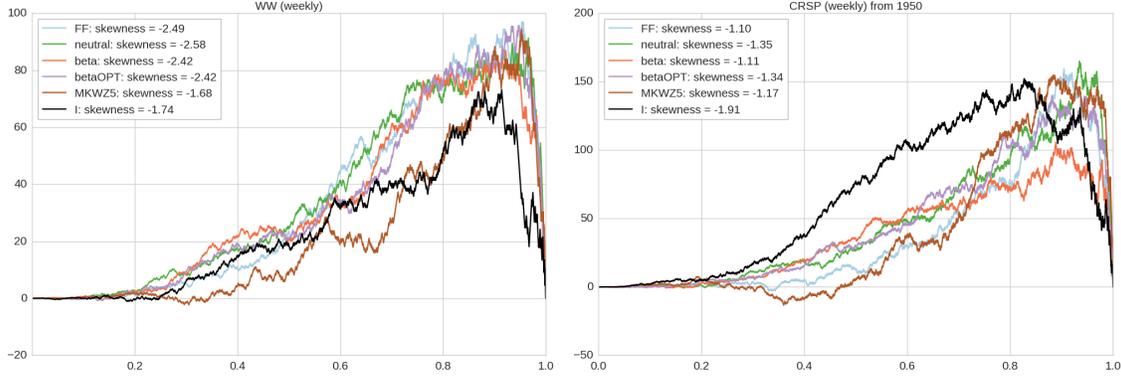


FIG. 4: The weekly P&Ls of the different strategies are reordered based on the amplitude, from the smallest to the largest in absolute value. The skewness can be computed directly from these data ([15]) and is shown in the legend. Left: world-wide back-tests over the last 20 years. Right: US data since 1950.

control (albeit indirectly) the average sector exposure. This monotonous behaviour is indeed observed in the plot. As sectors behave more like indexes than like stocks, and thus exhibit a negative skewness, we expect this empirical fact to have consequences on the tail distribution of the P&L as well (see next section).

IV. MOMENTUM: SKEWNESS AND TAIL CORRELATION

The results shown so far suggest that the better performance of the Markowitz approach is a consequence of a tighter control of the risk of the portfolio, at least in terms of bulk metrics like variance, correlations, and average exposures.

But what about the skewness or the tail risk of the strategy? This is known to be an issue for many equity factors, with Momentum as a case in point. More precisely, the Momentum tail risk is mostly due to strong market rebounds. For these reasons, we will now look explicitly at the skewness and the tail correlation of Momentum with the market.

Fig. 4 shows the weekly skewness of the world-wide (left) and US long term (right) Momentum strategy. We follow the approach introduced in [15] to visualize and compute the skewness of a P&L. The idea is to reorder the weekly P&L data based on the amplitude (i.e. absolute value) of the weekly P&L itself. This allows one to easily visualize how negative (if at all) are the contributions of the most volatile weeks. Or, equivalently, what

would be the total P&L if one was able to manage or hedge away the largest contributions (positive or negative). The market-cap index, which is known to be strongly negatively skewed, is also shown for comparison on the same graphs. We find a confirmation of the negative skewness of the Momentum strategy; moreover, the cash- and β -neutral approaches have heavier negative tails than FF and Markowitz.

One can learn more about the tails of the distribution by investigating the strategy's behaviour when the market-cap weighted index is either at a local minimum, or at a local maximum. Momentum is known to perform poorly when the market rebounds after a long-lasting draw-down. The usual explanation relies on the role of Value investors which step in after a long crisis and massively buy the stocks that look cheap based on some fundamental metrics. These stocks probably went down more than the average in the recent past and as such are more likely to sit on the short leg of a Momentum portfolio. We will now confirm that this picture is broadly correct, but once again it is dependent on the portfolio construction.

To this end, we introduce an operational definition of market kinks, which is illustrated in Fig. 5 and explained in the corresponding caption. The relevant parameter here is the depth of the local draw-down (or draw-up) measured in units of the (causal) rolling volatility. We then compute, for different values of this parameter, the average performance of the strategy over the next month. Here we want to quantify the extent to which the negative skewness is related to market rebounds, and how it depends on the portfolio construction.

In the left panel of Fig. 6 we see that all the score-based portfolio schemes except the Markowitz portfolio perform negatively after the index rebounds from a local minimum while the Markowitz portfolio is slightly positive. This feature in fact plays a major role in explaining why the overall performance is better. Moreover, the Markowitz portfolio is also among the best performing portfolios after the market hits a local maximum (right panel).

V. OTHER EQUITY FACTORS

The main message of the previous sections is that the Markowitz portfolio construction is, for a number of reasons ranging from risk control to tail correlation management, the best way to extract returns from a Momentum signal. But what about the other equity factors? In other words, how universal is this result?

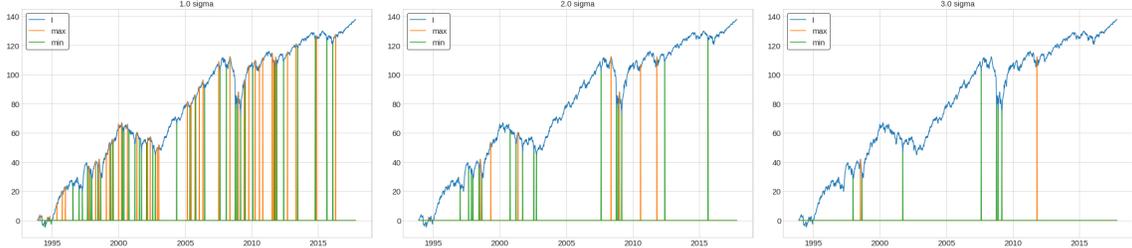


FIG. 5: Operational definitions of market kink for different values of σ . All the plots show a World Wide market index with vertical bars placed in correspondence of local maxima/minima identified by the following procedure. We first find local minima over periods of 9 weeks. If the corresponding draw-down is larger than n times the weekly volatility, then we retain the subsequent 4 weeks to compute the strategy’s statistics in Fig. 6. Local maxima are identified in a similar way. From left to right we show resulting kinks for respectively $n = 1$, $n = 2$ and $n = 3$.

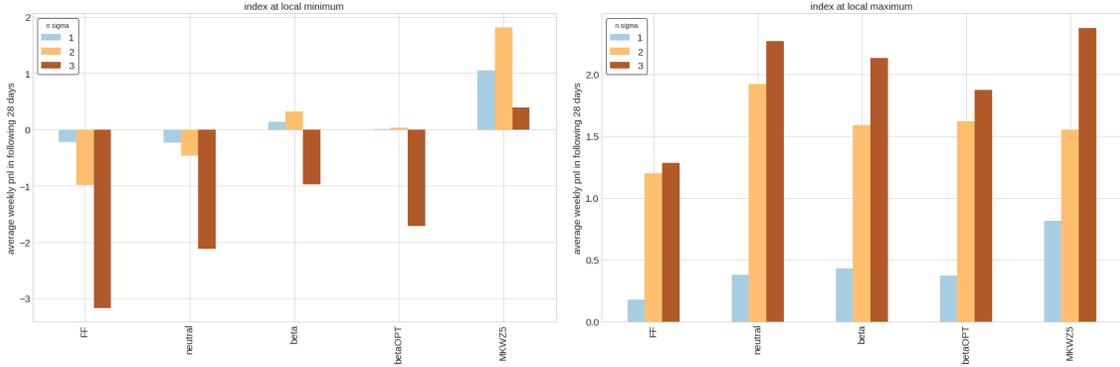


FIG. 6: Left: The bars represent, for different values of the parameter n described in the caption of Fig. 5, the average strategy’s performance conditioned to a market rebound. See text for more comments. Right: The strategy’s performance in periods of strong market corrections.

We have back-tested (using the same data and the same approach as before) many other fundamental equity factors and the results are very similar. We apply standard definitions of factors as can be found in the literature:

Accrual: is computed as the yearly increase of Net Operating Assets normalized by total assets ranked from lowest to highest.

Book value: total equity / market capitalization (lagged by 1 month) and ranked from lowest to highest.

Cash flow: Operating Cash flow / market capitalization (lagged by 1 month) and ranked from lowest to highest.

Dividend yield: Dividends / market capitalization (lagged by 1 month) and ranked from lowest to highest

Earning yield: Net Income / market capitalization (lagged by 1 month) and ranked from lowest to highest

Growth: Cash Flow / total asset (lagged by 1 month) and ranked from lowest to highest.

Quality: Net Income / total assets (lagged by 1 month) and ranked from lowest to highest.

Low Beta: the beta of each stock is computed from the first statistical factor (i.e. the Beta vector is the $\sqrt{\lambda_0}\mathbf{v}_0$) and ranked from highest to lowest.

Low Vol: we compute a 180 days rolling volatility (lagged by 1 month) and rank from highest to lowest.

Momentum: we compute 230 days rolling average returns (lagged by 1 month) and rank from lowest to highest

Size: we compute 250 days rolling averages market capitalizations (lagged by 1 month) and rank from highest to lowest

Fig. 7 shows that the Markowitz portfolio construction generates the highest Sharpe Ratio 8 times out of 11, and is neck-and-neck with Beta 2 times out of 11. The three “bad” cases are Dividend yield and Earning Yield, and in particular Book-value, whose performance is negative for all portfolio constructions. In some good cases, like for Momentum or the Accrual anomaly, the effect is quite spectacular. As for the Size effect, it seems to be the only way to get a positive Sharpe Ratio from the small-cap premium, although statistical significance may be debated.

Another interesting observation is that the low-risk models (Low-Vol and Low-Beta) can be significantly improved by simply choosing β -neutrality over cash-neutrality. This makes sense as long positions on less risky stocks need to be leveraged in order to achieve market neutrality, and that mechanically generates the net long exposure needed by the model (see [2] for more details on this point).

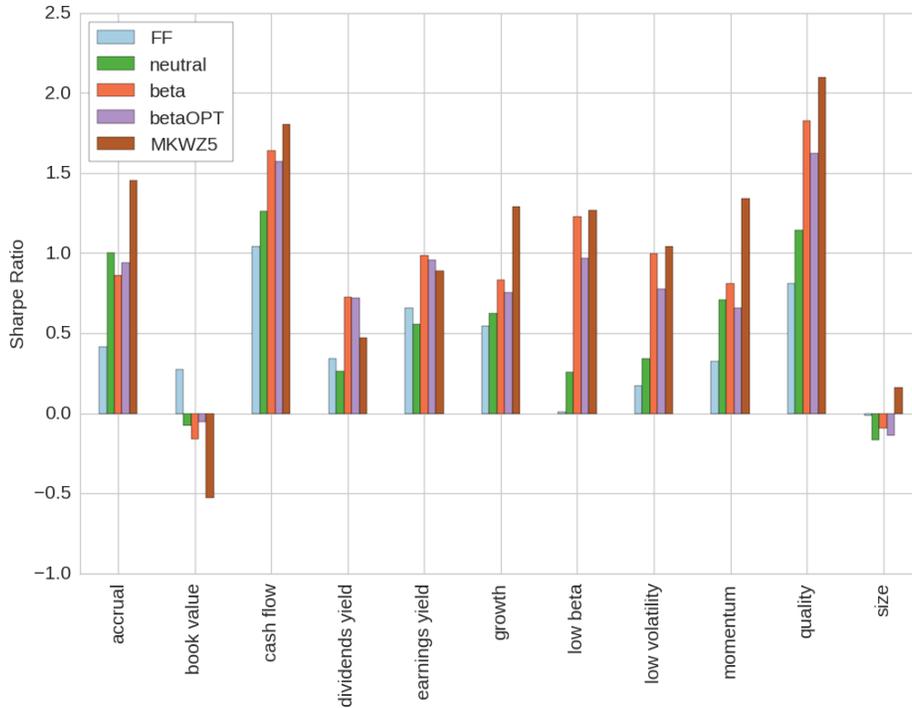


FIG. 7: The world-wide Sharpe Ratio for the main equity factors, and for all the portfolio constructions.

VI. INTRODUCING TRANSACTION COSTS

In this section we perform one more step towards reality as we include transaction costs in the portfolio construction problem. In the previous sections, this point was completely neglected and every day the portfolio was supposed to be built from scratch with no memory of previous positions. This is clearly unrealistic, so we briefly touch on this point now.

When executing orders, one faces a number of different costs: we can group them into three categories. There are commissions, including broker and exchange fees; linear costs, related to the bid-offer spread; and slippage costs, which are super-linear and take market impact into account. In a simplified set-up, we will neglect slippage costs as these would require a dedicated section on how we model them, and how we calibrate the parameters in the model. We will take all the linear costs into account: commissions, and half-spread costs.

When applied to the Momentum' portfolio mark-to-market, these costs have a strong impact on the total performance (see Fig. 8). The Sharpe Ratio actually becomes negative

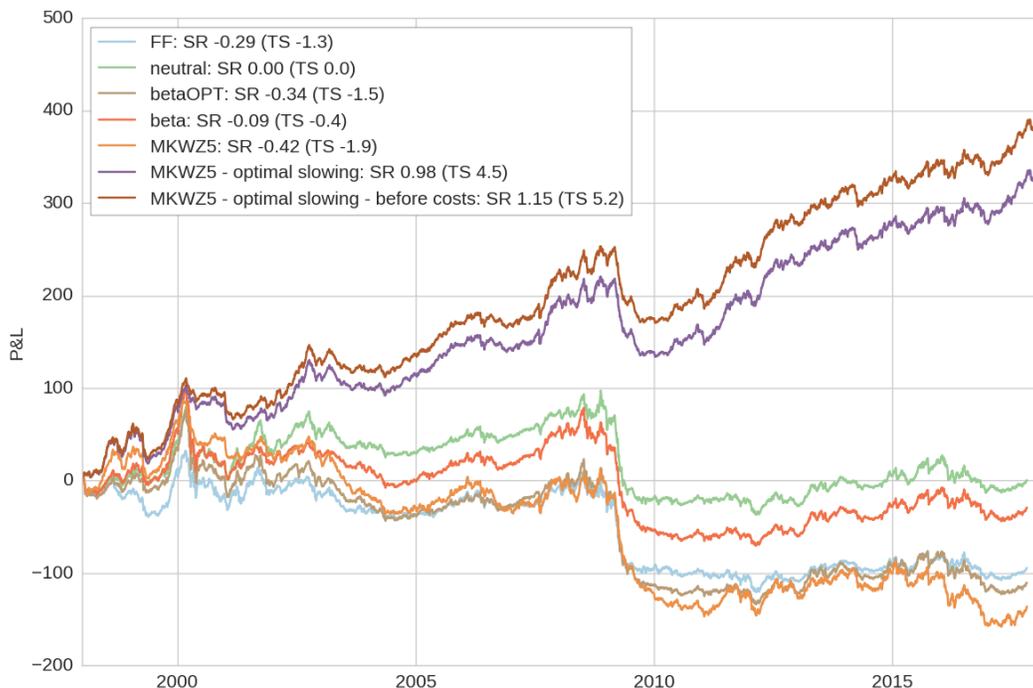


FIG. 8: The first five curves represent the world-wide P&L shown in Fig. 1 when we also include execution costs in the portfolio valuation. We observe a huge deterioration in the performance. The last two curves show the results (before and after costs) of a generalized mean-variance optimization problem where these executions costs are explicitly taken into account.

for all the approaches. This is due to the fact that these costs were not considered by the algorithm and the daily turnover, as a consequence, is artificially high. The key observation is that the Markowitz approach, as opposed to the others, allows for a generalization of the optimization problem which takes these costs into account. The mathematical formulation of the problem gets more involved and the details can be found for instance in [1, 12]. Here we report the main results.

The last curve in Fig. 8 (brown colour) is the result of the generalized Markowitz problem. In practice, the algorithm finds the optimal frequency at which the predictor should be slowed-down (similar to an exponential moving average) in order to maximise the gain left after execution costs are removed. As a result, the Sharpe Ratio computed before applying the cost formula is a bit worse than the “pure” one (1.15 vs 1.19). The main advantage is that if we now include the costs in the mark-to-market, the Sharpe Ratio gets reduced by only 15% and we are left with $SR=1$.

VII. CONCLUSIONS

In this paper we have shown that the portfolio construction process plays a crucial role in the implementation of an equity market neutral strategy. Although most of the details have only been shown for the Momentum strategy, the main results hold true for many classic equity strategies. We have shown that the portfolio construction step may lead to quite large differences in the resulting performance. We believe that this explains to a large extent the dispersion usually observed among market neutral managers.

As discussed in the paper, the Markowitz approach, once the correlation cleaning problem is properly dealt with, is the best way to deal with complex covariance structure in the single-name security space. This is clearly observed from a performance and risk perspective, whether bulk or tail metrics are considered.

Of note, the Markowitz approach lends itself to a straightforward generalization to the multi-signal case, at odds with e.g. the FF scheme which involves creating multiple embedded buckets of stocks where the ordering of signals plays a role in the construction of the portfolio.

We have also addressed the question of transaction costs, and how to build a portfolio construction algorithm that would slow-down the predictor in order to make the system trade as little as possible. It turns out that the main results of the present paper generalize when one uses a dynamical Markowitz approach that accounts for costs [1, 12].

Acknowledgements. The authors would like to thank Jean-Philippe Bouchaud, Yves Lempérière, Philip Seager, Emmanuel Sérié, Matthieu Cristelli, Guillaume Simon, Charles-Albert Lehalle and André Breedt for insightful comments and fruitful discussions.

-
- [1] Marc Abeille, Emmanuel Sérié, Alessandro Lazaric, and Xavier Brokmann. Lqg for portfolio optimization. *SSRN: <http://dx.doi.org/10.2139/ssrn.2863925>*, 2016.
 - [2] Alexios Beveratos, Jean-Philippe Bouchaud, Stefano Ciliberti, Laurent Laloux, Yves Lempérière, Marc Potters, and Guillaume Simon. Deconstructing the low-vol anomaly. *The Journal of Portfolio Management*, 44(1):91–103, 2017.
 - [3] Fischer Black and Robert Litterman. Global Portfolio Optimization. *Financial Analysts Journal*, 48:28–43, September/October 1992.

- [4] Joël Bun, Jean-Philippe Bouchaud, and Marc Potters. Cleaning large correlation matrices: Tools from random matrix theory. *Physics Reports*, 666:1 – 109, 2017.
- [5] Mark Carhart. On Persistence in Mutual Fund Performance. *Journal of Finance*, 52(1):57–82, 1997.
- [6] Nai-fu Chen and Jonathan E Ingersoll Jr. Exact pricing in linear factor models with finitely many assets: A note. *The Journal of Finance*, 38(3):985–988, 1983.
- [7] Nai-Fu Chen, Richard Roll, and Stephen A. Ross. Economic forces and the stock market. *The Journal of Business*, 59(3):383–403, 1986.
- [8] Kent Daniel and Tobias Moskowitz. Momentum crashes. *Journal of Financial Economics*, forthcoming, 2016.
- [9] Eugene Fama and Kenneth French. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56, 1993.
- [10] Eugene F. Fama. The behavior of stock-market prices. *Journal of Business*, 38(1):34–105, 1965.
- [11] Eugene F Fama, Lawrence Fisher, Michael C Jensen, and Richard Roll. The adjustment of stock prices to new information. *International economic review*, 10(1):1–21, 1969.
- [12] Nicolae Gârleanu and Lasse Heje Pedersen. Dynamic trading with predictable returns and transaction costs. *The Journal of Finance*, 68(6):2309–2340, 2013.
- [13] Campbell Harvey, Yan Liu, and Heqing Zhu. ... and the cross-section of expected returns. *Review of Financial Studies*, 29(1):5–68, 2016.
- [14] Narasimhan Jegadeesh and Sherdian Titman. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance*, 48(1):65–91, March 1993.
- [15] Y. Lempérière, C. Deremble, T. T. Nguyen, P. Seager, M. Potters, and J. P. Bouchaud. Risk premia: asymmetric tail risks and excess returns. *Quantitative Finance*, 17(1):1–14, 2017.
- [16] Burton G Malkiel and Eugene F Fama. Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, 25(2):383–417, 1970.
- [17] Harry Markowitz. Portfolio selection*. *The Journal of Finance*, 7(1):77–91, 1952.
- [18] Robert Merton. An intertemporal capital asset pricing model. *Econometrica*, 41(5):867–87, 1973.
- [19] Robert C Merton. Lifetime portfolio selection under uncertainty: The continuous-time case. *The review of Economics and Statistics*, pages 247–257, 1969.

- [20] Tobias J. Moskowitz, Yao Hua Ooi, and Lasse Heje Pedersen. Time series momentum. *Journal of Financial Economics*, 104(2):228–250, 2012.
- [21] Vasiliki Plerou, Parameswaran Gopikrishnan, Bernd Rosenow, Luis A. Nunes Amaral, and Eugene Stanley. A Random Matrix Approach to Cross-Correlations in Financial Data. *Physical Review Letter E*, 65(6):066126, 2002.
- [22] Richard Roll and Stephen A Ross. An empirical investigation of the arbitrage pricing theory. *The Journal of Finance*, 35(5):1073–1103, 1980.
- [23] Stephen A. Ross. The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, 13(3):341–360, 1976.
- [24] Arthur D. Roy. Safety First and the Holding of Assets. *Econometrica*, 20(3):431–449, July 1952.
- [25] G William Schwert. Anomalies and market efficiency. *Handbook of the Economics of Finance*, 1:939–974, 2003.
- [26] William F. Sharpe. Mutual Fund Performance. *Journal of Business*, 39(1):119–138, 1966.
- [27] Jack L Treynor. How to rate management of investment funds. *Harvard business review*, 43(1):63–75, 1965.
- [28] Lisa Uechi, Tatsuya Aktsu, Eugene Stanley, Alan Marcus, and Dror Kenett. Sector dominance ratio analysis of financial markets. *Physica A: Statistical Mechanics and its Applications*, 421:488–509, March 2015.
- [29] J. Zweig. *Your Money and Your Brain: How the New Science of Neuroeconomics Can Help Make You Rich*. Simon & Schuster, 2007.
- [30] A similar approach was independently proposed by Roy [24]
- [31] For “fairness” we however use the same cleaned covariance matrix as for the Markowitz construction.
- [32] Since there are no costs involved we prefer a flat average but all the results of the paper are unaffected if we use a market-cap weighted average of different geographical zones.