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Markowitz Meets Technical Analysis: Building Optimal Portfolios by Exploiting Information in Trend-Following Signals

André A. P. Santos*[1] and Hudson S. Torrent[2]

[1]University of Edinburgh Business School, 29 Buccleuch Place, Edinburgh, EH8 9JS, United Kingdom. e-mail: Andre.Santos@ed.ac.uk

[2]Department of Statistics, Universidade Federal do Rio Grande do Sul, Av. Paulo Gama, 110, Porto Alegre/RS, Brazil. e-mail: hudson.torrent@ufrgs.br

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Abstract

Technical indicators are widely used by market participants to identify trends in asset prices and in trading volumes. However, it is unclear how to reconcile this approach with a portfolio selection policy that guide investment decisions in many assets at the same time. We bridge the gap between Markowitz approach to mean-variance portfolios and technical analysis by devising a portfolio strategy in which optimal weights are directly parameterized as a function of multiple trend-following signals. We present an empirical application in which four commonly used technical indicators are employed to obtain portfolios of all constituents of the S&P500 index.

Keywords: bootstrap, parametric portfolios, risk-adjusted performance, transaction costs.

JEL classification: B26; C58; G11.

*Corresponding author. e-mail: Andre.Santos@ed.ac.uk

1 Introduction

Technical analysis (TA) has long been established as a set of tools used by a range of market participants in order to support investment decisions. While fundamental analysis utilizes economic factors to estimate the intrinsic values of securities, TA relies on historical data to construct different charting and trend-following indicators that could help anticipating future movements in asset prices and trading volumes. Existing literature indicates that TA is in fact able to generate profitable trading rules in different asset markets (Park and Irwin, 2007; Nazário et al., 2017). It is unclear, however, how to reconcile TA with a disciplined portfolio policy approach that guide investment decisions in multiple assets at the same time.

In this paper, we bridge the gap between Markowitz approach to mean-variance portfolios and TA by devising a portfolio strategy in which optimal weights are *directly parameterized* as a function of multiple trend-following signals. Our empirical application using 473 stocks belonging to the S&P500 index reveal that technical indicators are helpful in obtaining optimal portfolios with higher out-of-sample risk-adjusted returns in comparison to alternative benchmark strategies – including the *original* mean-variance formulation – both in the absence and in the presence of transaction costs. Our evidence shows that a trend-focused investor equipped with our proposed portfolio strategy can benefit from modeling first and second moments of technical-indicator returns in order to improve portfolio performance.

Our work departs from previous works that incorporate technical indicators into the portfolio construction problem (e.g. Zhu and Zhou (2009), Silva, Neves, and Horta (2015), and Macedo, Godinho, and Alves (2017)) in at least three dimensions. First, our portfolio policy does *not* require estimating first and second moments of *all* assets as in the traditional Markowitz approach and instead focus directly on the object of interest - the portfolio weights. Second, our method allows evaluating *how* and *why* technical indicators matter for the portfolio construction problem. Third, our method admits an analytical solution of policy coefficients, which reduces computational costs and allows constructing portfolios for vast cross-section dimensions.

The remainder is organized as follows. Section 2 describes our proposed portfolio policy. The results of an empirical application are discussed in Section 3. Section 4 concludes.

2 Methods

We now discuss a portfolio policy that is able to exploit information in trend-following signals obtained with technical indicators. We use the parametric portfolio policy of Brandt, Santa-Clara, and Valkanov (2009) along with a set of trend-following technical indicators in order to tilt a given benchmark portfolio toward stocks that help to increase the investor's utility. We consider four widely used technical indicators: two price-trend indicators - price moving average convergence/divergence (PriceMACD) (Appel, 2003) and relative strength index (RSI) (Wilder, 1978) - and two volume-trend indicators - VolumeMACD and on-balance volume (OBV) (Granville, 2018).[1] The technical-parametric portfolio at time t, $w_t(\theta) \in \mathbb{R}^{N_t}$, can be written as

$$w_t(\theta) = w_{b,t} + \left(\theta_1 \text{PriceMACD}_t + \theta_2 \text{RSI}_t + \theta_3 \text{VolumeMACD}_t + \theta_4 \text{OBV}_t\right)/N_t, \tag{1}$$

where $w_{b,t}$ is the benchmark portfolio at time t, θ_k is the coefficient associated with the kth technical indicator in the technical-parametric portfolio, and N_t is the number of stocks at time t. Each technical indicator is cross-sectionally standardized, which means that the deviations of the optimal portfolio weights from the benchmark weights $w_{b,t}$ sum to zero, and therefore, the optimal portfolio weights $w_t(\theta)$ always sum to one.[2]

The return of the technical-parametric portfolio at time $t+1$, denoted as $r_{p,t+1}$, can be written as

$$\begin{aligned} r_{p,t+1}(\theta) &= w_t(\theta)^\intercal r_{t+1} \\ &= w_{b,t}^\intercal r_{t+1} + \theta^\intercal X_t^\intercal r_{t+1}/N_t \\ &= r_{b,t+1} + \theta^\intercal r_{c,t+1}, \end{aligned} \tag{2}$$

where $r_{t+1} \in \mathbb{R}^{N_t}$ is the return vector at time $t+1$, $r_{b,t+1} = w_{b,t}^\intercal r_{t+1}$ is the benchmark portfolio return at time $t+1$, and $r_{c,t+1} = X_t^\intercal r_{t+1}/N_t$, with $X_t \in \mathbb{R}^{N_t \times K}$, is the technical-indicators return vector at time $t+1$, which contains the returns of the long-short portfolios corresponding to the $K = 4$ technical indicators scaled by the number of assets N_t. Equation (2) shows that the parametric portfolio return is the benchmark-portfolio return plus the return of the technical-indicators portfolio.

We employ a mean-variance criterion in order to obtain estimates of the coefficients θ of the technical-parametric portfolio in (1). The resulting policy is refereed to as mean-variance technical-parametric (MEV-TP) portfolios. For that purpose, we build on DeMiguel, Martin-Utrera, Nogales,

[1]The definitions of all indicators are provided in Section 3.

[2]This standardization implies that i) the cross-sectional distribution of a given technical indicator, x_t, is stationary through time, and ii) that the cross-sectional average of θx_t is zero. In this sense, x_t can be also seen as a *long-short* portfolio that will determine the extent to which optimal portfolio weights *deviate* from the benchmark weights. Finally, the term $1/N_t$ in (1) is a normalization that allows the portfolio weight function to be applied to an arbitrary and time-varying number of stocks.

and Uppal (2020) and assume a mean-variance investor that solves the following problem:

$$\min_{\theta} \ \frac{\gamma}{2}\text{var}\left[r_{p,t+1}(\theta)\right] - E\left[r_{p,t+1}(\theta)\right], \tag{3}$$

where γ is the risk-aversion parameter and $\text{var}\left[r_{p,t+1}(\theta)\right]$ and $E\left[r_{p,t+1}(\theta)\right]$ are the variance and mean of the technical-parametric portfolio return in (2), respectively. Given T historical observations of returns and characteristics, DeMiguel et al. (2020, Proposition 1) shows that the problem in (3) is equivalent to the quadratic optimization problem

$$\min_{\theta} \ (\gamma/2)\theta^{\intercal}\hat{\Sigma}_c\theta + \gamma\theta^{\intercal}\hat{\sigma}_{bc} - \theta^{\intercal}\hat{\mu}_c, \tag{4}$$

where $\hat{\Sigma}_c$ and $\hat{\mu}_c$ are, respectively, the sample covariance matrix and mean of the technical indicator-return vector r_c in (2), and $\hat{\sigma}_{bc}$ is the sample vector of covariances between the benchmark portfolio return r_b and the technical-indicator return vector r_c.[3]

Computing the first-order condition of the problem in (4) and solving for θ yields

$$\theta^{*} = \left(\gamma\hat{\Sigma}_c\right)^{-1}\left(\hat{\mu}_c - \gamma\hat{\sigma}_{bc}\right), \tag{5}$$

where γ is the risk-aversion coefficient, $\hat{\Sigma}_c$ and $\hat{\mu}_c$ are, respectively, the sample covariance matrix and mean of the technical indicator-return vector r_c, and $\hat{\sigma}_{bc}$ is the sample vector of covariances between the benchmark portfolio return r_b and the technical-indicator return vector r_c defined in (2). Eq. (5) shows that the coefficients of the mean-variance technical-parametric portfolios can be straightforwardly obtained in closed-form, which facilitates its application to high-dimensional problems by alleviating computational costs.

Finally, it is worth highlighting the differences between the *original* mean-variance formulation of Markowitz (1952) and the proposed MEV-TP strategy developed in this paper. The original mean-variance formulation of Markowitz (1952) requires modeling the expected returns, variances and covariances of *all* stocks. For a problem with N stocks, the traditional Markowitz approach requires modeling N first and $(N^2+N)/2$ second moments of stock returns. In contrast, the proposed MEV-TP portfolio strategy requires modeling K first and $(K^2+K)/2$ second moments of technical-indicator

[3]DeMiguel et al. (2020) use *firm characteristics* (such as book-to-market, investment, and profitability) to obtain parametric portfolios. While this approach is natural for portfolio allocation problems involving individual stocks, it is difficult to generalize to problems involving alternative assets such as ETFs, industry portfolios, or cryptocurrencies. The reason is that firm characteristics such as those used by DeMiguel et al. are difficult to obtain or simply not available for some of these alternative assets. In contrast, *price momentum and volume momentum technical indicators* such as those used in our paper are easy to construct even for a broad variety of assets since they only require information about prices and trading volumes, which are usually readily available.

returns; see eqs. (4)-(5). In our empirical exercise reported in Section 3, we use a sample with $N = 473$ stocks and $K = 4$ technical indicators. In this scenario, the traditional mean-variance formulation requires estimating a total of 112,574 first and second moments, whereas the proposed MEV-TP portfolio strategy requires estimating 14 first and second moments. Undoubtedly, the estimation burden of proposed MEV-TP portfolio strategy is much lower in comparison to that of the traditional mean-variance formulation.

2.1 Statistical inference

We implement a block bootstrap method (Efron and Tibshirani, 1994; Hastie, Tibshirani, and Wainwright, 2015) in order to establish whether the estimated coefficients of each technical indicator in eq. (1) are significantly different from zero. The block bootstrap method works as follows. First, 1,000 block bootstrap samples with block length equal to 21 are generated from the original dataset using sampling with replacement.[4] Second, the coefficients of the parametric portfolio policy are obtained for each block bootstrap sample using eq. (5). Finally, p-values are computed as the proportion of bootstrap samples for which a positive (negative) coefficient is nonpositive (nonnegative).

2.2 Marginal contribution of each technical indicator

To understand how and why a given technical indicator is important from a portfolio construction perspective, we follow DeMiguel et al. (2020) and consider the first-order optimality conditions for the mean-variance technical-parametric portfolio problem in (3). By decomposing the variance of the technical-indicator portfolio return, $\theta^\intercal \hat{\Sigma}_c \theta$, into a term associated with the technical-indicator own-variances, $\theta^\intercal \mathrm{diag}(\hat{\Sigma}_c)\theta$, and a term associated with the technical-indicator covariances, $\theta^\intercal(\hat{\Sigma}_c - \mathrm{diag}(\hat{\Sigma}_c))\theta$, where $\mathrm{diag}(\hat{\Sigma}_c)$ is the diagonal matrix whose kth diagonal element contains the variance of the kth technical-indicator return, the mean-variance technical-parametric portfolio problem in (3) can be rewritten as

$$\min_{\theta} \; \underbrace{(\gamma/2)\theta^\intercal \mathrm{diag}(\hat{\Sigma}_c)\theta}_{\text{own-var.}} + \underbrace{(\gamma/2)\theta^\intercal(\hat{\Sigma}_c - \mathrm{diag}(\hat{\Sigma}_c)\theta}_{\text{cov.}} + \underbrace{\gamma\theta^\intercal \hat{\sigma}_{bc}}_{\text{cov.(bench.)}} - \underbrace{\theta^\intercal \hat{\mu}_c}_{\text{mean}}. \tag{6}$$

The first-order optimality condition for problem (6) is

$$0 \in \underbrace{\gamma \mathrm{diag}(\hat{\Sigma}_c)\theta}_{\text{own-var.}} + \underbrace{\gamma(\hat{\Sigma}_c - \mathrm{diag}(\hat{\Sigma}_c))\theta}_{\text{cov.}} + \underbrace{\gamma\hat{\sigma}_{bc}}_{\text{cov.(bench.)}} - \underbrace{\hat{\mu}_c}_{\text{mean}}. \tag{7}$$

[4]We select a block length equal to 21 because our data described in Section 3 has daily frequency. We performed robustness checks by varying the block length and found that the results are qualitatively unchanged.

The four terms on the right-hand side of (7) are: the marginal contributions of the kth technical indicator to the technical-indicator own-variance, $\gamma \text{diag}(\hat{\Sigma}_c)\theta$; the technical-indicator covariance with other technical indicators, $\gamma(\hat{\Sigma}_c - \text{diag}(\hat{\Sigma}_c))\theta$; the covariance between the technical-indicator and benchmark portfolios, $\gamma\hat{\sigma}_{bc}$; the technical-indicator portfolio mean, $-\hat{\mu}_c$.

3 Empirical application

In this Section we provide an empirical application of the mean-variance technical-parametric (hereafter MEV-TP) strategy. The MEV-TP strategy is implemented assuming an investor with risk aversion parameter $\gamma = 5$. We use the equally-weighted (EW) strategy as a benchmark portfolio when computing the MEV-TP portfolio weights in (1). We download historical data from all constituents of the S&P500 index from 28/05/2015 to 30/12/2020 (1410 daily observations) and build a balanced panel by retaining only the stocks that were traded uninterruptedly during the sample period, yielding a total of 473 assets.[5]

Finally, we calculate for each period and each stock in our sample the following technical indicators:

Moving Average Convergence/Divergence (MACD): The MACD is the difference (or the ratio) between two exponential moving averages: a faster one (reflecting shorter term market trends) minus a slower one (reflecting longer term trends). We implement two MACD indicators in order to identify trends in asset prices and trading volumes:

- **PriceMACD**: The ratio between the 12-day and 26-day exponential moving averages of asset price;
- **VolumeMACD**: The ratio between the 12-day and 26-day exponential moving averages of asset trading volume.

Relative Strength Index (RSI): The RSI is a trend-following indicator for asset prices that oscillates between 0 and 100. The RSI is defined as

$$\text{RSI} = 100 - \left[\frac{100}{1 + j\text{-day relative strength}}\right],$$

where j-day relative strength is defined as the ratio between the averages of j day's price closes

[5] We performed a robustness check by collecting daily data on 25 sector ETFs and 49 Industry Portfolios between 28/05/2015 to 30/12/2020 (1410 observations). The 25 sector ETFs is available on `https://www.cnbc.com/sector-etfs/`. The 49 industry portfolios was obtained from Ken French's data library. We find that the MEV-TP portfolio consistently outperform the benchmark policies in terms of risk-adjusted returns in these two alternative data sets.

up and j day's price closes down. We compute the RSI using $j = 9$ days.

On-Balance Volume (OBV): The OBV aims at identifying trends in trading volume in order to predict bullish or bearish market conditions. The OBV is calculated as

$$\text{OBV} = \text{OBV}_{\text{prev}} + \begin{cases} \text{volume}, & \text{if close} > \text{close}_{\text{prev}} \\ 0, & \text{if close} = \text{close}_{\text{prev}} \\ -\text{volume}, & \text{if close} < \text{close}_{\text{prev}} \end{cases},$$

where OBV is the current on-balance volume level, OBV_{prev} is the previous on-balance volume level, volume is the latest trading volume amount, and close and $\text{close}_{\text{prev}}$ are the current and previous closing prices, respectively.

The parameter values used in the empirical exercise are standard in the literature and in line with those employed in previous studies. For instance, DeMiguel et al. (2020) assume a mean-variance investor with risk aversion coefficient $\gamma = 5$, which is the same used in our empirical exercise; Appel (2003) and Macedo et al. (2017) employ technical indicators with parameter values similar to those used in our paper.[6]

3.1 Assessing the importance of trend-following signals to the portfolio construction problem

We use the sample containing the 1160 daily observations from 26/05/2016 to 30/12/2020 to estimate the coefficients of the MEV-TP portfolio policy and to study the significance of coefficients associated to each technical indicators and their marginal contributions to the portfolio construction problem. Although our dataset has a total of 1410 observations, we drop the first 250 days so that the significance test is run on the exact same sample as the out-of-sample analysis reported in Section 3.2.

Table 1 reports the estimated coefficients and their significance along with the marginal contribution of each technical indicator. The last four columns of Table 1 give the marginal contribution of the technical indicator to: (i) the technical indicator own-variance, (ii) the covariance of the technical indicator with the other indicators in the portfolio, (iii) the covariance of the technical indicator with the benchmark portfolio, (iv) the technical indicator mean return; see Section 2.2.

[6] We conducted extensive robustness check to assess the sensitivity of our results with respect to changes in the set of baseline parameter values. In particular, we i) considered a an investor with coefficient of risk aversion $\gamma = 3$; ii) implemented alternative versions of the PriceMACD and VolumeMACD indicators by using the ratio between the 19-day and 39-day exponential moving averages of asset prices and trading volumes, respectively, and a RSI of 20 days. The results are qualitatively similar to those obtained under the baseline configurations.

Marginal contributions that drive the technical indicator to have a non-zero coefficient are in blue font, and marginal contributions that drive the technical indicator coefficient toward zero are in red font.[7]

We observe in Table 1 that price-trend indicators have coefficients that are highly significant for the MEV-TP strategy. Their marginal contributions indicate that the RSI indicator is significant because it has negative covariance with other indicators as well as with the benchmark portfolio, therefore contributing to a decrease in portfolio risk. The RSI also contributes to increase the mean return of the MEV-TP portfolios. The PriceMACD indicator in turn is significant only because it contributes to decrease portfolio risk via negative covariance with other indicators. As for the volume-trend indicators, we observe that only the OBV is marginally significant to the MEV-TP strategy as it contributes to decrease the portfolio risk (via negative covariance with other indicators and with the benchmark portfolio) and also to increase the portfolio mean return, but to a lesser extent in comparison to the contributions of the RSI indicator. The VolumeMACD indicator, although it contributes to decrease the risk because of its negative covariation with other indicators, have *positive* covariation with the benchmark portfolio and also contributes to *decrease* the portfolio mean return, and therefore its associated coefficient is statistically insignificant.

3.2 Out-of-sample analysis

We also perform an out-of-sample evaluation of the MEV-TP strategy in terms of returns, risk, and risk-adjusted returns measured by the Sharpe ratio (SR). For that purpose, we implement a rolling-window procedure similar to that used in DeMiguel et al. (2009). The total number of daily observations in the dataset is $T_{tot} = 1410$ and we choose an estimation window of $T = 250$ (one year). Second, using the return data over the estimation window, we compute the MEV-TP portfolios. Third, we repeat this rolling-window procedure for the next day, by including the data for the next day and dropping the data for the earliest day. At the end of this process, we have generated $T_{tot} - T = 1160$ portfolio-weight vectors, w_t, for $t = T, \ldots, T_{tot} - 1$. Holding the portfolio w_t for one day gives the out-of-sample return net of transaction costs at time $t + 1$:

$$r_{t+1} = (w_t)^\top r_{t+1} - c \times |w_t - (w_{t-1})^+|,$$

[7] Note that for characteristics with a positive technical-parametric portfolio weight, negative (positive) marginal contributions help to decrease (increase) the objective function in the minimization problem in (4) and thus increase (decrease) the investor's mean-variance utility. Therefore, for characteristics with positive technical-parametric portfolio weights, negative (positive) marginal contributions are in blue font (red font). The opposite color convention applies to characteristics with negative parametric-portfolio weights.

where c is the level of transaction costs, $(w_{t-1})^+$ is the portfolio before rebalancing at time t; that is

$$(w_{t-1})^+ = w_{t-1} \circ (e_{t-1} + r_t),$$

where e_{t-1} is the N_{t-1} dimensional vector of ones and $x \circ y$ is the elementwise product of vectors x and y. Then, we use the time series of r_{t+1} to compute the monthly out-of-sample mean, standard deviation, and SR of returns net of transaction costs, which is defined as the out-of-sample mean return in excess of the risk-free return divided by the standard deviation.[8] We follow Kirby and Ostdiek (2012) and consider two levels of transaction costs: $c = 0$ basis points (b.p.) and $c = 50$ b.p.

We also implement two benchmark strategies. The first is the equally-weighted (EW) portfolio. We consider this strategy because of its good results as reported in DeMiguel et al. (2009). The second benchmark strategy is the traditional mean-variance formulation, which requires modeling first and second moments of all stocks.[9] Our implementation of the traditional mean-variance policy follows DeMiguel et al. (2009) and we use the same value for the coefficient of risk aversion used in the implementation of the MEV-TP strategy ($\gamma = 5$).

We also test for the statistical significance of the differences in the portfolio variances and SR with respect to those obtained with the EW strategy by using the two-sided p-value of the prewhitened HAC_{PW} test described by Ledoit and Wolf (2011) and Ledoit and Wolf (2008) for the portfolio variance and the SR, respectively.

Table 2 reports portfolio performance statistics for the MEV-TP, traditional mean-variance, and EW strategies. Motivated by the findings reported in Table 1, we report the results MEV-TP strategy obtained with three alternative specifications: i) including only price-trend indicators, ii) including only volume-trend indicators, and iii) including price- and volume-trend indicators. We observe that MEV-TP portfolios with price-trend indicators achieve higher SR in comparison to the EW strategy both before and after transaction costs. Specifically, when only price-trend indicators are included, the net-of-costs SR is 0.67 whereas the figure for the EW strategy is 0.23 and the difference is statistically significant. On the other hand, when only volume-trend indicators are included, the SR of the MEV-TP portfolios is substantially lower with respect to that of the EW strategy. However, the MEV-TP portfolio with volume-trend indicators has the merit of delivering portfolios with lower risk in

[8]Monthly standard deviation and Sharpe ratio of portfolio returns are based on the daily figures multiplied by the robust scaling factor proposed by Lo (2002).

[9]Note that the length of the estimation used in the out-of-sample analysis, $T = 250$, is smaller than the cross-section dimension of our data set ($N = 473$). In this scenario, the sample covariance matrix of stock returns is ill-conditioned. To overcome this problem, we estimate the covariance matrix of stock returns using the linear shrinkage estimator proposed by Ledoit and Wolf (2004). We have also implemented the non-linear shrinkage estimator of Ledoit and Wolf (2017) and obtained qualitatively similar results.

comparison all other specifications when transaction costs are taken into account.

Table 2 also reveals the traditional mean-variance strategy performs well in terms of risk-adjusted returns *in the absence of transaction costs*. However, when transaction costs are properly taken into account, the out-of-sample after-fee performance of the traditional mean-variance strategy deteriorates to a point that it becomes *worse* in comparison to that obtained with all other strategies. In particular, Panel B of Table 2 shows that the net-of-costs Sharpe ratio of the traditional Markowitz strategy is −0.12 whereas the corresponding figures for the MEV-TP strategy with both price and volume indicators is 0.63, and differences with respect to Sharpe ratio obtained with the equally-weighted strategy (0.23) are significant in both cases.

We report in Table 3 descriptive statistics of the optimal weights of each portfolio policy considered in the paper. The Table reports in each column the time series averages of the following quantities: i) portfolio turnover, ii) absolute weight, iii) minimum weight, iv) maximum weight, v) sum of negative weights, and vi) fraction of negative weights. Not surprisingly, the traditional mean-variance policy has a very high level of portfolio turnover (1.22), which means that the policy requires trading around 60% of the total portfolio holdings at every period, on average. This is in sharp contrast with the substantially *lower* portfolio turnover of the MEV-TP portfolios, which requires trading 5% to 6% of the portfolio holdings at every period. These results help explaining the sharp deterioration in after-costs risk-adjusted performance of the original mean-variance formulation. Moreover, the traditional mean-variance strategy demands a much higher proportion of short positions: 47.5% of the weights are negative on average. In contrast, the different MEV-TP policies demand a near-zero proportion of short positions.

4 Concluding remarks

We propose in this paper a method to incorporate trend-following indicators in the optimal portfolio construction problem. Our results reveal that technical indicators are able to contribute to the portfolio construction problem. This contribution, however, is heterogeneous. While price-trend indicators contribute to deliver mean-variance portfolios with higher risk-adjusted returns, volume-trend indicators are able to deliver portfolio with lower risk in comparison to the benchmark strategy considered in the paper.

Tables

Table 1: **Estimated coefficients and marginal contributions of each technical indicator**

This table reports the significance of the estimated coefficients of the mean-variance technical-parametric (MEV-TP) strategies along with the marginal contributions of each technical indicator. The MEV-TP strategy is obtained for a risk-aversion parameter of $\gamma = 5$. All figures are obtained using 1160 daily observations from 26/05/2016 to 30/12/2020. One, two, and three asterisks indicate that the coefficient is significant at the 10%, 5% and 1% level, respectively, based on p-values obtained with the bootstrap procedure detailed in Section 2.1. The last four columns give the marginal contribution of the indicator to: (i) the indicator own-variance, (ii) the covariance of the indicator with the other indicators in the portfolio, (iii) the covariance of the indicator with the benchmark portfolio, and (iv) the indicator mean; see Section 2.2. Marginal contributions that drive the characteristic to be nonzero are in blue font, and marginal contributions that drive the characteristic toward zero are in red font.

		Marginal contributions ($\times 10^3$) to:			
	Coeff.	variance	cov.	cov (bench.)	mean
PriceMACD	-41.689***	-5.397	7.355	-0.124	-1.834
RSI	86.924***	8.572	-3.420	-0.078	-5.074
VolumeMACD	7.163	0.326	-0.585	0.089	0.170
OBV	15.019*	0.650	-0.287	-0.089	-0.274

Table 2: **Out-of-sample performance statistics for various portfolio strategies**

This table reports monthly out-of-sample performance statistics (mean portfolio return (%), standard deviation of portfolio returns (%), and Sharpe ratio) for the MEV-TP, traditional mean-variance and equally-weighted strategies. The data sets consists of 473 stocks belonging to the S&P500 index. All figures are obtained using 1160 out-of-sample porfolio returns from 26/05/2016 to 30/12/2020. The MEV-TP and the traditional mean-variance strategies are obtained assuming an investor with risk aversion parameter equal to $\gamma = 5$. MEV-TP portfolios are obtained under three alternative specifications: i) with price-trend indicators (PriceMACD and RSI), ii) with volume-trend indicators (VolumeMACD and OBV), and iii) with all price- and volume-trend indicators. Implementation of the traditional mean-variance policy follows DeMiguel et al. (2009). Panels A and B report results assuming two alternative levels of transaction costs: 0 basis points (b.p.) and 50 b.p. One, two, and three asterisks indicate that the differences in portfolio variance and in Sharpe ratios with respect to those of the equally-weighted portfolio are significant at the 10%, 5% and 1% level, respectively.

	Panel A: Transaction cost = 0 b.p.			Panel B: Transaction cost = 50 b.p.		
	Mean Return (%)	Standard Dev. (%)	Sharpe Ratio	Mean Return (%)	Standard Dev. (%)	Sharpe Ratio
MEV-TP portfolios						
Price indicators	5.181	5.799	0.877***	4.001	5.795	0.674***
Volume indicators	1.757	5.418***	0.307***	0.650	5.415***	0.102***
Price and volume indicators	4.998	5.864	0.836***	3.819	5.859	0.635***
Traditional mean-variance portfolios	12.279	4.615***	2.640***	-0.631	6.172***	-0.118**
Equally-weighted	1.576	5.838	0.254	1.414	5.838	0.226

Table 3: **Descriptive statistics of portfolio weights**

This table reports descriptive statistics of the distribution of portfolio weights of the strategies and of the three alternative specifications considered. The first column reports the name of each portfolio strategy followed by each specification. The remaining columns report the time series averages of the following quantities: portfolio turnover, absolute weight, minimum weight, maximum weight, sum of negative weights, and fraction of negative weights.

	$\sum \left\| w_{i,t} - w_{i,t-1}^{+} \right\|$	$\sum \|w_i\| \times 100$	$\min w_i \times 100$	$\max w_i \times 100$	$\sum w_i I\left(w_i < 0\right)$	$\sum I\left(w_i \leq 0\right)/N_t$
MEV-TP portfolios						
Price indicators	0.112	0.211	0.052	0.374	0.000	0.000
Volume indicators	0.105	0.212	-0.099	0.515	-0.002	0.007
Price and volume indicators	0.112	0.211	0.054	0.410	0.000	0.000
Traditional mean-variance portfolios	1.222	2.256	-8.578	10.063	-4.835	0.475
Equally-weighted	0.015	0.211	0.193	0.230	0.000	0.000

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