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Timing the Market with a Combination of Moving Averages*

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ABSTRACT

A combination of simple moving average trading strategies with several window lengths delivers a greater average return and skewness as well as a lower variance and kurtosis compared with buying and holding the underlying asset using daily returns of value-weighted US decile portfolios sorted by market size, book-to-market, momentum, and standard deviation as well as more than 1000 individual US stocks. The combination moving average (CMA) strategy generates risk-adjusted returns of 2% to 16% per year before transaction costs. The performance of the CMA strategy is driven largely by the volatility of stock returns and resembles the payoffs of an at-the-money protective put on the underlying buy-and-hold return. Conditional factor models with macroeconomic variables, especially the market dividend yield, short-term interest rates, and market conditions, can explain some of the abnormal returns. Standard market timing tests reveal ample evidence regarding the timing ability of the CMA strategy.

JEL Codes: G11; G12; G14

I. INTRODUCTION

Technical analysis involves the use of past and current market price, trading volume, and potentially, other publicly available information to predict future market prices. It is highly popular in practice with plentiful financial trading advice that is based largely, if not exclusively, on technical indicators. From the standpoint of classical economic and finance theory, it is not at all clear that technical analysis in general and moving averages in particular will have any role or power in predicting the returns of individual stocks as well as portfolios of stocks. Several potential reasons come to mind in terms of justifying the use of moving averages. First, investor heterogeneity as well as information asymmetry may lead to the persistent manifestation of behavioral biases in stock market prices. Prior studies that have touched upon these issues include Treynor and Ferguson (1985); Brown and Jennings (1989), and Hong and Stein (1999) among many others. Furthermore, the theoretical model in Wang (1993) shows explicitly

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how a rational economic agent inhabiting a classical model of choice under uncertainty and differential information will find signals based on average past prices quite useful, informative, and revealing of other agents' private information. Secondly, active investors in practice very often follow price trends which may lead to the continued persistence of trends, both upward as well as downward. These trends present other investors with the ability to follow them at least in the short-term. Academic work in this area is perhaps best exemplified by Fung and Hsieh (2001), and their construction of trend following indicators based on the returns of look back straddle options. Thirdly, the study by Brock et al. (1992) document the performance of various implementations of the moving average and conclude that it is the most popular strategy followed by investors who use technical analysis. More formally, Brock et al. (1992) find evidence that some technical indicators do have a significant predictive ability. Fourthly, Blume et al. (1994) present a theoretical framework using trading volume and price data leading to technical analysis being a part of a trader's learning process. A more thorough study of a large set of technical indicators by Lo et al. (2000) also found some predictive ability especially when moving averages are concerned. Zhu and Zhou (2009) provide a solid theoretical reason why technical indicators could be a potentially useful state variable in an environment where investors need to learn over time the fundamental value of the risky asset they invest in. More recently, Neely et al. (2010, 2011) find that technical analysis has as much forecasting power over the equity risk premium as the information provided by economic fundamentals. The practitioner's literature also includes Faber (2007) and Kilgallen (2012) who thoroughly document the risk-adjusted returns to the moving average strategy using various portfolios, commodities, and currencies. In addition, Huang and Zhou (2013) use the moving average indicator to predict the return on the US stock market while Goh et al. (2012) apply the same idea to government bond yields and risk premia. Motivated in part by the predictive power of the moving average indicator, Han et al. (2016) and Jiang (2013) construct a trend factor with considerable cross-sectional explanatory power and substantial historical performance. In a similar vein, Glabadanidis (2014, 2015a, 2015b) investigates and documents the performance of the simple moving average strategy with various US and international portfolios as well as individual US stocks.

The contribution of this paper is three-fold. First, I propose a novel strategy which is an equal-weighted average of simple moving average. The novelty here is that the investment or disinvestment in the underlying risky asset is proportional to the number of moving average windows that have generated a buy or sell signal, respectively. This is in stark contrast with trading signals generated by a single moving average window which involve either being completely invested in the risky asset or completely invested in the risk-free asset. Secondly, I report on the performance of the combination moving average strategy with a large number of portfolios and individual stocks. Finally, I provide a link between technical indicators and fundamental indicators by presenting evidence that the performance of the combination moving average strategy can be partially explained by a conditional asset pricing model with the market's dividend yield, short-term interest rates, and a recession indicator.

This paper is similar in spirit to Glabadanidis (2014, 2015a, 2015b) and Han et al. (2013). However, several important differences stand out. First, I use daily value-weighted returns of decile portfolios constructed by various characteristics like size, book-to-market, momentum, and standard deviation of return. Value-weighted portfolios at a daily frequency have a much smaller amount of trading going on inside the portfolio compared with the daily equal-weighted portfolios investigated by Han et al. (2013). Secondly, the cross-sectional results in this study are just an artefact of the decile portfolios and not the main focus of this paper, while Han et al. (2013) is mostly concerned with the inability of standard empirical tests to account for the moving average strategy average returns differences across portfolios. I argue that this is largely due to using the wrong benchmark pricing model. Using a dynamic market-timing tests and conditional asset pricing models with macroeconomic state variables leads to mostly negative or statistically insignificant risk-adjusted returns for the moving average strategy. In light of this, my take on the performance of the combination moving average strategy is that it is not an anomaly, but instead a dynamic trading strategy that exposes investors to potential upside returns derived from risky assets via its market timing ability. Similarly, the combination moving average strategy manages to avoid substantial market downturns more often than not, thus, insulating investors from periods of sustained bear markets. This performance is more pronounced the more volatile the returns of the underlying risky assets are. A final caveat is that I assume the moving average trading has no price impact. Large investors using this strategy will necessarily experience an inferior performance. This is largely due to the adverse price impact of liquidating and initiating large positions, especially for less liquid assets with lower trading volumes.

The highlights of this study are the superior performance of the combination moving average portfolios relative to buying and holding the underlying portfolios, the fact that the switching strategy returns resemble an imperfect at-the-money protective put, and that cross-sectional differences are not a new anomaly as maintained in Han et al. (2013), but are due to volatility differences in the underlying portfolios and stocks as well as factor exposure differences to a few macroeconomicstate variables. The returns of the combination moving average strategy relative to the buy-and-hold strategy are quite convex with respect to the return of the buy-and-hold strategy and, hence, will be hard to explain using standard linear asset pricing models. The anomalous risk-adjusted performance relative to standard linear asset pricing models appears to be largely due to omitting market timing factors in a simple piece-wise linear framework that captures the moving average strategy's convexity. Furthermore, the moving average strategy appears to be antifragile in the sense of Taleb (2012) meaning that for securities with more volatile returns there is a greater improvement of the moving average returns relative to buy-and-hold returns.

II. A COMBINATION OF SIMPLE MOVING AVERAGES

I use daily value-weighted[1] returns of sets of 10 portfolios sorted by market capitalization, book-to-market, momentum, and standard deviation. The data is readily available from Ken French Data Library. The sample period starts on January 4, 1960 and ends on December 31, 2013.

The following exposition of the moving average strategy follows closely the presentation in Han et al. (2013). Let R_{jt} be the return on portfolio j at the end of month t and let P_{jt} be the respective price level of that portfolio. Define the moving average of portfolio j $\bar{A}_{jt,L}$ at time t with length L periods as follows:

$$\overline{A}_{jt,L} = \frac{P_{jt-L+1} + P_{jt-L+2} + \cdots + P_{jt-1} + P_{jt}}{L} \tag{1}$$

Throughout the paper, I use a combination moving average comprised of an equal-weighted combination of simple moving averages of length $L=5$, $L=10$, $L=20$, $L=50$, $L=100$, and $L=200$ days. The way I implement the simple moving average strategy in this paper is to compare the closing price P_{jt} at the end of every day to the running moving average $\bar{A}_{jt,L}$. If the price is above the moving average this triggers a signal to invest (or stay invested if already invested at t-1) in the portfolio in the next day $t+1$. If the price is below the moving average this triggers a signal to leave the risky portfolio (or stay invested in cash if not invested at t-1) in the following day $t+1$.[2] As a proxy for the risk-free rate, I use the daily return on the 30-day US Treasury Bill.

More formally, the returns of the moving average switching strategy can be expressed as follows:

$$\widetilde{R}_{jt,L} = \begin{cases} R_{jt}, & \text{if } P_{jt-1} > \overline{A}_{jt-1,L} \\ r_{ft}, & \text{otherwise,} \end{cases} \tag{2}$$

in the absence of any transaction costs imposed on the switches. For the rest of the paper and in all of the empirical results quoted, I consider returns after the imposition of a one-way transaction cost of τ. Mathematically, this leads to the following four cases in the post-transaction cost returns:

1 I use value-weighted portfolio returns to control for the amount of rebalancing trading inside the various portfolios. The empirical results in this paper are much stronger when equal-weighted portfolios are used. However, this may understate the break-even transaction costs as equal weighted portfolios require a lot of trading to be replicated.

2 An alternative version of the switching strategy involves investing in the market portfolio instead of the risk-free asset. This version of the switching strategy has a somewhat inferior performance compared with the baseline case investigated in the article. Nevertheless, it is an interesting case to consider, and I am grateful to an anonymous referee for suggesting this idea to me.

$$\widetilde{R}_{jt,L} = \begin{cases} R_{jt}, & \text{if } P_{jt-1} > \overline{A}_{jt-1,L} \text{ and } P_{jt-2} > \overline{A}_{jt-2,L}, \\ R_{jt} - \tau, & \text{if } P_{jt-1} > \overline{A}_{jt-1,L} \text{ and } P_{jt-2} < \overline{A}_{jt-2,L}, \\ r_{ft}, & \text{if } P_{jt-1} < \overline{A}_{jt-1,L} \text{ and } P_{jt-2} < \overline{A}_{jt-2,L}, \\ r_{ft} - \tau, & \text{if } P_{jt-1} < \overline{A}_{jt-1,L} \text{ and } P_{jt-2} > \overline{A}_{jt-2,L}. \end{cases} \quad (3)$$

depending on whether the investor switches or not. Note that this imposes a cost on selling and buying the risky portfolio, but no cost is imposed on buying and selling the Treasury bill. This is consistent with prior studies like Balduzzi and Lynch (1999); Lynch and Balduzzi (2000), and Han (2006), among others. Regarding the appropriate size of the transaction cost, Balduzzi and Lynch (1999) propose using a value between 1 and 50 basis points. Lynch and Balduzzi (2000) use a mid-point value of 25-basis point. Instead of choosing a controversial value for the one-way transaction cost, I use $\tau = 0$ and report the break-event one-way transaction cost that will completely eliminate any outperformance of the combination moving average strategy relative to the buy-and-hold strategy.

$$\widetilde{CR}_{jt} = \frac{\widetilde{R}_{jt,5} + \widetilde{R}_{jt,10} + \widetilde{R}_{jt,20} + \widetilde{R}_{jt,50} + \widetilde{R}_{jt,100} + \widetilde{R}_{jt,200}}{6} \quad (4)$$

I construct excess returns as zero-cost portfolios that are long the combination moving average (CMA) switching strategy and short the underlying portfolio to determine the relative performance of the moving average strategy against the buy-and-hold strategy. Denote the resulting difference between the return of the CMA strategy for portfolio *j* at the end of month *t*, $\widetilde{CR}_{jt} - R_{jt}$, and the return of portfolio *j* at the end of month *t*, R_{jt}, as follows:

$$\text{CMAP}_{jt} = \widetilde{CR}_{jt} - R_{jt}, \quad j = 1, \ldots, N \quad (5)$$

The presence of significant abnormal returns can be interpreted as evidence in favor of superiority of the moving average switching strategy over the buy-and-hold strategy of the underlying portfolio. Naturally, the moving average switching strategy is a dynamic trading strategy, so it is perhaps unfair to compare its returns to the buy-and-hold returns of being long the underlying portfolio.

Table 1 presents the first four moments and the Sharpe ratio of the buy-and-hold (BH) strategy, the CMA strategy and the combination moving average portfolio (CMAP) strategy for decile portfolio sorted by market capitalization, book-to-market, momentum, and standard deviation of return. The first strong finding that emerges for all portfolios is that the standard deviation of return is reduced by the CMA strategy relative to the BH strategy. Secondly, the risk-return trade-off is improved for all portfolios as evidenced by the increased Sharpe ratios for all portfolios. Thirdly, in the vast majority of cases the average return of the CMA strategy exceeds the average return of the BH strategy. The only exception are decile high sorted by size and decile eight sorted by momentum. Fourthly, the kurtosis of almost all portfolios is reduced as well with the exception of

Table 1 Summary statistics

Panel A: size sorted portfolios

p	μ	σ	*s*	*k*	*SR*	μ	σ	*s*	*k*	*SR*	μ	σ	*s*	*k*	*SR*
	BH portfolios					CMA portfolios					CMAP portfolios				
Low	11.88	13.58	−0.90	14.82	0.52	23.61	7.43	−0.34	9.57	2.53	11.73	9.47	1.68	42.24	1.24
2	11.82	16.71	−0.46	13.86	0.42	20.25	9.07	−0.50	10.56	1.71	8.43	11.65	0.52	36.55	0.72
3	12.90	16.59	−0.48	12.03	0.49	19.70	9.19	−0.41	9.00	1.62	6.80	11.38	0.62	32.86	0.60
4	12.10	16.32	−0.48	12.49	0.45	18.36	8.94	−0.44	8.77	1.52	6.25	11.29	0.66	35.91	0.55
5	12.62	16.22	−0.47	11.97	0.48	18.10	8.99	−0.45	8.87	1.48	5.48	11.19	0.62	34.38	0.49
6	12.16	15.32	−0.53	13.43	0.48	17.76	8.45	−0.40	8.11	1.54	5.60	10.61	0.87	41.62	0.53
7	12.19	15.47	−0.55	15.55	0.48	17.48	8.51	−0.34	8.70	1.49	5.28	10.72	0.95	48.95	0.49
8	11.91	15.69	−0.51	16.63	0.45	16.02	8.68	−0.30	8.37	1.30	4.11	10.82	0.85	54.89	0.38
9	11.48	15.45	−0.59	20.91	0.43	14.02	8.55	−0.23	7.97	1.08	2.54	10.68	1.04	72.40	0.24
High	10.09	15.99	−0.49	21.64	0.33	9.74	8.88	−0.18	7.74	0.56	−0.34	11.01	0.94	78.14	−0.03

Panel B: book-to-market sorted portfolios

p	μ	σ	*s*	*k*	*SR*	μ	σ	*s*	*k*	*SR*	μ	σ	*s*	*k*	*SR*
	BH portfolios					CMA portfolios					CMAP portfolios				
Low	9.32	17.52	−0.17	13.47	0.26	12.27	9.58	−0.17	7.42	0.78	2.95	12.21	0.05	42.84	0.24
2	10.89	16.06	−0.39	16.38	0.38	12.44	9.01	−0.13	7.93	0.85	1.55	11.04	0.77	57.39	0.14
3	11.01	15.42	−0.51	20.71	0.40	13.03	8.75	−0.04	7.28	0.94	2.02	10.47	1.06	78.27	0.19
4	10.82	15.79	−0.71	20.94	0.38	13.25	8.87	−0.20	8.86	0.96	2.43	10.81	1.54	73.64	0.22
5	11.10	15.61	−0.45	23.03	0.41	12.34	8.73	−0.30	9.13	0.87	1.24	10.75	0.59	80.18	0.12
6	11.77	15.14	−0.44	16.96	0.46	13.44	8.55	−0.23	8.10	1.01	1.67	10.26	0.72	59.03	0.16
7	12.43	14.89	−0.64	22.73	0.51	14.09	8.55	−0.20	8.60	1.09	1.65	10.02	1.24	87.83	0.16
8	12.89	15.81	−0.60	30.17	0.51	14.15	8.87	−1.20	25.12	1.06	1.26	10.93	0.81	92.42	0.12
9	13.82	15.99	−0.68	20.85	0.57	15.45	9.26	−0.46	11.05	1.15	1.64	10.74	1.04	72.16	0.15
High	14.90	17.77	−0.46	15.87	0.57	18.43	10.32	−0.27	11.15	1.32	3.53	11.87	0.97	53.66	0.30

Table 1 (*continued*)

Panel C: momentum sorted portfolios

p	μ	σ	*s*	*k*	*SR*	μ	σ	*s*	*k*	*SR*	μ	σ	*s*	*k*	*SR*
	BH portfolios					CMA portfolios					CMAP portfolios				
Low	2.51	24.92	0.41	25.73	−0.09	16.23	12.33	0.51	41.68	0.93	13.72	18.28	−0.58	46.59	0.75
2	7.92	20.34	0.16	22.19	0.15	14.78	10.98	−0.37	34.60	0.91	6.86	14.39	−0.74	51.81	0.48
3	10.21	17.58	0.04	17.99	0.31	13.80	9.70	−0.09	14.68	0.93	3.59	12.17	−0.29	43.70	0.29
4	10.15	16.60	−0.15	18.82	0.32	13.08	9.15	0.06	11.36	0.91	2.92	11.43	0.27	56.09	0.26
5	10.00	15.89	0.01	21.66	0.33	11.63	8.86	−0.10	13.88	0.77	1.63	10.93	−0.29	68.11	0.15
6	10.84	15.35	−0.58	26.69	0.39	12.19	8.65	−0.26	10.04	0.86	1.35	10.48	1.21	99.19	0.13
7	10.76	15.19	−0.55	22.87	0.39	12.51	8.51	−0.25	7.45	0.91	1.76	10.41	1.08	86.63	0.17
8	13.42	15.49	−0.73	21.20	0.56	13.27	9.16	−0.27	7.75	0.93	−0.15	10.14	1.71	93.02	−0.01
9	12.66	16.46	−0.53	15.10	0.48	13.92	9.46	−0.29	7.35	0.97	1.26	11.05	0.90	56.48	0.11
High	17.71	20.36	−0.50	12.74	0.63	19.69	11.69	−0.44	7.57	1.28	1.98	13.64	0.64	45.42	0.15

Panel D: standard deviation sorted portfolios

p	μ	σ	*s*	*k*	*SR*	μ	σ	*s*	*k*	*SR*	μ	σ	*s*	*k*	*SR*
	BH portfolios					CMA portfolios					CMAP portfolios				
High	40.03	20.26	0.10	14.39	1.74	49.35	13.03	1.16	15.15	3.42	9.32	12.64	0.33	50.77	0.74
2	17.70	19.29	−0.31	14.53	0.67	28.52	10.74	0.32	13.08	2.21	10.82	13.37	0.80	41.93	0.81
3	15.14	18.25	−0.38	16.40	0.57	24.73	9.93	−0.04	11.51	2.01	9.59	12.82	0.78	47.10	0.75
4	15.67	16.88	−0.47	18.78	0.64	23.10	9.19	−0.12	10.99	1.99	7.43	11.88	0.88	54.03	0.63
5	15.60	15.51	−0.55	20.48	0.70	22.41	8.45	−0.20	10.74	2.09	6.81	10.88	0.90	60.56	0.63
6	14.74	14.38	−0.67	24.46	0.69	20.91	7.81	−0.27	10.44	2.07	6.18	10.11	1.08	73.82	0.61
7	14.30	12.77	−0.66	28.32	0.75	19.94	7.01	−0.16	9.13	2.16	5.64	8.97	1.03	94.82	0.63
8	13.60	11.15	−0.78	36.33	0.79	18.81	6.12	−0.00	7.95	2.29	5.21	7.90	1.53	127.66	0.66
9	12.47	9.27	−0.58	54.74	0.83	17.54	5.04	0.17	8.69	2.53	5.07	6.68	1.00	187.69	0.76
Low	10.77	6.86	−0.47	71.63	0.87	16.03	3.72	0.51	10.76	3.03	5.25	4.94	0.73	245.31	1.06

This table reports summary statistics for the respective buy and hold (BH) portfolio returns, the combination moving average (CMA) switching strategy portfolio returns and the excess return of CMA over BH (CMAP) using sets of 10 portfolios sorted by size, book-to-market, momentum and standard deviation of return. The sample period covers January 4, 1960 until December 31, 2013 with value-weighted portfolio returns. μ is the annualized average return, σ is annualized standarddeviation of returns, *s* is the annualized skewness, *k* is the annualized kurtosis, and *SR* is the annualized Sharpe ratio. The lengths of the moving average windows are 5, 10, 20, 50, 100, and 200 days. The CMA portfoliois an equal-weighted combination of the six individual moving average returns.

Table 2 Factor regressions results

Panel A: size sorted portfolios

Portfolio	α	β_m	β_s	β_h	β_u	$\overline{R}^2$
Low	16.111***	−0.483***	−0.497***	−0.157***	−0.012**	0.653
2	13.737***	−0.625***	−0.579***	−0.190***	0.010*	0.705
3	11.706***	−0.615***	−0.531***	−0.130***	0.010*	0.713
4	10.980***	−0.613***	−0.483***	−0.096***	0.004	0.714
5	9.843***	−0.608***	−0.425***	−0.068***	0.018***	0.708
6	9.603***	−0.576***	−0.306***	−0.044***	0.005	0.691
7	9.346***	−0.586***	−0.246***	−0.069***	0.009*	0.687
8	8.111***	−0.597***	−0.173***	−0.072***	0.013**	0.697
9	6.447***	−0.589***	−0.062***	−0.079***	0.004	0.699
High	2.392***	−0.579***	0.137***	0.036***	0.040***	0.718

Panel B: book-to-market sorted portfolios.

Portfolio	α	β_m	β_s	β_h	β_u	$\overline{R}^2$
Low	4.633***	−0.595***	0.036***	0.307***	0.048***	0.703
2	4.569***	−0.576***	0.017**	0.062***	0.009*	0.681
3	5.371***	−0.549***	0.019***	0.012	−0.023***	0.663
4	6.551***	−0.589***	−0.011	−0.169***	0.018***	0.674
5	5.486***	−0.577***	−0.019***	−0.215***	0.021***	0.645
6	5.730***	−0.555***	−0.071***	−0.195***	0.026***	0.652
7	6.201***	−0.545***	−0.030***	−0.278***	−0.002	0.647
8	6.464***	−0.590***	−0.066***	−0.441***	0.047***	0.651
9	7.182***	−0.591***	−0.082***	−0.405***	−0.011**	0.651
High	9.581***	−0.647***	−0.181***	−0.455***	0.013**	0.642

Panel C: momentum sorted portfolios

Portfolio	α	β_m	β_s	β_h	β_u	$\overline{R}^2$
Low	14.460***	−0.845***	−0.310***	−0.043***	0.596***	0.682
2	7.962***	−0.691***	−0.108***	−0.050***	0.410***	0.689
3	5.155***	−0.600***	−0.037***	−0.086***	0.295***	0.684
4	5.621***	−0.591***	0.004	−0.118***	0.162***	0.672
5	4.603***	−0.566***	0.001	−0.079***	0.089***	0.650
6	5.043***	−0.553***	0.024***	−0.112***	0.006	0.643
7	5.836***	−0.557***	0.013*	−0.092***	−0.046***	0.654
8	4.597***	−0.544***	0.018***	−0.124***	−0.120***	0.645
9	6.708***	−0.602***	−0.059***	−0.082***	−0.174***	0.669
High	8.596***	−0.696***	−0.192***	0.057***	−0.301***	0.645

Panel D: standard deviation sorted portfolios

Portfolio	α	β_m	β_s	β_h	β_u	$\overline{R}^2$
High	13.784***	−0.569***	−0.491***	−0.133***	0.026***	0.496
2	15.651***	−0.684***	−0.474***	−0.128***	0.057***	0.625
3	14.676***	−0.680***	−0.429***	−0.179***	0.044***	0.652
4	12.321***	−0.635***	−0.370***	−0.215***	0.045***	0.651
5	11.445***	−0.584***	−0.300***	−0.229***	0.036***	0.644

Table 2 (*continued*)

Panel D: standard deviation sorted portfolios

Portfolio	α	β_m	β_s	β_h	β_u	$\overline{R}^2$
6	10.511***	−0.545***	−0.236***	−0.224***	0.030***	0.642
7	9.459***	−0.475***	−0.162***	−0.185***	0.008	0.612
8	8.531***	−0.407***	−0.111***	−0.152***	−0.008*	0.574
9	7.756***	−0.320***	−0.071***	−0.129***	−0.013***	0.493
Low	6.823***	−0.179***	−0.017***	−0.055***	−0.029***	0.284

This table reports alphas, betas, and adjusted R^2 of the regressions of the CMAP excess returns on the Carhart four-factors using portfolios sorted by size, book-to-market, momentum, and standard deviation of return. The alphas are annualized and in percent. The sample period covers January 4, 1960 until December 31, 2013 with value-weighted portfolio returns. The lengths of the moving average windows are 5, 10, 20, 50, 100, and 200 days. Newey and West (1987) standard errors with three lags are used in reporting statistical significance of a two-sided null hypothesis at the 1, 5, and 10% level is given by a ***, a **, and a *, respectively.

momentum deciles low and two as well as decile high of the standard deviation sorted portfolios. Finally, portfolio skewness increases for most of the portfolios with the exception of book-to-market decile eight and momentum deciles two, three, and five. Overall, the findings are that the CMA strategy improves all four of the first moments of all but a handful of portfolios relative to the BH strategy.

A. Abnormal returns

The asset pricing model that I consider in this section is the four-factor Carhart (1997) model[3]:

$$\text{CMAP}_{jt,L} = \alpha_j + \beta_{j,m} r_{mkt,t} + \beta_{j,s} r_{smb,t} + \beta_{j,h} r_{hml,t} + \beta_{j,u} r_{umd,t} + \varepsilon_{jt}, \quad j = 1, \ldots, N \tag{6}$$

where $r_{mkt,t}$ is the excess return on the market portfolio at the end of month t, $r_{smb,t}$ is the return on the small minus big (SMB) factor at the end of month t, $r_{hml,t}$ is the return on the high minus low (HML) factor at the end of month t, and $r_{umd,t}$ is the return of the up minus down (UMD) factor at the end of month t. Note that all of the risk-adjusted alphas are highly statistically significant (see Table 2). Moreover, they are all still quite substantial economically ranging between 2.4% and 16.1% per year. The factor loadings on the market portfolio, SMB, and HML are largely unchanged across the three sets of decile portfolios while the loadings on the UMD factor are mostly positive and highly statistically significant (with only a few exceptions). This suggests that all four factors have a role to play in driving the performance of the CMAP returns. Nevertheless, the average adjusted R^2 values indicate that only between one half and two thirds of the return variation

3 Results for the CAPM and Fama–French three factor models yield very similar and, frequently, stronger than the results for the Carhart (1997) model. These additional findings are not reported in the paper in the interest of saving space. They are available from the author upon request.

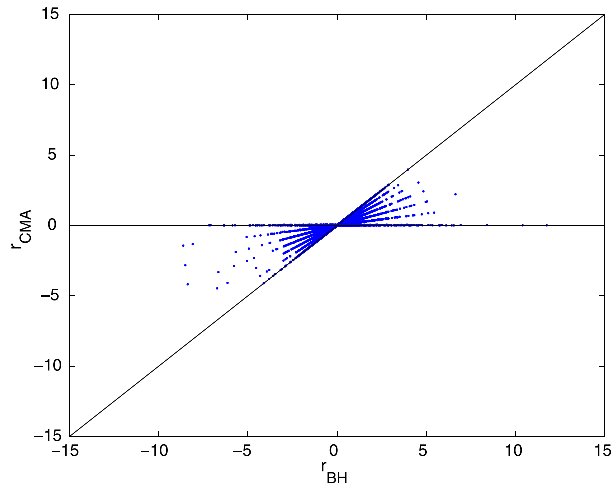

Figure 1 Scatter Plot of Buy-and-Hold returns versus the Combination Moving Average returns: High ME Decile Portfolio.

Notes: Figure 1 presents a scatter plot of the returns of the high ME decile buy-and-hold portfolio returns versus the combination moving average strategy returns. The sample contains 13,592 daily observations and the data covers the January 4, 1960 until December 31, 2013.

can be explained and accounted for by the market portfolio return, size, value, and momentum. This leaves a large portion of return variation that cannot be accounted for. Finally, it is worthwhile noting that all of β_m values are negative and statistically significant, indicating that the market beta of the CMA strategy significantly exceeds the market beta of the BH strategy. With some exceptions, this is also the case for β_s and β_h. The loadings on the momentum factor are both positive and negative indicating that for some portfolios, the momentum beta of the CMA strategy is exceeded by the momentum beta of the BH strategy, while for other portfolios; it is the other way around.

B. Explanation

Before making an attempt at explaining the reasons for the profitability of the moving average (MA) strategies performance, it is useful to inspect a scatter plot of the MA strategy returns versus the underlying BH strategy returns for the same portfolio. For ease of exposition, I provide a plot for a single portfolio only.[4] Figure 1 presents the scatter plot for the first decile of the market-capitalization sorted deciles.

The strategy is clearly triggering false positive signals, where we are told to stay invested or switch into the underlying asset with a subsequent negative return

4 The scatter plots for the other portfolios sorted on the various characteristics are available from the author upon request.

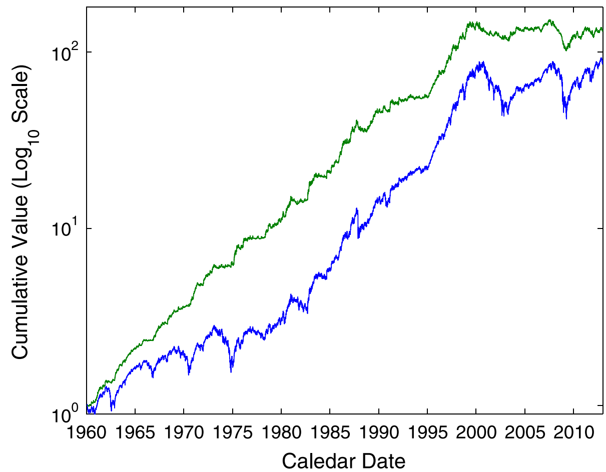

Figure 2 Time Series Plot of Cumulative Values of the Buy-and-Hold and the Combination Moving Average returns: High ME Decile Portfolio.
Notes: Figure 2 presents a time series plot of the cumulative values of the buy-and-hold portfolio returns versus the combination moving average strategy returns for the high ME decile. The sample contains 13,592 daily observations and the data covers the January 4, 1960 until December 31, 2013.

(negative quadrant of returns in the figure). Similarly, there are a few instances of a false negative signal where we switch into the risk-free asset, while the underlying risky asset has a positive excess return in the following period. Nevertheless, the signal is right about two out of every three times, and in those instances, the scatter plot resembles the payoff of an at-the-money put option combined with a long position in the underlying risky asset. This positive convexity is the driving factor for the relative outperformance of the moving average strategy relative to the buy-and-hold strategy (see Figure 2). Holding the signal success rate constant, risky assets with more volatile returns will experience a higher average outperformance, and this is evidenced in all of the previous tables.

III. ROBUSTNESS CHECKS

In this section, I report my findings for several robustness checks performed on the performance of the CMA strategy versus the BH strategy for decile portfolios sorted on market capitalization, book-to-market ratios, momentum, and standard deviation.

A. Subperiods

In this robustness check, I split the sample in two subperiods of roughly equal length. The first subperiod runs from January 4, 1960 to December 31, 1987.

The second subperiod goes from January 4, 1989 to December 31, 2013. For the sake of brevity, Table 3 reports the only the annualized abnormal returns and the goodness-of-fit using the CAPM, the Fama–French and Carhart models in either subperiod. The findings show robust and unaccounted for abnormal returns for portfolios sorted on market capitalization and standard deviation of return in both subperiods. For the book-to-market and momentum decile portfolios, there are only a few statistically significant abnormal returns in the second subperiod compared with statistical significance across the board in the first subperiod. Nevertheless, the second subperiod abnormal returns of the highest book-to-market decile portfolio is significant using the CAPM, while book-to-market deciles 5–10 show significant abnormal returns using the Fama–French and Carhart model. Similarly, the second subperiod abnormal returns of momentum deciles 1–3 are positive and statistically significant using the CAPM. Using the Fama–French model, it appears that momentum decile portfolios 1–4 have positive and statistically significant abnormal returns in the second subperiod, while the Carhart model reveals that only the extreme momentum deciles (1–2 and 10) have positive and statistically significant abnormal returns in the second subperiod. Furthermore, the abnormal returns in both subperiods are lower for large-cap portfolios, value portfolios, winner portfolios, and portfolios of stocks with high standard deviation of return in the past.

B. Buy-and-hold as a benchmark

An alternative way of judging the performance of the CMA strategy is to use the BH strategy as a benchmark. One simple way of to do this is to regress the CMA return on a constant and the BH return. A positive and statistically significant intercept indicates a superior performance of the active CMA return relative to the passive BH benchmark.

$$\widetilde{CR}_{i,t} = \alpha_i + \beta_{BH,i} R_{i,t} + \varepsilon_{i,t} \tag{7}$$

A modified version of this regression involves testing for any market timing ability of the active strategy by including the negative BH return in the regression along the lines of the market timing tests of Henriksson and Merton (1981)

$$\widetilde{CR}_{i,t} = \alpha_i + \beta_{BH,i} R_{i,t} + \gamma_{BH,i}\, max\left(-R_{i,t}, 0\right) + \varepsilon_{i,t} \tag{8}$$

Table 4 presents the findings of the simple regression of the active CMA return on the passive BH benchmark as well as the modified regression involving the negative component of the passive BH return. The most striking finding to emerge from these regression results is large and statistically as well as economically significant intercepts. Secondly, the exposure of the CMA return to the BH return ranges between 0.35 and 0.51 for the first regression specification in (7) and between 0.37 and 0.63 for the second regression specification in (8). Finally,

Table 3 Factor regressions results in subperiods

Panel A: size sorted portfolios

p	α	$\bar{R}^2$	α	$\bar{R}^2$	α	$\bar{R}^2$	α	$\bar{R}^2$	α	$\bar{R}^2$	α	$\bar{R}^2$
	1960/01/04–1987/12/31						1988/01/04–2013/12/31					
	CAPM		Fama–French		Carhart		CAPM		Fama–French		Carhart	
Low	17.449***	0.447	19.386***	0.700	19.394***	0.700	10.570***	0.509	11.911***	0.651	12.040***	0.652
2	15.896***	0.511	17.566***	0.711	17.846***	0.711	7.078***	0.577	8.760***	0.711	8.585***	0.712
3	14.707***	0.538	16.224***	0.717	16.585***	0.719	5.008***	0.610	6.304***	0.718	6.057***	0.719
4	14.165***	0.560	15.480***	0.712	15.963***	0.715	4.536***	0.633	5.606***	0.722	5.363***	0.723
5	13.352***	0.578	14.555***	0.711	15.023***	0.714	3.906**	0.653	4.731***	0.714	4.299***	0.716
6	13.095***	0.611	14.207***	0.703	14.778***	0.707	4.156***	0.665	4.658***	0.695	4.295***	0.696
7	12.579***	0.629	13.396***	0.697	13.802***	0.698	4.264***	0.676	4.871***	0.695	4.562***	0.696
8	11.437***	0.657	12.237***	0.693	12.732***	0.696	3.231**	0.700	3.713***	0.708	3.305**	0.710
9	10.206***	0.675	10.654***	0.685	11.108***	0.687	1.309	0.713	1.702	0.718	1.448	0.718
High	6.337***	0.685	5.636***	0.696	5.958***	0.697	–0.126	0.725	–0.362	0.735	–1.139	0.741

Panel B: book-to-market sorted portfolios

P	α	$\bar{R}^2$	α	$\bar{R}^2$	α	$\bar{R}^2$	α	$\bar{R}^2$	α	$\bar{R}^2$	α	$\bar{R}^2$
	1960/01/04–1987/12/31						1988/01/04–2013/12/31					
	CAPM		Fama–French		Carhart		CAPM		Fama–French		Carhart	
Low	11.742***	0.684	9.349***	0.708	9.560***	0.708	1.374	0.677	0.322	0.706	–0.584	0.713
2	9.687***	0.673	8.892***	0.681	9.318***	0.683	0.039	0.690	–0.141	0.693	–0.506	0.694
3	9.758***	0.660	9.389***	0.665	9.907***	0.667	0.350	0.672	0.292	0.675	0.349	0.675
4	9.943***	0.657	10.242***	0.660	10.552***	0.661	1.309	0.667	2.153	0.694	1.820	0.695
5	8.662***	0.625	8.909***	0.628	9.530***	0.633	–0.041	0.628	1.065	0.672	0.581	0.674
6	7.262***	0.605	8.101***	0.618	8.454***	0.620	2.062	0.650	3.015**	0.680	2.559*	0.682
7	7.425***	0.587	8.715***	0.599	9.287***	0.603	1.673	0.625	2.888**	0.681	2.698**	0.681
8	7.060***	0.608	9.170***	0.639	9.690***	0.643	1.476	0.545	3.549**	0.664	2.673*	0.670
9	7.685***	0.579	10.219***	0.621	11.053***	0.630	1.436	0.587	3.155**	0.672	2.914**	0.673
High	9.388***	0.582	11.959***	0.632	12.663***	0.637	4.089**	0.553	6.288***	0.657	5.808***	0.659

Table 3 (*continued*)

Panel C: momentum sorted portfolios

P	α	$\overline{R}^2$	α	$\overline{R}^2$	α	$\overline{R}^2$	α	$\overline{R}^2$	α	$\overline{R}^2$	α	$\overline{R}^2$
	1960/01/04–1987/12/31						1988/01/04–2013/12/31					
	CAPM		Fama–French		Carhart		CAPM		Fama–French		Carhart	
Low	20.051***	0.622	19.904***	0.649	16.822***	0.703	17.511***	0.535	19.209***	0.559	12.067***	0.688
2	14.169***	0.619	14.102***	0.627	11.818***	0.670	7.669***	0.596	8.693***	0.611	3.905**	0.708
3	9.627***	0.621	9.532***	0.628	7.767***	0.661	4.376**	0.619	5.284***	0.642	1.929	0.710
4	9.927***	0.648	9.791***	0.650	9.114***	0.655	2.493	0.641	3.362**	0.669	1.393	0.698
5	9.389***	0.656	9.509***	0.659	9.439***	0.659	0.106	0.634	0.609	0.647	–0.642	0.660
6	9.554***	0.640	9.704***	0.640	10.101***	0.642	–0.978	0.644	–0.426	0.661	–0.728	0.662
7	9.387***	0.653	9.644***	0.655	10.485***	0.662	0.186	0.655	0.538	0.664	0.773	0.665
8	7.509***	0.631	7.999***	0.633	9.534***	0.657	–2.066	0.633	–1.718	0.642	–0.750	0.652
9	8.989***	0.631	9.338***	0.641	11.367***	0.677	0.031	0.654	0.203	0.655	1.753	0.677
High	9.689***	0.582	9.781***	0.605	12.898***	0.664	1.844	0.567	1.334	0.590	4.221**	0.638

Panel D: standard deviation sorted portfolios

P	α	$\overline{R}^2$	α	$\overline{R}^2$	α	$\overline{R}^2$	α	$\overline{R}^2$	α	$\overline{R}^2$	α	$\overline{R}^2$
	1960/01/04–1987/12/31						1988/01/04–2013/12/31					
	CAPM		Fama–French		Carhart				Fama–French		Carhart	
High	15.596***	0.416	17.447***	0.596	16.860***	0.598	8.085***	0.410	9.475***	0.483	9.168***	0.484
2	18.273***	0.523	20.032***	0.677	19.937***	0.677	10.333***	0.574	11.672***	0.631	10.721***	0.637
3	17.547***	0.550	19.262***	0.694	19.398***	0.694	8.468***	0.608	9.962***	0.669	9.150***	0.674
4	15.135***	0.552	16.800***	0.692	16.893***	0.693	5.976***	0.602	7.518***	0.664	6.785***	0.668
5	14.080***	0.561	15.650***	0.690	15.890***	0.691	5.285***	0.597	6.774***	0.662	6.120***	0.665
6	13.109***	0.581	14.458***	0.683	14.681***	0.684	4.622***	0.595	5.987***	0.655	5.461***	0.658
7	12.037***	0.585	13.356***	0.670	13.533***	0.670	3.881***	0.575	4.903***	0.622	4.662***	0.623
8	10.705***	0.584	11.955***	0.653	12.161***	0.653	3.623***	0.534	4.405***	0.574	4.306***	0.574
9	9.000***	0.572	10.167***	0.628	10.241***	0.628	4.184***	0.419	4.831***	0.462	4.814***	0.462
Low	7.933***	0.527	9.053***	0.579	9.022***	0.579	4.163***	0.145	4.369***	0.164	4.515***	0.165

This table reports alphas and adjusted R^2 of the regressions of the CMAP excess returns on the market factor, the Fama–French three-factors, and the Carhart four-factors in two subperiods using portfolios sorted by size, book-to-market, momentum, and standard deviation of return. The alphas are annualized and in percent. The sample period covers January 4, 1960 until December 31, 2013 with value-weighted portfolio returns and is split in two sub-periods of equal length. The lengths of the moving average windows are 5, 10, 20, 50, 100, and 200 days. Newey and West (1987) standard errors with 24 lags are used in reporting statistical significance of a two-sided null hypothesis at the 1, 5, and 10% level is given by a ***, a **, and a *, respectively. α is the intercept of the regression, β_m is the factor loading on MKT, β_s os the factor loading on SMB, β_h is the factor loading on HML, β_u is the factor loading on UMD, and $\overline{R}^2$ is the adjusted R-squared of the regression.

Table 4 Regression of CMA returns on BH returns

Panel A: size sorted portfolios

Portfolio	α	β_{BH}	$\bar{R}^2$	α	β_{BH}	γ_{BH}	$\bar{R}^2$
Low	18.781***	0.406***	0.551	7.654***	0.493***	0.155***	0.563
2	15.472***	0.404***	0.554	12.446***	0.423***	0.035***	0.555
3	14.306***	0.418***	0.570	11.405***	0.435***	0.033***	0.570
4	13.383***	0.411***	0.563	10.999***	0.425***	0.027***	0.563
5	12.857***	0.415***	0.562	10.521***	0.430***	0.027***	0.563
6	12.744***	0.412***	0.559	8.964***	0.436***	0.046***	0.560
7	12.465***	0.411***	0.558	7.801***	0.441***	0.056***	0.560
8	11.074***	0.415***	0.563	7.553***	0.437***	0.042***	0.564
9	9.263***	0.414***	0.561	6.319***	0.433***	0.036***	0.561
High	5.538***	0.417***	0.564	5.116***	0.419***	0.005	0.564

Panel B: book-to-market sorted portfolios

Portfolio	α	β_{BH}	$\bar{R}^2$	α	β_{BH}	γ_{BH}	$\bar{R}^2$
Low	8.482***	0.407***	0.554	8.005***	0.409***	0.005	0.554
2	7.849***	0.421***	0.564	4.740***	0.439***	0.036***	0.565
3	8.293***	0.430***	0.575	3.717***	0.458***	0.055***	0.576
4	8.669***	0.423***	0.569	4.123***	0.451***	0.054***	0.570
5	7.687***	0.420***	0.562	6.587***	0.426***	0.013	0.562
6	8.381***	0.430***	0.579	6.446***	0.442***	0.024***	0.579
7	8.640***	0.438***	0.583	5.795***	0.456***	0.036***	0.583
8	8.760***	0.418***	0.556	9.216***	0.415***	−0.006	0.556
9	9.344***	0.442***	0.583	7.621***	0.453***	0.020**	0.583
High	11.792***	0.446***	0.589	6.039***	0.476***	0.061***	0.591

Panel C: momentum sorted portfolios

Portfolio	α	β_{BH}	$\bar{R}^2$	α	β_{BH}	γ_{BH}	$\bar{R}^2$
Low	15.343***	0.353***	0.509	9.854***	0.375***	0.046***	0.511
2	11.648***	0.396***	0.537	10.259***	0.402***	0.014*	0.537
3	9.588***	0.413***	0.559	7.415***	0.424***	0.024***	0.559
4	8.867***	0.415***	0.567	4.933***	0.437***	0.046***	0.568
5	7.442***	0.419***	0.564	7.061***	0.421***	0.005	0.564
6	7.573***	0.426***	0.570	5.782***	0.437***	0.022**	0.571
7	7.973***	0.422***	0.568	5.750***	0.436***	0.027***	0.568
8	7.091***	0.460***	0.607	4.042***	0.479***	0.036***	0.607
9	8.354***	0.440***	0.586	6.568***	0.450***	0.020**	0.586
High	11.891***	0.440***	0.589	12.480***	0.438***	−0.005	0.589

Panel D: standard deviation sorted portfolios

Portfolio	α	β_{BH}	$\bar{R}^2$	α	β_{BH}	γ_{BH}	$\bar{R}^2$
High	28.846***	0.512***	0.634	0.407	0.633***	0.265***	0.657
2	21.177***	0.415***	0.555	6.039***	0.491***	0.148***	0.565
3	18.652***	0.401***	0.544	8.735***	0.455***	0.103***	0.549
4	16.815***	0.401***	0.542	8.785***	0.448***	0.092***	0.546
5	16.134***	0.402***	0.545	8.599***	0.451***	0.094***	0.549

Table 4 (*continued*)

Panel D: standard deviation sorted portfolios

Portfolio	α	β_{BH}	$\overline{R}^2$	α	β_{BH}	γ_{BH}	$\overline{R}^2$
6	15.014***	0.400***	0.543	8.145***	0.449***	0.093***	0.547
7	14.155***	0.404***	0.542	7.401***	0.458***	0.102***	0.547
8	13.378***	0.400***	0.530	4.958***	0.476***	0.145***	0.540
9	12.701***	0.388***	0.508	4.759***	0.476***	0.168***	0.522
Low	11.851***	0.388***	0.511	4.762***	0.496***	0.210***	0.534

This table reports alphas, betas, and adjusted R^2 of the regressions of the CMA returns on the BH returns as well as the negative component of the BH return using portfolios sorted by size, book-to-market, momentum, and standard deviation of return. The alphas are annualized and in percent. The sample period covers January 4, 1960 until December 31, 2013 with value-weighted portfolio returns. The lengths of the moving average windows are 5, 10, 20, 50, 100, and 200 days. Newey and West (1987) standard errors with three lags are used in reporting statistical significance of a two-sided null hypothesis at the 1, 5, and 10% level is given by a ***, a **, and a *, respectively.

the market timing coefficient, γ_{BH} is almost always positive and statistically significant, especially for portfolios sorted on market capitalization and standard deviation of return.

C. Statistical significance, trading intensity, and break-even transaction costs

Table 5 reports the statistical significance in the improvement of the average return $\Delta\mu$ of the CMA portfolio over the BH portfolio as well as the reduction in the return standard deviation $\Delta\sigma$. The evidence points towards a substantial improvement in a mean-variance sense for all sets of portfolios under consideration with the exception of the highest market cap decile and momentum decile eight. The annualized improvement in the average return ranges from over 1% to just under 14% per annum, while the reduction in the standard deviation is between approximately 3% to over 12%. The CMA strategy is active more often than not ranging between 54% and 71% of the sample. Yet, the number of transactions, number of trades (NT), is never above 6000 and can be as little as under 4000 for decile 10 of standard deviation sorted portfolios. In a sample of 13,592 days this translates into average holding periods of between 2 and 3 days between transactions. Next, I report the break-even transaction costs, break-even transaction costs (BETC), calculated as the level of one-way proportional transaction cost in percent that would eliminate completely the average CMAP portfolio return. The values of the BETC for the various sets of portfolio range between almost 0.00% and as high as 0.15%. Finally, the last two columns report the fraction of months that the CMA strategy generates a positive return (p_1) as well as a return that is in excess of the risk-free rate (p_2). With the exception of three momentum, all the reported fractions range from 68% to 75% success rate of the CMA strategy delivering a positive return and 51% to 60% probability of the

Table 5 Trading frequency and break-even transaction cost

Panel A: size sorted portfolios

Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1	p_2
Low	11.73	6.15	0.62	4247	0.15	0.75	0.58
2	8.43	7.64	0.62	4656	0.10	0.73	0.56
3	6.80	7.40	0.64	4740	0.08	0.72	0.56
4	6.25	7.38	0.64	4882	0.07	0.72	0.56
5	5.48	7.23	0.64	4906	0.06	0.71	0.56
6	5.60	6.87	0.65	4935	0.06	0.71	0.56
7	5.28	6.96	0.65	4950	0.06	0.71	0.55
8	4.11	7.01	0.65	5080	0.04	0.70	0.55
9	2.54	6.90	0.65	5332	0.03	0.70	0.54
High	−0.34	7.12	0.64	5655	−0.00	0.68	0.53

Panel B: book-to-market sorted portfolios

Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1	p_2
Low	2.95	7.94	0.61	5559	0.03	0.70	0.53
2	1.55	7.06	0.63	5495	0.02	0.69	0.53
3	2.02	6.67	0.64	5513	0.02	0.69	0.53
4	2.43	6.93	0.64	5376	0.02	0.69	0.54
5	1.24	6.87	0.64	5509	0.01	0.68	0.53
6	1.67	6.58	0.65	5256	0.02	0.68	0.54
7	1.65	6.34	0.65	5313	0.02	0.69	0.54
8	1.26	6.94	0.66	5312	0.01	0.68	0.54
9	1.64	6.73	0.66	5209	0.02	0.68	0.54
High	3.53	7.46	0.65	5175	0.04	0.69	0.54

Panel C: momentum sorted portfolios

Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1	p_2
Low	13.72	12.59	0.54	5217	0.14	0.73	0.51
2	6.86	9.36	0.58	5391	0.07	0.71	0.51
3	3.59	7.88	0.62	5458	0.04	0.69	0.52
4	2.92	7.46	0.62	5420	0.03	0.69	0.53
5	1.63	7.03	0.63	5493	0.02	0.69	0.53
6	1.35	6.70	0.64	5478	0.01	0.69	0.53
7	1.76	6.68	0.64	5423	0.02	0.69	0.54
8	−0.15	6.33	0.66	5532	−0.00	0.69	0.55
9	1.26	7.00	0.65	5445	0.01	0.69	0.54
High	1.98	8.68	0.65	5201	0.02	0.70	0.56

Panel D: standard deviation sorted portfolios

Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1	p_2
High	9.32	7.23	0.67	4316	0.12	0.72	0.58
2	10.82	8.55	0.62	4738	0.12	0.73	0.56
3	9.59	8.32	0.63	4715	0.11	0.73	0.56
4	7.43	7.69	0.65	4711	0.09	0.72	0.57
5	6.81	7.05	0.66	4641	0.08	0.72	0.57

Table 5 (*continued*)

Panel D: standard deviation sorted portfolios

Portfolio	$\Delta\mu$	$\Delta\sigma$	p_A	NT	BETC	p_1	p_2
6	6.18	6.57	0.67	4630	0.07	0.71	0.57
7	5.64	5.76	0.68	4603	0.07	0.72	0.58
8	5.21	5.03	0.69	4612	0.06	0.71	0.58
9	5.07	4.22	0.70	4441	0.06	0.72	0.59
Low	5.25	3.14	0.71	3961	0.07	0.73	0.60

This table reports the results for the improvement delivered by the MA switching strategy over the buy-and-hold strategy, the trading frequency as well as the break-even transaction cost using 10 decile portfolios sorted by size, book-to-market, momentum, and standard deviation of return. The sample period covers January 4, 1960 until December 31, 2013 with value-weighted portfolio returns. $\Delta\mu$ is the annualized improvement in the average in-sample daily return, $\Delta\sigma$ isthe annualized improvement in the return standard deviation, p_A is the proportion of days during which there is a hold signal, NT is the number of transactions (buy or sell) over the entire sample period, BETC is the break-even one-sided transaction cost in percent, p_1 is the proportion of days during which a buy signal was followed by a positive return of the underlying portfolio and p_2 is the proportion of days during which a buy signal was followed by a portfolio return in excess of the risk-free rate. The lengths of the moving average windows are 5, 10, 20, 50, 100, and 200 days. The moving average portfolio is an equal-weighted combination of the six individual moving average returns.

CMA strategy having a positive excess return. These values indicate that, more often than not, the CMA strategy is on the right side of the market. These considerably favorable odds are in line with the evidence reported previously regarding the superior performance of the CMA switching strategy.

IV. DRIVERS OF ABNORMAL RETURNS

In this section, I investigate the reasons for the superior returns of the CMAP portfolios. To this end, I control the CMAP performance for economic expansions and contractions as well as other state contingencies like the sign of the lagged market return. Furthermore, I investigate the conditional performance of the CMAP returns while controlling for three instrumental variables with documented predictive power over stock returns.

A. Market timing

The first approach towards testing for market timing ability is the quadratic regression of Treynor and Mazuy (1966)

$$\mathrm{CMAP}_{jt,L} = \alpha_j + \beta_{j,m} r_{mkt,t} + \beta_{j,m^2} r_{mkt,t}^2 + \varepsilon_{jt}, \quad j = 1, \ldots, N \tag{9}$$

where statistically significant evidence of a positive β_{j,m^2} can be interpreted as evidence in favor of market timing ability. The second approach is to allow for a state-contingent $\beta_{j,m}$ based on the direction of move of the market return as in Henriksson and Merton (1981)

$$\text{CMAP}_{jt,L} = \alpha_j + \beta_{j,m} r_{mkt,t} + \gamma_{j,m} r_{mkt,t} I_{\{r_{mkt,t}>0\}} + \varepsilon_{jt}, \quad j = 1, \ldots, N \tag{10}$$

where $I_{\{r_{mkt,t}>0\}}$ is an indicator function of the event of a positive market return. A statistically significant value of $\gamma_{j,m}$ is usually interpreted as evidence of successful market timing ability.

Table 6 presents the results of the two market timing regressions for various sets of value-weighted decile portfolios. Panel TM presents the empirical results from the Treynor and Mazuy (1966) quadratic regression while Panel HM presents the results for the state-contingent beta regression of Henriksson and Merton (1981). In both regressions, both β_{j,m^2} and $\gamma_{j,m}$ are highly statistically significant, indicating there is strong evidence of market timing ability of the switching moving average strategy. Nevertheless, a few portfolios have negative or insignificant values of β_{m^a} and γ_m suggesting that the market timing ability of the CMA strategy does not apply for all of the portfolios under consideration. This finding suggests that market timing alone is not the sole driver of the abnormal returns generated by the combination moving average strategy.

B. Business cycles and market states

Following Han et al. (2013), I investigate the performance of the CMAP portfolio returns conditional on the dividend yield of the stock market as well as the short-term risk-free rate. Table 7 presents the results for the various sets of portfolio deciles. The evidence overwhelmingly indicates that CMAP abnormal returns are higher small-cap portfolios, high book-to-market portfolio, loser portfolios as well as both high and low risk portfolios sorted on standard deviation of return.

The first notable finding in Table 7 is the reduced statistical significance of the abnormal returns. The α s are reduced in value as well, occasionally turning negative and, for the most part, not statistically significant. This is an indication that this conditional model is capable of capturing some of the apparent abnormal performance detected by the unconditional models presented previously in the paper.

The majority of CMAP portfolios experience an increase in average return when the market dividend yield increases. Similarly, for most portfolios there is an increase in average returns when the short-term risk-free rate rises. In term of the time-varying factor loadings, most market betas of the CMAP portfolios become less negative when the market's dividend yield increases. The impact of the risk-free rate on the market betas is the opposite. A less consistent pattern emerges for the time-varying SMB loading. The SMB beta of the CMAP spread increases with DP_m for portfolios sorted on market capitalization is mixed for portfolios sorted on book-to-market and decreases with DP_m for portfolios sorted on momentum and standard deviation of return. The effect of the risk-free rate on

Table 6 Market timing Regressions

Panel A: size sorted portfolios

Portfolio	α	β_m	β_{m^2}	$\overline{R}^2$	α	β_m	γ_m	$\overline{R}^2$
	TM				HM			
Low	11.499***	−0.419***	0.011***	0.488	3.257**	−0.355***	0.133***	0.489
2	10.661***	−0.555***	0.004***	0.551	6.084***	−0.522***	0.068***	0.552
3	9.370***	−0.558***	0.003***	0.581	6.131***	−0.534***	0.048***	0.581
4	8.861***	−0.564***	0.003***	0.604	6.620***	−0.546***	0.036***	0.604
5	8.252***	−0.568***	0.002**	0.622	6.113***	−0.552***	0.033***	0.622
6	7.783***	−0.546***	0.004***	0.642	5.484***	−0.527***	0.041***	0.642
7	7.375***	−0.557***	0.005***	0.656	5.045***	−0.537***	0.043***	0.655
8	6.242***	−0.573***	0.005***	0.681	4.278***	−0.555***	0.039***	0.680
9	4.311***	−0.571***	0.007***	0.696	3.706***	−0.560***	0.027***	0.695
High	1.881**	−0.595***	0.005***	0.709	3.550***	−0.600***	−0.004	0.708

Panel B: book-to-market sorted portfolios

Portfolio	α	β_m	β_{m^2}	$\overline{R}^2$	α	β_m	γ_m	$\overline{R}^2$
	TM				HM			
Low	7.119***	−0.646***	−0.001	0.673	9.258***	−0.661***	−0.030***	0.673
2	4.021***	−0.585***	0.004***	0.680	5.087***	−0.587***	−0.001	0.680
3	3.728***	−0.547***	0.006***	0.664	3.797***	−0.540***	0.018*	0.663
4	3.225***	−0.561***	0.010***	0.664	2.248*	−0.544***	0.043***	0.661
5	3.427***	−0.545***	0.004***	0.624	4.633***	−0.548***	−0.002	0.623
6	3.506***	−0.522***	0.005***	0.631	3.521***	−0.517***	0.015	0.630
7	2.638***	−0.500***	0.008***	0.610	2.004*	−0.487***	0.032***	0.608
8	2.853***	−0.524***	0.006***	0.560	3.087**	−0.519***	0.016	0.559
9	2.803***	−0.523***	0.008***	0.581	2.601**	−0.513***	0.026**	0.579
High	4.914***	−0.567***	0.008***	0.559	4.149***	−0.554***	0.033***	0.557

Table 6 (*continued*)

Panel C: momentum sorted portfolios

Portfolio	α	β_m	β_{m^2}	$\overline{R}^2$	α	β_m	γ_m	$\overline{R}^2$
	TM				HM			
Low	21.010***	−0.874***	−0.009***	0.546	23.220***	−0.898***	−0.053***	0.545
2	13.002***	−0.716***	−0.008***	0.592	16.258***	−0.745***	−0.063***	0.591
3	8.981***	−0.615***	−0.007***	0.610	11.261***	−0.637***	−0.049***	0.609
4	6.017***	−0.588***	0.002*	0.638	6.966***	−0.592***	−0.007	0.638
5	5.339***	−0.564***	−0.002*	0.638	7.862***	−0.581***	−0.035***	0.638
6	3.015***	−0.536***	0.006***	0.638	4.725***	−0.540***	−0.002	0.637
7	3.502***	−0.538***	0.006***	0.651	3.749***	−0.533***	0.015	0.650
8	0.358	−0.513***	0.010***	0.631	−0.304	−0.497***	0.039***	0.627
9	2.847***	−0.567***	0.007***	0.643	2.071***	−0.554***	0.031***	0.641
High	3.543***	−0.659***	0.010***	0.572	1.684	−0.637***	0.051***	0.570

Panel D: standard deviation sorted portfolios

Portfolio	α	β_m	β_{m^2}	$\overline{R}^2$	α	β_m	γ_m	$\overline{R}^2$
	TM				HM			
High	11.014***	−0.515***	0.006***	0.404	5.661***	−0.475***	0.081***	0.405
2	12.659***	−0.633***	0.008***	0.547	6.690***	−0.587***	0.096***	0.547
3	12.054***	−0.625***	0.005***	0.578	8.706***	−0.599***	0.056***	0.578
4	9.650***	−0.580***	0.005***	0.578	7.071***	−0.558***	0.046***	0.578
5	8.674***	−0.531***	0.005***	0.579	5.550***	−0.506***	0.054***	0.579
6	7.449***	−0.496***	0.007***	0.588	4.258***	−0.468***	0.059***	0.587
7	6.669***	−0.435***	0.006***	0.576	4.304***	−0.413***	0.048***	0.575
8	5.274***	−0.373***	0.009***	0.552	2.153**	−0.343***	0.064***	0.549
9	4.617***	−0.291***	0.009***	0.478	0.986	−0.259***	0.071***	0.474
Low	4.149***	−0.163***	0.009***	0.288	0.730	−0.133***	0.067***	0.282

This table reports alphas, betas, and adjusted R^2 of the market timing regressions of the CMAP excess returns on the market factor using portfolios sorted by size, book-to-market, momentum and standard deviation of return. The TM panel reports the results using the Treynor and Mazuy (1966) quadratic regression with the squared market factor (β_{m^2}) while the HM panel reports the results using the Henriksson and Merton (1981) regression with option-like returns on the market (γ_m). The sample period covers January 4, 1960 until December 31, 2013 with value-weighted portfolio returns. The lengths of the moving average windows are 5, 10, 20, 50, 100, and 200 days. The moving average portfolio is an equal-weighted combination of the six individual moving average returns. Newey and West (1987) standard errors with 3 lags are used in reporting statistical significance of a two-sided null hypothesis at the 1, 5, and 10% level is given by a ***, a **, and a *, respectively.

Table 7 Conditional regressions with market dividend yield and treasury bill rate

Panel A: size sorted portfolios

P	α	DP_m	r_f	β_m	β_s	β_h	β_u	$r_m \times DP_m$
Low	13.443***	−0.007	1.478***	−0.582***	−0.393***	−0.523***	−0.042***	0.059***
2	6.037**	0.001	1.289***	−0.853***	−0.592***	−0.638***	0.051***	0.101***
3	0.719	0.009***	0.733*	−0.867***	−0.551***	−0.545***	0.077***	0.115***
4	−0.352	0.009**	0.754**	−0.881***	−0.501***	−0.487***	0.079***	0.125***
5	−2.668	0.013***	0.345	−0.893***	−0.418***	−0.426***	0.107***	0.132***
6	−1.724	0.012***	0.428	−0.813***	−0.232***	−0.335***	0.098***	0.116***
7	0.180	0.009**	0.356	−0.826***	−0.168***	−0.417***	0.061***	0.110***
8	−2.056	0.010**	0.378	−0.860***	−0.110***	−0.392***	0.095***	0.119***
9	−4.844**	0.014***	0.061	−0.833***	0.042**	−0.390***	0.049***	0.105***
High	−3.076	0.011***	−0.599*	−0.796***	0.154***	−0.132***	0.138***	0.092***

Panel B: book-to-market sorted portfolios

P	α	DP_m	r_f	β_m	β_s	β_h	β_u	$r_m \times DP_m$
Low	−9.240***	0.021***	−0.401	−0.706***	0.144***	0.149***	0.108***	0.049***
2	−6.610**	0.016***	−0.269	−0.798***	0.129***	−0.291***	0.102***	0.090***
3	−5.211**	0.011***	0.358	−0.757***	0.140***	−0.367***	0.037***	0.093***
4	−2.494	0.011***	0.041	−0.809***	0.085***	−0.567***	0.034***	0.090***
5	−0.746	0.005	0.317	−0.864***	−0.012	−0.759***	0.100***	0.120***
6	−0.849	0.008*	0.042	−0.835***	−0.018	−0.583***	0.096***	0.108***
7	−0.288	0.006	0.360	−0.770***	0.032*	−0.672***	0.071***	0.087***
8	0.393	0.007	0.005	−0.756***	−0.006	−0.780***	0.118***	0.062***
9	1.567	0.007*	−0.035	−0.830***	−0.037*	−0.722***	0.117***	0.087***
High	2.134	0.012**	−0.392	−0.828***	−0.086***	−0.871***	0.153***	0.066***

Panel C: momentum sorted portfolios

P	α	DP_m	r_f	β_m	β_s	β_h	β_u	$r_m \times DP_m$
Low	12.035***	−0.004	0.838	−1.174***	−0.452***	−0.534***	0.975***	0.167***
2	0.395	0.008	0.151	−1.019***	−0.120***	−0.448***	0.634***	0.131***
3	−1.453	0.010**	−0.363	−0.874***	0.064***	−0.487***	0.404***	0.107***
4	−2.238	0.009**	0.125	−0.809***	0.131***	−0.507***	0.242***	0.082***
5	−6.022**	0.012***	0.242	−0.728***	0.164***	−0.333***	0.156***	0.058***
6	−7.755***	0.015***	0.257	−0.709***	0.166***	−0.418***	0.052***	0.054***
7	−3.062	0.007	0.744**	−0.733***	0.183***	−0.369***	−0.000	0.073***
8	−7.007***	0.013***	0.360	−0.706***	0.170***	−0.380***	−0.071***	0.063***
9	−3.984	0.013***	0.088	−0.765***	0.099***	−0.318***	−0.125***	0.071***
High	−4.622	0.019***	−0.398	−0.871***	−0.033	−0.063**	−0.322***	0.085***

Panel D: standard deviation sorted portfolios

P	α	DP_m	r_f	β_m	β_s	β_h	β_u	$r_m \times DP_m$
High	11.674***	0.006	−0.644	−0.554***	−0.182***	−0.508***	0.012	0.006
2	6.758*	0.010*	0.208	−0.768***	−0.218***	−0.636***	0.171***	0.054***
3	3.590	0.013**	0.282	−0.755***	−0.132***	−0.669***	0.139***	0.039***
4	0.744	0.014***	0.155	−0.753***	−0.095***	−0.683***	0.117***	0.046***
5	0.480	0.013***	0.234	−0.701***	−0.013	−0.681***	0.113***	0.044***
6	0.405	0.011***	0.279	−0.687***	0.009	−0.664***	0.085***	0.055***
7	0.867	0.007*	0.606*	−0.602***	0.068***	−0.583***	0.047***	0.055***
8	1.508	0.006*	0.427	−0.494***	0.095***	−0.479***	0.022**	0.040***
9	3.678*	0.003	0.354	−0.363***	0.081***	−0.405***	0.010	0.031***
Low	4.102**	0.003	0.216	−0.082***	0.142***	−0.107***	−0.034***	−0.024***

Table 7 (*continued*)

Panel A: size sorted portfolios

P	$r_s \times DP_m$	$r_h \times DP_m$	$r_u \times DP_m$	$r_m \times r_f$	$r_s \times r_f$	$r_h \times r_f$	$r_u \times r_f$	$\overline{R}^2$
Low	0.024***	0.152***	0.017***	−4.879***	−10.772***	−4.080***	−0.329	0.673
2	0.052***	0.207***	−0.009	−3.302***	−7.580***	−6.060***	−1.298**	0.719
3	0.063***	0.185***	−0.026***	−4.298***	−8.758***	−5.695***	−0.325	0.729
4	0.071***	0.176***	−0.029***	−5.157***	−10.058***	−6.506***	−0.392	0.732
5	0.081***	0.145***	−0.039***	−4.937***	−12.411***	−3.947***	0.076	0.731
6	0.040***	0.111***	−0.047***	−5.608***	−10.377***	−3.323***	1.373***	0.713
7	0.053***	0.153***	−0.022***	−4.566***	−12.575***	−5.318***	−0.103	0.708
8	0.048***	0.152***	−0.035***	−4.749***	−11.050***	−6.973***	0.087	0.718
9	0.014*	0.152***	−0.019***	−3.469***	−8.231***	−6.249***	−0.120	0.718
High	0.010	0.059***	−0.060***	−1.897***	−1.964***	−0.474	2.623***	0.731

Panel B: book-to-market sorted portfolios

P	$r_s \times DP_m$	$r_h \times DP_m$	$r_u \times DP_m$	$r_m \times r_f$	$r_s \times r_f$	$r_h \times r_f$	$r_u \times r_f$	$\overline{R}^2$
Low	−0.011	0.017	−0.056***	−1.274***	−4.049***	5.340***	4.373***	0.711
2	−0.016*	0.202***	−0.046***	−2.797***	−4.897***	−10.659***	1.329***	0.702
3	−0.018**	0.182***	−0.044***	−4.167***	−5.347***	−7.583***	3.319***	0.684
4	−0.014*	0.210***	0.010*	−1.919***	−3.679***	−7.680***	−2.873***	0.692
5	0.048***	0.262***	−0.023***	−2.717***	−7.987***	−7.951***	−1.847***	0.671
6	0.009	0.213***	−0.029***	−1.627***	−4.547***	−9.329***	−0.287	0.676
7	0.007	0.215***	−0.033***	−1.688***	−5.249***	−9.403***	0.417	0.669
8	0.031***	0.160***	−0.004	0.546	−7.492***	−2.411***	−4.656***	0.667
9	0.000	0.192***	−0.052***	−0.353	−2.673***	−9.501***	−0.439	0.672
High	−0.002	0.212***	−0.048***	−0.129	−5.446***	−6.070***	−1.751***	0.660

Panel C: momentum sorted portfolios

P	$r_s \times DP_m$	$r_h \times DP_m$	$r_u \times DP_m$	$r_m \times r_f$	$r_s \times r_f$	$r_h \times r_f$	$r_u \times r_f$	$\overline{R}^2$
Low	0.176***	0.062***	−0.215***	−6.269***	−17.333***	13.240***	8.324***	0.711
2	0.066***	0.150***	−0.132***	−1.847***	−8.611***	−1.126	5.374***	0.709
3	0.018*	0.182***	−0.062***	−1.509***	−8.265***	−4.413***	2.068***	0.704
4	−0.021**	0.198***	−0.036***	−0.797*	−4.215***	−6.267***	0.174	0.690
5	−0.019**	0.111***	−0.048***	−0.254	−6.230***	−1.826**	2.672***	0.664
6	−0.034***	0.162***	−0.036***	−0.637	−3.551***	−6.418***	2.636***	0.660
7	−0.040***	0.150***	−0.023***	−2.500***	−4.107***	−6.996***	0.549	0.671
8	−0.054***	0.149***	−0.024***	−1.575***	−1.142*	−7.424***	0.564	0.661
9	−0.039***	0.106***	−0.025***	−2.332***	−3.311***	−2.800***	0.581	0.680
High	−0.020*	−0.014	0.005	−2.520***	−4.598***	7.884***	−0.478	0.657

Panel D: standard deviation sorted portfolios

P	$r_s \times DP_m$	$r_h \times DP_m$	$r_u \times DP_m$	$r_m \times r_f$	$r_s \times r_f$	$r_h \times r_f$	$r_u \times r_f$	$\overline{R}^2$
High	−0.017	0.145***	−0.006	−4.074***	−16.779***	−2.224*	2.597***	0.523
2	−0.016	0.226***	−0.057***	−6.076***	−14.611***	−7.389***	2.584***	0.653
3	−0.034***	0.230***	−0.046***	−4.050***	−13.832***	−7.600***	1.871***	0.682
4	−0.032***	0.233***	−0.030***	−2.073***	−12.118***	−7.829***	0.285	0.680
5	−0.044***	0.238***	−0.027***	−1.791***	−10.990***	−8.997***	−0.406	0.679
6	−0.035***	0.223***	−0.021***	−1.821***	−9.622***	−7.633***	−0.147	0.674
7	−0.030***	0.214***	−0.020***	−3.459***	−10.125***	−10.167***	1.089**	0.651
8	−0.024***	0.181***	−0.019***	−3.502***	−9.827***	−9.726***	1.836***	0.615
9	−0.006	0.153***	−0.015***	−4.864***	−9.888***	−9.783***	1.992***	0.541
Low	−0.025***	0.052***	0.002	−4.414***	−7.472***	−7.701***	1.492***	0.358

This table reports alphas, betas, and adjusted R^2 of the market timing regressions of the CMAP excess returns on the C4 factors along with two instrumental variables and interaction terms of the instrumental variables with the C4 factors using portfolios sorted by various characteristics. Alphas are annualized and in percent. The sample period covers 1960/01/04 until 2013/12/31. The lengths of the moving average windows are 5, 10, 20, 50, 100, and 200 days. Newey and West (1987) standard errors with 3 lags are used in reporting statistical significance of a two−sided null hypothesis at the 1, 5, and 10% level is given by a ***, a **, and a **, respectively.

the SMB loading of the CMAP portfolios is uniformly negative. A much more consistent pattern emerges for the HML time-varying loading. All HML betas of the CMAP spreads increase with DP_m and decrease with r_f. Furthermore, these effects are very highly statistically significant. Finally, the UMD loadings of the CMAP portfolios uniformly increase with DP_m but have a mixed reaction to r_f. The risk-free rate has a mixed effect on the UMD loadings of CMAP portfolio sorted on market capitalization and book-to-market and, largely, a positive impact for portfolios sorted on momentum and standard deviation of return.

C. Conditional models with macroeconomic variables

Ferson and Schadt (1996) make a strong case for using predetermined variables in controlling for changes in economic conditions while evaluating investment performance. I augment the four-factor Carhart (1997) model with an intercept that is a linear function of a set of instruments as well as cross-products of the instrumental variables with the market return to allow for state-dependent betas with the market factor. In this conditional model, the state variables Z_t consist of a recession indicator taking on value of one during economic contractions, and a value of zero during economic expansions as well as a down market dummy variable taking on a value of one when the portfolio return is negative and a value of zero otherwise

$$\begin{aligned}\mathrm{CMAP}_{jt,L} = {} & \alpha_j + \beta_{j,m} r_{mkt,t} + \beta_{j,s} r_{smb,t} + \beta_{j,h} r_{hml,t} + \beta_{j,u} r_{umd,t} + \\ & \gamma_{j,Z}\left(Z_{t-1} \otimes \left[1_T, r_{mkt,t}, r_{smb,t}, r_{hml,t}, r_{umd,t}\right]\right) + \varepsilon_{jt}, \quad j = 1, \ldots, N.\end{aligned}$$

Table 8 presents the results of the conditional model estimation. The most notable result that emerges is that the abnormal returns increase in magnitude and are uniformly statistically significant. Despite this disconcerting finding, it is still of interest to note the response of the CMAP returns and factor loadings to the two state variables. First, it is notable that the abnormal returns of all CMAP spread portfolios are larger during economic recessions though the coefficients are statistically significant mostly for portfolios sorted on market capitalization and standard deviation of return. Secondly, the abnormal returns of the CMAP portfolios are uniformly reduced during down markets with all of the coefficients highly statistically significant. Furthermore, the CMAP portfolio loadings on all four factors are reduced during recessions, while the same effect in down markets is only apparent for loadings on the SMB factor. Conversely, the loadings on the momentum factor appear to increase during down markets though this finding is statistically significant mostly for the CMAP portfolios sorted on market capitalization and book-to-market with only a handful of momentum and standard deviation portfolios exhibiting statistical significance for this coefficient.

Finally, I consider estimating a conditional model using the market's dividend yield and a recession indicator as the two state variables with the four Carhart (1997) factors as well as interactions between the instrumental variables and the factor returns. Table 9 presents the empirical findings of this conditional

Table 8 Conditional regressions with recession indicator and down market indicator

Panel A: size sorted portfolios

P	α	RI	DN	β_m	β_s	β_h	β_u	$r_m \times RI$
Low	29.089***	0.044***	–0.167***	–0.462***	–0.444***	–0.128***	–0.036***	–0.181***
2	40.610***	0.030***	–0.226***	–0.658***	–0.527***	–0.164***	–0.032***	–0.241***
3	40.359***	0.030***	–0.231***	–0.663***	–0.477***	–0.102***	–0.028***	–0.215***
4	42.304***	0.029***	–0.249***	–0.681***0	–0.441***	–0.078***	–0.031***	–0.175***
5	41.313***	0.031***	–0.256***	–0.663***	–0.383***	–0.026**	–0.025***	–0.193***
6	39.200***	0.027***	–0.256***	–0.625***	–0.264***	–0.020*	–0.028***	–0.166***
7	38.067***	0.030***	–0.256***	–0.614***	–0.215***	–0.026**	–0.037***	–0.203***
8	38.550***	0.025***	–0.273***	–0.632***	–0.137***	–0.030***	–0.033***	–0.195***
9	37.909***	0.023***	–0.280***	–0.625***	–0.020**	–0.045***	–0.049***	–0.198***
High	32.747***	0.012	–0.271***	–0.616***	0.177***	0.047***	–0.008	–0.171***

Panel B: book-to-market sorted portfolios

P	α	RI	DN	β_m	β_s	β_h	β_u	$r_m \times RI$
Low	32.447***	0.027***	–0.237***	–0.631***	0.070***	0.274***	–0.022**	–0.186***
2	34.914***	0.019**	–0.261***	–0.640***	0.063***	0.035***	–0.007	–0.150***
3	33.586***	0.014	–0.253***	–0.590***	0.053***	–0.021*	–0.041***	–0.190***
4	34.116***	0.020**	–0.261***	–0.599***	0.043***	–0.112***	–0.040***	–0.211***
5	36.038***	0.009	–0.253***	–0.607***	0.013	–0.154***	–0.018**	–0.227***
6	35.112***	0.026***	–0.251***	–0.607***	–0.032***	–0.157***	–0.008	–0.157***
7	31.625***	0.017*	–0.227***	–0.573***	0.035***	–0.253***	–0.031***	–0.165***
8	33.432***	0.007	–0.228***	–0.577***	0.013	–0.309***	–0.043***	–0.254***
9	36.562***	0.009	–0.246***	–0.648***	–0.034***	–0.376***	–0.019**	–0.148***
High	35.316***	0.022*	–0.215***	–0.673***	–0.117***	–0.398***	–0.025**	–0.213***

Panel C: momentum sorted portfolios

P	α	RI	DN	β_m	β_s	β_h	β_u	$r_m \times RI$
Low	43.575***	0.032*	–0.249***	–0.836***	–0.273***	0.056***	0.410***	–0.224***
2	37.441***	0.043***	–0.247***	–0.705***	–0.045***	0.002	0.325***	–0.267***
3	30.378***	0.041***	–0.211***	–0.604***	0.022**	–0.018	0.224***	–0.251***
4	32.462***	0.022**	–0.239***	–0.592***	0.057***	–0.089***	0.080***	–0.260***
5	35.722***	0.019*	–0.252***	–0.605***	0.037***	–0.058***	0.049***	–0.226***
6	33.913***	0.027***	–0.250***	–0.588***	0.076***	–0.114***	–0.018**	–0.202***
7	35.198***	0.011	–0.255***	–0.603***	0.058***	–0.098***	–0.069***	–0.166***
8	31.968***	0.015	–0.248***	–0.584***	0.059***	–0.131***	–0.149***	–0.136***
9	37.478***	0.021**	–0.259***	–0.647***	–0.023**	–0.031**	–0.217***	–0.161***
High	45.521***	0.020	–0.303***	–0.762***	–0.161***	0.147***	–0.340***	–0.140***

Panel D: standard deviation sorted portfolios

P	α	RI	DN	β_m	β_s	β_h	β_u	$r_m \times RI$
High	38.434***	0.024	–0.226***	–0.596***	–0.440***	–0.129***	–0.002	–0.172***
2	42.732***	0.033**	–0.261***	–0.703***	–0.411***	–0.139***	0.012	–0.231***
3	44.202***	0.040***	–0.255***	–0.709***	–0.371***	–0.176***	–0.018*	–0.267***
4	43.082***	0.036***	–0.264***	–0.656***	–0.317***	–0.172***	–0.009	–0.300***
5	38.868***	0.037***	–0.248***	–0.592***	–0.244***	–0.184***	–0.009	–0.296***
6	36.464***	0.038***	–0.245***	–0.541***	–0.176***	–0.166***	–0.021**	–0.296***
7	32.819***	0.035***	–0.220***	–0.482***	–0.116***	–0.153***	–0.020**	–0.246***
8	27.828***	0.030***	–0.200***	–0.408***	–0.091***	–0.128***	–0.023***	–0.194***
9	20.571***	0.026***	–0.153***	–0.295***	–0.053***	–0.094***	–0.027***	–0.186***
Low	9.808***	0.020***	–0.072***	–0.141***	–0.001	–0.030***	–0.031***	–0.109***

Table 8 (*continued*)

Panel A: size sorted portfolios								
P	$r_s \times RI$	$r_h \times RI$	$r_u \times RI$	$r_m \times DN$	$r_s \times DN$	$r_h \times DN$	$r_u \times DN$	$\overline{R}^2$
Low	−0.171***	−0.069***	−0.063***	−0.052***	−0.026*	0.027*	−0.008	0.683
2	−0.225***	−0.099***	−0.123***	0.030***	−0.019	0.047***	0.034***	0.737
3	−0.216***	−0.092***	−0.124***	0.040***	−0.033**	0.033**	0.039***	0.744
4	−0.175***	−0.066***	−0.105***	0.045***	−0.025*	0.032**	0.036***	0.743
5	−0.126***	−0.095***	−0.099***	0.034***	−0.044***	0.009	0.043***	0.741
6	−0.097***	−0.057***	−0.086***	0.009	−0.054***	0.020	0.028***	0.724
7	−0.028*	−0.063***	−0.073***	−0.003	−0.058***	−0.004	0.029***	0.725
8	−0.045***	−0.077***	−0.078***	−0.007	−0.061***	0.007	0.036***	0.735
9	−0.061***	−0.032**	−0.068***	−0.009	−0.070***	−0.003	0.039***	0.742
High	0.016	0.002	−0.060***	−0.015*	−0.103***	0.014	0.045***	0.755

Panel B: book-to-market sorted portfolios								
P	$r_s \times RI$	$r_h \times RI$	$r_u \times RI$	$r_m \times DN$	$r_s \times DN$	$r_h \times DN$	$r_u \times DN$	$\overline{R}^2$
Low	0.002	0.069***	−0.019	0.019*	−0.081***	0.062***	0.046***	0.732
2	−0.079***	0.085***	−0.126***	0.003	−0.087***	0.013	0.042***	0.714
3	−0.066***	0.113***	−0.123***	−0.012	−0.064***	0.014	0.022**	0.704
4	−0.078***	−0.078***	−0.054***	−0.032***	−0.079***	−0.011	0.036***	0.715
5	−0.012	−0.131***	−0.106***	0.015	−0.074***	0.004	0.027**	0.686
6	−0.092***	−0.053***	−0.091***	0.008	−0.052***	−0.015	0.042***	0.685
7	−0.076***	−0.018	−0.081***	−0.015	−0.115***	−0.009	0.026***	0.681
8	−0.094***	−0.336***	0.007	0.010	−0.103***	0.030*	0.021**	0.702
9	−0.110***	−0.065***	−0.126***	0.009	−0.068***	0.004	0.019*	0.679
High	−0.201***	−0.122***	−0.100***	0.017	−0.054***	0.002	0.023*	0.669

Panel C: momentum sorted portfolios								
P	$r_s \times RI$	$r_h \times RI$	$r_u \times RI$	$r_m \times DN$	$r_s \times DN$	$r_h \times DN$	$r_u \times DN$	$\overline{R}^2$
Low	0.095***	−0.319***	0.172***	0.032*	−0.079***	0.119***	0.103***	0.708
2	−0.011	−0.149***	−0.041***	0.031**	−0.131***	0.052***	0.048***	0.719
3	−0.004	−0.133***	−0.055***	0.021*	−0.132***	0.002	0.046***	0.718
4	−0.032*	−0.057***	−0.047***	−0.002	−0.103***	0.034**	0.056***	0.715
5	−0.022	−0.069***	−0.082***	0.032***	−0.077***	0.044***	0.008	0.690
6	−0.075***	0.049***	−0.073***	0.004	−0.087***	0.007	−0.015	0.684
7	−0.058***	0.013	−0.087***	−0.001	−0.080***	0.032**	0.011	0.690
8	−0.051***	0.055***	−0.037***	−0.016*	−0.067***	0.014	−0.000	0.678
9	−0.066***	−0.056***	−0.041***	0.008	−0.049***	−0.026*	0.015	0.700
High	0.019	−0.131***	−0.048***	0.013	−0.078***	−0.055***	0.022	0.670

Panel D: standard deviation sorted portfolios								
P	$r_s \times RI$	$r_h \times RI$	$r_u \times RI$	$r_m \times DN$	$r_s \times DN$	$r_h \times DN$	$r_u \times DN$	$\overline{R}^2$
High	−0.122***	0.054**	−0.070***	−0.016	−0.061***	−0.013	0.009	0.518
2	−0.177***	0.099***	−0.100***	−0.030**	−0.068***	−0.006	0.037**	0.656
3	−0.214***	0.049**	−0.099***	0.015	−0.043**	0.002	0.045***	0.688
4	−0.201***	−0.058***	−0.125***	0.016	−0.033**	−0.003	0.031**	0.696
5	−0.199***	−0.079***	−0.131***	0.001	−0.041***	0.007	0.020*	0.694
6	−0.181***	−0.109***	−0.115***	−0.013	−0.049***	0.005	0.022**	0.700
7	−0.131***	−0.039***	−0.123***	−0.013	−0.049***	−0.002	0.010	0.667
8	−0.060***	−0.000	−0.102***	−0.038***	−0.023*	−0.016	0.002	0.626
9	−0.039***	0.001	−0.080***	−0.056***	−0.021*	−0.038***	−0.009	0.550
Low	−0.015	0.023*	−0.039***	−0.064***	−0.023**	−0.045***	−0.018**	0.322

This table reports alphas, betas, and adjusted R^2 of the market timing regressions of the CMAP excess returns on the C4 factors along with two instrumental variables and interaction terms of the instrumental variables with the C4 factors using portfolios sorted by various characteristics. Alphas are annualized and in percent. The sample period covers 1960/01/04 until 2013/12/31. The lengths of the moving average windows are 5, 10, 20, 50, 100, and 200 days. Newey and West (1987) standard errors with 3 lags are used in reporting statistical significance of a two−sided null hypothesis at the 1, 5, and 10% level is given by a ***, a **, and a *, respectively.

Table 9 Conditional regressions with market dividend yield and recession indicator

Panel A: size sorted portfolios

P	α	DP_m	RI	β_m	β_s	β_h	β_u	$r_m \times DP_m$
Low	10.646***	0.004	0.042***	−0.484***	−0.338***	−0.322***	−0.077***	0.021***
2	3.159	0.012***	0.017*	−0.762***	−0.546***	−0.476***	0.012	0.082***
3	−1.767	0.016***	0.013	−0.772***	−0.500***	−0.364***	0.045***	0.087***
4	−2.847	0.017***	0.010	−0.783***	−0.443***	−0.300***	0.048***	0.088***
5	−5.114**	0.018***	0.014	−0.789***	−0.366***	−0.208***	0.074***	0.096***
6	−4.121	0.017***	0.011	−0.713***	−0.180***	−0.122***	0.069***	0.076***
7	−2.468	0.014***	0.018**	−0.714***	−0.115***	−0.205***	0.023*	0.077***
8	−4.701*	0.015***	0.014	−0.745***	−0.051***	−0.189***	0.058***	0.085***
9	−6.935***	0.016***	0.012	−0.736***	0.087***	−0.232***	0.009	0.084***
High	−4.215*	0.008***	0.008	−0.738***	0.166***	−0.026	0.111***	0.088***

Panel B: book-to-market sorted portfolios

P	α	DP_m	RI	β_m	β_s	β_h	β_u	$r_m \times DP_m$
Low	−10.162***	0.019***	0.015	−0.660***	0.138***	0.269***	0.074***	0.052***
2	−8.016***	0.016***	0.007	−0.727***	0.171***	−0.218***	0.093***	0.074***
3	−7.385***	0.016***	0.001	−0.676***	0.182***	−0.247***	0.023*	0.069***
4	−4.361*	0.013***	0.014	−0.724***	0.124***	−0.456***	−0.015	0.081***
5	−3.470	0.011***	−0.006	−0.761***	0.035*	−0.597***	0.065***	0.102***
6	−2.439	0.009***	0.016*	−0.759***	0.022	−0.497***	0.073***	0.100***
7	−2.108	0.010***	0.007	−0.691***	0.074***	−0.584***	0.046***	0.077***
8	−1.484	0.010***	−0.006	−0.654***	0.028	−0.608***	0.040***	0.067***
9	0.203	0.009***	−0.005	−0.770***	−0.007	−0.675***	0.104***	0.088***
High	1.049	0.010***	0.008	−0.757***	−0.059***	−0.776***	0.116***	0.070***

Panel C: momentum sorted portfolios

P	α	DP_m	RI	β_m	β_s	β_h	β_u	$r_m \times DP_m$
Low	9.110**	0.005	0.037**	−1.004***	−0.394***	−0.088**	0.873***	0.118***
2	−1.898	0.011**	0.029**	−0.902***	−0.085***	−0.236***	0.582***	0.124***
3	−3.370	0.009**	0.029***	−0.767***	0.100***	−0.314***	0.359***	0.100***
4	−4.269*	0.011***	0.017*	−0.717***	0.162***	−0.391***	0.189***	0.084***
5	−8.053***	0.016***	−0.006	−0.653***	0.179***	−0.207***	0.126***	0.063***
6	−9.353***	0.018***	0.001	−0.640***	0.191***	−0.345***	0.023*	0.058***
7	−5.313**	0.015***	−0.006	−0.660***	0.219***	−0.271***	−0.023*	0.059***
8	−8.445***	0.017***	−0.003	−0.646***	0.202***	−0.327***	−0.101***	0.057***
9	−5.566**	0.016***	0.003	−0.694***	0.129***	−0.196***	−0.160***	0.059***
High	−6.139*	0.019***	−0.001	−0.826***	−0.037	0.109***	−0.349***	0.073***

Panel D: standard deviation sorted portfolios

P	α	DP_m	RI	β_m	β_s	β_h	β_u	$r_m \times DP_m$
High	10.497***	0.003	0.017	−0.461***	−0.138***	−0.301***	−0.009	−0.026***
2	4.508	0.013***	0.030**	−0.648***	−0.150***	−0.415***	0.137***	0.010*
3	1.378	0.016***	0.030**	−0.637***	−0.073***	−0.471***	0.097***	0.012**
4	−1.597	0.017***	0.021*	−0.640***	−0.047**	−0.505***	0.073***	0.035***
5	−1.907	0.016***	0.022**	−0.589***	0.036*	−0.517***	0.071***	0.034***
6	−2.018	0.014***	0.026***	−0.576***	0.055***	−0.493***	0.039***	0.046***
7	−1.820	0.013***	0.022***	−0.488***	0.127***	−0.415***	0.018	0.031***
8	−0.824	0.011***	0.023***	−0.390***	0.152***	−0.328***	0.003	0.013***
9	1.364	0.007***	0.024***	−0.251***	0.148***	−0.231***	−0.013	−0.007**
Low	2.571	0.005**	0.023***	0.002	0.198***	0.025	−0.048***	−0.060***

Table 9 (*continued*)

Panel A: size sorted portfolios

P	$r_s \times DP_m$	$r_h \times DP_m$	$r_u \times DP_m$	$r_m \times RI$	$r_s \times RI$	$r_h \times RI$	$r_u \times RI$	$\overline{R}^2$
Low	−0.050***	0.089***	0.014***	−0.198***	−0.146***	−0.109***	−0.064***	0.678
2	0.007	0.138***	−0.016***	−0.282***	−0.217***	−0.122***	−0.126***	0.735
3	0.008	0.113***	−0.028***	−0.264***	−0.208***	−0.104***	−0.127***	0.742
4	0.002	0.096***	−0.031***	−0.229***	−0.164***	−0.073***	−0.107***	0.739
5	−0.006	0.075***	−0.040***	−0.256***	−0.111***	−0.092***	−0.102***	0.739
6	−0.036***	0.046***	−0.042***	−0.226***	−0.069***	−0.056***	−0.085***	0.719
7	−0.044***	0.074***	−0.026***	−0.259***	0.002	−0.073***	−0.075***	0.720
8	−0.038***	0.067***	−0.038***	−0.257***	−0.016	−0.082***	−0.080***	0.730
9	−0.048***	0.077***	−0.024***	−0.261***	−0.030*	−0.042***	−0.073***	0.734
High	−0.005	0.029***	−0.050***	−0.243***	0.026*	0.013	−0.063***	0.749

Panel B: book-to-market sorted portfolios

P	$r_s \times DP_m$	$r_h \times DP_m$	$r_u \times DP_m$	$r_m \times RI$	$r_s \times RI$	$r_h \times RI$	$r_u \times RI$	$\overline{R}^2$
Low	−0.036***	0.015*	−0.036***	−0.239***	0.027	0.070***	−0.017	0.726
2	−0.055***	0.110***	−0.040***	−0.198***	−0.037**	0.062***	−0.123***	0.709
3	−0.059***	0.099***	−0.028***	−0.237***	−0.026	0.090***	−0.121***	0.699
4	−0.044***	0.142***	−0.010**	−0.260***	−0.048***	−0.112***	−0.060***	0.709
5	−0.019***	0.185***	−0.036***	−0.272***	0.016	−0.162***	−0.105***	0.689
6	−0.025***	0.137***	−0.033***	−0.210***	−0.065***	−0.071***	−0.094***	0.685
7	−0.034***	0.136***	−0.033***	−0.207***	−0.046***	−0.045***	−0.080***	0.678
8	−0.023***	0.132***	−0.035***	−0.291***	−0.068***	−0.366***	0.011	0.697
9	−0.019***	0.125***	−0.054***	−0.197***	−0.083***	−0.083***	−0.120***	0.678
High	−0.033***	0.160***	−0.058***	−0.243***	−0.161***	−0.158***	−0.088***	0.672

Panel C: momentum sorted portfolios

P	$r_s \times DP_m$	$r_h \times DP_m$	$r_u \times DP_m$	$r_m \times RI$	$r_s \times RI$	$r_h \times RI$	$r_u \times RI$	$\overline{R}^2$
Low	0.042***	0.078***	−0.185***	−0.287***	0.117***	−0.291***	0.203***	0.719
2	0.001	0.105***	−0.109***	−0.331***	0.017	−0.132***	−0.028*	0.727
3	−0.048***	0.123***	−0.056***	−0.300***	0.039**	−0.138***	−0.051***	0.724
4	−0.056***	0.134***	−0.042***	−0.304***	0.012	−0.079***	−0.043***	0.715
5	−0.065***	0.074***	−0.036***	−0.273***	0.023	−0.084***	−0.075***	0.684
6	−0.059***	0.101***	−0.025***	−0.243***	−0.035**	0.020	−0.069***	0.676
7	−0.075***	0.082***	−0.022***	−0.211***	−0.012	−0.009	−0.083***	0.682
8	−0.066***	0.087***	−0.025***	−0.179***	−0.009	0.029*	−0.033***	0.671
9	−0.064***	0.066***	−0.026***	−0.211***	−0.025	−0.075***	−0.040***	0.693
High	−0.052***	0.005	0.001	−0.218***	0.042*	−0.130***	−0.062***	0.663

Panel D: standard deviation sorted portfolios

P	$r_s \times DP_m$	$r_h \times DP_m$	$r_u \times DP_m$	$r_m \times RI$	$r_s \times RI$	$r_h \times RI$	$r_u \times RI$	$\overline{R}^2$
High	−0.137***	0.081***	0.006	−0.180***	−0.048*	−0.018	−0.059***	0.519
2	−0.121***	0.124***	−0.046***	−0.250***	−0.098***	0.032	−0.081***	0.656
3	−0.130***	0.135***	−0.039***	−0.282***	−0.128***	−0.019	−0.080***	0.691
4	−0.115***	0.147***	−0.030***	−0.324***	−0.124***	−0.118***	−0.112***	0.697
5	−0.121***	0.149***	−0.032***	−0.316***	−0.119***	−0.139***	−0.116***	0.699
6	−0.102***	0.144***	−0.024***	−0.323***	−0.114***	−0.160***	−0.105***	0.701
7	−0.107***	0.116***	−0.016***	−0.268***	−0.066***	−0.087***	−0.114***	0.668
8	−0.103***	0.087***	−0.012***	−0.212***	−0.000	−0.048***	−0.093***	0.625
9	−0.088***	0.056***	−0.008**	−0.196***	0.009	−0.044***	−0.072***	0.548
Low	−0.090***	−0.023***	0.007*	−0.101***	0.026**	−0.018	−0.031***	0.346

This table reports alphas, betas, and adjusted R^2 of the market timing regressions of the CMAP excess returns on the C4 factors along with two instrumental variables and interaction terms of the instrumental variables with the C4 factors using portfolios sorted by various characteristics. Alphas are annualized and in percent. The sample period covers 1960/01/04 until 2013/12/31. The lengths of the moving average windows are 5, 10, 20, 50, 100, and 200 days. Newey and West (1987) standard errors with 3 lags are used in reporting statistical significance of a two−sided null hypothesis at the 1, 5, and 10% level is given by a ***, a **, and a *, respectively.

model specification. The first notable finding is that once again, the abnormal returns are reduced just as in Table 7, previously. Most of the α s turn negative with the exception of market-cap, momentum and standard deviation decile one which have all positive and statistically as well as economically significant values. Nevertheless, it is reassuring that for all other CMAP portfolios the abnormal returns are negative and, mostly, insignificant with a few deciles having negative *and* highly significant α s.

The dividend yield on the market appears the affect positively and significantly the abnormal returns for all decile portfolios under investigation. At the same time, the recession indicator has a positive and statistically significant impact on the abnormal returns of the standard deviation deciles only. Positive and significant coefficients on the RI dummy variable obtain only for market-cap deciles one and seven as well as momentum deciles one through four. The rest of the CMAP portfolios' α s appear to be unaffected by general economic conditions. Next, I investigate the impact of the state variables on the loadings of the four factors. The market's dividend yield has a strong and positive effect on both the market and HML beta for all CMAP portfolios. Conversely, the SMB and UMD factor loadings are reduced whenever the market's dividend yield increases. The recession indicator has mostly a negative impact on all factor loadings with a few exceptions.

D. Comparison with simple moving average strategies

In this subsection, I compare the performance of the CMA strategy against the simple moving average strategy (SMA). Specifically, I use two popular window lengths of 10 days (SMA(10)) and 20 days (SMA(20)). Table 10 reports the trading frequency (NT) and the BETC for all three strategies across the four sets of portfolios investigated in this article. The NT and BETC for the CMA require a bit more discussion regarding the fair comparison with the SMA strategy. The values for NT and BETC reported previously in Table 5 have been adjusted by a factor of six in order to make the comparison with the SMA more equitable. Specifically, the NT value for CMA in Table 5 has been divided by a factor of six and reported in Table 10 to reflect the fact that the CMA is an equal-weighted portfolio of six SMA strategies. Similarly, the BETC value for CMA in Table 5 has been multiplied by a factor of six and reported in Table 10.

One thing that emerges from Table 10 is that the trading intensity of the CMA strategy is lower than the trading intensity of the two SMA strategies, while the break-even transaction cost of the CMA strategy exceeds the BETC of SMA(10) and SMA(20). The NT and BETC values are almost uniformly monotonic from low to high decile portfolios sorted by market capitalization of equity, book-to-market ratios, and price momentum. The trading intensity and break-even transaction costs are also monotonic for decile portfolios sorted by standard deviation with the exception of the reverse sorting where the first decile is high and

Table 10 CMA versus Simple MA: trading Frequency and Break–Even Transaction Costs

Panel A: size sorted portfolios

Portfolio	CMA		SMA(10)		SMA(20)	
	NT	BETC	NT	BETC	NT	BETC
Low	708	0.90	1484	0.58	932	0.81
2	776	0.59	1714	0.38	1072	0.51
3	790	0.47	1726	0.32	1090	0.43
4	814	0.42	1778	0.29	1148	0.38
5	818	0.36	1808	0.24	1140	0.31
6	823	0.37	1742	0.29	1166	0.30
7	825	0.35	1810	0.22	1146	0.29
8	847	0.26	1832	0.20	1194	0.21
9	889	0.16	1938	0.11	314	0.09
High	943	–0.02	2116	–0.01	1502	–0.04

Panel B: book-to-market sorted portfolios

Portfolio	CMA		SMA(10)		SMA(20)	
	NT	BETC	NT	BETC	NT	BETC
Low	927	0.17	2106	0.08	1410	0.12
2	916	0.09	2032	0.08	1340	0.08
3	919	0.12	2070	0.07	1346	0.09
4	896	0.15	1956	0.11	1316	0.11
5	918	0.07	2070	0.03	1408	0.01
6	876	0.10	1948	0.10	1260	0.07
7	886	0.10	2016	0.03	1302	0.06
8	885	0.08	2012	0.05	1316	0.05
9	868	0.10	1950	0.08	1310	0.07
High	863	0.22	1896	0.18	1282	0.15

Panel C: momentum sorted portfolios

Portfolio	CMA		SMA(10)		SMA(20)	
	NT	BETC	NT	BETC	NT	BETC
Low	870	0.86	1832	0.53	1198	0.74
2	899	0.42	1932	0.27	1296	0.36
3	910	0.21	2060	0.14	1316	0.23
4	903	0.18	2064	0.10	1360	0.15
5	916	0.10	2060	0.07	1362	0.08
6	913	0.08	2098	0.06	1402	0.05
7	904	0.11	1996	0.08	1356	0.04
8	922	–0.01	2086	–0.00	1390	–0.01
9	908	0.08	2016	0.04	1436	0.03
High	867	0.12	1938	0.07	1308	0.09

Panel D: standard deviation sorted portfolios

Portfolio	CMA		SMA(10)		SMA(20)	
	NT	BETC	NT	BETC	NT	BETC
High	719	0.70	1558	0.52	936	0.75
2	790	0.74	1650	0.53	1098	0.68
3	786	0.66	1634	0.48	1042	0.63
4	785	0.51	1674	0.36	1054	0.48

Table 10 (*continued*)

Panel D: standard deviation sorted portfolios

Portfolio	CMA		SMA(10)		SMA(20)	
	NT	BETC	NT	BETC	NT	BETC
5	774	0.48	1624	0.34	1026	0.44
6	772	0.44	1646	0.32	1048	0.35
7	767	0.40	1664	0.27	1092	0.32
8	769	0.37	1640	0.25	990	0.36
9	740	0.37	1546	0.27	928	0.38
Low	660	0.43	1350	0.32	832	0.40

This table reports findings from a comparison of the performance of the combination MA (CMA) strategy to a simple MA strategy with 10 and 20 days window. Below I report the equivalent trading frequency, NT, for the combination MA strategy as well as the equivalent break-even transaction cost for the combination MA strategy, BETC, using 10 decile portfolios sorted by size, book-to-market, momentum, and standard deviation of return. The sample period covers January 4, 1960 until December 31, 2013 with value-weighted portfolio returns. SMA(q) refers to the simple MA strategy with q days in the window. The lengths of the moving average windows in the combination MA strategy are 5, 10, 20, 50, 100, and 200 days. The combination moving average portfolio is an equal-weighted combination of the six individual simple moving average returns.

contains 10% of the stocks with the highest historical volatility, while the tenth decile is low and contains stocks with the lowest historical volatility.

Next, I turn to the comparison of the mean and variance improvement of the CMA strategy relative to SMA(10) and SMA(20). Table 11 reports the mean improvement, $\Delta\mu$, and the risk reduction, $\Delta\sigma$, for all three strategies. A very consistent and curious pattern of findings emerges from all four panels. The CMA strategy uniformly produces a lower improvement in average return relative to buy-and-hold when compared with both the SMA(10) and SMA(20). However, it is also always the case that the risk reduction attained by the CMA strategy relative to buy-and-hold uniformly exceeds the risk reduction achieved by both SMA(10) and SMA(20). Both $\Delta\mu$ and $\Delta\sigma$ are almost exhibit interesting patterns cross-sectionally, in particular, return improvement is almost monotonic across the 10 decile portfolios, while the risk reduction is almost the same across deciles for size and book-to-market portfolios while monotonic for momentum and volatility-sorted portfolios.

Finally, I turn to a simple predictive regression comparison where I use a conditional version of the Carhart 4-factor model with a moving average indicator as a predetermined state variable

$$\begin{aligned}\mathrm{CMAP}_{jt,L} = \alpha_j + \beta_{j,m} r_{mkt,t} + \beta_{j,s} r_{smb,t} + \beta_{j,h} r_{hml,t} + \beta_{j,u} r_{umd,t} + \\ \phi_{j,Z}\left(Z_{t-1} \otimes \left[1_T, r_{mkt,t}, r_{smb,t}, r_{hml,t}, r_{umd,t}\right]\right) + \varepsilon_{jt}, \quad j = 1, \ldots, N.\end{aligned}$$

where Z_{t-1} is represented by a moving average indicator variable equal to one of the MA signal indicates a buy and zero otherwise for the SMA strategy. For the CMA strategy, the moving indicator is the equal-weighted average of the six SMA indicator variables. In the interest of brevity, I report only the adjusted

Table 11 CMA versus simple MA: improvement in mean and ariance

Panel A: size sorted portfolios

Portfolio	CMA		SMA(10)		SMA(20)	
	$\Delta\mu$	$\Delta\sigma$	$\Delta\mu$	$\Delta\sigma$	$\Delta\mu$	$\Delta\sigma$
Low	11.73	6.15	15.90	5.14	13.86	5.24
2	8.43	7.64	11.93	6.12	10.11	6.19
3	6.80	7.40	10.19	5.95	8.63	6.13
4	6.25	7.38	9.37	5.93	7.98	6.01
5	5.48	7.23	8.08	5.83	6.42	5.92
6	5.60	6.87	9.21	5.60	6.35	5.60
7	5.28	6.96	7.49	5.65	6.03	5.66
8	4.11	7.01	6.82	5.67	4.57	5.71
9	2.54	6.90	3.80	5.60	2.21	5.72
High	−0.34	7.12	−0.44	5.71	−1.09	5.86

Panel B: book-to-market sorted portfolios

Portfolio	CMA		SMA(10)		SMA(20)	
	$\Delta\mu$	$\Delta\sigma$	$\Delta\mu$	$\Delta\sigma$	$\Delta\mu$	$\Delta\sigma$
Low	2.95	7.94	3.20	6.40	3.08	6.60
2	1.55	7.06	2.87	5.77	2.02	5.83
3	2.02	6.67	2.70	5.42	2.33	5.49
4	2.43	6.93	4.00	5.65	2.68	5.59
5	1.24	6.87	1.16	5.37	0.29	5.52
6	1.67	6.58	3.49	5.21	1.56	5.33
7	1.65	6.34	1.15	5.05	1.45	5.14
8	1.26	6.94	1.95	5.36	1.17	5.55
9	1.64	6.73	2.90	5.52	1.66	5.51
High	3.53	7.46	6.12	6.02	3.65	6.05

Panel C: momentum sorted portfolios

Portfolio	CMA		SMA(10)		SMA(20)	
	$\Delta\mu$	$\Delta\sigma$	$\Delta\mu$	$\Delta\sigma$	$\Delta\mu$	$\Delta\sigma$
Low	13.72	12.59	17.74	8.44	16.21	9.07
2	6.86	9.36	9.56	6.75	8.63	7.08
3	3.59	7.88	5.15	5.67	5.63	5.91
4	2.92	7.46	3.86	5.44	3.67	5.76
5	1.63	7.03	2.66	5.43	1.88	5.42
6	1.35	6.70	2.35	5.41	1.41	5.33
7	1.76	6.68	3.07	5.29	1.10	5.41
8	−0.15	6.33	−0.07	5.43	−0.18	5.37
9	1.26	7.00	1.44	5.95	0.73	6.06
High	1.98	8.68	2.61	7.51	2.07	7.73

Table 11 (*continued*)

Panel D: standard deviation sorted portfolios

Portfolio	CMA		SMA(10)		SMA(20)	
	$\Delta\mu$	$\Delta\sigma$	$\Delta\mu$	$\Delta\sigma$	$\Delta\mu$	$\Delta\sigma$
High	9.32	7.23	14.85	6.08	12.83	6.21
2	10.82	8.55	16.23	6.73	13.64	7.06
3	9.59	8.32	14.47	6.56	12.10	6.76
4	7.43	7.69	10.94	6.07	9.22	6.18
5	6.81	7.05	10.21	5.61	8.31	5.66
6	6.18	6.57	9.76	5.23	6.69	5.23
7	5.64	5.76	8.30	4.62	6.42	4.71
8	5.21	5.03	7.46	4.12	6.55	4.24
9	5.07	4.22	7.71	3.59	6.40	3.65
Low	5.25	3.14	7.98	2.74	6.06	2.75

This table reports findings from a comparison of the performance of the combination MA (CMA) strategy to a simple MA strategy with 10 and 20 days window. I report the improvement in the mean return, $\Delta\mu$, and the improvement in the standard deviation, $\Delta\sigma$, for the combination MA strategy relative to the BH strategy using 10 decile portfolios sorted by size, book-to-market, momentum, and standard deviation of return. The sample period covers January 4, 1960 until December 31, 2013 with value-weighted portfolio returns. SMA(q) refers to the simple MA strategy with q days in the window. The lengths of the moving average windows in the combination MA strategy are 5, 10, 20, 50, 100, and 200 days. The combination moving average portfolio is an equal-weighted combination of the six individual simple moving average returns.

goodness-of-fit for the CMA, SMA(10), and SMA(20) in Table 12.[5] The reported findings indicate that the adjusted R^2 from these conditional predictive regressions for the CMA strategy exceeds that goodness-of-fit of the same regression for the SMA(20) strategy which in turn exceeds to goodness-of-fit of the SMA (10) strategy. This finding is robust across all four sets of decile portfolios and is probably due to the fact that the CMA strategy aggregates six signals from six different SMA strategies with various window lengths. To the extent that there may be any incremental value-added across SMA strategies of varying lengths then an aggregative signal like the CMA equal-weighted averaging over several SMA signals may improve the chances of the signal being on the right side of the market.

E. Individual stocks

In this subsection, I report results on the performance of moving average strategies with individual stocks in the Center for Research in Security Prices (CRSP) database starting in January 4, 1988 until December 30, 2011 that have continuously non-missing daily return observation during this entire sample period. This

5 The full results of these conditional regressions are available from the author upon request.

Table 12 CMA versus simple MA: predictive regressions goodness-of-fit

Panel A: size sorted portfolios			
Portfolio	$\overline{R}^2_{CMA}$	$\overline{R}^2_{MA(10)}$	$\overline{R}^2_{MA(20)}$
Low	0.687	0.488	0.557
2	0.746	0.506	0.586
3	0.772	0.515	0.621
4	0.769	0.508	0.610
5	0.767	0.509	0.605
6	0.736	0.494	0.589
7	0.735	0.484	0.582
8	0.739	0.494	0.582
9	0.754	0.483	0.580
High	0.776	0.492	0.580
Panel B: book-to-market sorted portfolios			
Portfolio	$\overline{R}^2_{CMA}$	$\overline{R}^2_{MA(10)}$	$\overline{R}^2_{MA(20)}$
Low	0.740	0.457	0.558
2	0.703	0.451	0.546
3	0.690	0.457	0.540
4	0.666	0.432	0.532
5	0.649	0.437	0.506
6	0.671	0.459	0.534
7	0.666	0.448	0.517
8	0.676	0.477	0.558
9	0.686	0.460	0.550
High	0.643	0.464	0.527
Panel C: momentum sorted portfolios			
Portfolio	$\overline{R}^2_{CMA}$	$\overline{R}^2_{MA(10)}$	$\overline{R}^2_{MA(20)}$
Low	0.672	0.487	0.593
2	0.715	0.517	0.619
3	0.710	0.514	0.608
4	0.680	0.481	0.577
5	0.664	0.450	0.535
6	0.659	0.431	0.514
7	0.684	0.451	0.518
8	0.700	0.437	0.519
9	0.700	0.446	0.515
High	0.722	0.448	0.518
Panel D: standard deviation sorted portfolios			
Portfolio	$\overline{R}^2_{CMA}$	$\overline{R}^2_{MA(10)}$	$\overline{R}^2_{MA(20)}$
High	0.466	0.363	0.403
2	0.689	0.507	0.581
3	0.713	0.521	0.590
4	0.719	0.508	0.597

Table 12 (*continued*)

Panel D: standard deviation sorted portfolios

Portfolio	$\overline{R}^2_{CMA}$	$\overline{R}^2_{MA(10)}$	$\overline{R}^2_{MA(20)}$
5	0.728	0.523	0.607
6	0.724	0.525	0.589
7	0.715	0.516	0.584
8	0.693	0.491	0.579
9	0.619	0.447	0.528
Low	0.362	0.280	0.310

This table reports goodness-of-fit results in predictive regressions of the conditional Carhart model with an MA indicator as a state variable for the combination MA (CMA) strategy with the simple MA strategy with 10 and 20 days window. I report the adjusted R^2 for the combination MA strategy relative to the BH strategy using 10 decile portfolios sorted by size, book-to-market, momentum and standard deviation of return. The sample period covers January 4, 1960 until December 31, 2013 with value-weighted portfolio returns. SMA(q) refers to the simple MA strategy with q days in the window. The lengths of the moving average windows in the combination MA strategy are 5, 10, 20, 50, 100, and 200 days. The combination moving average portfolio is an equal-weighted combination of the six individual simple moving average returns.

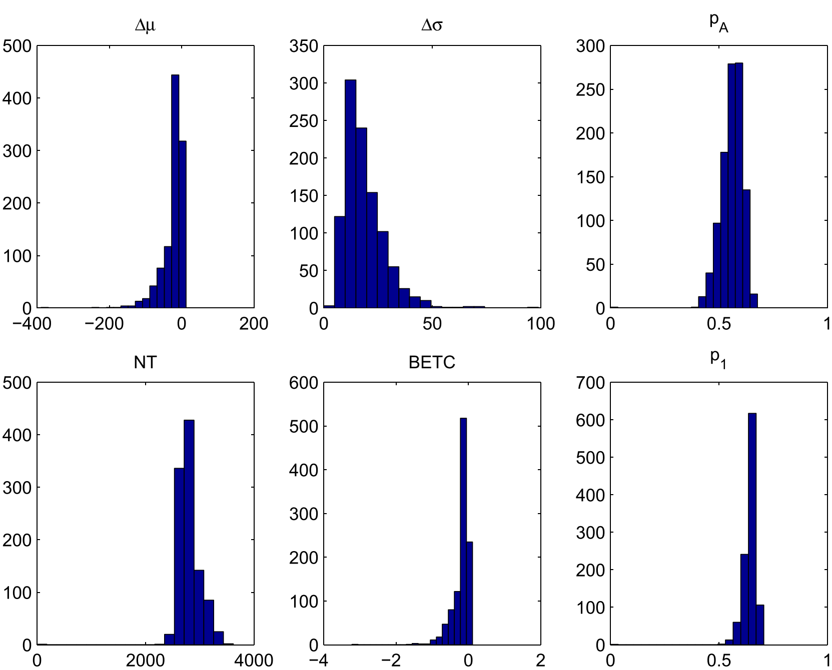

Figure 3 Histograms of the Relative Performance of CMA versus BH using Individual US Stocks.

Notes: Figure 3 presents histogram plots of $\Delta\mu$, $\Delta\sigma$, p_A, *NT*, *BETC*, and p_1 of the relative performance of the combination moving average strategy versus the buy and hold strategy using 1040 individual US stocks. The sample contains 6052 daily observations, and the data covers the January 4, 1988 until December 30, 2011.

results in 1040 individual stocks. Instead of reporting the results in tabular form, I report the key attributes in Figure 3 as histograms.

The performance of the CMA strategy with individual stocks is largely consistent with the performance of the CMA strategy with portfolios. The risk of the CMA strategy is uniformly always smaller than the risk of the underlying stock. The difference in average returns between the CMA and BH strategies is negative for 1011 or more than 97% of all individual stocks I investigate. The findings for the BETC are identical as the latter is calculated as a function of the former. The inferior performance of the CMA strategy relative the BH strategy for individual stocks comes as a surprise compared with the findings for the portfolios presented in the previous section. Nevertheless, there is a universal reduction in risk indicated by the uniformly positive values for $\Delta\sigma$. The majority of negative values for $\Delta\mu$ could be due to the shorter time period under investigation relative to the findings for the stock portfolios.

Figure 4 presents histograms of the distribution of $\widehat{\beta}_{m^2}$ and $\widehat{\gamma}_m$ across 1040 individual stocks. The findings of both market timing specifications are both qualitatively and quantitatively similar. Only 30% (TM) to 34% (HM) of the market timing coefficients are positive with less than a half of those statistically significant. At the same time, 66% (HM) to 70% (TM) of the market timing coefficients

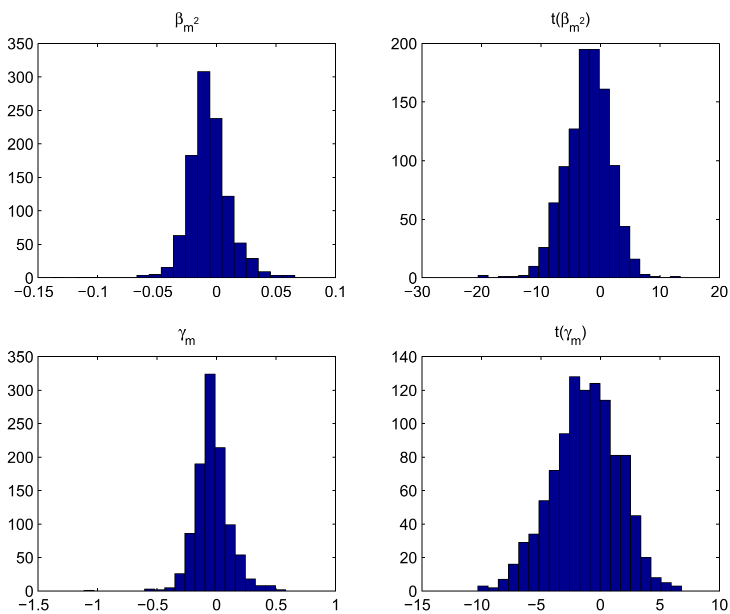

Figure 4 Histograms of the Market Timing Regression Coefficients of CMA Strategy using Individual US Stocks.
Notes: Figure 4 presents histogram plots of the market timing regression coefficients β_{m^2} and γ_m as well as the associated *t*-statistics of the combination moving average strategy using 1040 individual US stocks. The sample contains 6052 daily observations and the data covers the January 4, 1988 until December 30, 2011.

are negative with the majority being statistically significant. These findings indicate that the CMA strategy performed on individual stocks fails to time the market in the right direction.

F. Discussion

The large values of the risk-adjusted abnormal returns presented in the previous subsection demonstrate the profitability of the CMA switching strategy. This raises the question as to what ultimately drives of the performance of the CMA strategy. So far, the evidence points towards a strategy that is contrarian, with a focus on large-cap growth stocks and short the market. However, the goodness-of-fit statistics indicate that this is at most only half the story. A more fundamental question that arises is how can this strategy survive in competitive financial markets. A few potential reasons seem plausible.

First, there is ample evidence that stock returns are predictable at various frequencies at least to a certain degree. This level of predictability is not perfect but is sufficient to improve forecasts of future stock returns when stock return predictability is ignored. Some of the early evidence presented in Fama and Schwert (1977) and Campbell (1987) as well as more recent work by Cochrane (2008) clearly demonstrates that stock return predictability is an important feature that investors should ignore at their own peril.

Evidence regarding the performance of the moving average technical indicator is present in Brock et al. (1992) in the context of predicting future moments of the Dow Jones Industrial Average. Lo et al. (2000) provide further evidence using a wide range of technical indicators with wide popularity among traders showing that this adds value even at the individual stock level over and above the performance of a stock index. More recently, Neely et al. (2010) provide evidence in favor of the usefulness of technical analysis in forecasting the stock market risk premium.

Second, early work on the performance of filter rules by Fama and Blume (1966); Jensen and Benington (1970) concluded that such rules were dominated by buy and hold strategies especially after transaction costs. Malkiel (1996) makes a forceful and memorable point against technical indicators: "*Obviously, I'm biased against the chartist. This is not only a personal predilection but a professional one as well. Technical analysis is anathema to the academic world. We love to pick on it. Our bullying tactics are prompted by two considerations: (1) after paying transaction costs, the method does not do better than a buy-and-hold strategy for investors, and (2) it's easy to pick on. And while it may seem a bit unfair to pick on such a sorry target, just remember: It's your money we are trying to save.*" In a follow up on Brock et al. (1992); Bessembinder and Chan (1998) attribute the forecasting power of technical analysis to measurement errors arising from non-synchronous trading. Ready (2002) goes even further and claims the results in Brock et al. (1992) are spurious and due to data snooping. Formal tests using White's Reality Check are conducted in Sullivan et al. (1999) confirm that Brock et al. (1992) results are robust to data snooping and perform even better out of sample though there is evidence of time variation in performance across subperiods. A more recent study using White's Reality Check and Hansen's Superior Predictive Ability (SPA) test is Hsu and Kuan (2005) who find evidence of profitability of technical analysis using relatively "young" markets like the National Association of Securities Dealers and Quotes (NASDAQ) Composite index and the Russell 2000 both in-sample and out-of-sample.

Furthermore, Treynor and Ferguson (1985) make a strong case in favor of investor's learning and Bayesian updating conditional on new information received rationally combining past prices can result in abnormal profitability. Sweeney (1988) revisits Fama and Blume (1966) and finds that filter rules can be profitable to floor traders in the 1970–1982 time period. Neftci (1991) presents a formal analysis of Wiener–Kolmogorov prediction theory which provides optimal linear forecasts. He concludes that if the underlying price processes are nonlinear in nature then technical analysis rules might capture some useful information that is ignored by the linear prediction rules. More involved and inherently non-linear rules are investigated in the context of foreign currency exchange rates by Neely et al. (1997) using a genetic programming approach. Gencay (1998) goes even further in using non-linear predictors based on simple moving average rules on the Dow Jones Industrial Average over a long time period between 1897 and 1988. In a similar vein, Allen and Karjalainen (1999) use genetic algorithms to search for functions of past prices find that can outperform a simple buy-and-hold strategy and report negative excess returns for most of the strategies they consider.

Thirdly, it is entirely possible that market prices of financial assets can persistently deviate from fundamental values. Those fundamental values themselves are subject to incomplete information and, perhaps, imperfect understanding of valuation tools as well as dispersion of beliefs and objective and behavioral biases across the pool of traders and investors who regularly interact in financial markets. When investors' information is incomplete, and they learn continuously over time, the true fundamental value, Zhu and Zhou (2009) as well as Han et al. (2016) show theoretically that the moving average price is a useful state variable that aids in investors' learning and improves their wellbeing and utility.

Behavioral and cognitive biases have been proposed in Daniel et al. (1998) and Hong and Stein (1999), among others, as a potential driver of both price underreaction and over-reaction in conjunction with the observed price continuation of stock prices. An alternative explanation for price continuation was proposed in Zhang (2006). He argues that investors sub-optimally underweight newly arriving public information leading to a persistent deviation of the market price from the fundamental intrinsic value.

Note also that despite the apparent similarity of the CMA switching strategy to the momentum strategy, the four-factor alphas reported previously are statistically significant and of large magnitudes. This is perhaps not surprising given that the payoff of the CMA strategy resembles an at-the-money protective put strategy. The non-linearity this induces makes the asset pricing task much more difficult when linear models are used.

V. CONCLUSION

In this paper, I report results for the performance of a combination moving average strategy applied to decile portfolios sorted by size, book-to-market, momentum, and standard deviation of return. Further unreported findings for portfolios of stocks sorted by various measures of yield, past returns, and industry classification support the reported findings. There is overwhelming evidence that the combination moving average strategy dominates in a mean-variance sense buying and holding any of the decile portfolios. The excess returns of the CMA returns over BH returns of the underlying portfolios are relatively insensitive to the four Carhart (1997) factors and generate high statistically and economically significant abnormal returns. Furthermore, the abnormal returns for most deciles decline substantially after controlling for the market's dividend yield, the short-term risk-free rate, recessions, and up/down markets. This CMA strategy does not involve overly excessive trading when implemented with daily returns and has positive break-even transaction costs, suggesting that it will be actionable even for large institutional investors. These findings are robust with respect to portfolio construction, various lag lengths of the moving average, alternative sets of portfolios, and individual stocks. The risk-adjusted performance is reduced substantially only in the context of a conditional asset pricing model with the market's dividend yield and a recession indicator as predetermined state variables. Hence, it appears that the success of the CMA strategy does not represent an anomaly and is consistent with rational asset pricing. In addition, any abnormal returns surviving the previously mentioned tests may not be actionable in practice because of limits to arbitrage and price impact of trading on illiquid risky assets with low trading volumes.

Further work would be necessary to investigate the potential link between the returns of the CMA switching strategy and the payoffs of protective put options on the underlying asset. One potential alternative is to combine all first four moments using a utility function over them and convert the gains into certainty equivalent utility gains. Comparing the certainty equivalent utility gains to the break-even transaction costs will provide further evidence into whether the CMA switching strategy is desirable for investors who care about the first four moments of asset returns. In addition, more theoretical studies along the lines of Zhu and Zhou (2009) as well as Han et al. (2016)would provide a further justification of the practical application of technical analysis and the continued investigation of technical analysis role in empirical asset pricing.

Considering the vast literature on technical analysis and the numerous technical indicators following by some traders in practice, this study is just a first step towards investigating the performance and implementation of one common technical indicator. Future work will determine which other technical indicators perform well, and whether they produce significant abnormal returns over and above the relevant transaction costs.

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