The Profitability of the Moving Average Strategy in the French Stock Market

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Abstract

This paper studies the cross-sectional profitability of moving average timing portfolios in the French stock market over the period from January 1, 1995 to December 31, 2012. The results provide strong evidence that the moving average timing outperforms the buy-and-hold strategy with higher returns and less risk exposure. On average, moving average portfolios generate an abnormal return of 3.72% per annum and always perform better than buy-and-hold benchmark portfolios across different lag length and volatility portfolios. Moreover, our results prevail after we control for transaction costs.

Keywords: Technical analysis, moving average, cross-sectional profit.

1. Introduction

For years, the profitability of technical analysis has been the subject of intensive studies. Technical analysis, or the use of historical data to forecast the future market movement, has been a useful technique for investors and brokers from the very beginning of financial markets. Since technical analysis came into practice before the existence of modern financial theory and thus lacks a theoretical framework, academic studies always cast doubt on the effectiveness of using technical analysis (Fama and Blume, 1966; Jensen and Benington, 1970; Isakov and Hollistein, 1999). Critics of technical analysis base their arguments on three main reasons. First, if the application of technical analysis is proved profitable, it provides evidence against a well-known efficient market hypothesis (EMH) which suggests that investors cannot earn over-the-market returns by observing the historical price, as the prices fully reflect all available information and the true value of securities (Malkiel and Fama, 1970; Isakov and Hollistein, 1999; Vlad Pavlov and Stan Hurn, 2012). Second, technical trading rules heavily rely on graphical analysis, and thus, lack precise rules to be fully investigated (Isakov and Hollistein, 1999). Finally, early tests of technical analysis have provided very poor evidence which deepen academics' concerns over the effectiveness of technical trading rules (Fama and Blume, 1966; Jensen and Benington, 1970; Hendrik Bessembinder and Kalok Chan, 1998; Isakov and Hollistein, 1999). However, investors often refuse to reject technical analysis, even if there is a skew towards using technical analysis rather than fundamental analysis at a shorter time horizon, according to the survey of Taylor and Allen (1992). In addition, recent studies find strong evidence of the profitability of employing technical analysis (Brock, Lakonishok, and LeBaron, 1992; Hendrik Bessembinder and Kalok Chan, 1998; Lo, Mamaysky, and Wang, 2000; Todea, Zoicaş-Ienciu, and Filip, 2009; Vlad Pavlov and Stan Hurn, 2012). Especially, Han, Yang, and Zhou (2011) prove that the moving average timing strategy substantially outperforms a corresponding buy-and-hold strategy. Furthermore, Park and Irwin (2007) reviewed the evidence on the profitability of technical analysis in diversified markets since the early 1990s and report that a majority of modern studies indicate the economic profit of technical trading rules.

In this paper, we extend the research of Han, Yang, and Zhou (2011) to the French stock market with the main interest being on the cross-sectional profitability of using the moving average timing strategy. Our objective is to seek a persuasive answer for the controversial issue of whether technical analysis is profitable in the French stock market or not. Further, if technical analysis is profitable, how does the moving average strategy outperforms a buy-and-hold strategy? Previous studies provide little evidence on the cross-sectional profitability of moving average trading rules, and to our knowledge, there have not been any papers differentiating the performance of moving average portfolios and the buy-and hold ones in the French stock market. Our paper contributes to the existing literature by examining the abnormal returns of volatility quintile portfolios in the French stock market. Finally, we address the serious problems of previous studies when dealing with time-series data by robust testing.

We use daily data from January 1, 1995 to December 31, 2012. We first calculate the daily return and standard deviation for all individual stocks in the French stock market, then categorize these stocks into 5 increasing volatility quintile portfolios based on their standard deviations. Among the 5 quintile volatility portfolios, the 1st quintile portfolio contains stocks with the lowest standard deviation and the highest standard deviation stocks belong to the 5th quintile portfolio. Once portfolios are constructed, we calculate the return and standard deviation of quintile portfolios, the corresponding portfolio index level and the moving average (MA) index. Following Han, Yang, and Zhou (2011), the rule of trading is as follows: for each quintile portfolio, when today's price exceeds its 10-day moving average (MA) price, we will buy or keep holding the portfolio a day later; otherwise, we will invest in a risk free asset (1-month French treasury bill). We shed light on the difference in returns between 10-day MA timing portfolios and relative buy-and-hold portfolios and define it as the return of MA Portfolios (MAPs). We find that the moving average portfolio outperforms the buy and hold portfolio in all subsamples by 3.38% to 13.57%. Moreover, the difference in return is larger for medium and high volatility samples than for low volatility ones. When we analyze abnormal returns using CAMP alpha, we find that the abnormal returns increase substantially across the quintile portfolios, ranging from 3.87% to 15.92% per annum. Furthermore, market betas of MA portfolios are often smaller than that of volatility quintile portfolios, indicating the negative sign for the market betas of MAPs.

We address the robustness of the profitability of MAPs using several approaches. We first consider different lag lengths for assessing a complete performance of MA timing strategy. We then estimate the holding days and trading frequency of the strategy as well as the break-even transaction cost. Finally, we examine the profitability of MAPs in two equal sub-periods. Overall, the abnormal returns and beta coefficients from the CAPM model in different lag lengths as well as in sub-periods are highly consistent with results of the previous tests.

The rest of the paper is structured as follows. Section 2 discusses the literature review. Section 3 reports the methodology and data description. Section 4 discusses the results of empirical analysis by providing summary statistics and explanations for abnormal return. Section 5 examines robustness of the profitability of MA timing strategy in several approaches. Section 6 provides concluding remarks and reports research limitations.

2. Literature review

Previous research about the profitability of technical analysis provides different findings for the existing literature. A number of studies on technical analysis, including Fama and Blume (1966) and Jensen and Benington (1970), conclude that technical trading rules are not profitable (Hendrik Bessembinder and Kalok Chan, 1998; Richard J. Sweeney, 1988). Critics of technical analysis base their arguments on the efficient-market hypothesis (EMH) developed by Fama (1970) which suggests that investors cannot earn over-the-market returns in the long run by observing the historical price, as the prices fully reflect all available information and true value of securities (Malkiel and Fama, 1970; Isakov and Hollistein, 1999; Vlad Pavlov and Stan Hurn, 2012). Although EMH is considered as one of the greatest contributions of twentieth century economics, it remains a controversial theory as the profitability of technical analysis is getting more and more support from recent studies (Brock, Lakonishok, and LeBaron, 1992; Hendrik Bessembinder and Kalok Chan, 1998; Lo, Mamaysky, and Wang, 2000; Vlad Pavlov and Stan Hurn, 2012). More specifically, Brock, Lakonishok, and LeBaron (1992) provide strong support for technical strategies by testing two of the simplest and most popular trading rules: moving average and trading range break on the Dow Jones Industrial Average. Similarly, Kwon and Kish (2002) apply three popular technical trading rules to the New York Stock Exchange (NYSE) indices and find that technical trading rules are profitable over various models when compared to the buy-and-hold strategy. Especially, Han, Yang, and Zhou (2011) successfully prove that the moving average timing strategy substantially outperforms the corresponding buy-and-hold strategy. Furthermore, Park and Irwin (2007) review the evidence on the profitability of technical analysis in diversified markets since the early 1990s and report that a majority of modern studies indicate an economic profit from using technical trading rules.

The evidence from the international market is even more convincing. Gunasekarage and Power (2001) analyse four emerging South Asian capital markets and support that technical trading rules have forecasting ability in these markets and moving average strategy outperforms the naive buy-and-hold strategy. Similarly, Fifield, Power, and Knipe (2008), in their research on the profitability of moving average rules over 15 emerging and three developed markets in the period of 1989-2003, conclude that technical analysis is even more profitable in emerging stock markets. In their research on the Australian stock market, Metghalchi, Glasure, Garza-Gomez, and Chien Chen (2007) support the probability of technical trading rules and point out the break-even one-way transaction cost ranges from 0.61 to 2.36%. Among studies of European markets, Isakov and Hollistein (1999) confirm the profitability of simple technical trading rules on Swiss stock prices and the profitability is limited for a particular group of investors when taking into account the existence of transaction costs. Hudson, Dempsey, and Keasey (1996) find the same conclusion about the predictability of technical trading rules in UK markets. Todea, Zoicas-Ienciu, and Filip (2009) investigate the profitability of the optimum moving average strategy on the main European capital markets, including France, and support the existence of abnormal returns using technical analysis. This research, however, does not consider the serious problems that may arise when dealing with time-series data, including data snooping, robustness checks and estimation of transaction costs that may significantly distort the final performance of technical trading rules (Park and Irwin, 2007). As previous studies provide no evidence of the cross-sectional profitability of moving average trading rules, our paper contributes to the existing literature by examining the abnormal returns on volatility quintile portfolios in the French stock market. Furthermore, we address the serious problems of previous studies when dealing with time-series data by robustness testing. The following sections will discuss the methodology of this research in more detail.

3. Data and methodology

Among trading strategies using technical analysis, moving average is one of the most popular and widely used tools thanks to its simplicity and ease of application in diversified markets. This paper tests the profitability of the moving average strategy in the French market with data extracted from Datastream (DS) by using the method suggested by Han, Yang, and Zhou (2011). Particularly, we first calculate the daily return and standard deviation for all individual stocks in the French stock market, then categorize these stocks into 5 increasing volatility quintile portfolios based on their standard deviations. Among the 5 quintile volatility portfolios, the 1st quintile portfolio contains stocks with the lowest standard deviation and the highest standard deviation stocks belong to the 5th quintile portfolio. Once portfolios are constructed, we calculate the return and standard deviation of quintile portfolios and the corresponding portfolio index level. For all portfolios, we use equal weight for each stock and hence, the return of each portfolio is the average return of its individual stocks. We test the sample period from January 1, 1995 to December 31, 2012.

Secondly, we calculate the moving average (MA) index by employing the model of Han, Yang, and Zhou (2011). The MA at time t of lag L is defined as the average price of the last L days.

$$MA_{it,\,L} = \frac{P_{it-L-1} + P_{it-L-2} + \ldots + P_{it-1} + P_{it}}{\mathrm{L}} \quad (1)$$

where P_{it} ($i = 1,\ldots,5$) is the portfolio index and L is lag length. Following Brock, Lakonishok, and LeBaron (1992) and Han, Yang, and Zhou (2011), we examine a wide range of moving averages (10, 20, 50, 100 and 200 days) to comprehensively assess the effectiveness of this strategy. The wide range of lag lengths investigated in this paper overcomes the limitation of the research of Isakov and Hollistein (1999) as these authors consider shorter lengths for lag periods of 5, 10 and 30 days. In addition, we want to examine the performance of moving average portfolios when the lag lengths increase to 100- and 200-days.

The idea of using moving average strategy is based on the fact that financial series are volatile but follow certain trends (Isakov and Hollistein, 1999; Todea, Zoicaş-Ienciu, and Filip, 2009). According to this rule, investors should hold a risky asset when its price witnesses a continuously upward trend; otherwise, they should invest in a risk free asset (Han, Yang, and Zhou, 2011). Following the method suggested by Han, Yang, and Zhou (2011), we will invest in the quintile portfolio *i* for trading day *t* only if the closing price P_{it-1} exceeds the moving average price $MA_{it-1,L}$, otherwise we will invest in a risk free asset (1-month French Treasury bill). The return on moving average timing strategy is illustrated by the following rules:

$$R^{*}_{it,L} = \begin{cases} R_{it} \text{ ,} if \;\; P_{it-1} > MA_{it-1,\,L}, ; \\ RF_{t,} \;\; otherwise, \end{cases} \quad (2)$$

where R_{it} is the return on the *i-th* volatility quintile portfolio on day *t*, $R^{*}_{it,L}$ is the return on MA timing portfolio with lag L and RF_t is the return on 1-month Treasury Bills at time *t*.

Finally, similar to the research of Han, Yang, and Zhow, (2011) and Chao-Hui Yeh (2012), we shed light on the cross-sectional profitability of the MA timing strategy relative to the basic buy-and-hold (B-H) strategy of 5 quintile portfolios. We focus on the difference between $R^*_{it,L}$ and R_{it} as the difference is a good measure of how much MA outperforms B-H strategy as well as how effective the MA strategy is. Calling this difference as MAP, with 5 quintile portfolios, we obtain 5 MAPs following the equation:

$$MAP_{it,L} = R^*_{it,L} - R_{it} \quad \text{with } i=1,\ldots,5 \qquad (3)$$

According to Han, Yang, and Zhou (2011), the existence of the abnormal return of MAPs will indicate the profitability of the MA strategy.

4. Empirical analysis

This section provides evidence for profitability of MA strategy by reporting the summary statistics of the investigated portfolios as well as the abnormal return (CAPM alpha) of MAPs. At the end of this section, we suggest some explanations for the abnormal performance of using the MA timing strategy.

4.1. Summary statistic

Table 1 provides a summary of the returns on the quintile portfolios, R_{it} , the returns on the 10 day MA timing portfolios, $R^*_{it,L=10}$, as well as the returns on MAPs, $MAP_{it,L=10}$. Panel A reports the average return, the standard deviation, the skewness, and the Sharpe ratio of volatility quintile portfolios; whereas, Panel B reports the result of MA portfolios and Panel C focuses on the results for MAPs.

More specifically, the average returns on the volatility quintile portfolios follow an increasing trend, beginning with 9.32% per annum for the lowest quintile and reaching a peak of 37.95% per annum for the highest quintile. Similarly, MA portfolios witness an uninterruptedly upward trend with the figures ranging from 12.7% to 45.42% per annum. Compared with quintile portfolios, MA timing portfolios not only enjoy a larger amount of average returns but also witness significantly smaller standard deviations. For instance, the standard deviation of volatility quintile portfolios ranges from 5.54% to 22.94%, while that figure for the MA portfolios ranges from 3.77% to 17.99%. The Sharpe ratios, as a result, are much higher for MA portfolios than for volatility quintile portfolios, about twice higher on average. Furthermore, in term of skewness, while the majority of volatility quintile portfolios achieve significantly negative skewness, MA timing portfolios enjoy positive skewness (except for the 3rd quintile portfolio with a very small negative of -0.03). When it comes to Panel C, the returns of MAPs increase from 3.38% to 13.57% per annum across the quintiles, except for the highest volatility quintile). The standard deviations of MAPs are much smaller than that of volatility quintile portfolios but see no big difference to the figures of MA portfolios. The skewness of MAP is significantly positive across the quintiles, except for the highest volatility quintile. The last column of Panel C reports the success rate of the MA timing strategy which is measured by the fraction of trading days when the MA timing strategy outperforms a buy-and-hold (B-H) strategy. The success rate is about 54% across all quintiles, indicating that the performance of the MA timing strategy is relatively superior to that of a B-H strategy.

Table 1: Summary statistics

Rank	Avg Ret	Std Dev	Skew	SRatio	Avg Ret	Std Dev	Skew	SRatio	Avg Ret	Std Dev	Skew	Success
	Panel A Volatility Quintile Portfolios (Buy-and-Hold)				**Panel B** MA (10) Timing Portfolios				**Panel C** MAP (Difference)			
Low	9.32	5.54	-1.00	1.32	12.70	3.77	0.22	2.84	3.38	4.03	2.43	0.55
2	14.68	9.88	-0.49	1.28	19.10	6.57	0.07	2.60	4.42	7.35	0.90	0.55
3	12.94	13.61	-0.44	0.80	21.49	8.64	-0.03	2.26	8.55	10.47	0.72	0.55
4	15.29	17.44	-0.18	0.76	28.86	11.72	0.68	2.29	13.57	12.82	0.75	0.55
High	37.95	23.83	0.74	1.51	45.42	17.99	1.80	2.41	7.47	15.57	-0.28	0.54
High - Low	28.63	22.94	0.91	1.16	32.72	17.89	1.83	1.72	4.09	14.92	-0.54	0.54

Note: Table 1 reports the average return (Avg Ret), the standard deviation (Std Dev), the skewness (Skew) and the Sharpe ratio (SRatio) for buy-and-hold quintile portfolios (Panel A), 10-day moving average timing quintile portfolios (Panel B) as well the differences between these portfolios (Panel C). We calculate the daily return and its standard deviation for all individual stocks in the French stock market, then categorize these stocks into 5 increasing volatility quintile portfolios as shown in panel A. For each quintile portfolio, when yesterday's price exceeds its 10-days moving average (MA) price, we buy or keep holding the portfolio today; otherwise, we will invest in a risk free asset (1-month French Treasury bill). We define the difference between 10-day MA timing portfolios and relative buy-and-hold portfolios as MAPs. The results are annualized and in percentage. We also report the success rate for the MAPs in Panel C. The sample period is from January 1, 1995 to December 31, 2012.

In brief, according to the summary statistic, the MA timing strategy does work well in the investigated period. With higher average returns and lower standard deviations, MA timing portfolios enjoy a higher Sharpe ratio, compared to that of volatility quintile portfolios. In addition, MA portfolios and MAPs have either less negative or positive skewness, and in particular the MAPs enjoy a success rate of 54%, which suggests that it is more than usual that the MA timing strategy results in positive returns.

4.2. CAPM alpha

We test the abnormal return of the MA timing strategy by considering the capital asset pricing model (CAPM) regression of return on market portfolio,

$$MAP_{it,L} = \alpha_i + \beta_i (RM_t - RF_t) + \varepsilon_{it}; \; i = 1,\ldots,5 \quad (4)$$

where RM_t and RF_t are market return and risk-free rate at time t; and (RM_t - RF_t) is the daily excess return on market portfolio. To prove that the MA timing strategy outperforms Buy-and-hold strategy, α_i should be signifi-

Table 2: CAPM alpha

Rank	α	βmkt	Adj. R^2
		CAPM Model	
Low	3.87***	-0.08***	21.20
	(4.58)	(-35.52)	
2	5.56***	-0.18***	31.42
	(3.87)	(-46.35)	
3	10.24***	-0.27***	32.74
	(5.04)	(-47.77)	
4	15.92***	-0.31***	30.39
	(6.29)	(-45.24)	
High	9.1**	-0.24***	12.00
	(2.63)	(-25.30)	
High - Low	5.23***	-0.16***	5.63
	(-1.52)	(-16.75)	

*Note: Table 2 reports the results of CAPM regression of MAPs constructed from MA timing strategy. We run the regression of the 10-day MA timing strategy on the market factor to derive alphas, betas and the adjusted R-squares. The alphas are annualized and in percentage. We use robust t-statistics of Newey and West (1987) for testing the significance. The signals ***, **, and * show that the null hypothesis is rejected at 1%, 5%, and 10% level of significance, respectively. The sample period is from January 1, 1995 to December 31, 2012.*

cantly positive. Therefore, the Null hypotheses should be: H_o: $\alpha_i = 0$. Table 2 reports the results of CAPM regression of MAPs constructed from the 10 day MA timing strategy.

The risk-adjusted returns (alpha) are higher than the unadjusted ones, ranging from 3.87% to 15.92% per annum. The alphas increase across the quintile portfolios, except for the highest volatility quintile. However, the highest quintile still yields an alpha that is nearly triple that of the lowest one, 9.1% compared to 3.87%. In addition, taking into account Newey and West's (1987) robust t-statistic, all results are highly significant at either 1% or 5% significance. The large and positive risk-adjusted returns in Table 2 strongly indicate the profitability of the MA timing strategy. Furthermore, we are interested in negative market betas of MAPs, which ranges from -0.08 to -0.31. The rationale for these negative numbers takes its root in the motivation for using technical analysis. Technical analysis in general and MA timing strategy in particular is designed to limit negative portfolio returns (Han, Yang, and Zhou, 2011). When the market goes down and the portfolio returns are significantly negative, MA portfolios enjoy much better returns than volatility quintile portfolio thanks to their successful investing rules. On the other hand, when the markets are booming and the portfolio returns turn to positive, because of the lag periods, MA portfolios may have smaller returns than quintile portfolios. In both cases, market betas of MA portfolios, therefore, are often smaller than that of volatility quintile portfolios, indicating the negative sign for the market betas of MAPs (Han, Yang, and Zhou, 2011).

4.3. Explanation

The results of the previous tests indicate that the profitability of MA timing strategy in the French stock market is strong and significant. But what could be the reasonable explanation for the abnormal returns in such a competitive market as France? In fact, the success of technical analysis is relative to its ability to forecast the market movement (Han, Yang, and Zhou, 2011).

Back in the 1970s, a number of studies on stock movement believed that stock prices follow the random walk model, and thus, are assumed to be unpredictable during a specific period (Malkiel and Fama, 1970; Jensen and Benington, 1970). Among studies of the random walk model, efficient market hypothesis (EMH) by Fama (1970) is one of the most well-known and widely used. The hypotheses argue that stock prices in strong-efficient markets fully reflect the all available information and thus, no one can earn excess returns. If this assumption is to hold, technical analysis is meaningless in making abnormal returns (Fama, 1970). Recent studies, however, provide contrary evidence on return predictability, and hence, indicate the probability of earning profits when using technical trading rules (Campbell, 1987; Campbell and Thompson, 2008; Rapach, Strauss, and Zhou, 2010). Furthermore, Park and Irwin (2007) report that the majority of modern studies indicate an economic profit for technical trading rules.

From the theoretical literature, the motivation to use technical trading rules relies on the incomplete information contained in fundamental analysis (Han, Yang, and Zhou, 2011). More specifically, Blume, Easley, and O'Hara

(1994) prove that traders who rely on both fundamental analysis and technical analysis often do better than those who use only one technique. In addition, Brown and Jennings (1989) point out that the rational trader can gain abnormal returns by using information indicated in historical data. In case of uncertainty and incomplete information, the moving averages strategy can help forecast future market movements (Zhu and Zhou, 2009). The idea of using the moving average strategy is based on the argument that financial series are volatile but follow certain trends (Isakov and Hollistein, 1999; Todea, Zoicaş-Ienciu, and Filip, 2009). According to this rule, an investor should hold an asset when its price witnesses a continuously upward trend, as this trend will continue for a reasonable period of time due to investor behavioral biases, especially "under-reaction" to new information, which is often described as "herd mentality" (Zhang, 2006). The Moving average timing strategy is ideally used to capture the psychological phenomenon as this strategy is a trend-following approach. The longer a trend continues the better the performance the strategy generates (Han, Yang, and Zhou, 2011). Furthermore, the moving average is considered as one of the most popular and widely used tools for trading strategy thanks to its simplicity and ease of application in diversified markets.

In summary, the theoretical literature and recent studies well explain the profitability of technical analysis and the moving average, particularly.

5. Robustness

This section examines the robustness of profitability of MAPs in several approaches. We first consider different lag lengths for assessing a complete performance of MA timing strategy. We then estimate the holding days and trading frequency of the strategy as well as the break-even transaction cost. Finally, we examine the profitability of MAPs in two sub-periods for assessing the effect of the time-scale factor on the strategy.

5.1. Alternative lag lengths

Previous researches employ different lag lengths to test the volatility of the profitability of MA timing strategy. For example, Fifield, Power, and Knipe (2008) examine moving average rules in a wide range of lag lengths from 1 to 200 days in 15 emerging markets and three developed ones over the period of 1989-2003. Following Brock, Lakonishok, and LeBaron (1992) and Han, Yang, and Zhou (2011), in addition to 10-day moving averages, we consider a variety of alternative moving averages (20-, 50-, 100- and 200- days) for comprehensively assessing the effectiveness of this strategy. These lag lengths overcome the limitation of the research of Isakov and Hollistein (1999) as these authors consider shorter lengths for periods of 5, 10 and 30 days.

Table 3 reports the average return and CAPM alphas of the MAPs for various lag lengths.

Overall, the results of alternative moving averages are highly consistent with that of a 10-day lag length. Table 3 reports two striking features of these results. First, regardless of the lag lengths, the MA timing strategy outperforms the buy-and-hold strategy by generating both higher average returns and abnormal returns. For instance, even at 100-day lag length, the risk-adjusted returns, reflected by the alphas of MAPs, are significantly positive, ranging from

Table 3: Alternative moving averages lag lengths

Rank	Avg Ret	CAPM α	Avg Ret	CAPM α	Avg Ret	CAPM α	Avg Ret	CAPM α	Raw Ret	CAPM α
	MAP (20)		**MAP (50)**		**MAP (100)**		**MAP (200)**		**Random Switching**	
Low	3.21***	3.78***	2.52***	3.08***	2.58***	3.04***	2.01***	2.42***	-3.90***	-3.42***
	(3.44)	(4.54)	(2.84)	(3.89)	(3.13)	(4.07)	(2.68)	(3.44)	(-4.26)	(-4.09)
2	3.86**	5.14***	3.72**	5.05***	3.27**	4.42***	1.72	2.77*	-5.25***	-4.17***
	(2.26)	(3.64)	(2.23)	(3.67)	(2.03)	(3.30)	(1.16)	(2.14)	(-3.12)	(-2.86)
3	8.53***	10.47***	5.96***	8.01***	4.68*	6.56**	2.28	4.16*	-5.47***	-4.01**
	(3.42)	(5.18)	(2.38)	(3.94)	(1.89)	(3.29)	(0.95)	(2.07)	-2.38	-2.01
4	12.47***	14.82***	8.82***	11.40***	7.00**	9.27***	4.46	6.91**	-9.83***	-8.23***
	(4.04)	(5.85)	(2.81)	(4.48)	(2.27)	(3.68)	(1.45)	(2.68)	(-3.52)	(-3.29)
High	10.53***	12.25***	5.05	6.80**	2.34	3.83	1.10	2.42	-22.49***	-21.37***
	(2.91)	(3.61)	(1.42)	(2.03)	(0.67)	(1.16)	(0.33)	(0.74)	(-5.61)	(-5.45)
High - Low	7.33**	8.47*	2.53	3.72	-0.25	0.79	-0.92	0.01	-18.59***	-17.95***
	(2.11)	(2.52)	(0.74)	(1.12)	(-0.07)	(0.24)	(-0.28)	(0.00)	(-5.03)	(-4.52)

*Note: *, **, *** indicate significance at 0.10, 0.05 and 0.01 level, respectively.*

Table 3 reports the results of robustness test for MAPs abnormal returns when they are formed by different lag lengths. We calculate the average returns (Avg Ret) and the CAPM alphas (CAPM α) of different lag length 20-, 50-, 100- and 200-day MAPs. To assess the performance of the MA timing strategy, we report the raw returns and the CAPM alphas of the random switching strategy, which are the averages taken from 5000 repeats. The sample period is from January 1, 1995 to December 31, 2012.

3.04% to 9.27% per annum. However, there is a downward trend in both abnormal return and average return as the lag lengths increase. Take the 4th volatility quintile portfolio as an example. The CAPM alpha of the 20-day MA is 14.82%, which is about 93% of the 10-day MA alpha (15.92% per annum reported in Table 2). The alphas with 100-day MA and 200-day MA are of 9.27% and 6.91% per annum, which is about 58% and 43% of the 10-day abnormal return, respectively. Similarly, when it comes to average returns, average returns with 100-day MA and 200-day MA are 7% and 4.46% per annum, which are about 24% and 15% of the 10-day MA average return (28.86% per annum reported in Table 1).

Second, regardless of the lag lengths, the abnormal returns do increase across the quintiles, except for the case of the highest volatility quintile where its alpha is relatively smaller than that of the second highest volatility quintile. The average returns, on the other hand, do not follow that trend, especially after L = 100. Only in 100-day MA and 200-day MA do the high-low spreads, as reported in the last row of Table 3, generate a negative number (-0.25 for 100-day MA and -0.92 for 200-day MA). However, differences between the highest and lowest quintiles in both average return and abnormal return do decline as the lag time increases. For example, the difference in average return is 7.33% and significant at 5% when L = 20, but turns into a negative number, -0.92, and is insignificant when L = 200. Similarly, the gap between the highest and lowest quintiles in abnormal return is 8.47% when L = 20, but is only 0.01% when L = 200. Overall, the second largest volatility quintile portfolio seems to be the best performer in all lag lengths.

Furthermore, we examine the performance of a random switching strategy in comparison with that of an MA timing strategy. The last panel in Table 3 reports the average performance of 5,000 random switching portfolios. Both the raw returns and risk-adjusted returns of random switching portfolios are substantially negative at either 1% or 5% significance. The average returns, however, do decrease across the quintiles with the gap between the highest and the lowest quintile being -18.59% per annum, indicating the huge loss for using a random switching strategy.

5.2. Average holding days, trading frequency and break-even transaction costs

A good investment strategy is a good starting point, but how often it trades, as well as how much it spends on transaction costs, will directly determine its final performance. In the case of MA timing strategy, whether this strategy remains profitable after taking into account the transaction costs is of our interest. We address this issue by considering the average holding days and the trading frequency of MA portfolios as well as the break-even transaction point.

Table 5 reports a positive correlation between the average holding periods and the lag lengths. In other words, the longer the lag length is, the longer the holding period the portfolios require. For instance, the 10-day MA timing strategy has about 39 to 45 days holding days; whereas, that figure for the 100-day MA portfolios ranges from 158 to 328 days. The rationale for this positive relation is that longer lag length expects to capture longer investing trend, and therefore, it requires more time to hold the portfolio. We are interested in

Table 4: Trading frequency and break-even transaction cost

Rank	Holding	Trading	BETC	Holding	Trading	BETC	Holding	Trading	BETC	Holding	Trading	BETC	Holding	Trading	BETC
	MA (10)			**MA (20)**			**MA (50)**			**MA (100)**			**MA (200)**		
Low	45.07	0.022	62.20	69.81	0.014	84.88	136.68	0.007	134.19	328.36	0.003	348.63	449.70	0.002	394.54
2	47.34	0.021	76.35	77.95	0.013	122.73	178.73	0.005	263.97	255.39	0.004	324.99	899.40	0.001	720.41
3	41.48	0.024	146.18	64.07	0.015	211.12	119.15	0.008	277.10	158.52	0.006	304.42	204.41	0.004	211.34
4	49.86	0.020	262.48	60.74	0.016	295.60	125.59	0.008	448.54	183.88	0.005	522.49	374.75	0.002	784.91
High	39.39	0.025	120.07	64.07	0.015	230.63	119.15	0.008	214.89	270.41	0.003	220.63	281.06	0.003	108.16

Note: Table 4 reports the estimated average holding days (Holding), trading frequency as a fraction of trading days (Trading) and the break-even transaction costs in basis point (BETC) of the MAPs across different lag lengths. The break-even transaction costs are calculated on the constraint that the average returns of the MAPs equal zero. The sample period is from January 1, 1995 to December 31, 2012.

two striking features in Table 5. First, holding days, on average, are even longer than MA lag lengths. This finding provides a totally opposite result to that which Han, Yang, and Zhou (2011) observe in the NYSE/Amex indexes. Differences between the stock exchanges in the US and France could explain some of the differences in these findings. Even though these two markets are well-developed and highly liquid, the US stock exchanges seem to be relatively more volatile than the French market in terms of both daily stock price and the movement of monthly market indexes (Grouard, Lévy, Lubochinsky, 2003). Following the moving average rules that suggests the buying and selling signals only if timing trends are captured, it may take a longer time for portfolios being traded in the French market than in the US market. The average holding periods in French markets, as a result, may be longer than those in the US.

Second, for further assessing trading activities, we consider the trading frequency[1], which is defined as the ratio of the trading days over the total number of days. Table 4 reports the results of trading frequency in the column labelled "Trading". As the average holding days increase with the increase in lag lengths, the ratio then goes down across lag lengths accordingly. For example, the highest volatility quintile of the 10-day MA strategy requires a trade frequency of 2.5%, whereas, that figure of the 100-day MA and the 200-day MA strategy is only 0.3% of the total number of days.

Finally, we address the issue of transaction costs by setting the average returns of MAPs to zero to test if the generated abnormal return could compensate for the transaction costs. In this research, we assume that the impact of a

1-month treasury bill transaction cost is negligible and could be ignored. This assumption is highly consistent with the arguments of Balduzzi and Lynch (1999), Lynch and Balduzzi (2000), and Han (2006). Table 4 reports the results of the break-even transaction costs[2] in basic points (bps) in column "BETC" with two remarkable features. First, break-even transaction costs increase across the lag lengths, which is consistent with the tendency of average holding days. For instance, in term of the lowest volatility quintile, the 10-day MA has a break-even transaction cost of 62.2 bps while that figure for the100-day MA and the 200-day MA is 348.63 bps and 394.54 bps, respectively. Second, the break-even transaction costs increase as portfolios become more volatile, except for $L \geq 100$. This result is contrary to what Han, Yang, and Zhou (2011) observe in the US where financial markets are well-developed and highly liquid. Overall, the break-even transaction costs are substantially positive, implying that the MA strategy is very economically effective in the French market even after taking into account the cost of transactions.

5.3. Sub-periods

The effect of the time-scale factor on the investing strategy is one of our greatest concerns. To avoid serious problems of data snooping and other possible bias, we examine the profitability of MAPs out of the sample by simply dividing the sample period into 2 equal sub-periods, from January 1995 to December 2003 and from January 2004 to December 2012.

Table 5 reports the performance of the 10-day MA timing strategy in two equal sub-periods. Overall, the abnormal returns and beta coefficients from the CAPM model in the sub-periods are highly consistent with the results of the previous tests. First, abnormal returns, reflected by CAPM alphas, are positively correlated with the portfolio's volatility, except for the highest volatility quintiles in the second sub-period. More specifically, in the first sub-period, the alphas turn from a negative number to a positive one across the volatility quintiles with the abnormal return appearing from the 3rd volatility quintile. The high-low spread, reported in the last row of Table 5, is 18.79% per annum and at 5% significance. Similarly, in the second sub-period, alphas are significantly positive and follow an upward trend across the volatility quintiles, except for the highest volatility quintile where the alpha turns to negative, -0.25% per annum. Compared to previous results, on average, the CAPM alphas in the first sub-period (-0.07% to 19.2%) are higher than those of the second sub-period (-0.25% to 13.6%) and the entire sample period (3.87% to 15.92%). Second and finally, all market betas, reported in column "βmkt" in Table 5, are significantly negative across time and volatilities, indicating that MAPs are less exposed to market risks compared to buy-and-hold portfolios. In brief, the results in sub-periods do support the abnormal performance of the MA timing strategy.

In summary, the abnormal returns and beta coefficients from the CAPM model in different lag lengths as well as in sub-periods are highly consistent with the results of the previous tests. The break-even transaction costs are substantially positive, implying that the MA strategy is very economically effective in the French market even after taking into account the cost of transactions. Robustness tests, therefore, do support the profitability of MA timing strategy

Table 5: Sub-periods

	Panel A: Period January 1, 1995 - December 31, 2003			Panel B: Period January 1, 2004 - December 31, 2012		
Rank	α	βmkt	Adj. R^2	α	βmkt	Adj. R^2
	Panel A: CAPM Model			Panel B: CAPM Model		
Low	-0.07	-0.05***	11.48	7.61***	-0.11***	30.58
	(-0.06)	(-17.45)		(5.94)	(-32.11)	
2	-0.42	-0.15***	24.56	11.36***	-0.21***	38.11
	(-0.21)	(-27.61)		(5.55)	(-37.96)	
3	7.01*	-0.20***	21.15	13.06***	-0.32***	44.43
	(2.43)	(-25.06)		(4.67)	(-43.25)	
4	19.20***	-0.28***	22.22	12.48***	-0.34***	40.52
	(4.88)	(-25.87)		(3.93)	(-39.92)	
High	18.72**	-0.28***	11.11	-0.25	-0.20***	15.19
	(3.21)	(-17.13)		(-0.07)	(-20.49)	
High - Low	18.79**	-0.23***		-7.85*	-0.09***	
	(-3.22)	(-13.95)		(-2.22)	(-9.82)	

*Note: *, **, *** indicate significance at 0.10, 0.05 and 0.01 level, respectively.*
Table 5 reports the performance of the 10-day MA timing strategy in two equal sub-periods: from January 1, 1995 to December 31, 2003 (Panel A) and from January 1, 2004 to December 31, 2012 (Panel B). The alphas are annualized and in percentage. We use the robust t-statistics of Newey and West (1987) for testing the significance.

in the French stock market.

6. Conclusion

In this paper, we study the cross-sectional profitability of a moving average timing portfolio in the French stock market over the period from January 1, 1995 to December 31, 2012. Following the methodology suggested by Han, Yang, and Zhou (2011), we find that moving average timing portfolios generate an abnormal return of 3.72% per annum, on average, and outperform the buy-and-hold portfolios with higher returns and less risk exposure. These findings are robust across different lag lengths and in two sub-periods. The analysis of the break-even transaction costs also support the superior performance of a moving average strategy over a buy-and-hold strategy.

The central contribution of this research is that we not only examine the excess return of moving average portfolios (MAPs) over corresponding buy-and-hold portfolios across volatility quintiles but also employ the CAPM regression model to test the risk-adjusted return as well as market betas. As previous studies provide no evidence on the cross-sectional profitability of moving average trading rules, our paper contributes to the existing literature by examining the abnormal returns on volatility quintile portfolios in the French stock market. We also address the common problems of previous studies when dealing with time-series data by robustness testing.

This research has some limitations. First, we employ the CAPM model to test abnormal return for MAPs. Since the CAPM model does not take into account other risk factors and thus, may not fully explain the abnormal return of moving average portfolios, we suggest future research should employ other approaches to dig deeper into this issue. Second and finally, we overcome the limitations of previous research when dealing with time-series data by robustness testing. To fully correct the serious problem of data snooping and other possible biases when doing empirical research with time-series data, we suggest future research should combine robustness tests and other approaches for comprehensively assessing the performance of technical trading rules.

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Notes:

1. Trading Frequency = (total trading days)/ (total holding days + total trading days).
2. Break-even transaction costs are the costs upon which average return of MAPs turn to zero (Han, Yang, and Zhou, 2011).

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