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Time-series momentum in the Portuguese stock market: an analysis of the last 120 years of data

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Abstract

The momentum effect is a very well known anomaly in the finance field that still persists nowadays, even after the recognition of its existence. Although cross-sectional momentum is heavily studied in finance, a new approach to this anomaly was introduced more recently by Moskowitz, Ooi and Pederson (2012). Time-series momentum represents an alternative way of investors to beat the market by taking long (short) positions in assets which past return was positive (negative).

Previous research of this anomaly was performed for the US market and, later, for some other markets, however no study was conducted in order to investigate the presence and profitability of time-series momentum in the Portuguese stock market. In order to study time-series momentum, I use long-term data, never used before for the Portuguese stock market and rarely used in studies about this topic, covering the period between 1900 and 2020, so that I can understand how this anomaly evolved through this period of time. After running regressions for several look-back periods, this study founds return continuation in the Portuguese stock market for 12-13 months, indicating the existence of the time-series momentum anomaly in this market. Additionally, regressing the time-series momentum returns against the Fama-French factors, for the period 1990-2020, the results indicated that the time-series momentum strategy which seemed to perform better in the Portuguese stock market was the strategy with 1-month look-back period and a holding period of 12 months.

In this study it is also compared the profitability of time-series momentum strategies with a buy-and-hold strategy and it is found that time-series momentum strategies exhibit a better performance than the buy-and-hold strategy in the long run, being this better performance even enlarged during periods of crises.

Therefore, this is the first study about this anomaly in the Portuguese stock market and it is a study performed using long term data, improving the existing literature about this topic and, due to the results supporting the existence and outperformance of time-series momentum strategies, this study suggests a new way of investors to construct their portfolios in order to gain better returns.

Key-words: Momentum; Time-series Momentum; Asset pricing models; Portugal; Stock market.

JEL-Codes: G12, G14, G15

Resumo

O efeito momentum é uma anomalia financeira muito conhecida ainda presente nos mercados atualmente, mesmo após a sua descoberta. Apessar do momentum tradicional ser exaustivamente estudado pela literatura, uma nova versão desta anomalia foi recentemente introduzida por Moskowitz, Ooi and Pederson (2012). Time-series momentum representa uma forma alternativa dos investidores ganharem dinheiro no mercado ao assumirem posições longas (curtas) em ativos quando o seu retorno passado fora positivo (negativo).

Estudos anteriores sobre esta anomalia foram conduzidos para o mercado dos EUA e outros mercados, no entanto nenhum estudo foi desenvolvido de maneira a estudar a presença e rentabilidade do time-series momentum no mercado de ações Português. De modo a estudar time-series momentum, este estudo usa dados de longa data, nunca antes usados para o mercado de ações Português e raramente usados em estudos sobre este tópico, cobrindo o periodo entre 1900 e 2020 de forma a entender de que maneira esta anomalia evoluiu neste período temporal. Depois de calcular regressões para diferentes períodos, continuidade nos retornos para o mercado Português foi encontrada nos primeiros 12 a 13 meses, indicando assim a existência da anomalia time-series momentum neste mercado. Foram também calculadas regressões dos retornos das estratégias time-series momentum contra os factores de Fama-French, para o periodo de 1990-2020, e os resultados indicaram que a estratégia que parece ter a melhor performance no mercado de ações Português é a estratégia com 1 mês de "look-back period" e um "holding period" de 12 meses.

Adicionalmente, neste estudo é comparada a rentabilidade das estratégias time-series momentum com a estratégia buy-and-hold e os resultados indicaram que todas as estratégias time-series momentum estudadas apresentaram uma melhor rentabilidade do que a estratégia passiva no longo prazo, sendo esta melhor rentabilidade alargada durante periodos de crise.

Portanto, este é o primeiro estudo sobre esta anomalia no mercado de ações português e é um estudo que usa dados de longa data, melhorando assim a literatura já existente sobre este tópico e, devido à confirmação da existência e melhor performance deste tipo de estratégias, este estudo sugere uma nova maneira dos investidores construírem os seus portefólios de modo a obterem melhores retornos.

Palavras-chave: Momentum; Time-series Momentum; Modelo de avaliação de ativos financeiros; Portugal; Mercado de Ações.

JEL-Codes: G12, G14, G15

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1. Introduction

The momentum effect is a financial anomaly that was first introduced by Jegadeesh and Titman (1993). This anomaly is a market phenomenon in which it can be observed that asset prices tend to maintain their current trend for a long time, meaning that winners tend to keep winning and losers tend to remain losers.

The discovery of the momentum effect was relevant in the finance field because soon several studies started to conclude that investors could obtain abnormal returns by basing their investments on this anomaly, as Jegadeesh and Titman (1993) which demonstrated that the construction of cross-sectional momentum portfolios could generate an annual return higher than investing on a stock index, such as the S&P 500.

After an extensive anaysis of this anomaly over the years by many studies, Moskowitz, Ooi, and Pedersen (2012) introduce a new concept that focuses in the absolute performance instead of the relative performance of an asset. They named it time-series momentum and described this strategy as investing in certain assets based on their own past performance, instead of the relative. Their study documented the existence of time-series momentum in various asset classes on the US market and demonstrated that using a strategy based on this anomaly over time would generate better risk-adjusted returns than using a passive long strategy. Additionaly, they concluded that this strategies were specially profitable during extreme down and up markets.

Thus, in this dissertation aims to investigate the presence of time-series momentum in the Portuguese stock market for the past 120 years, from 1900 until 2020, and to construct strategies based on this anomaly (i.e. invest on the market based on its past performance) in order to understand if the usage of this type of strategies could be beneficial in the Portuguese stock market and generate better excess results than using a passive long strategy. Additionaly, I also intend to analyze the performance of time-series momentum strategies during the different crises that affected the Portuguese economy in the last 120 years and, therefore, the performance of this strategies in extreme up and down market's condictions.

The results of this dissertation suggest that the time-series momentum effect is also present in the Portuguese stock market and that strategies based on this anomaly outperform a simple buy-and-hold strategy in the long run. Moreover, it is found that the time-series momentum strategy that seems to produce the highest returns of the time-series momentum strategies analyzed in this dissertation is the strategy with a look-back period of 1 month and holding period of 12 months.

This dissertations contributes to the literature about momentum for essentially two motives. Firstly, although some studies about cross-sectional momentum exist for the Portuguese market, no empirical study exists about time-series momentum for this market, being this dissertation the first one to analyze the existence and profitability of time-series momentum in the Portuguese stock market. Secondly, this dissertation is conducted using a very large long-term sample of data, which uses stock prices for the last 120 years, from 1900 until 2020, never used before to study momentum in the Portuguese market. Even in international studies, the testing of long-term data is not very common. Two examples of international studies conducted using old data are Geczy and Samonov (2015) and Goetzmann and Huang (2018) that focuses on the US market from 1801 to 2012 and on the Russian market using a dataset of stock prices from 1865 to 1914, respectively, which used a cross-sectional momentum approach as a basis for their security selection.

Therefore, this dissertation is contributing to the knowledge of this anomaly, testing it in a new market and extending the momentum analysis to new data, in order to create a more complete picture of this anomaly and its potential returns. In order to conduct this study, a methodology based on the one from Moskowitz et al. (2012) is used, applying it to a dataset of monthly index prices from 1900 to 2020. Also, because the results suggested that the time-series momentum effect is present in the Portuguese stock market and that strategies based on this anomaly are profitable, investors may find a new way of gain better returns in the market by contructing portfolios based on time-series momentum, especially during periods of crises.

This dissertation is structured as follows: in Chapter 2 it is presented a literature review about the topic. Chapter 3 elaborates on the data and methodology used on this dissertation, Chapter 4 presents the results obtained and the analysis of the empiricl results, and Chapter 5 focuses on the conclusions of this dissertation.

2. Literature Review

It already exists an extensive literature about momentum in its traditional approah (cross-sectional momentum), however, time-series momentum is a relatively new approach not as explored on the financial field. In this chapter, it will be presented some studies about the traditional cross-sectional momentum and then the literature will keep exploring studies about time-series momentum, presenting different ways of constructing strategies based on this anomaly, evidence about the presence of this anomaly in different instruments, countries and time periods, and some explanations for it.

2.1. Traditional Momentum

Since Jegadeesh and Titman (1993) first studied the profitability of momentum strategies and found that past winners tend to outperform past losers in the short run, other studies started to be conducted in order to understand this anomaly. Some examined momentum in an international setting (e. g., Rouwenhorst (1998), Asness, Moskowitz, and Pedersen (2013)) and others performed studies applying very old data, such as, Chabot, Ghysels, and Jagannathan (2009) which used U.K. data from the Victorian age, Goetzmann and Huang (2018) which focused on the Russian market from 1865 to 1914 and Geczy and Samonov (2015) which demonstrated the presence of momentum in the U.S. equity market since 1800.

Afterwards, other studies tried to suggest some explanations for this anomaly, as Daniel, Hirshleifer, and Subrahmanyam (1998) that developed a psychological explanation for momentum based on investor's overconfidence, implying that investors wouldn't adjust their expectations as much as they should when new public information was available, or Hong and Stein (1999) that observed the way agents interacted with each other dividing them into newswatchers, traders that will make decisions only based on their private information and, on the other hand, momentum traders which will trade based on past price changes. Moreover, Hong, Lim, and Stein (2000) added that firm size would impact the way information flows, since information about small firms would spread more slowly, namely due to bigger costs and lower analyst coverage, causing bigger momentum returns.

Also, Barberis, Shleifer, and Vishny (1998) built a model of investor sentiment consistent with conservatism, involving a slow adjustment of individuals' beliefs when new information is released which creates underreaction. A flow-based explanation for momentum was provided by Lou (2012) in which winning mutual funds would invest their capital inflows in their holdings formed by past winners, hence increasing the returns of past winners, but, on the other hand, losing mutual funds would liquidate their holdings in past losing stocks, leading losing stocks to keep underperforming winning stocks. Grinblatt and Han (2005) connected momentum with the disposition effect, i.e., the tendency to sell winners too quick and to hold on to losers. When new information arrived, in the case of good news, investors would sell their assets too soon, not letting the price reach its fundamental value, but, in the case of bad news, investors would be reluctant to sell, slowing down the fall of the price. A rational explanation for momentum effect was provided by Berk, Green, and Naik (1999) in which they constructed a dynamic real options model.

Regarding studies about the Portuguese stock market, Lobão and Mota (2014) explored the momentum effect, from January 1988 to April 2012, using stocks from the Portuguese Stock Index Geral (PSI Geral). Analyzing 32 different momentum strategies, they reported the existence of momentum profits in the Portuguese stock market in the short-run, corroborating the results found by other studies for several countries. Additionally, Lobão and Azeredo (2018) investigated the connection between the momentum and the value-growth effect using data from the Portuguese stock market from January 1988 to February 2015. They concluded that growth stocks exhibit higher momentum than value stocks and that a mixed strategy that combines value and momentum is able to generate statistically significant excess annual returns of 10.8%.

Some other studies were conducted in order to better comprehend this anomaly, however, all of these studies focused on cross-sectional momentum and it was not until Moskowitz et al. (2012) that a different type of momentum started to be explored.

2.2. Introducing time-series momentum

The concept of time-series momentum was first introduced by Moskowitz et al. (2012) and it differs from the cross-sectional momentum heavily studied in finance literature. While cross-sectional momentum consists in an evaluation of relative performance, meaning that when applying a cross-sectional momentum-based strategy investors will take long (short) positions in assets which past performance was relatively better (worse) than their peers, time-series momentum focuses on the absolute performance and, instead of comparing assets' performances, investors will assume long positions in assets whose past performance reached a predetermined benchmark.

Moskowitz et al. (2012) tested time-series momentum for 58 futures and forwards contracts from 4 different asset classes (commodities, equities, government bonds and currencies) from 1985 to 2009 reporting positive t-statistics for the first 12 months and negative t-statistics after that, indicating a return continuation for the first 12 months and reversals for longer horizons. Then, analyzing the profitability of time-series momentum strategies over several look-back periods, i.e., the number of months that the returns are lagged so that the signal used to create the portfolio can be defined, and holding periods, they chose to focus on what they name a TSMOM strategy, i.e. 12-month time-series momentum strategy with a 1-month holding period, founding that all futures contracts have positive time-series momentum returns. They showed that a time-series strategy provided a steady stream of positive returns that outperformed a passive long strategy. These positive profits were especially high during the Global Financial Crisis and sharply declined when the crisis ended in 2009. Also, they compared the TSMOM returns with the S&P 500 returns, finding the "time-series momentum smile", which indicates higher TSMOM profits during extreme up and down markets.

Comparing time-series momentum with cross-sectional momentum, they found that these two types of momentum are significantly correlated with each other, but that time-series momentum is not fully captured by cross-sectional momentum, meaning that they are not the same. Because the main component of time-series momentum is the auto-covariance of returns and it does not depend on the cross-serial correlations across assets, TSMOM will produce bigger profits than the cross-sectional momentum strategy. Following this conclusion other authors proceeded to compare both momentums in order to understand which one could develop the strategy with the better performance. Bird, Gao, and Yeung (2017), concentrating on 24 major equity markets, found that both strategies were profitable, but that time-series momentum strategies exhibited a better performance, supporting the findings of Moskowitz et al. (2012) that time-series momentum strategies outperformed the cross-sectional ones. Also, Ham, Cho, Kim and Ryu (2019) contributed with evidence from the Chinese market and reached the same conclusions.

Other studies argued that because in time-series strategies there is a net long position in risky assets, the measurement of relative performance cannot be done using cross-alpha regressions with excess returns. Therefore, in order to compare the strategies, Goyal and Jegadeesh (2018), using a sample of US common stocks from 1946 to 2013, concluded that the overperformance of time-series strategies was due to its net long positions and, after adjusting for it, the excess returns of the two strategies were similar. Following these conclusions, Mu and He (2019) also decided to compare the two strategies building the strategies in order to make them zero-cost and concluded that, in general, the time-series momentum strategy outperformed but that neither of them is fully captured by the other when portfolios are equally weighted. Hence, they determined that the explanations provided by Goyal and Jegadeesh (2018) were unable to justify the differences between the strategies and that instead it could be related to weighting scheme, length of look-back periods and of holding periods.

2.3. Revisiting the topic and new ways of constructing TSM strategies

After Moskowitz et al. (2012) published their paper, other authors started to pay attention to this anomaly expanding their research and even revisiting the original paper.

Kim, Tse, and Wald (2016) contested the findings of Moskowitz et al. (2012) and stated that "they scale the returns of the different futures contracts by a simple lagged estimate of volatility" (p. 104) which influenced the final results. Therefore, their results suggested that using a volatility scaling approach would originate higher returns than using a standard equally-weighted returns approach. More specifically, they found that TSMOM only outperformed other strategies if the volatility scaling method was used and, thus, an unscaled TSMOM strategy was unable of outperforming an unscaled cross-sectional and buy-and-hold strategy. Following these issues, Jo and Kim (2019) re-examined time-series momentum strategies and concluded that regardless of the volatility-scaling method employed, time-series strategies outperformed the passive long ones in any case of volatility scaling, indicating that they are independent of scaled positions. However, and in agreement with Kim et al. (2016), they found that the scaling method could influence the magnitude of the anomaly.

Additionally, Huang, Li, Wang, and Zhou (2020) using the same dataset of Moskowitz et al. (2012), decided to reexamine time-series momentum. They found evidence of a weak time-series momentum and due to different mean returns on the assets, size distortions and volatility scaling, they stated that the high t-statistics found on Moskowitz et al. (2012) are not statistically significant in corroborating the presence of this anomaly and attributed the results to volatility scaling. Ultimately, they found that the performance of time-series momentum strategies should not be attributed to predictability, but that it was more likely driven by differences in mean returns.

One study that supported the results of Moskowitz et al. (2012) is Chevallier and Ielpo (2014) that applied the same methodology to a dataset of commodities, equities, currencies and bonds from 1995 to 2012. In their analysis, they obtained similar results as in Moskowitz et al. (2012) and found that for most assets, the time-series strategy yielded positive returns. Also, Baltas and Kosowski (2013) used the same methodology on a dataset of 71 futures across assets classes from 1974 to 2012, constructing time-series strategies for different lookback and holding periods frequencies and found time-series momentum to be present across all frequencies.

Observing that the usage of these strategies could be a new way of investors obtaining good returns, some studies started to focus on the optimal way of exploring them and even in new ways of constructing time-series strategies to enhance profits. He, Li, and Li (2018) demonstrated that by considering the timing opportunity with respect to volatility, market trend and market fundamentals, the optimal portfolio would be defined by a combination of the time-series momentum and mean-reverting strategy. Also, trying to find the optimal looking-back period in the Chinese market, Qin, Pan, and Bai (2020) found that it changes across different assets and over time.

Pitkäjärvi, Suominen, and Vaittinen (2020) studied the simple (single-asset) time-series momentum and a cross-asset time-series momentum, finding that cross-asset strategies outperformed traditional time-series strategies, which they explained by the slow-moving capital in equity and bond markets. Elaut and Erdős (2019) introduced a new time-series strategy that did not build on a binary long/short signal, but that incorporated signal strength instead of only assessing the direction of one signal. It was also found that constructing a time-series momentum strategy based on twitter sentiment, meaning that investors would take a long position if the past sentiment change was higher than zero, could generate positive returns (Groß-Klußmann, König & Ebner, 2019).

Because taking a position in every listed stock may be something that a common investor is not able to accomplish, Lim, Wang, and Yao (2018) proposed two TSMOM strategies capable of reducing the number of assets required to invest: the Revised TSMOM and the Dual-momentum. D'Souza, Srichanachaichok, Wang, and Yao (2016) also showed that if investors used a dual-momentum strategy, the return obtained would be nearly the triple comparing with the annual return of a time-series strategy. Moreover, realizing that it may be required to rebalance the time-series strategy from time to time, due to volatility changes, Baltas and Kosowski (2015) proposed a new way of constructing time-series strategies using open-high-low-close prices and reducing the number of times the position changes when there isn't a significant price trend, resulting in a reduction of the turnover without reducing the risk-adjusted performance.

Gao, Han, Li, and Zhou (2018) investigated if the time-series pattern could also be found in an intraday level and observed that the first half-hour return on the market since the previous day's market close could predict the last half-hour return on the market, indicating a strong presence of intraday time-series momentum (ITSM) for the US market. Also, Li, Sakkas, and Urquhart (2019) compared the profitability of the ITSM strategy with Always-long and Buy-and-hold strategies and observed that 12 out of the 16 markets indicated significant economic benefits of using ITSM strategies.

In addition to these other ways of constructing time-series momentum strategies, Zakamulin and Rubio (2020) contributed to the study of this anomaly by using another methodology to investigate it, given that, according to them, the autocorrelation in excess monthly returns is very weak and it may not be captured by traditional estimation methods. Therefore, they proposed a "methodology that uses excess returns aggregated over multiple months" and found "the parameters of the AR(p) process that produce the best fit to a theoretical model" (p.3). They found that over short and medium-term horizons (5 to 10 years), the probability of the TSMOM strategy outperforming the buy-and-hold one was less than 60%, being this a reason for some researchers not founding in some of their studies that this type of strategies are profitable.

2.4. Evidence from different instruments, countries and time periods

Some studies were conducted in order to examine the time-series momentum anomaly in various instruments, different time periods and countries. For example, Hurst, Ooi, and Pedersen (2013) used data for 58 futures and currency forwards between 1985 to 2012 and found evidence of high Sharpe ratios in every time-series momentum strategy and a relatively worse performance in the equities class. Also, Georgopoulou and Wang (2017) investigating this anomaly in equity and commodity markets, concluded that these strategies could be applied not only to futures but also to more traditional instruments. Lim et al. (2018) also found evidence of this effect in U.S. equity markets from 1927 to 2017.

Focusing solely on the currency market, Menkhoff, Sarno, Schmeling and Schrimpf (2012) found that the cross-sectional strategies, unlike in other markets, outperformed time-series momentum strategies. Examining exchange-traded funds for several countries, Tse

(2015) reported that the time-series strategy earned higher profits than the buy-and-hold strategy, which was largely due to the period between 2007 and 2009.

With the relevance of the Green stock market increasing more and more, Chakrabarti and Sen (2020) decided to test the profitability of time-series strategies in this market. Using Green Indexes from the USA, Europe and Asia Pacific region and covering the period from 2003 to 2019, they concluded that less than 50% of the time-series strategies were profitable for all indexes. Additionally, they found that for the equally weighted global green portfolio these strategies could outperform the buy and sell-only strategies in 75.5% of the cases.

Besides more traditional instruments, this anomaly was also found in Bitcoins returns, though only showing 8 weeks of return continuation, while other assets studied on Moskowitz et al. (2012) exhibited 1-year return continuation. An explanation for this may be the fact that Bitcoin investors are faster to react to news (Hong, 2017). In terms of the cryptocurrency market as a group, including a sample set of 143 cryptocurrencies, Grobys and Sapkota (2019) did not find any evidence of time-series momentum in this market, indicating that this new market appears to be more efficient than traditional asset markets.

Furthermore, some studies were conducted for a diverse set of countries with the objective of understanding if time-series momentum was only characteristic of the US market or if it could be also found in several other markets. D'Souza et al. (2016) using a sample from 1927 to 2014 found that not only time-series strategies were profitable in the US market regardless of formation and holding periods, but that they additionally produced significant profits in international stock markets.

Focusing solely on the Chinese market, Shi and Zhou (2017) used a sample of three stock indices and A-share individual stocks from 1991 to 2015 and found that the time-series momentum effect was stronger in the US market than in the Chinese one, suggesting the market efficiency of the Chinese market was higher than the US market's. This conclusion is also found in Ham et al. (2019) and justified by the Chinese futures market being highly volatile and attracting many speculators, which resulted in time-series momentum being maintained for a shorter period of time and, therefore, generating less profits.

The profitability of this anomaly was also studied for the Japanese market by Cheema, Nartea and Man (2018) that found that these time-series strategies were also profitable, using stocks listed on Japanese stock exchanges between 1990 and 2014. Applying a similar methodology, Cheema and Nartea (2018) also found that time-series outperformed cross-sectional strategies in Islamic stocks and Chowdhury (2018), focusing on the Saudi Arabia stock market, obtained evidence of the presence of time-series momentum profits, namely when formation period was 3 months and for the holding periods of 6 up until 12 months.

Regarding the study of time-series momentum in the Portuguese market, it was not yet performed any study that explores this anomaly in the Portuguese market, contrasting with the analysis of cross-sectional momentum, for which some studies were already conducted in order to explore its existence and profitability in the Portuguese market, as presented previously.

Dividing emerging and developed markets, it was found that in emerging markets time-series strategies obtain much higher returns than in developed markets (Georgopoulou & Wang, 2017). Nevertheless, these higher profits were of a shorter duration and started to dissipate more quickly in emerging markets when there was not a control for the currency component. Also, Conover, Jensen, Johnson and Szakmary (2017) examined the existence and profitability of time-series momentum strategies in lesser-developed markets covering a period of 38 years and found that in emerging markets the time-series strategies, although generating excess returns, did not outperform the cross-sectional momentum strategies.

Then, following what Moskowitz et al. (2012) observed when analyzing the years of the Global Financial Crisis, other studies started to focus their analysis on this period. Most studies concluded that during the 2008 crisis the strategy based on time-series momentum was most profitable, but that in the following period the profits declined substantially. One of these studies was Hurst, Ooi, and Pedersen (2017) which showed that the time-series strategy had a consistent good performance over the long-time horizon studied, from 1903 to 2012, in spite of it including the Great Depression, several recessions and expansions, the Global Financial Crisis and other periods of wars, stagflation and rising/falling interest rates.

Furthermore, time-series momentum strategies seemed to perform even better in extreme up or down years, which was also documented by other authors. This was found for the ETFs market (Tse, 2015) and for the equity and commodities markets (Georgopoulou & Wang, 2017). Their explanation for this performance during bear markets particularly is that bear markets do not occur abruptly, allowing trend-followers to go short in the beginning of the decline and to profit afterwards when the market continues to go down. Georgopoulou and Wang (2017) studying the period represented by the global financial crisis, documented that time-series strategies suffered losses when the downturn started, then obtained profits for a long time and suffered losses again when the market started to recover.

This indicated that when there was a reversal in direction, because of existing long or short positions, time-series strategies would firstly obtain losses and adjust its positions afterwards.

Additionally, Bird et al. (2017) advanced that the reason for time-series momentum's performance being superior in extremely up and down markets when comparing with cross-sectional strategies could be due to its holdings being adjusted to the market conditions. In fact, when markets were down, cross-sectional momentum's performance went down two times more than time-series momentum's performance, which was explained by the fact that, even when all stocks had poor performances, in order to construct the winner portfolio, the investor had to select stocks which had poor absolute performance but relatively better than others. In contrast, under the time-series momentum strategy, stocks would only be added to the winner portfolio if their past absolute performance met the threshold.

Goyal and Jegadeesh (2015) also tried to explain this phenomenon by stating that cross-sectional strategies were zero net-investment strategies, but that time-series momentum strategies assumed net long (short) positions in risky assets. Hence, time-series strategies would outperform cross-sectional strategies because they earned a risk premium as a compensation for their net long position. Cheema, Nartea, and Szulczyk (2018) expanded the Goyal and Jegadeesh (2015) study and added that time-series outperforms cross-sectional momentum also due to its net short position when markets continue in the down state.

Regarding market changes, Cheema et al. (2018) found that time-series and cross-sectional momentum strategies were only profitable if the market did not change its state and that the time-series strategy outperformed when the market state was the same. This happened because they could time the market well when it assumed a net long (short) position and there was a market state continuation, while, when the market state changed, the net long (short) position of the time-series strategy would have a negative correlation with the market returns of the next period, resulting in negative results for this strategy. Similarly, Pettersson (2015) found that time-series momentum was influenced by the volatility state and that in low volatility states it produced higher returns and outperformed the high volatility time-series strategy.

Hutchinson and O'Brien (2020) added that, although time-series momentum strategies presented positive returns in expansions and recessions, these returns were stronger during expansions. Thus, their finding indicated that time-series returns were also connected with some macroeconomic factors related to the business cycle and noticed that time-series momentum's performance was better when the uncertainty in the economy was reduced, which is related to the findings that after periods of financial crisis this anomaly had a worse performance. In contrast, Lim et al. (2018) found that during down markets TSMOM would produce positive and significant returns but negative returns when markets were up.

Recently, some studies started to display concern about the efficiency of this strategy during the current market environment, due to the increasing competition, the lack of clear trends or even because of central banks' interventions on the market, such as the quantitative easing monetary policy, that could have a negative impact on the profitability of time-series momentum strategies (Georgopoulou & Wang, 2017). One example is Baltas and Kosowski (2015) that regarding the recent underperformance of time-series momentum strategies after 2008, found evidence that the shortage of significant price trends and the increasing correlations across assets could be a justification for it, given the fact that the construction of TSMOM strategies failed to adjust for the aggregate level of co-movement. However, Hurst et al. (2017) advocated that trend-followers still constituted a very small fraction of the market and therefore should not have a big influence on markets' trend dynamics. Regarding the more recent market environment, they estimated that the drawdowns during 2009-2012 were not that large and that, although the performance was not the best, there was no evidence that the environment played a role in that. It should be noted that after the beginning of the Global Financial Crisis the market became more correlated and, thereafter, independent trends to profit from became less available, being this true for many other investment strategies.

To conclude, investors are still likely to be suffering from the same behavioral biases, the diversification benefits of this strategy are still very important and developments like the reduction of transactions costs are positive signs for the continuity of the time-series strategy's good profits.

2.5. Biases/Explanations

After the discovery of this anomaly, some studies tried to elaborate explanations for its existence and profitability. D'Souza et al. (2016) showed that the profitability of time-series momentum could not be explained by the existing rational based models, but that, on the other hand, behavioral models, particularly investor's underreaction, seemed to better explain it. As for the behavioral model based on investor overconfidence, they found that, because there was not an asymmetric reaction to market states, it was not likely that investors' overreaction motivated time-series momentum profits.

He and Li (2015) proposed a continuous-time model that separated fundamental, momentum and contrarian traders. Because momentum strategies were based on the expectations that the market had previously underreacted and that it would follow the price trend, these strategies would destabilize the market price when the activity of momentum traders was more intense. On the other hand, contrarians would tend to induce market stability, due to this strategy being based on the hypothesis of market overreaction. Thus, the profitability of momentum strategies would not only depend on the time horizon but also on the market dominance of momentum traders. Also, Lim et al. (2018) tried to explain this anomaly by demonstrating that a traditional model without private information contagion would produce a random return direction, but, by incorporating private information contagion, the returns would remain positive for shorter horizons and reverse for longer horizons. Because private information is gradually spread and agents do not know if they are receiving brand new information or not, they will ignore if their private information is relevant and will enter the market, causing the number of momentum traders to increase gradually over time. Therefore, while some traders will start to adopt contrarian strategies, others will receive delayed private information and produce market overreaction. With time, more and more investors will revert their strategy and returns reversal will occur.

Additionally, Andrei and Cujean (2017) presented a model where time-series momentum persisted even when there was not any behavioral biases. Momentum occurred not only when investors learned from prices but also when private information spread simultaneously at an increasing rate. Assuming then that an infinite crowd of investors and meetings would not overlap, as the meeting intensity increases, returns would exhibit momentum and as the meeting intensity became infinite the momentum effect would disappear. Thus, some agents would be better informed than others and would become contrarians, while others would become momentum traders, allowing momentum to persist.

Another study tried to find a connection between the anchoring bias and the profitability of time-series momentum strategies. Hsu and Chien (2020) using the nearness to the Dow 52-week high to capture underreaction, concluded that market-timing TSMOM strategies based on nearness to the 52-week high outperforms the simple time-series momentum strategy. Hence, they observed that investor's reluctance to increase the price they were willing to pay for the stock after the disclosure of new positive information, due to the anchoring bias, led to underreaction for stocks close to the Dow 52-week high which allowed time-series momentum strategies to be profitable.

3. Data and Methodology

After presenting different studies about time-series momentum, in this section, it will be described the data, which will be applied in this dissertation and the methodology employed, in order to achieve all the defined objectives.

3.1. Data

Regarding the data, in this study, it will be used index stock prices from the General Index of the Portuguese stock market between the years of 1900 and 2020 and the risk-free rate for the Portuguese market corresponding to the same period. This data, from 1900 until March 2014, was collected by Mata, Costa and Justino (2017) that decided to create the history of the Portuguese stock market after observing that no data from this market was included in the book by Dimson, Marsh and Staunton (2002) that analyzed more than a century of history of 16 stock market. For data after 2014, I collected the prices from PSI General[1] to complete the sample until December 2020.

In order to build back the BVL-General (now called PSI General) Index, which was only available starting in 1988, Mata et al. (2017) reunited a team of students to collect along with them data from the Lisbon Stock Exchange, Bank of Portugal and archives in Lisbon, being the main source of information the daily bulletins kept in the archive of the Lisbon Exchange. Thus, they decided to extend the index on a weekly basis in order to deal with the traditional lack of liquidity of the domestic equity market and, choosing to do it on Wednesdays, they tried to avoid the weekend effect. Because time-series momentum is usually studied in a monthly basis, the data was converted to monthly values using the methodology presented in Martinović, Stoić, Duspara, Samardžić and Stoić (2016).

Regarding the time period after April 25th of 1974, when the Lisbon Stock Exchange remained closed until 1977, they had to reflect about the best methodology to use in order to surpass this constrain. Ultimately, they decide to exclude the first year after the market reopened (1977) due to quotations being below the average, explained by the turbulence of the revolution, and due to the number of listed companies being extremely reduced plus investor's increased risk aversion caused by the political and economic events that happened following the revolution.

[1] Data retrieved from https://www.investing.com/indices/psi-general-historical-data

Furthermore, the risk-free rate used is also provided by Mata et al. (2017) until 2014. After that, I use the EONIA daily rate as a proxy, given that Mata et al. (2012) also based their calculations for the risk-free rate on the EONIA after the closing of the Portuguese IMM market in 2008.

The data correspondent to the Fama-French factors was retrieved from Kenneth R. French's website[2]. Because it does not exist data available solely for the Portuguese equity market, data for the European equity market from 1990 until 2020, which includes data from Portugal in its calculation, was used as a proxy.

Table 1 presents the descriptive statistics of the data used in this dissertation.

Table 1: Descriptive Statistics.

	1900-2020	**1900-1974**	**1978-2020**
Daily Mean	0.015%	0.013%	0.019%
Monthly Mean	0.53%	0.53%	0.52%
Daily SD	0.249%	0.166%	0.348%
Skewness	1.506	0.407	1.425
Kurtosis	24.747	3.315	16.23

3.2. Regression analysis: predicting price continuation and reversal

In order to perform this study about time-series momentum, I will be using a methodology based on Moskowitz et al. (2012) that I will further describe.

To regress the excess return of different assets, Moskowitz et al. (2012) divide all returns by their volatility with the objective of controlling for potential cross-sectional heteroskedasticity caused by different levels of volatility. Regarding this volatility scaling method, they claim that the results will still be qualitatively the same even when they run regressions without adjusting for each asset's volatility. Also, Barroso and Santa-Clara (2015) demonstrate that scaling momentum can ensure that the risk stays relatively stable over the time period studied, which is important especially in periods with a high level of risk. Although in this study only one asset is investigated, I will apply this technique in order to control for potential heteroskedasticities so that the strategy's performance is not overly

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

influenced by times of elevated risk. This method is similar to the generalized least squares (GLS).

Thus, following Moskowitz et al. (2012), the ex-ante annualized variance is calculated as a sum of exponentially weighted squared returns, wherein multiplying by 12 is applied to convert the variance into annual:

$$\sigma_t^2 = 12 \sum_{i=0}^{\infty} (1 - \delta)\delta^i \, (r_{t-1-i} - \bar{r}_t)^2 \tag{1}$$

In Moskowitz et al. (2012), the parameter δ is chosen so that the mass center of the variance is equal to 60 days ($\delta/(1 - \delta) = 60$) and the returns used are daily returns. Because I do not have access to daily returns and I will be working with monthly prices, I follow their methodology by choosing a mass center of 2 months ($\delta/(1 - \delta) = 2$). The average monthly return $(\bar{r}_t)$ is also calculated as the exponentially weighted average, applying the same weights.

In order to detect price continuation patterns across different time horizons, which could indicate return predictability and suggest that time-series momentum strategies could possibly generate profits, given the fact that these are considered trend following strategies, I will regress the excess return, scaled by volatility, in month t on its return lagged h months, with lags of h=1,2,…,60 months, signifying that 60 regressions will be estimated as follows:

$$\frac{r_t}{\sigma_{t-1}} = \alpha + \beta_h \left(\frac{r_{t-h}}{\sigma_{t-h-1}} \right) + \varepsilon_t \tag{2}$$

where r_t and σ_{t-1} are the excess return in month t and ex-ante volatility, and r_{t-h} and σ_{t-h-1} are the excess return in month t and ex-ante volatility lagged h months. I applied the ex-ante volatility at time $t - 1$ with the returns at time-t to overcome the look-ahead bias.

This regression will be used to examinate the t-statistics of the β_h, where a positive value for the t-statistic will indicate return continuation and a negative value will indicate a reversal.

Alternatively, Moskowitz et al. (2012) propose another way of investigating time-series predictability focusing only on the signs of the past excess return, which is even simpler than the previous mentioned strategy. Thus, the equation will be the following, with lags of h=1,2,…,60 months:

$$\frac{r_t}{\sigma_{t-1}} = \alpha + \beta_h sign(r_{t-h}) + \varepsilon_t \tag{3}$$

The sign will be defined as +1 if return at month t-h is positive and −1 if return at month t-h is negative. Similarly, the t-statistics of the β_h will be retrieved from this equation in order to investigate the existence of time-series return predictability. According to Moskowitz et al. (2012), both equations (2) and (3) will lead to similar results.

3.3. Constructing time series momentum strategies

After investigating the presence of time-series momentum, it follows the investigation of the profitability of the strategies based on this anomaly for different look-back (k) and holding periods (h). To accomplish this, it will be considered that if the excess return over the past k months is positive the strategy is to go long for the holding period of h months. On the other hand, if the past k months return is negative the strategy is to go short. The use of ex-ante volatility in the equation is helpful to construct strategies that are not dominated by a few volatile periods.

The return will be calculated based on the sign of the past return from time t-k-1 to t-1. Then, the return will be computed based on the sign of the past return from t-k-2 to t-2 and so on. For each (k,h) a single time series of monthly returns is obtained by computing the return of all currently active portfolios, meaning that even if the holding period is superior to one, the monthly return is computed as the equally-weighted average across the h active portfolios, following the overlapping methodology of Jegadeesh and Titman (1993).

Therefore, the return of the time-series momentum strategy will be computed using the following equation:

$$r_{t,t+h}^{TSM} = sign(r_{t-k,t})\frac{r_{t,t+h}}{\sigma_{t-1}} \tag{4}$$

Where the $r_{t,t+h}^{TSM}$ is the return of the time series momentum strategy, $sign(r_{t-k,t})$ is the sign of the k lagged return (-1 or +1) and the σ_t the volatility at time t.

Then, to evaluate the abnormal performance of these strategies, I will be regressing time-series momentum returns on some factors to better investigate the drivers of time-series momentum profitability. Because the Fama-French factors are not available for the Portuguese stock market, this study will be using the risk factors calculated by Kenneth R. French and found on his website[3] for the European market, which includes data from the Portuguese one. Additionally, because this data is only available from 1990 up until 2020, I will be restricting this analysis to that period of time. The regression model will be as follows:

$$R_t^{TSM(k,h)} - R_{f,t} = \alpha + \beta_1\left(R_{m,t} - R_{f,t}\right) + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_t \tag{5}$$

Where, $R_t^{TSM(k,h)}$ is the return of the time-series momentum strategy lagged k months and hold h months, $R_{m,t}$ the return on the market, $R_{f,t}$ the risk-free return and the SMB and HML factors are the Fama-French size and value factors calculated for the European market.

As in Moskowitz et al. (2012) I will be focusing in the TSMOM_12_1 strategy with a look-back period of 12 months and holding period of 1 month because it serves as the benchmark in momentum literature. To create the passive long strategy to compare the TSMOM_12_1 strategy with, it is only required to replace $sign(r_{t-12,t})$ with 1. Moskowitz et al. (2012) also add a volatility scaling factor such that a predefined target volatility level σ_{target} is reached:

$$r_{t,t+1}^{TSMOM} = sign(r_{t-12,t})\frac{\sigma_{target}}{\sigma_t} \tag{6}$$

$$r_{t,t+h}^{buy} = \frac{\sigma_{target}}{\sigma_t} r_{t,t+h} \tag{7}$$

Moskowitz et al. (2012) and Baltas and Kosowski (2013) use a volatility target of 40%, which I will be following in this study. This choice is motivated by the observation that this scaling factor matches, approximately, the level of volatility of the equity risk factors

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

such as those constructed by Fama and French (1993) and Asness et al. (2013) and therefore enables a comparison between these portfolios and others present in the literature.

3.4. Performance over time and in extreme markets

To conclude the analysis, it will be plotted the cumulative excess return of the time-series momentum strategies over time, in order to compare them with the cumulative excess return of a passive long position, so it can be understood the performance of these strategies over time and in different market conditions, following what Moskowitz et al. (2012) present on their paper. Then, to examine the performance of this strategy in extreme bear/bull markets I will be plotting the returns of the time-series momentum strategies against the returns of the market in order to understand if the "time-series momentum smile", as observed on Moskowitz et al. (2012), is also found on the Portuguese stock market.

4. Empirical Results

4.1. Regression Analysis: Predicting price continuation and reversal

In the following chapter it will be described the results from the estimation of the regressions defined in (3.2) that, using lags from 1 to 60 months, test the existence of price continuation patterns. Firstly, the analysis will be performed using all data available from February 1900 until December 2020, noting that, given the close of the stock market after the Carnation Revolution, there is no available data for the period between May 1974 and December 1977. Then, the regressions will be estimated using data from the first sample period corresponding to February 1900 until April 1974 and, finally, they will be estimated for the second sample period using data from February 1978 until December 2020.

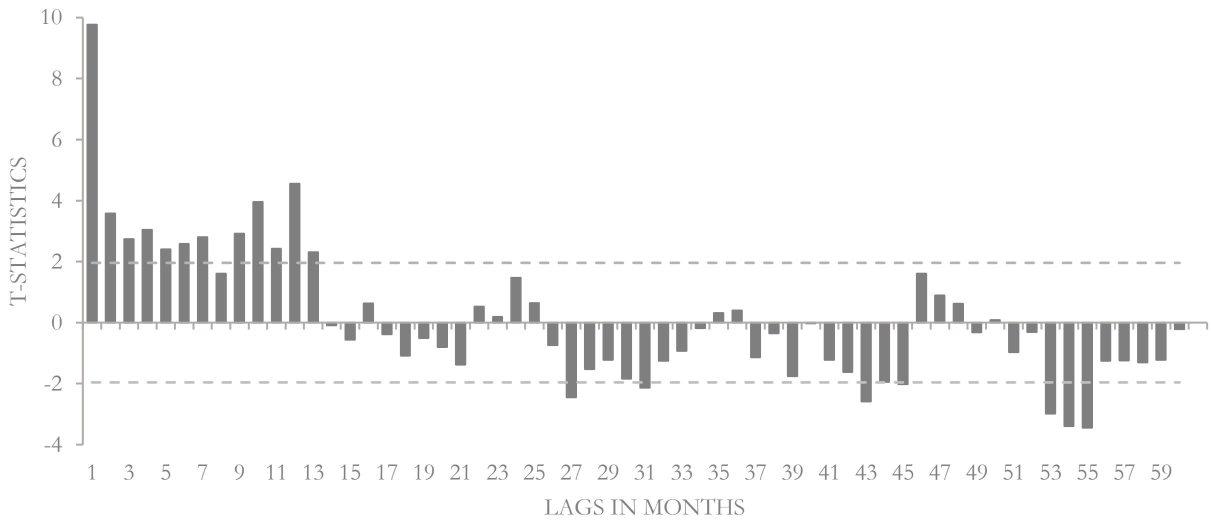
4.1.1. Sample period 1900-2020

The results reported are estimated using the two different equations defined by Moskowitz et al. (2012) in order to test return continuation and reversals. In Equation (1) the excess monthly return in month t, scaled by its ex-ante volatility, is regressed on its excess monthly return lagged h months, which is scaled by its ex-ante volatility lagged h months. Equation (2), alternatively, uses the signs of the past excess monthly return, meaning that the excess monthly return in month t, scaled by its ex-ante volatility, is regressed on the signs of the excess monthly return on month t-h.

Figure 1 reports the t-statistics associated with the β_h by month lag h, using Equation (1). A positive t-statistic is indicative of returns continuation, while negative t-statistics indicate reversals. When examining all data from the sample period through February 1900 until December 2000, noting that the values for the period from May 1974 and December 1977 are non-existent, we can observe a return continuation for the first 13 lagged months, with positive and significant t-statistics, except for 8 lagged months, which t-statistic is not statistically significant for 5%. Additionally, the highest t-statistic is observed at 1-lagged month. After 13 lagged months, we can observe a reversal, being nearly every t-statistic negative and not significant. This result is similar to Moskowitz et al. (2012).

In addition, the t-statistics for 12, 24 and 36, the multiples of month lag 12, are all positive, although not statistically significant at level 5% for 24 and 36 lagged months. Positive t-statistics for the multiples of month lag of 12 can be an indication of seasonality in time-series returns, as investigated and also found by Heston and Sadka (2008) in which they measured the seasonal effect on the cross-section of stock returns for NYSE-and AMEX-listed firms.

Figure 1: Time series predictability using equation 1 (1900-2020).

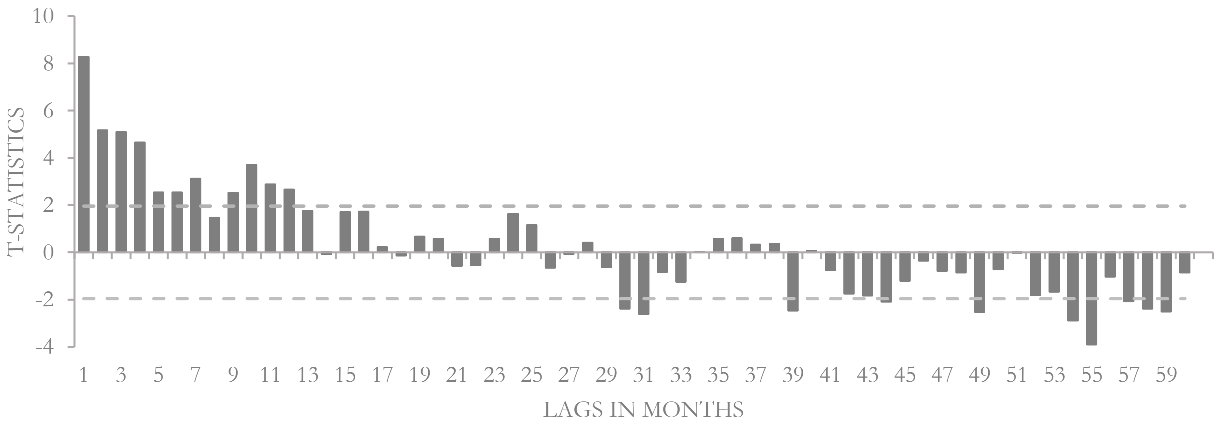


Notes: The graph shows the results of the regression of the monthly excess returns on its lagged excess return. Reported are the t-statistics computed using the lagged monthly excess returns as independent variables for lags h=1, 2, ..., 60 and returns are scaled by their correspondent ex-ante volatility. The dashed lines represent significance level at 5%. The sample covers the period February 1900 through December 2020.

Analyzing Equation (2) and using data for the whole sample period, similar results can be found on Figure 2. The t-statistics are positive and significant until 12 lagged months, except for 8 lagged months that displays a t-statistic positive but not significant, and the t-statistic for 1 lagged month is, as well, the largest. Afterwards, the t-statistics cease to be statistically relevant at confidence level of 95% and a reversal can be observed. The t-statistics are also positive for the multiples of 12, although not statistically significant for 24 and 36 lagged months.

Thus, the previous results presented on the graphs, suggest that the Portuguese stock market presents evidence of return continuation for the first year and weak reversals after that. These findings are consistent with those documented by Moskowitz et al. (2012). Additionally, other studies conducted for the Chinese and Saudi Arabian markets, Cho and Kim (2019) and Chowdhury (2018) respectively, also found the highest and significantly positive t-statistics for 1-month lagged.

Figure 2: Time series predictability using equation 2 (1900-2020).

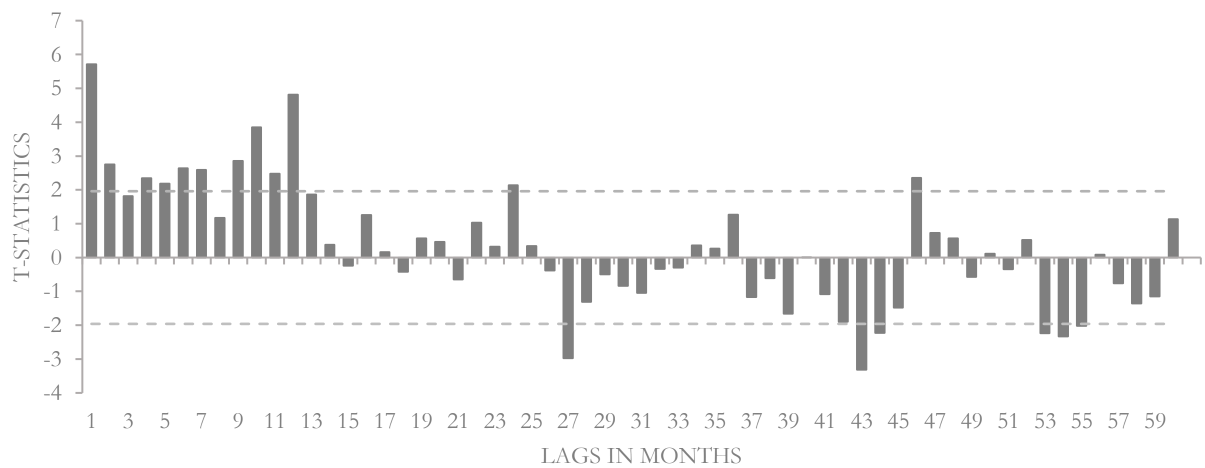


Notes: The graph shows the results of the regression of the monthly excess returns on its lagged excess return. Reported are the t-statistics computed using the signs of the lagged monthly excess returns as independent variables for lags h=1, 2, ..., 60. and returns are scaled by their correspondent ex-ante volatility. The dashed lines represent significance level at 5%. The sample covers the period February 1900 through December 2020.

4.1.2. Sample period 1900-1974

After the analysis of the full sample period, it is analyzed the t-statistics computed by dividing the sample period of 1900 to 2020 into two sample periods. As it can be observed in Figure 3, when using the first equation for the sample period between 1900 and 1974, the t-statistics for the first 12 months are sizable, positive and significant (with the exception of 3 and 8 lagged months), which is in accordance with the results of Moskowitz et al (2012) and suggests return continuation.

Figure 3: Time series predictability using equation 1 (1900-1974).

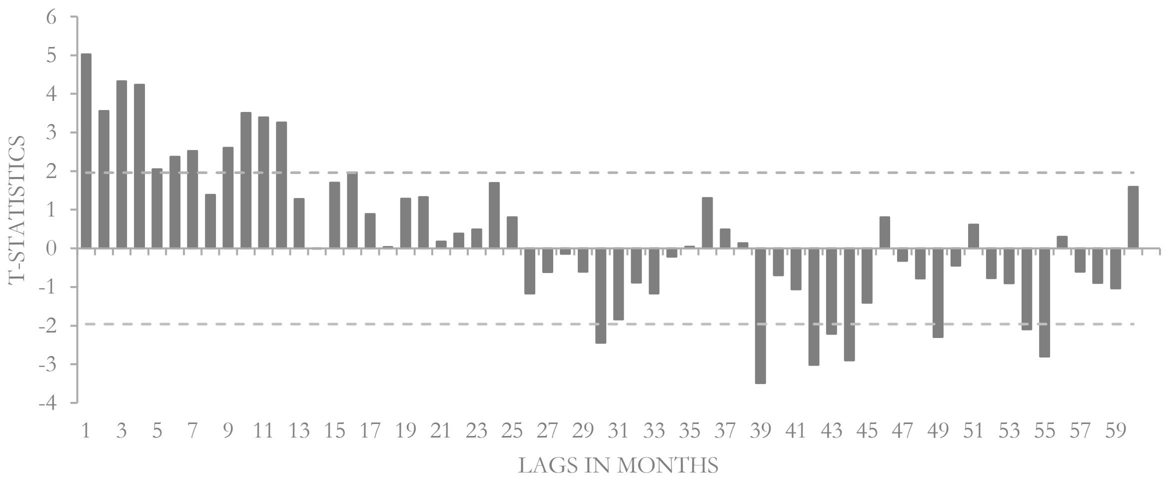


Notes: The graph shows the results of the regression of the monthly excess returns on its lagged excess return. Reported are the t-statistics computed using the lagged monthly excess returns as independent variables for lags h=1, 2, ..., 60 and returns are scaled by their correspondent ex-ante volatility. The dashed lines represent significance level at 5%. The sample covers the period February 1900 through April 1974.

Furthermore, over longer horizons, the t-statistics become smaller and, in some cases, significantly negative and. It can also be noted that the t-statistics for the multiples of 12 are all positive, indicating seasonality in time-series returns, similarly with Heston and Sadka (2008)'s results for cross-section returns.

Using Equation (2) for the same sample period, similar results were obtained, as illustrated by Figure 4. The t-statistics are also positive and significant until the 12th month lagged (except in month lag 8). Between 15 and 25 lagged months, the t-statistics remain positive, although mostly insignificant, and for more than 25 lagged months mostly t-statistics become negative and some statistically significant. Similarly, the t-statistics for the multiples of month lag 12 are all positive, although statistically insignificant for 24 and 36 lagged months. Moreover, the graphic shows that the longest trend continuation is at 13 months horizon, given that the t-statistics of this first 13 months are all positive and mainly significant.

Figure 4: Time series predictability using equation 2 (1900-1974).



Notes: The graph shows the results of the regression of the monthly excess returns on its lagged excess return. Reported are the t-statistics computed using the signs of the lagged monthly excess returns as independent variables for lags h=1, 2, ..., 60. and returns are scaled by their correspondent ex-ante volatility. The dashed lines represent significance level at 5%. The sample covers the period February 1900 through April 1974.

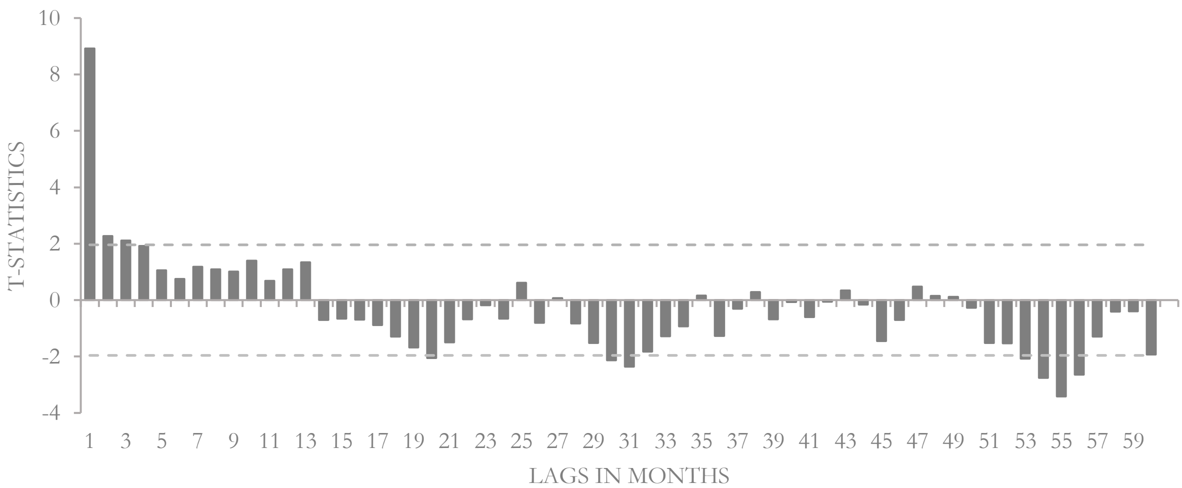
Therefore, for the period between 1900 and 1974, both equations indicate return continuation for the first 12 months, with positive and significant t-statistics, that subsequently originates weaker reversals, which, as a result, confirms the hypothesis for time-series return predictability and suggests that past returns are capable of predicting future returns.

4.1.3. Sample period 1978-2020

Analyzing the period between 1978 and 2020, Figure 5 illustrates the t-statistics for the Equation (1), indicating positive t-statistics for the first 13 lagged months and a reversal after that. Contrary to the same regression results for the period between 1900 and 1974, the t-statistics are merely significant from 1 to 3 lagged months and a large gap can be observed between the value of the t-statistic for 1 lagged month and the values for the other t-statistics from 2 until 13 lagged months. Furthermore, the seasonality in time-series returns previously found, could not be found in this sample period, given that the t-statistics for the multiples of 12 lagged months are not positive. After 13 lagged months, the majority of t-statistics are negative, although mostly insignificant and weaker reversals can be observed.

The lower t-statistics in this period may be attributed to the fact that this sample period is less extensive. Also, for equity indexes futures and considering that Moskowitz et al. (2012) analyzed a period (1985 to 2009) contained in this sample period, the results of that study present values similar to these, being the t-statistics lower than the t-statistics found for all asset classes.

Figure 5: Time series predictability using equation 1 (1978-2020).

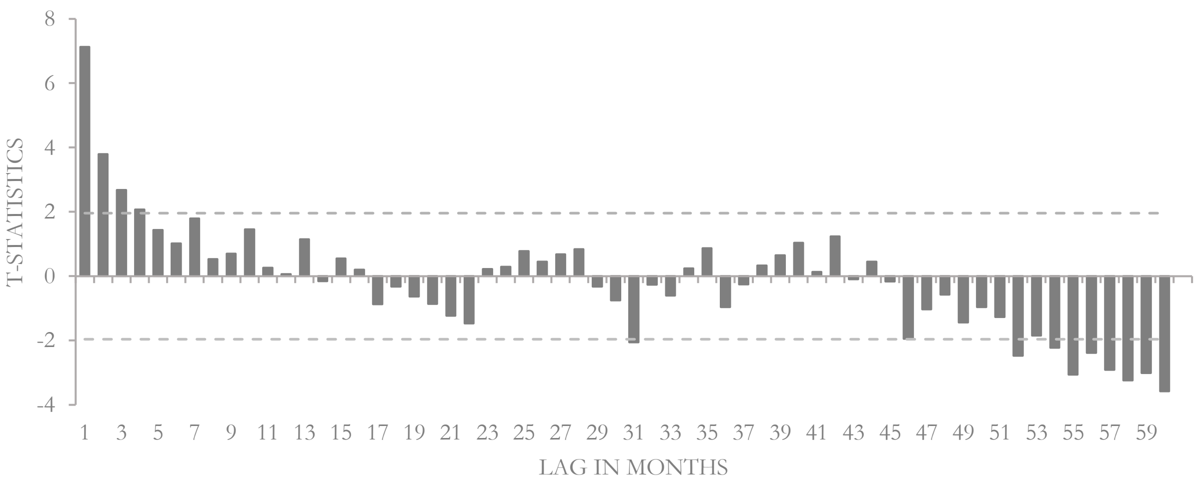


Notes: The graph shows the results of the regression of the monthly excess returns on its lagged excess return. Reported are the t-statistics computed using the lagged monthly excess returns as independent variables for lags h=1, 2, ..., 60 and returns are scaled by their correspondent ex-ante volatility. The dashed lines represent significance level at 5%. The sample covers the period February 1978 through December 2020.

Using the second regression, similar results were obtained, as observed in Figure 6. Therefore, using the regression with the lagged excess returns as independent variables, the results show positive t-statistics for the first 13 months lagged. The value of the t-statistic for

1 lagged month is also relatively higher than the positive values until the 13 lagged month value, where a reversal occurs, and only the first 4 lagged months are significant. The significant positive t-statistics for the first month, can suggest that the most recent month has the strongest and most significant return continuation, indicating a shorter return continuation period for the Portuguese stock market during this sample period than what was observed by Moskowitz et al. (2012).

Figure 6: Time series predictability using equation 2 (1978-2020).



Notes: The graph shows the results of the regression of the monthly excess returns on its lagged excess return. Reported are the t-statistics computed using the signs of the lagged monthly excess returns as independent variables for lags h=1, 2, ..., 60. and returns are scaled by their correspondent ex-ante volatility. The dashed lines represent significance level at 5%. The sample covers the period February 1978 through December 2020.

4.2. Time series momentum strategies

4.2.1. Risk exposure

After calculating the returns of time-series momentum strategies for the different combinations of look-back and holding periods (1, 3, 6, 9, 12, 24, 36, 48), the excess returns were regressed on the Fama-French factors (SMB and HML), so that the abnormal performance of the strategies could be evaluated by observing the t-statistics of the estimated alphas, i.e., the intercept of the regression. For now, the coefficients of the risk factors will not be analyzed, which will be later accomplished during the in-depth analyze of some time-series momentum strategies. The sample period analyzed is July 1990 to December 2020.

As shown in Table 2, the strategy with 1-month look-back and 12-months holding period (denominated in this study by TSMOM_1_12) reveals the highest t-statistic and highest significance for the Portuguese's stock market, unlike the findings of Moskowitz et al. (2012) for the US market, which indicated a higher t-statistic for the strategy with a look-back period of 12 months and a holding period of 1 month (denominated in this study by TSMOM_12_1). Moreover, for all look-back and holding periods combinations, the highest t-statistics value is always observed for the 1-month look-back period. Note that the results from the analysis of the existence of price continuation for the whole time period between 1900-2020 also indicated a significantly higher and more significant t-statistic for 1 lagged month when comparing with the next 12 lagged months.

This can be an indication that this anomaly is less persistent in the Portuguese market than in the US market and that time-series momentum may only be maintained for a comparatively shorter period of time in the Portuguese market, suggesting that strategies with only 1-month look-back period perform better in this market. Although not being similar to the results found for the US market, Ham, Cho and Kim (2019) also found that strategies with 1-month look-back perform better than the others in the Chinese market and Chowdhury (2018) reached similar conclusions for the Saudi Arabian market.

Table 2: t-statistics of the alphas of time series momentum strategies with different look-back and holding periods.

		Holding period							
		1	3	6	9	12	24	36	48
Lookback period	1	6.15	7.01	8.57	9.42	9.93	8.73	8.61	8.61
	3	4.76	5.05	6.01	6.51	6.81	6.45	6.74	7.03
	6	4.59	4.92	5.37	5.61	5.48	3.81	2.67	2.00
	9	3.44	3.87	4.27	4.18	4.07	2.56	1.40	0.11
	12	2.18	2.03	2.32	2.29	1.91	-0.25	-1.98	-4.47
	24	1.05	0.36	1.07	0.66	0.20	-0.86	-1.47	-5.23
	36	1.37	0.29	1.73	1.82	1.77	0.57	-2.44	-7.45
	48	0.84	-1.01	0.00	-0.31	-0.52	-3.83	-10.17	-14.74

Notes: Reported are the t-statistics of the alphas from the regression of the time-series returns of the different time-series momentum strategies constructed using different look-back and holding periods (1, 3, 6, 9, 12, 24, 36, 48). The time-series momentum excess monthly returns were regressed against the excess monthly return on the market and the Fama-French factors, SMB and HML. The sample period is July 1990 to December 2020.

4.2.2. Time-series momentum strategies returns against the Fama-French factors

In Table 3 is illustrated the TSMOM _12_1 returns against the Fama-French factors, SMB and HML. The analysis is also performed for the sample period of July 1990 to December 2020. The alpha coefficient is shown to be 0.0419% (annualized 0.5028%) at 5% significance level), indicating that the strategy outperforms the regression-based benchmark by this amount. Comparing with the value found on Moskowitz et al. (2012) of 1.58%, this value is notorious inferior, yet expected since the previous analysis shows a lower t-statistic for this strategy comparing with other strategies and the analysis of return continuation exhibited lower t-statistics until the 12th month, for the sample period of 1978-2020, than the t-statistics found on Moskowitz et al. (2012).

The Rm-Rf coefficient is 1.03, very close to 1, indicating that this strategy closely mimics the market. The coefficient correspondent to SMB is insignificant and and HML loading is 1.81. The value of the R-square is low, which suggests that the variation in the factor returns is not driving the variation in TSMOM_12_1 returns.

Table 3: Performance of the TSMOM_12_1 strategy

		Rm-Rf	**SMB**	**HML**	**Intercept**	**R^2**
TSMOM	Coeficient	1.030055	0.852493	1.807730	0.0419%	4.1042%
	t-stat	(2.494579)	(0.948656)	(2.353004)	(2.183016)	

Notes: The table reports the coefficients and t-statistics from the regression of the excess monthly returns of the time-series momentum strategy with 12 look-back months and 1 holding month against the excess monthly returns of the market and the Fama-French factors, SMB and HML. The sample period is July 1990 to December 2020.

Because the previous results pointed out to a better performance of the 1-month look-back and holding period strategy (denominated in this study by TSMOM_1_1), I decided to also perform a more detailed analysis of the returns of this strategy against the Fama-French factors. Table 4 presents the results of regression the time-series momentum strategy of 1 month look-back and holding period. As in the TSMOM_12_1 strategy, the alpha presents a positive and significant value and an even higher value than the one found on Table 2. The Rm-Rf coefficient is also very close to 1 and the other coefficients are statistically insignificant. Therefore, the returns of this strategy indicate no significant relationship with the risk factors, meaning that the returns are not explained by them.

Table 4: Performance of the TSMOM_1_1 strategy

		Rm-Rf	SMB	HML	Intercept	R^2
k=1 and h=1	Coeficient	0.968853	0.352769	0.427560	0.1144%	2.0327%
	t-stat	(2.423046)	(0.405392)	(0.574715)	(6.152511)	

Notes: The table reports the coefficients and t-statistics from the regression of the excess monthly returns of the time-series momentum strategy with 1 look-back month and 1 holding month against the excess monthly returns of the market and the Fama-French factors, SMB and HML. The sample period is July 1990 to December 2020.

Additionally, Table 5 presents the results of the TSMOM_1_12 strategy's regression against the Fama-French factors. As it can be observed, this strategy is the one with the highest coefficient value for the intercept, 0.24%. The Rm-Rf coefficient is a slightly greater than 1 and, although the SMB factor is not significant, the HML coefficient is positive and significant. Similarly with the outputs for the other strategies, the R-squared is very small.

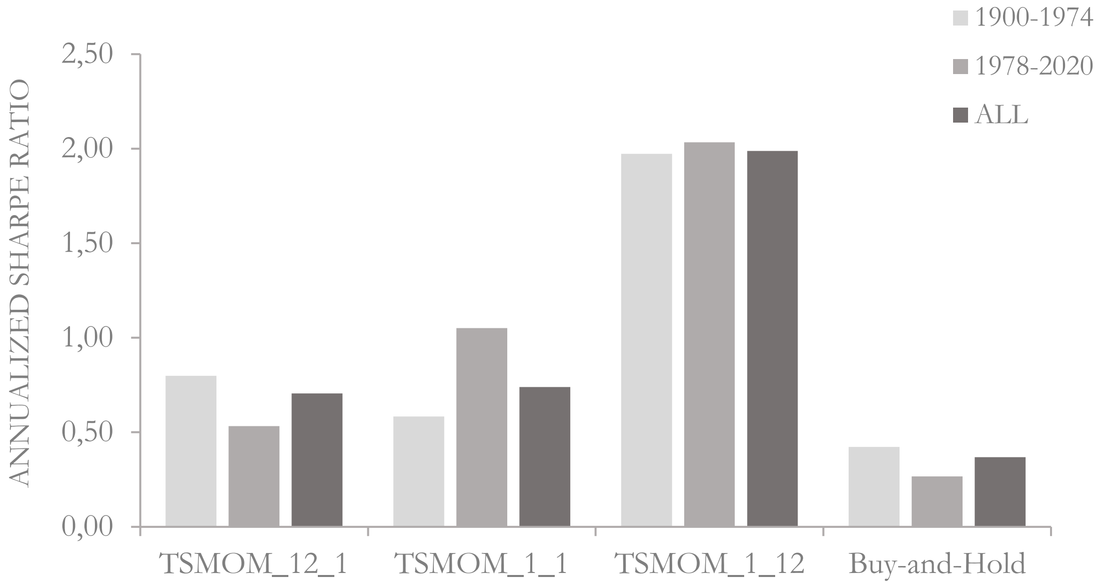
Table 5: coefficients and t-statistics from the r-egression of the time-series momentum strategy with 1 look-back month and 1 holding month returns against the Fama-French factors (SMB and HML)

		Rm-Rf	SMB	HML	Intercept	R^2
k=1 ; h=12	Coeficient	1.464783	-1.900747	2.157768	0.2385%	4.48%
	t-stat	(2.834617)	(-1.690153)	(2.244285)	(9.925180)	

Notes: The table reports the coefficients and t-statistics from the regression of the excess monthly returns of the time-series momentum strategy with 1 look-back month and 12 holding months against the excess monthly returns of the market and the Fama-French factors, SMB and HML. The sample period is July 1990 to December 2020.

Figure 7 shows the Sharpe Ratios for the TSMOM_12_1 strategy (i.e., the strategy with look-back period of 12 months and holding period of 1 month), the TSMOM_1_12 strategy (i.e., the strategy with look-back period of 1 month and holding period of 12 months), the TSMOM_1_1 strategy (1-month look-back and holding period strategy), and for the Buy-and-Hold strategy. The Sharpe Ratios are useful to understand the excess return a portfolio receives for enduring higher risk. All time-series momentum strategies exhibit positive Sharpe Ratios for both sample periods (0.8 for 1900-1974 and 0.53 for 1978-2020) and higher Sharpe Ratios than the Buy-and-hold strategy, although this passive strategy also displaying positive Sharpe Ratios. Comparing the Sharpe Ratios between the time-series momentum strategies the one than shows the lowest Sharpe Ratio for the period 1900-1974 is the TSMOM_1_1 strategy and the lowest Sharpe Ratio for the period 1978-2020 is found for the TSMOM_12_1 strategy. Furthermore, the TSMOM_1_12 strategy displays the highest Sharpe Ratio for both sample periods and for the whole sample period (1900-2020).

Figure 7: Annualized Sharpe Ratios of the TSMOM_12_1, TSMOM_1_1, TSMOM_1_12 and the Buy-and-Hold strategy



Therefore, comparing the Sharpe Ratios of the strategies, the worst strategy to follow seems to be the Buy-and-hold strategy. For both sample periods the best strategy to follow is the TSMOM_1_12 and for the sample period of 1978-2020, the Sharpe Ratio indicates that the strategies with 1-month look-back have a superior performance, which is in accordance with the previous finding these strategies performed better than the strategy with a 12 months look-back period, in the sample period of 1990-2020.

4.3. Performance over time

In order to analyze the performance over time of the time-series momentum strategies and comparing them with the performance of the Buy-and-Hold strategy, the calculations will be firstly performed using all data available, from 1900 to 2020, considering the close of the market after the Carnation Revolution of 1974 and assigning return of 0%

for these years. Then, the calculations will be divided into two sample periods, 1900-1974 and 1978-2020, in order to analyze with more detail each period. It will also be analyzed the implications of the different crises that occurred during the last 120 years on the performance of both strategies.

Regarding the monthly mean of the returns of the strategies, Table 5 exhibits these values. As we can observe, all strategies display higher returns, in average, than the returns of the market. Furthermore, in all three sample periods the TSMOM_1_12 strategy is the strategy with the highest monthly mean returns.

Table 6: Comparing monthly mean returns

	TSMOM_12_1	**TSMOM_1_1**	**TSMOM_1_12**	**Market**
1900-2020	0,93%	1,18%	4,31%	0,53%
1900-1974	0,83%	0,81%	3,72%	0,53%
1978-2020	1,10%	1,82%	5,33%	0,52%

Note: This table shows the monthly average returns of the TSMOM_12_1, TSMOM_1_1, TSMOM_1_12 and Buy-and-Hold strategies in order to compare the values with the monthly average returns of the market for the sample period of 1900-2020 and subperiods of 1900-1974 and 1978-2020.

4.3.1. Sample period 1900-2020

Figure 9 indicates that both time-series momentum strategies exhibited a better performance over time, from 1900 until 2020, than the simple buy-and-hold strategy. In order to present a figure with data for the whole sample period, I assumed return of 0% for all the years that the stock market was closed after the Carnation Revolution of 1974 and until its opening in 1978. Additionally, and in accordance with previous results, Figure 9 reveals a superior cumulative performance of the TSMOM_12_1 strategy over the TSMOM_1_12 strategy, particularly in the second sample period of 1978-2020 in which the difference between the returns of the two strategies is even larger. Figure 10 illustrates the relative performance of the time-series momentum strategies against the buy-and-hold strategy. Note that the sample period for this analysis starts in January 1916, due to the values between 1900 and 1915 being extremely high, which would complicate the comprehension of the graph. For this reason, the figure showing the values between 1900 and 1915 is in annex.

The analysis of the years and reasons that explain the enlargement of the difference between the performance of the time-series momentum strategies and the Buy-and-Hold strategy will be explained with detail in the examination of the two sample periods separately.

Figure 8: Cumulative excess return of the TSMOM_12_1, TSMOM_1_12 and Buy-and-Hold strategy, February 1901 to December 2020.

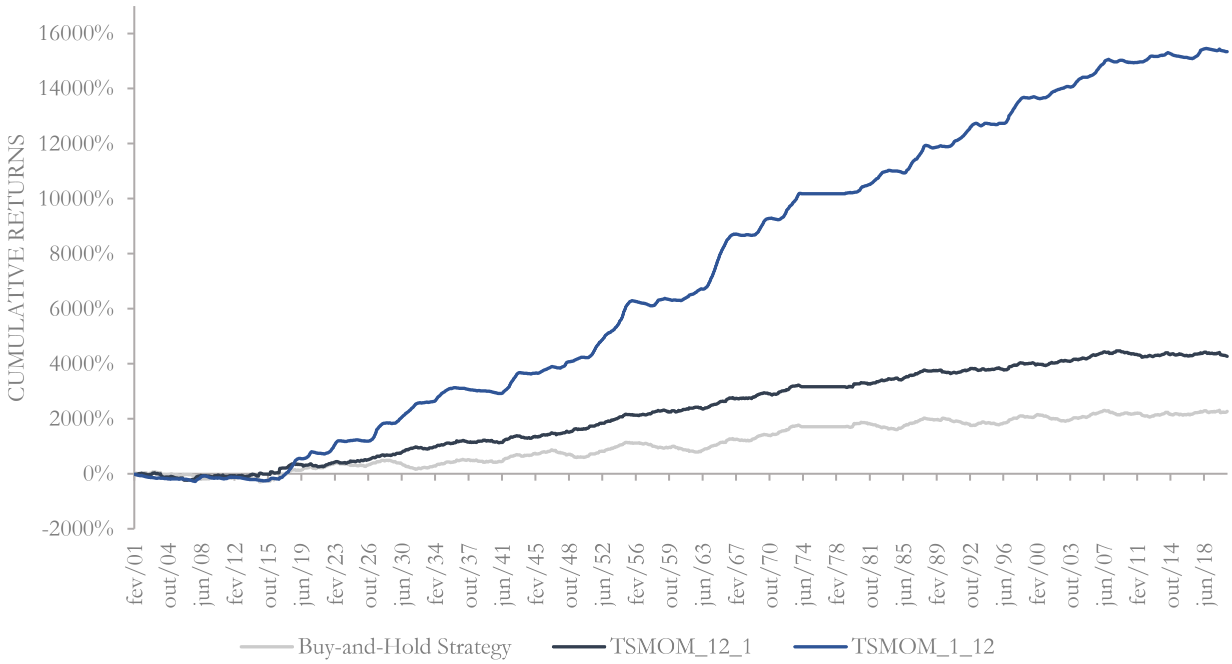
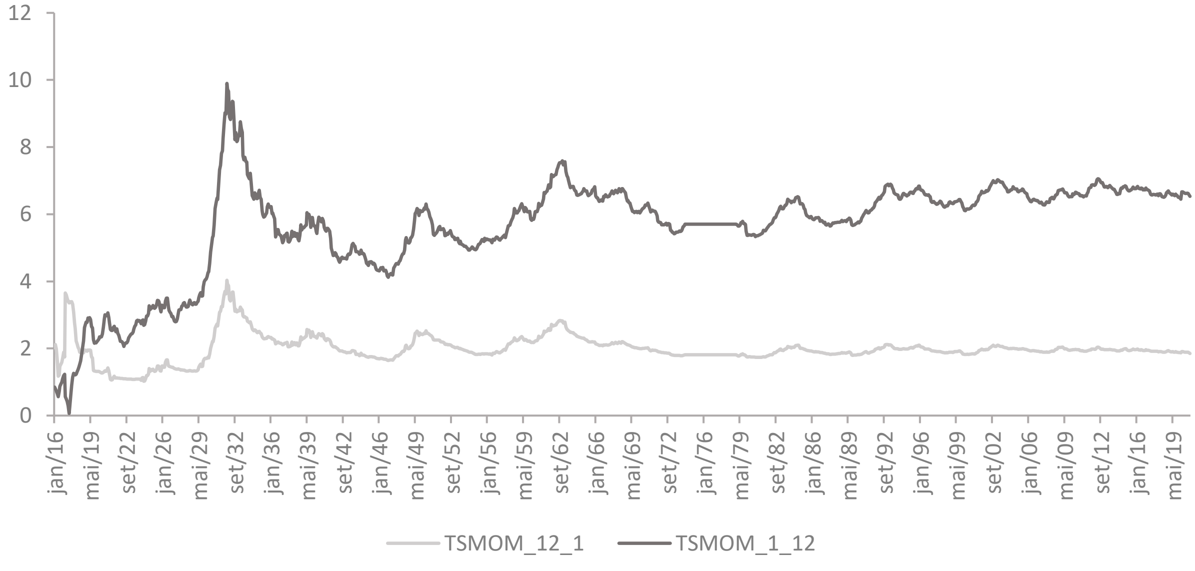


Figure 9: Relative performance between the time-series strategies and Buy-and-Hold strategy (January 1916 until December 2020).

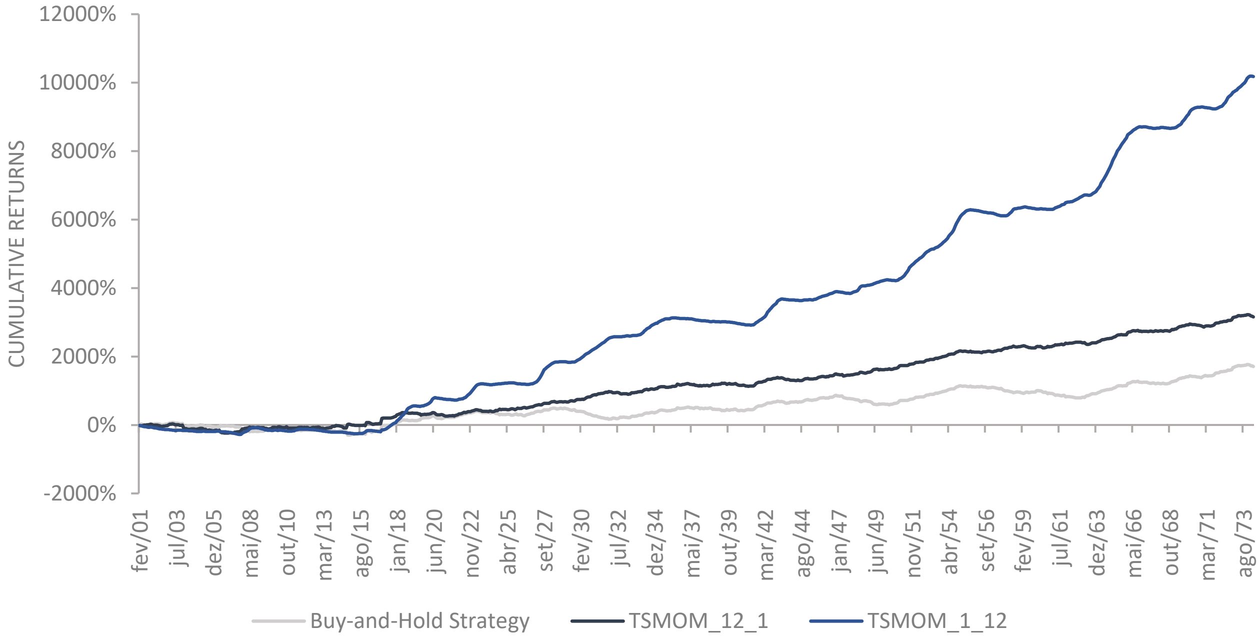


Note: This figure shows the relative performance between the TSMOM_12_1, TSMOM_1_12 strategy and the buy-and-hold strategy by dividing the returns of the time-series strategies by the returns of the passive strategy, implying that when the value increases the time-series strategy extends its profitability against the buy-and-hold strategy and, for example, a value of 2 means that the time-series strategy exhibited returns 2 times superior than the buy-and-hold strategy.

4.3.2. Sample period 1900-1974

Figure 10 shows the cumulative returns of the TSMOM_1_12, TSMOM_12_1 and the passive long (buy-and-hold) strategy from February 1900 until April 1974. As we can observe, the cumulative performance of both time-series momentum strategies outperforms the buy-and-hold strategy in the long run. Moreover, it can be observed that in some periods the time-series momentum strategies performed even better than the passive hold strategy, meaning that the time-series strategies gained value while the Buy-and-Hold strategy lost. This analysis can be better understood by looking at Figure 11.

Figure 10: Cumulative excess return of the TSMOM_12_1, TSMOM_1_12 and Buy-and-Hold strategy, February 1901 to April 1974.

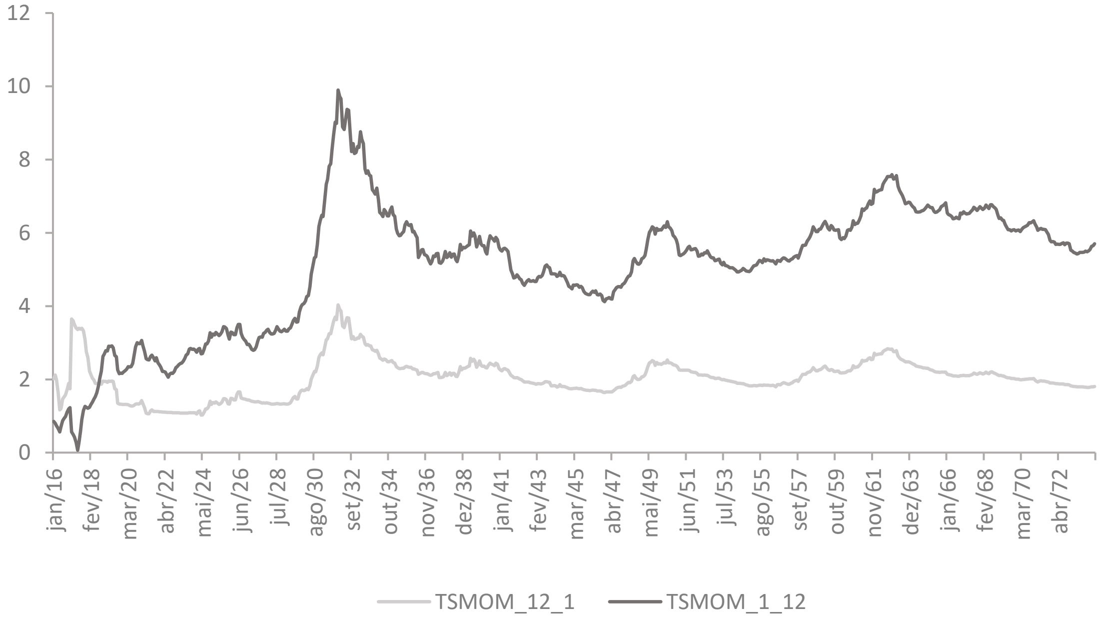


These results indicate that both time-series momentum strategies start to perform better than the passive buy-and-hold strategy around the beginning of World War I. Furthermore, we can observe those strategies gaining value, while the Buy-and-Hold strategy is losing, in the beginning of the 1930s. The study by Batista, Martins, Pinheiro and Reis (1997) point to a decrease of the Portuguese PIB by 9.7% in 1928. In fact, this period is characterized by the Great Depression, which started in the US, and the appointment of António de Oliveira Salazar to the finance ministry, who implemented austerity policies in order to solve the problem of the massive public debt. According to Telo (1994) this period, known as the "Financial Dictatorship" served as the starting point to the creation of the new economic model and social basis of the of the Estado Novo dictatorial regime.

Another point in time where time-series momentum strategies start gained value and the Buy-and-Hold strategy lost value is in 1947, when a deterioration of the economic and financial situation of Portugal occurred. The policies adopted to combat this situation were ineffective and, in 1948, Portugal had to request the North American financial help, which was initially rejected by Portugal in 1947 when the country joined the European Recovery Program (ERP), more commonly known as the Marshall Plan (Rollo, 1994).

This superior performance of time-series momentum strategies during periods of crisis was already documented in some papers about the topic, such as Moskowitz et al. (2012), Hurst, Ooi, and Pedersen (2017) or Georgopoulou and Wang (2017). One potential reason for this performance was advanced by Georgopoulou and Wang (2017) that explain that, because bear markets occur gradually, investors could assume a long or short position based on the past returns, given that those returns would be positively correlated. On the other hand, time-series momentum strategies would lose value at the end of crisis because the position would have a negative correlation with the future market returns.

Figure 11: Relative performance between the time-series strategies and Buy-and-Hold strategy (August 1917 until April 1974).

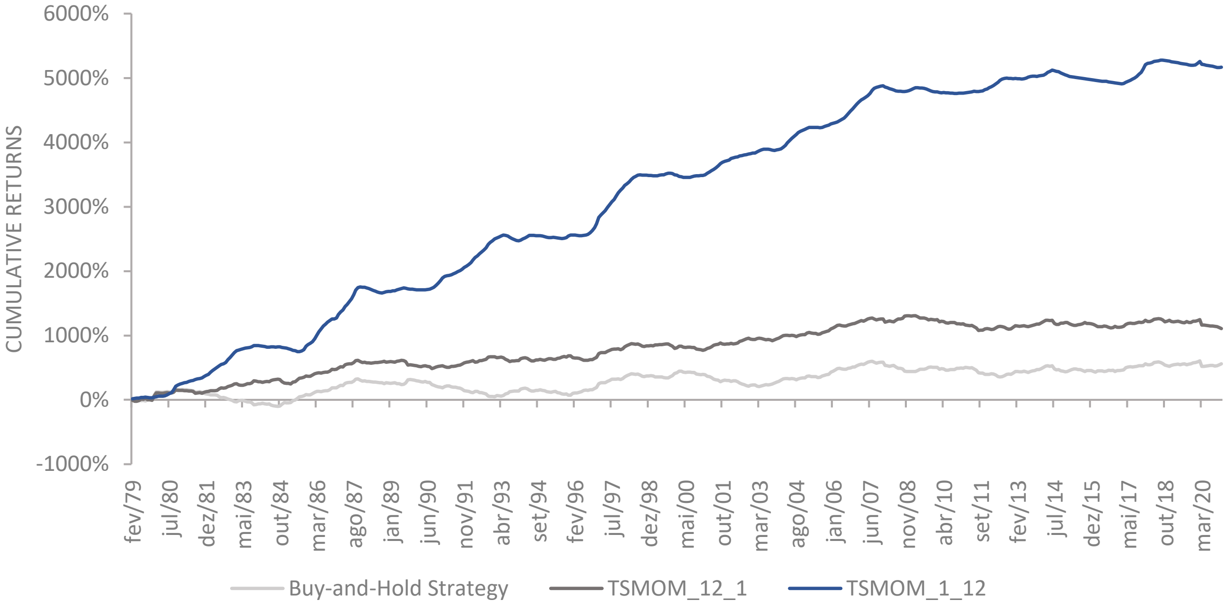


Note: This figure shows the relative performance between the TSMOM_12_1, TSMOM_1_12 strategy and the buy-and-hold strategy by dividing the returns of the time-series strategies by the returns of the passive strategy, implying that when the value increases the time-series strategy extends its profitability against the buy-and-hold strategy and, for example, a value of 2 means that the time-series strategy exhibited returns 2 times superior than the buy-and-hold strategy

4.3.3. Sample period 1978-2020

Figure 12 illustrates the growth of the three investment strategies over time for the sample period of 1978-2020. As well as the results obtained for the first sample period, the time-series momentum strategies in this sample period overperformed the passive long strategy over time, wherein the TSMOM_12_1 overtakes the buy-and-hold strategy quicker than the TSMOM_1_12 strategy.

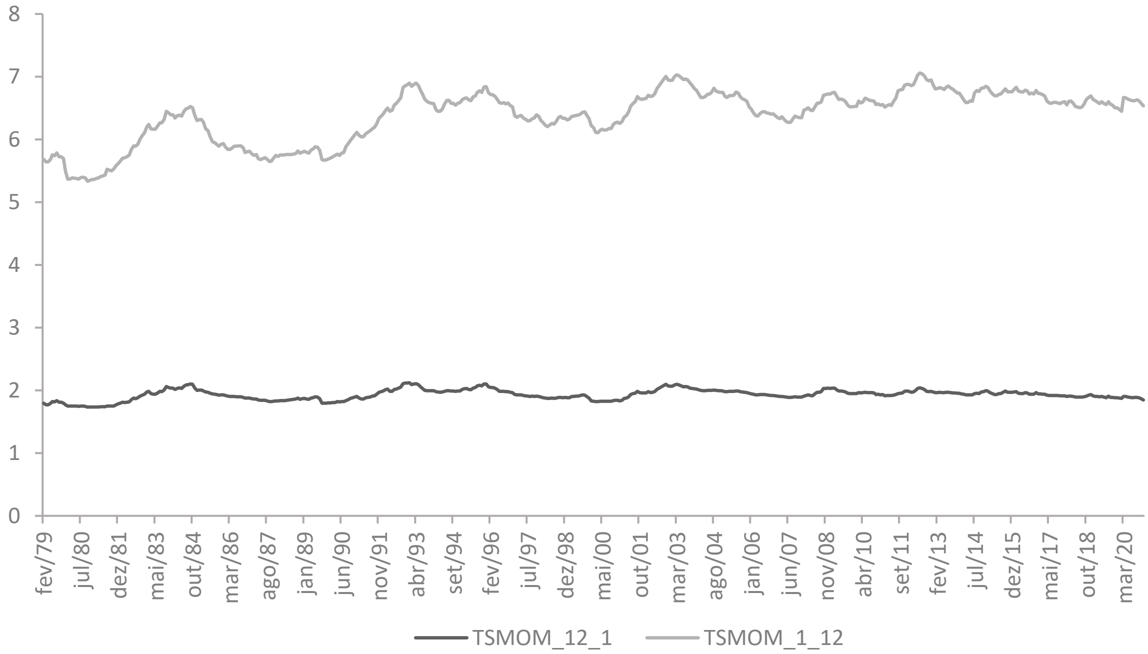
Figure 12: Cumulative excess return of time series momentum and Buy-and-Hold strategy, February 1979 to December 2020.



Another inference that can be made by studying Figure 12 is that the time-series momentum strategies exhibit an increase in value when the market starts to crash, while the passive long strategy decreases its value. By observing Figure 13, we can better highlight some periods where the buy-and-hold strategy loses value and, by contrast, the time-series momentum strategies gain, which correspond to the periods of five crisis that impacted Portugal during this sample period.

The earlies 1980s gave rise to an economic recession that affected many countries of the world. This severe economic recession was triggered by the 1979 energy crisis, caused by a political crisis in Iran, which led to a fast and substantial rise of the oil prices. Consequently, this event impacted the prices of many goods and services and inflation increased even more, leading many countries to strengthen their monetary policies, increasing interest rates. To fight the external crisis, the Portuguese government used some policies to stimulate the economy, increasing the public expenditure and decreasing interest rates. Nevertheless, inflation increased and the government tried to control it by fixing the prices themselves, which resulted in many companies struggling, given that they did not have the autonomy to increase the prices of their goods/services to compensate for the higher costs. This economic context led to an increase of the external deficit and the government decided to use other policies, namely the increase of the interest rates. The Portuguese economy entered in a recession, just like what had happened in the other developed economies. As a consequence, the PIB per capita decreased, the industrial production fell, the unemployment increased and the consumption rate and investment decreased.[4]

Figure 13: Relative performance between the time-series strategies and Buy-and-Hold strategy (February 1979 until December 2020).



Note: This figure shows the relative performance between the TSMOM_1_12 strategy and the buy-and-hold strategy by dividing the returns of both strategies, implying that when the value increases the TSMOM_1_12 extends its profitability against the buy-and-hold strategy and, for example, a value of 2 means that the TSMOM_1_12 exhibited returns 2 times superior than the buy-and-hold strategy

As we can observe, there is a rapid decrease of the returns of the buy-and-hold strategy in this period, but the time-series momentum strategies perform better, which can be a sign that this strategy has a superior performance during crises. When the crisis ends in

[4] https://www.ffms.pt/assets-recessoes/reports/Recessao_1983-1984.pdf

1984, Figure 13 shows that the time-series strategies suffer sharp losses, indicating that the ending of the crisis created strong trend reversals which causes losses on trend following strategies.

Another period when we can observe that time-series momentum strategies increased its value while the buy-and-hold strategy decreased is in the earlies 1990s, which is another period characterized by a recession, caused by the rise of the oil prices and the increase of the German interest rates, which led to the increased of the interest rates of the other European countries, given that the German Mark was linked to the exchange rates of the other European currencies. This led to a recession in most European countries, including Portugal. Additionally, the internal policies also gave an impulse to the accentuation of the recession. The industrial production fell, the unemployment increased and consumption, exports and investment decreased.[5]

Then, in the turn of the century, which was when Portugal joined the single currency, the reduction of the interest rates led to an increase of the debt of companies and families. Also, the adhesion to Euro, obligated Portugal to new budgetary rules that limited the budget deficit. This new context led to political instability and expectations of public spending cuts and increase of taxes, culminating in the decreased of the economic sentiment, decrease of the consumption and investment, and a fall of the real PIB per capita.[6] As in other crises, by observing Figure 12 and 13, we can also observe an increase in value for the momentum strategies compared to the passive investment strategy.

Additionally, this event can also be found, even though in a lower degree, during the market crash of 2008 and later in the market crash of 2010. In the summer of 2007, another financial international crisis had origin in the US with the subprime crisis. The crisis aggravated in 2008 with the bankruptcy of Lehman Brothers and, rapidly, the US recession became a global recession. The Portuguese financial system was badly affected and the already high public debt, stagnation of the economic growth and increased of the unemployment, did not help the Portuguese situation.[7] After the 2008 crisis, investors were apprehensive and with a high aversion to risk. Portugal exhibited very high levels of public and private debt, a weak economic growth and the interest charges became unbearable. Additionally, the restrictive policies used by the government, provoked a recession. After

[5] https://www.ffms.pt/assets-recessoes/reports/Recessao_1992-1993.pdf
[6] https://www.ffms.pt/assets-recessoes/reports/Recessao_2002-2003.pdf
[7] https://www.ffms.pt/assets-recessoes/reports/Recessao_2008-2009.pdf

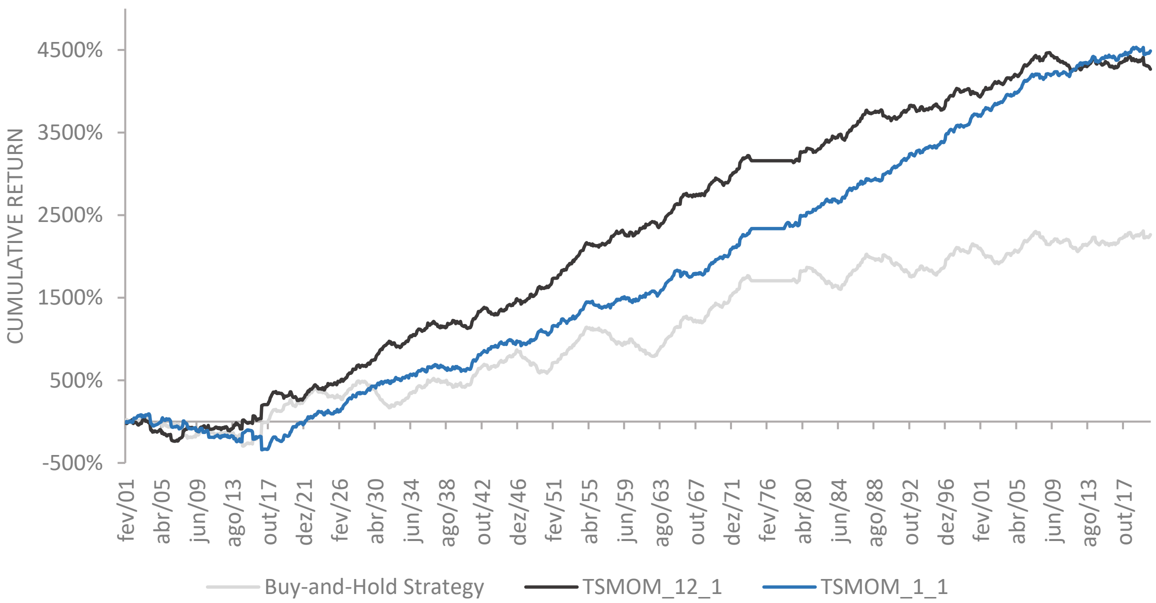
that, the Europe also enter in a recession and the harsh, recessive and short-term policies contained in the financial bailout (troika), excavated even more the crisis.[8]

To conclude, Figure 13 shows that the TSMOM_1_12 increases more its performance during crisis than the TSMOM_12_1, indicating that this strategy has more value during crises, but, nevertheless, losses value, more sharply, when crises end.

4.3.4. Comparing with the strategy with 1-month look back period

Regarding the strategy that uses 1-month look-back and holding periods, we can observe in Figure 14 that this strategy performs better than the buy-and-hold strategy but that it underperforms the TSMOM strategy in the sample period of 1900-2012. This result is in accordance with the previous results that indicated that the best strategy for early years was the TSMOM, namely the Sharpe ratio. For the second sample period, the TSMOM_1_1 starts to shorten its underperformance relative to the TSMOM_12_1 strategy and outperforms this strategy as from 2012, which is also in agreement with the results for the analysis performed in the last two points. Concerning the performance of this strategy in periods of crisis, it is similar with the way that the TSMOM strategy performed, which is reasonable since they are trend following strategies.

Figure 14: Cumulative excess return of the TSMOM_12_1, TSMOM_1_1 and Buy-and-Hold strategy, February 1901 to December 2020.

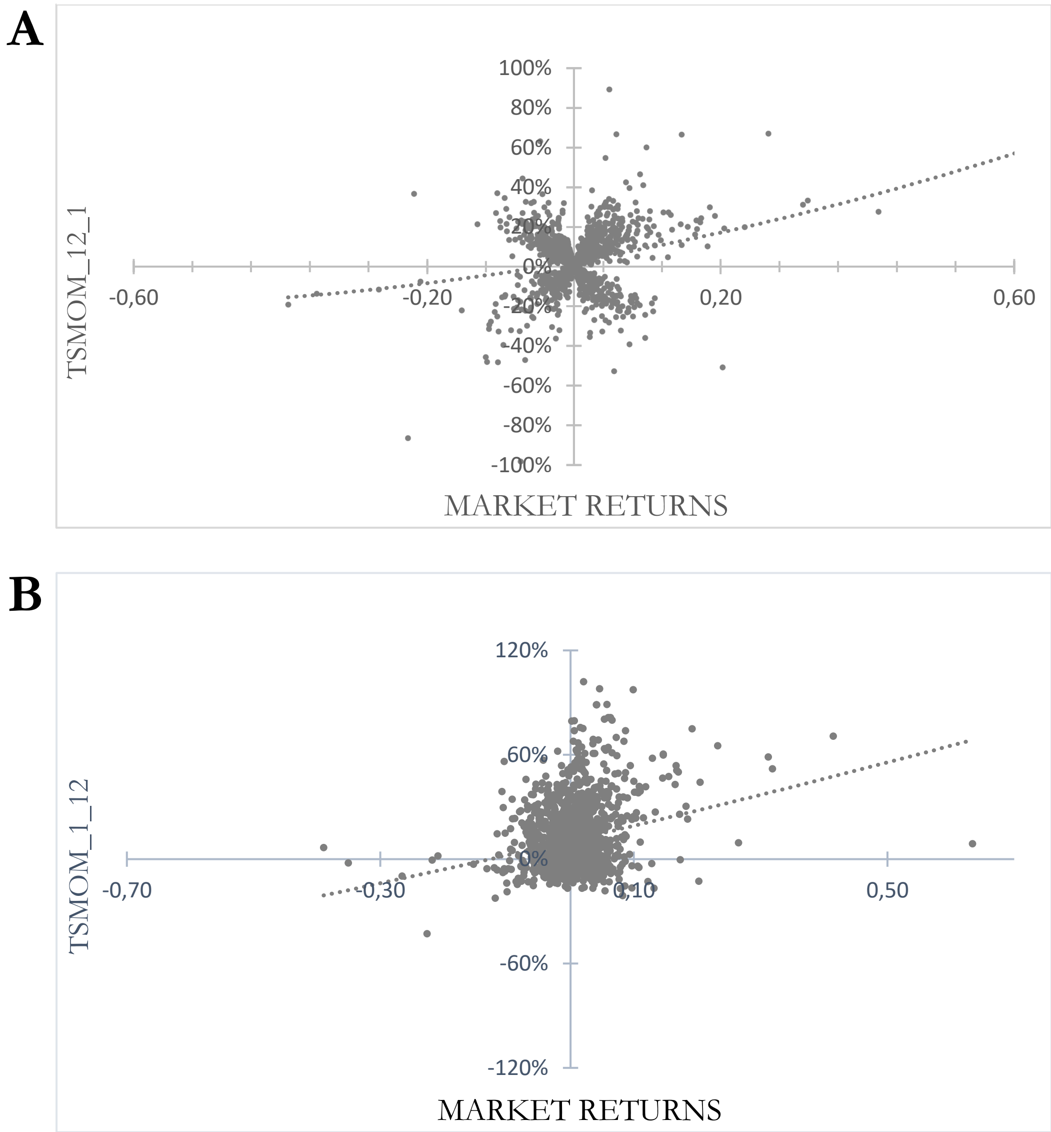


[8] https://www.ffms.pt/assets-recessoes/reports/Recessao_2010-2013.pdf

4.3.5. Performance in extreme up and down markets

Plotting the returns of the TSMOM_12_1 and TSMOM_1_12 against the returns of the market, as in Figure 15, it can be highlighted the behavior of the time-series momentum strategies in extreme up and down markets. In both strategies in can be observed that in extreme up markets, the time-series momentum strategies perform better, while in negative markets, the performance of this strategies is not especially good.

Figure 15: Time-series momentum "smile" (1901-2020).



Note: The figure presents the scatterplot of TSMOM_1_12 and TSMOM_12_1 monthly returns against the returns of the market. The dashed line represents the quadratic fit. The sample covers the period February 1901 through December 2020. Panel A plots the TSMOM_12_1 returns against the market. Panel B plots the TSMOM_1_12 returns against the market

As in Moskowitz et al. (2012), for the sample period of 1900-1974, Figure 16 exhibits a "smile" for both time-series momentum strategies indicating that these strategies perform better in extreme up and down markets. Additionally, both time-series momentum strategies seem to perform better when the market is up than when the market is down.

Figure 16: Time-series momentum "smile" (1901-1974).

A

B

Note: The figure presents the scatterplot of time-series momentum monthly returns against the returns of the market. The dashed line represents the quadratic fit. The sample covers the period February 1901 through December 2020. Panel A plots the TSMOM_12_1 returns against the market. Panel B plots the TSMOM_1_12 returns against the market.

Analyzing the sample period of 1979-2020, it can be noted in Figure 17 that, in contrast to the previous sample period, time-series momentum strategies do not appear to have positive returns when the market is down, although presenting better returns than the market. In up markets, the strategy appears to have a good performance.

Figure 17: Time-series momentum "smile" (1979-2020).

A

B

Note: The figure presents the scatterplot of time-series momentum monthly returns against the returns of the market. The dashed line represents the quadratic fit. The sample covers the period February 1979 through December 2020. Panel A plots the TSMOM_12_1 returns against the market. Panel B plots the TSMOM_1_12 returns against the market.

To conclude, as Hurst, Ooi, and Pedersen (2017) emphasize, these strategies will not always profit during extreme markets. In come cases, if the market crashes quickly not allowing the strategy to switch its positions, the strategy may incur in losses and not benefit from the collapse of the market. This can be the reason why in extreme down markets, time-series strategies do not exhibit mainly positive returns in the Portuguese stock market. and a perfect time-series momentum strategy is not found as in Moskowitz et al. (2012).

5. Summary and conclusions

In this dissertation it is studied the existence and implications of the time-series momentum effect on the Portuguese stock market. Using data from the last 120 years, I studied the existence of return continuation and reversals, by observing the t-statistics retrieved when regressing the excess return, scaled by volatility, in month t on its return lagged h months or by focusing on the signs of the past excess return. The results confirm the existence of return continuation in the Portuguese stock market and reversals after the first 12 to 13 months. Although, when dividing the data in two sample periods, the results differ slightly in respect to the duration of the return continuation, both sample periods point to return continuation followed by reversals.

In order to understand what was driving the returns of the time-series momentum strategies, I regressed the returns against the Fama-French factors (SMB and HML), limiting the analysis to the sample period of 1990 up until 2020 and using the Fama-French factors equivalent to the European market. Firstly, the findings showed higher t-statistics for strategies with 1 month look-back period, being the highest t-statistic the one from the 1-month look-back and 12-months holding periods, while Moskowitz et al. (2012) found the highest t-statistic in the strategy of 12-months look-back and 1-month holding periods.

Performing a more in-deep analysis for the TSMOM strategy and the 1-month look-back and holding periods strategy, I found that the returns of the strategies do not indicate a significant relationship with the risk factors, suggesting that the returns of the time-series momentum strategies are not explained by them.

In terms of Sharpe Ratios, the three time-series momentum strategies studied present higher Sharpe Ratios than the ones found for the Buy-and-Hold strategy, being the highest Sharpe Ratio for the sample period of 1900-2020, the value of 1.99 corresponding to the strategy TSMOM_1_12, while the Sharpe Ratio for this period of the Buy-and-hold strategy is 0.37. These results indicate that the use of this strategies is more optimal than the use of a passive long strategy, based on the Sharpe Ratios.

Overall, I found that the three time-series momentum strategies studied exhibited higher excess monthly average returns than the average excess monthly return of the market, being that the TSMOM_12_1 strategy exhibited 0.93% excess monthly average return for the whole sample period of 1900-2020, 1.18% for the TSMOM_1_1 strategy and the TSMOM_1_12 strategy presented the highest excess monthly average return of 4.31%, while the market only exhibit an excess monthly average return of 0.53% for the whole period.

Using the data provided by AQR (2021) that extended the data of Moskowitz et al. (2012) in order to cover the sample period of 1985-2020, it can be observed that the average monthly return of the TSMOM_12_1 strategy for the equity indices is 1.30%, which is lower than the value exhibit by this strategy for the Portuguese stock market. Nevertheless, comparing this strategy with the TSMOM_1_12 strategy, the TSMOM_1_12 strategy in the Portuguese stock market displayed a better performance.

Additionally, while Lobão and Lopes (2014) found that a traditional momentum strategy generated a return of 1.84% per month, this study shows that the TSMOM_1_12 strategy can be more profitable than the traditional momentum strategy.

Regarding the performance of time-series momentum strategies over time, when comparing with a simple Buy-and-Hold strategy, this study obtained results that suggest that the use of time-series momentum strategies, namely the TSMOM_1_12 strategy, can enable investors to retrieved better profits than when investing in a Buy-and-Hold strategy. These results hold for both sample periods.

Additionally, the hypothesis raised by Moskowitz et al. (2012) that time-series momentum strategies performed better in periods of crises was also validated by the empirical results of this study. In both sample periods, it can be observed a rise in the time-series momentum strategies' value, while the Buy-and-Hold strategy loses value, followed by a sharp decline of the time-series momentum strategy profits when crisis ended. These results are in accordance with the results found on Moskowitz et al. (2012) and several other studies about time-series momentum, including Georgopoulou and Wang (2017) that explain this performance during crisis by stating that bear market do not occur abruptly, but gradually.

This was the first study about time-series momentum in the Portuguese stock market and that used a sample of data of 120 years for Portugal, therefore these findings will improve the existent literature about time-series momentum. Also, the results supported the existence and profitability of time-series momentum-based strategies in the Portuguese stock market, meaning that investors may be able to use portfolios constructed based on time-series momentum to gain better returns in the market, especially during market crashes.

Some limitations of this study are the non-existence of data regarding the Fama-French factors for the Portuguese stock market and, therefore, the results may not be totally according to reality given the use of European data for the factors. Additionally, because I performed a long-term study using old data for the Portuguese stock market, it must be noted that some potential biases can affect the collecting of old data and, therefore, the results may be impacted by these issues. Because it was found that time-series momentum strategies were profitable in the Portuguese market, we suggest studying other combinations of look-back and holding periods of time-series momentum strategies, studying this anomaly using data from several indexes in order to construct a portfolio based on time-series momentum and, because other studies conducted for the US market found that combining the traditional momentum and time-series momentum to construct a portfolio would generate higher profits than only using one of the momentums, we suggest to apply this to the Portuguese market and also study the two momentum combined.

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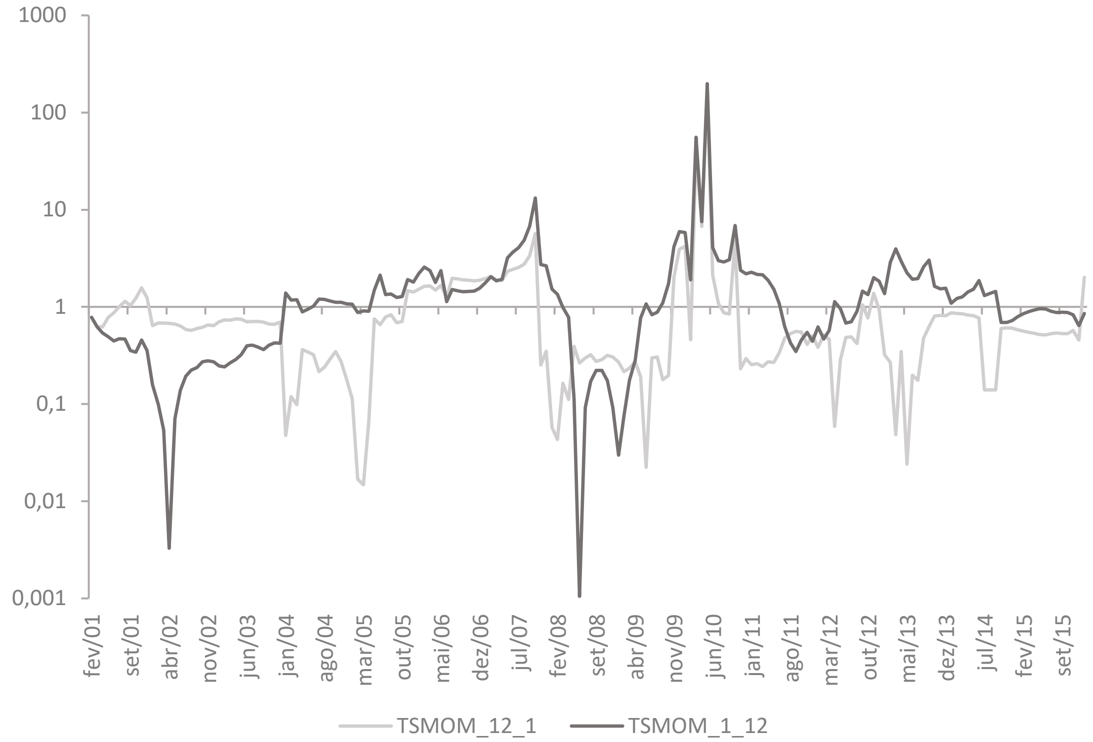
Annexes

Figure 18: Relative performance between the time-series strategies and Buy-and-Hold strategy (February 1901 until December 1915).



Note: This figure shows the relative performance between the TSMOM_12_1, TSMOM_1_12 strategy and the buy-and-hold strategy by dividing the returns of the time-series strategies by the returns of the passive strategy, implying that when the value increases the time-series strategy extends its profitability against the buy-and-hold strategy and, for example, a value of 2 means that the time-series strategy exhibited returns 2 times superior than the buy-and-hold strategy. The figure is presented in a logarithm scale.