Scientific Annals of Economics and Business
70 (3), 2023, 335-352
DOI: 10.47743/saeb-2023-0021

Time-Series Momentum in a Small European Stock Market: Evidence from a New Historical Financial Dataset

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Abstract: In this paper, we examine the Portuguese stock market for indication of time-series momentum effects using a new historical financial dataset that covers about 120 years of data. We find strong time-series momentum effects that cannot be explained by conventional risk factors. The positive return continuation seems to last for a period of 12 months, being heavily concentrated at the first month. At longer investment horizons, returns tend to mean-revert. The market exhibited significant time-series momentum for all look-back and holding periods of 12 months or less. A strategy with a 1-month look-back period and a 12-month holding period is shown to be the most profitable yielding a Sharpe ratio roughly 5.4 times that generated by a passive strategy. Time-series momentum strategies tend to perform best during extreme up-market periods and deliver the worst returns during down markets. This suggests that the strategy may not offer significant diversification benefits. Our findings add to the evidence that time-series momentum effects are not a product of data mining and are difficult to reconcile with the assertion that stock markets follow a random walk.

Keywords: asset pricing; market efficiency; Portugal; time-series momentum; return predictability.

JEL classification: G12; G14; G15.

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Article history: Received 2 June 2022 | Accepted 18 March 2023 | Published online 20 September 2023

To cite this article: Lobão, J., Rosário, A. (2023). Time-Series Momentum in a Small European Stock Market: Evidence from a New Historical Financial Dataset. *Scientific Annals of Economics and Business*, 70(3), 335-352. https://doi.org/10.47743/saeb-2023-0021.

1. INTRODUCTION

In the context of the Efficient Market Hypothesis (EMH) (Fama, 1965, 1970), stock prices are expected to fully and instantaneously reflect all available information. This means that none of the market participants should be able to systematically predict the evolution of financial prices. However, suggestive evidence that the returns of financial assets are, to some extent, predictable has been piling up during the last decades (Fama & French, 1989; Sarantis, 2001; Baker & Wurgler, 2007; Koijen & Van Nieuwerburgh, 2011) Momentum effects are one of the most notorious patterns of predictability. These effects in asset pricing can be found in cross-sectional and time-series data. In the traditional cross-sectional momentum proposed by Jegadeesh and Titman (1993), assets that outperformed their peers in the recent past tend to continue to do so for periods up to a year. In the last decades, extensive research has found supportive evidence of cross-sectional momentum profitability in international stock markets (Rouwenhorst, 1998; Griffin *et al.*, 2005; Asness *et al.*, 2013).

More recently, Moskowitz *et al.* (2012) introduced the notion of time-series momentum, describing a strong positive predictability of a security's own past returns. Specifically, a time-series momentum strategy involves buying a particular asset if it had positive returns in some prior period, and selling the asset if it had negative returns.

The importance of finding persistent momentum effects in financial markets is difficult to be overstated. Since these effects imply a return predictability based on past returns, the anomaly of momentum indicates that financial markets are not efficient even in the weak form. According to Fama and French (1996), momentum represents the main embarrassment to rational asset pricing models.

Time-series momentum has arisen a lot of interest in the literature, with most studies confirming the significance of the phenomenon (e.g., He & Li, 2015; Georgopoulou & Wang, 2017; Ham *et al.*, 2019). Despite this, fears persist that time-series momentum effects might be just the result of a data mining bias (Zakamulin, 2014). An effective way to dispel these concerns is to use datasets different from those researchers used to document the effects in the first place (Lakonishok & Smidt, 1988). The study of historical databases is part of this effort, having led to the conclusion that cross-sectional momentum existed in ages as remote as in the Russia of the Tsars or in Victorian England (Chabot *et al.*, 2008; Goetzmann & Huang, 2018). However, in spite of recent calls for the use of long-term series (Subrahmanyam, 2018), the examination of time-series momentum in historical datasets has been practically non-existent.

Our paper adds to this literature by examining for the first time the Portuguese stock market for indication of time-series momentum effects using a novel and still unexplored historical financial dataset that covers about 120 years of data. We analyse the price predictability of the market's own returns considering different look-back and holding periods. We also investigate if the time-series returns can be attributed to risk and compare the Sharpe ratios of the different strategies to that of a passive strategy for different sample periods. Finally, we scrutinize the cyclicality of the time-series momentum effects by analyzing the relationship between the returns generated by the strategy and the contemporaneous returns of the stock market.

We report strong time-series momentum effects that cannot be attributed to risk factors. The positive return continuation seems to last for a period of 12 months and it is heavily concentrated at the first month. At longer investment horizons, returns tend to revert to the mean. Time-series momentum strategies tend to perform best during extreme up-market periods and generate the worst returns during down markets. Overall, our findings add to the evidence that time-series momentum effects are not a product of data mining and seem difficult to reconcile with the idea that stock markets follow a random walk.

The remainder of this paper is organized as follows. Section 2 reviews the related research. Section 3 describes the dataset used in our study and develops the methodology. Section 4 discusses our empirical findings. Section 5 discusses our findings and their implications. Section 6 presents the main findings, some limitations of the study, and suggestions for further research.

2. LITERATURE REVIEW

Moskowitz *et al.* (2012) were the first to introduce the concept of time-series momentum in the scientific literature. The authors showed for a large set of futures and forward contracts traded in the US from 1965 through 2009 that their recent returns, that is, returns observed in the past one to 12 months, were positive predictors of future returns. Moreover, the abnormal returns obtained by a time-series momentum strategy could not be explained by risk, which suggests the existence of a true market anomaly. Ham *et al.* (2019) corroborated these findings in China's commodity futures markets in the period 2016-2018. Moreover, they showed that a time-series momentum strategy with a 1-month look-back period and a 1-month holding period exhibited the best performance. Hurst *et al.* (2013) and Baltas and Kosowski (2020) document that time-series momentum strategies are so important that they are able to explain a significant part of the performance of futures and commodity trading advisors. However, in a recent study, Huang *et al.* (2020) cast some doubts on the results obtained by Moskowitz *et al.* (2012). They re-examined an expanded version of the dataset used by Moskowitz *et al.* (2012) to conclude that the signs of time-series momentum are weaker than initially reported, although a strategy based on that effect remains profitable.

Despite the recent interest in time-series momentum, existing studies applied to stock markets continue to be relatively scarce. He and Li (2015) provide evidence of persistent time-series momentum in the S&P500 over the period 1988-2012. In a follow-up study, He *et al.* (2018) show that this pattern of price continuation and reversal in the US stock market can yield significant abnormal profits. Cheema *et al.* (2018) report that time-series momentum strategies applied to the US stock market from 1946 through 2015 generate returns of 1.81% (3.19%) per month when the market trend is positive (negative). Georgopoulou and Wang (2017) document a robust and consistent time-series momentum effect in a set of forty-five equity indices, covering developed and emerging markets from 1969 to 2015. Returns tend to persist for the first 12 months, reverting over longer horizons. Shi and Zhou (2017) corroborate these results in the Chinese stock market, highlighting that the profitability of time-series momentum strategies seems to be related to firm-specific characteristics.

The profitability of time-series momentum strategies has been found to extend to individual stocks in developed markets (Szakmary & Lancaster, 2015; D'Souza *et al.*, 2016; Goyal & Jegadeesh, 2018; Lim *et al.*, 2018; Chakrabarti & Sen, 2020).

The importance of the phenomenon has been so widely recognized that time-series momentum has begun to be used as an independent risk factor. This is the case, for example, of Koijen *et al.* (2018) who analyzed the exposure of carry trade returns observed in several markets to the returns generated by time-series momentum strategies. Still, the role of momentum as a distinct risk factor remains under dispute. For example, in a recent article, Ehsani and Linnainmaa (2022) argue that the effect simply results from autocorrelations in other factors.

On a related research, Wang *et al.* (2021) document that a comprehensive sample of stock market anomalies exhibits a strong time-series momentum.

Some studies highlight the relationship between time-series momentum and technical trading rules based on past returns. For example, K. J. Hong and Satchell (2015) argue that the popularity of moving average trading rules amongst stock market investors may be due to the existence of time-series momentum. In the same vein, Marshall *et al.* (2017) analyze ten international stock markets during the period 1973-2013 to reach the conclusion that time-series momentum and moving average trading rules are closely related.

More recently, the phenomenon has been researched in intraday prices. For example, Y. Li *et al.* (2020) examined the intraday time-series momentum in the Chinese stock index futures market finding that the first trading-session return positively predicts the last trading-session return. These results have been subsequently confirmed in commodity futures (Jin *et al.*, 2020; Zhang *et al.*, 2020), exchange-traded funds (Gao *et al.*, 2018; Onishchenko *et al.*, 2021), cryptocurrencies (Shen *et al.*, 2022), and developed stock markets (Z. Li *et al.*, 2022).

In a synthesis of the literature on equity market momentum, Subrahmanyam (2018) urges researchers to increase the power of their analysis by considering longer time series. In spite of this appeal, to the best of our knowledge, only Lim *et al.* (2018) and Zakamulin and Giner (2022) studied time-series momentum effects using a long-run financial database. Lim *et al.* (2018) examined all the individual stocks listed on the NYSE, NASDAQ, and AMEX from 1927 to 2017 in addition to stock data of 13 other European stock markets. They document that the effect is strong and is not specific to sub-periods, firm sizes, formation and holding periods, or geographical markets. The profits of the strategy tend to be more pronounced during (extreme) down markets.

In a recent article, Zakamulin and Giner (2022) examine the same effects on the S&P Composite stock price index using a historical dataset that covers the period 1857-2018 (162 years of data). They report compelling evidence of the presence of short-term time-series momentum. The authors also show that suggest another methodology to better investigate the topic, as they argue that because the autocorrelation in excess monthly returns tends to be very weak, the time-series momentum may not be captured by traditional estimation methods.

On a related note, it is worth mentioning that some recent studies such as those conducted by Chabot *et al.* (2008), Geczy and Samonov (2016), Hurst *et al.* (2017), Goetzmann and Huang (2018), and Trigilia and Wang (2019) have been using financial history databases to perform out-of-sample analyses and to backtest trading strategies based on cross-sectional momentum effects.

In the context of the Portuguese stock market, the phenomenon of time-series momentum has not been studied yet. However, there are some articles about the related cross-sectional momentum effects in this market. For instance, Soares and Serra (2005) analyzed the period 1988-2003 and found weak evidence in support of momentum effects. The authors attributed these effects to an insufficient reaction to earnings announcements surprises. Lobão and Lopes (2014) studied the same topic in a significantly larger sample, covering the period 1988-2012. The main result is that momentum strategies can generate significant positive returns over three to twelve months holding periods. Concerning the performance of momentum strategies in the long run, the results seem to support the underreaction hypothesis.

More recently, Lobão and Azeredo (2018) confirmed that the Portuguese stock market exhibited significant levels of momentum in the period 1988-2015, and that momentum strategies can be combined with value strategies to increase investors' profits.

Our paper adds to this limited body of evidence by examining the existence of time-series momentum in an understudied market using a novel and still unexplored historical financial dataset. Thus, the hypothesis being tested in our study is that there is time-series momentum (i.e., return continuation) in the Portuguese stock market.

3. DATA AND METHODOLOGY

3.1 Data

In this empirical study, we consider the Portuguese stock index and the risk-free interest rate for Portugal from January 1900 to December 2020. For the period 1900-2013, we used the database with weekly frequency created by Mata *et al.* (2017). This new dataset covers the period January 1900-1974 and 1978-2013 since the stock market in Portugal was closed for about three years following the Carnation Revolution in 25 April 1974. The main source of numerical data of Mata *et al.* (2017) is the collection of Daily Bulletins published by the Lisbon Stock Exchange for the period December 1899 – December 1987, available in the Documentation Centre of the Lisbon Exchange. The data provided by Mata *et al.* (2017), which refer to the evolution of the market as a whole, were converted to a monthly basis following the method proposed by Martinović *et al.* (2016). The data algorithmic conversion process suggested by Martinović *et al.* (2016) can be seen as a method of data compression. The method is based on the concept of "average data value" and is found to generate a negligible conversion error (i.e., loss of the original value). Subsequently, the database was completed with the values of the stock index PSI Geral for the period 2014-2020 obtained from Datastream, since "the time series from 1900 replicates as closely as possible the methodology of the PSI Geral index of the Lisbon stock exchange for the entire century" (Mata *et al.*, 2017, p. 71). The PSI Geral is a market capitalization-weighted price index of the eligible companies listed on Euronext Lisbon. The index is based on the last trade prices of the stocks and the weights are based on the current market capitalization. To estimate the cross-asset time-series momentum alphas, the Fama-French risk factors referring to the Portuguese stock market are needed. Since there is no data available referring to the Portuguese market on Prof. Kenneth French's website, data on the European stock market for the period 1990-2020 obtained from the same source were used as a proxy. In addition, data on the Portuguese risk-free interest rate were also provided by Mata *et al.* (2017) for the period 1900-2013 and were completed with the Euro Overnight Index Average (EONIA) rate for the period 2014-2020, following the same criteria adopted by the authors.

Table no. 1 presents the descriptive statistics on the data used in this study.

It is worth noting that the monthly mean of returns was remarkably similar in the subperiods 1900-1974 and 1978-2020. However, the market has been more volatile in the subperiod 1978-2020. The measures of skewness and, especially, kurtosis are, in general, inconsistent with normality. In fact, all the return series show a positive skewness which indicates a longer right tail. They also exhibit excessive kurtosis, which means that their distributions are leptokurtic.

Table no. 1 – Descriptive statistics of the data

	1900-2020	1900-1974	1978-2020
Daily Mean	0.015%	0.013%	0.019%
Monthly Mean	0.535%	0.532%	0.538%
Daily St. Dev.	0.249%	0.166%	0.348%
Skewness	1.506	0.407	1.425
Kurtosis	24.747	3.315	16.231

The new database provides an interesting opportunity to compare the historical returns of the Portuguese stock market with those of some of the most important world markets. Thus, we collected the historical returns for the national stock markets of the US, the UK, Germany, and France using the Asset Allocation Database of Global Financial Data. The Asset Allocation Database includes historical return indices for stocks of 50 countries.

Figure no. 1 depicts the mean annual returns of the stock markets of those markets in different historical periods.

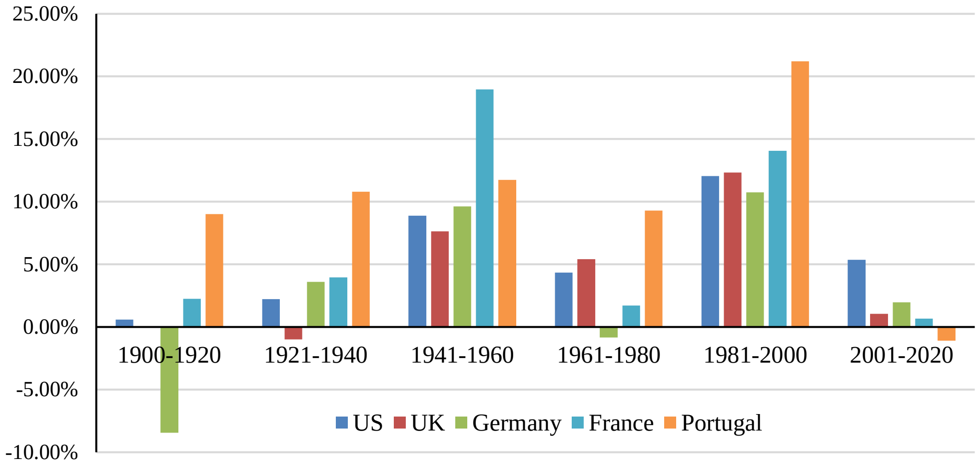


Figure no. 1 – Mean annual returns of the national stock markets of the US, the UK, Germany, France, and Portugal in several historical periods[1]

In the period 1900-1920, the Portuguese stock market had a mean annual return higher than the markets of the US, Germany, and France. It is not possible to make a comparison with the UK market, as we only have data for this market from the year 1933 onwards. It is worth noting the significant negative mean return on the German market in this period, marked by the political and economic turmoil that followed the First World War (1914-1918).

In the periods 1921-1940 and 1941-1960, the Portuguese market exhibited a mean annual return of almost 11%. The annual returns for all markets increased in the period 1941-1960 in comparison to the previous period. This performance can be associated with the events that characterized the world financial history in these two eras: the period 1921-1940 witnessed the Great Depression, whereas the period 1941-1960 includes the post-Second World War reconstruction of Europe and the positive effects of the Marshall Plan.

The mean return of the Portuguese stock market was the highest among all the markets under analysis in the period 1961-1980. In this period, an investor in the Portuguese stock market could have obtained a mean annual return close to 10%. The development of the Portuguese capital markets throughout the 1980s and the country's entry into the European Union in 1986 attracted large flows of capital that boosted the gains of the national stock market. As a result, the returns on this market once again exceeded those of the other markets in the period 1981-2000. The mean returns of all markets suffered a sharp decrease in the most recent period (2001-2020) with an emphasis on the negative mean return of the Portuguese stock market. The poor performance of this market has been attributed to the stagnation of the country's GDP in the period after the accession to the euro area. Moreover, the stock market was severely impacted by the Global Financial Crisis and the economic crisis associated with the COVID-19 pandemic (Blanchard, 2007; Baer *et al.*, 2013; Mata *et al.*, 2017; Phan & Narayan, 2020).

3.2. Methodology

Following Moskowitz *et al.* (2012) and Ham *et al.* (2019), we begin our empirical analysis by examining the time-series predictability of the market. We scale the returns to control for potential heteroskedasticity caused by different levels of volatility. The objective is that the performance of the strategy is not overly influenced by periods of heightened risk. The ex-ante annualized variance is calculated as the sum of exponentially weighted squared returns:

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

In Moskowitz *et al.* (2012) and Ham *et al.* (2019), the parameter δ is chosen so that the mass center of the variance is equal to 60 days (δ/(1 − δ) = 60) since the authors consider daily returns in their analyses. Because we will be operating with monthly returns, we selected a mass center of 2 months (δ/(1 − δ) = 2) instead. The average monthly return ($\bar{r}_t$) is calculated as the exponentially weighted average, applying the same weights. We scale all the returns by dividing them by their ex-ante volatility.

In order to detect price continuation patterns across different time horizons, we then perform a pooled panel regression, with lags of *h*= 1, 2,…, 60 months, 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 respectively the excess return in month *t* and ex-ante volatility, and r_{t-h} and σ_{t-h-1} are respectively the excess return in month *t* and the ex-ante volatility lagged *h* months. The excess return in month *t* is calculated as the difference between the return of the Portuguese stock market for that month and the corresponding risk-free interest rate. Finally, we compute *t*-statistics for group clustering.

Following the literature on the topic, we further examine the time-series predictability of the data by investigating whether the signs of the market lagged returns are significant predictors of future returns. This analysis is thus independent of the magnitude of the excess returns. Accordingly, the excess monthly return in month *t*, scaled by its ex-ante volatility, is regressed against the signs of the excess monthly return on month *t-h*, with lags of *h* = 1, 2,…, 60 months:

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

where the sign is defined as +1 if the excess return at month *t-h* is positive and −1 if the excess return at month *t-h* is negative.

Then, in order to assess the influence of risk on the phenomenon we proceed to calculate the *t*-statistics of the alphas of time-series momentum strategies for the different combinations of look-back and holding periods (1, 3, 6, 9, 12, 24, 36, or 48 months). As a robustness test, we examine the subject by calculating and comparing the Sharpe ratio of the different strategies. The Sharpe ratio takes into account the total risk inherent in each strategy and is defined as the average return earned in excess of the risk-free rate per unit of the standard deviation of returns.

Finally, we study the cyclicality of the time-series momentum effects. For this purpose, we adopt the procedure used by Moskowitz *et al.* (2012), which consists of regressing the returns generated by the time-series momentum strategies against the contemporaneous returns of the stock market in order to analyse the market conditions that favor a more pronounced profitability of the strategy.

4. EMPIRICAL RESULTS

4.1 Time-series return predictability

Figure no. 2 plots the *t*-statistics of β_h by month lag h resulting from the estimation of equation (2), where positive *t*-statistics indicate return continuations and negative *t*-statistics indicate return reversals.

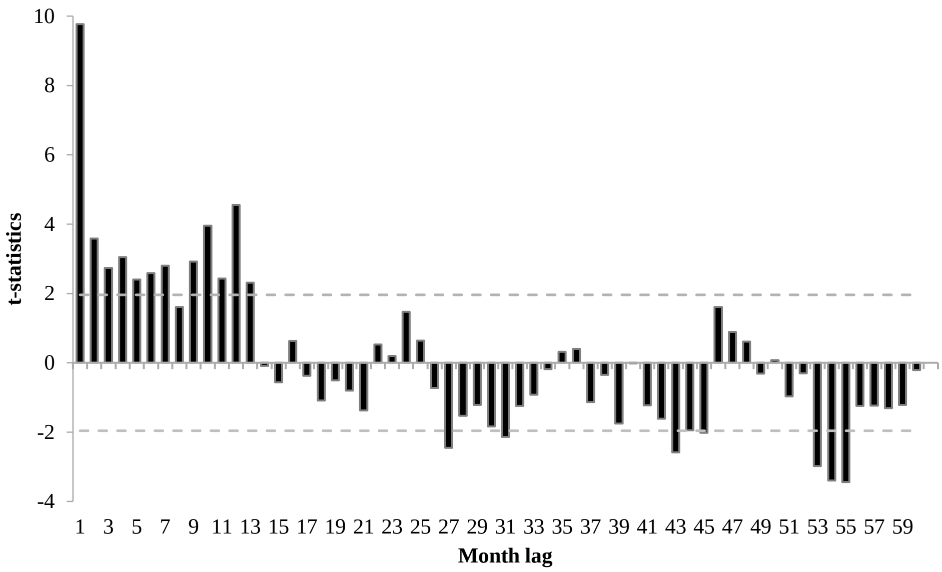


Figure no. 2 – Time-series return predictability (eq. 2)[2]

The figure depicts a pattern of positive *t*-statistics for the first 12 months, indicating return continuations over the first year, and mostly negative *t*-statistics thereafter, suggesting return reversals over the next four years. Moreover, Figure no. 2 shows that the market exhibits the strongest return continuation in the most recent month. These results are similar to those presented by Moskowitz *et al.* (2012) for a set of index futures and forwards traded in the US. The *t*-statistics of the β_h in equation (3) are depicted in Figure no. 3.

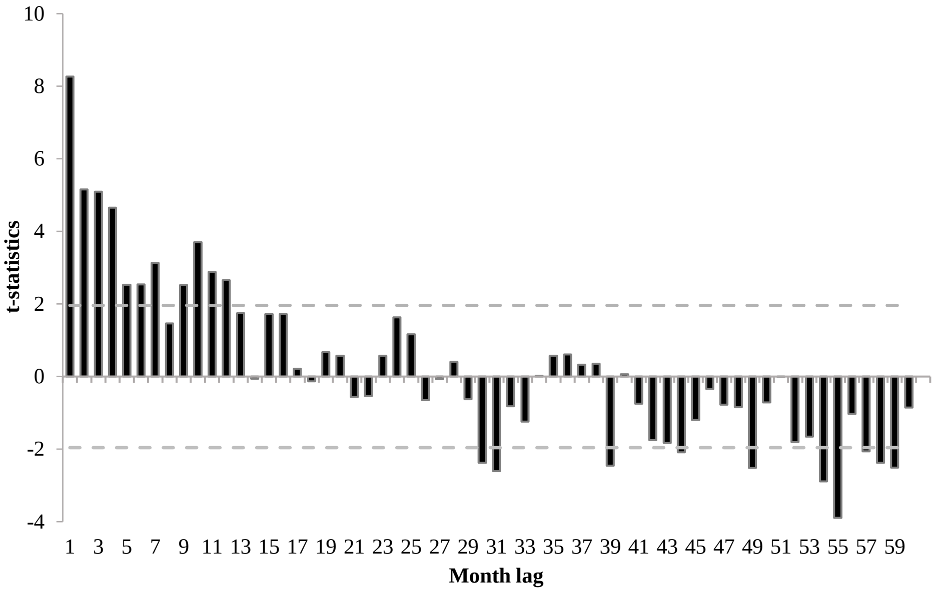


Figure no. 3 – Time-series return predictability (eq. 3)[3]

Figure no. 3 confirms the general pattern of continuation and reversal previously described: a very strong return continuation in the most recent month and one to 12-month positive time-series momentum followed by reversals at longer time horizons. Again, the positive return continuation is heavily concentrated at the first month.

4.2 Robustness to risk factors

In this section, we investigate if the time-series momentum returns simply reflect exposure to conventional risk factors.

In this regard, Table no. 2 shows the *t*-statistics of the alphas of time-series momentum strategies with different look-back and holding periods.

The table reveals that a significant time-series momentum was observed for all look-back and holding periods of 12 months or less. For all look-back and holding periods combinations, the highest *t*-statistics are observed in the case of the 1-month look-back period. The importance of the 1-month look-back period is consistent with our previous evidence regarding the existence of price continuation in the period 1900-2020. The higher *t*-statistic is observed for the strategy with a look-back period of 1 month and a holding period of 12 months (henceforth TSMOM_1_12 strategy).

Table no. 2 – *t*-statistics of the alphas of time-series momentum strategies with different look-back and holding periods[4]

		Holding period (in months)							
		1	**3**	**6**	**9**	**12**	**24**	**36**	**48**
Look-back period (in months)	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

As a robustness test, we proceed with the computation of the Sharpe ratios, one of the most widely recognized measures of reward-to-total risk. In addition to the strategy that seems to be more profitable in the Portuguese stock market (TSMOM_1_12) we consider two other strategies in our analysis that are often referred to in the literature (e.g., Moskowitz *et al.*, 2012): the strategy with a look-back period of 12 months and a holding period of 1 month (henceforth TSMOM_12_1 strategy) and the strategy with a look- back period and a holding period of 1 month (henceforth TSMOM_1_1 strategy). Figure no. 4 depicts the annualized Sharpe ratios for the three time-series momentum strategies (TSMOM_12_1, TSMOM_1_12, and TSMOM_1_1) and for the buy-and-hold strategy for the whole sample period and also for the subsample periods of 1900-1974 and 1978-2020. We report a Sharpe ratio of 0.37 for the Portuguese market portfolio during the whole sample period which is remarkably close to the figure of 0.39 computed by Daniel and Hirshleifer (2015) for the US stock market during the period 1963-2014. We observe that in all the sample periods under scrutiny the time-series momentum strategies deliver higher Sharpe ratios than the passive strategy. The TSMOM_1_12 strategy significantly outperforms all other strategies yielding a Sharpe ratio of 1.99 on an annual basis, or roughly 5.4 times the Sharpe ratio generated by the passive strategy during the period 1900-2020.

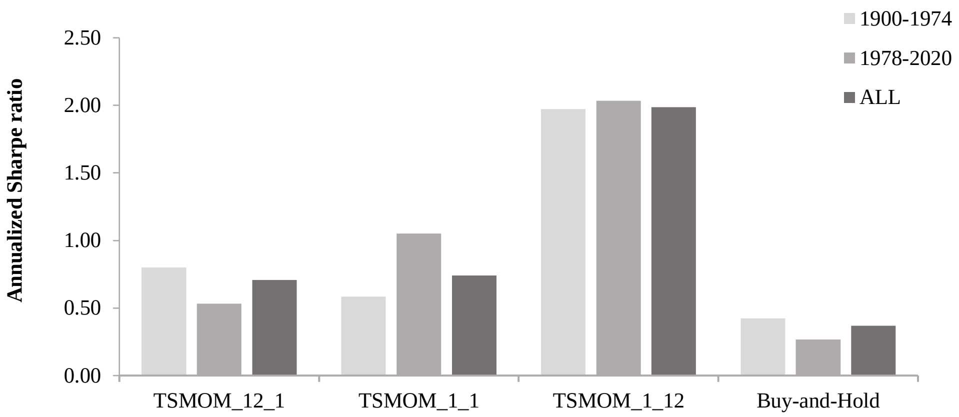


Figure no. 4 – Annualized Sharpe ratios of the time-series momentum strategies and the buy-and-hold strategy

4.3 Performance over time and in extreme market conditions

Figure no. 5 presents the cumulative returns of the TSMOM_12_1, TSMOM_1_12, and the buy-and-hold strategy from 1900 to 2020. The figure shows that the TSMOM_1_12 strategy produces the highest cumulative returns, outperforming the remaining strategies.

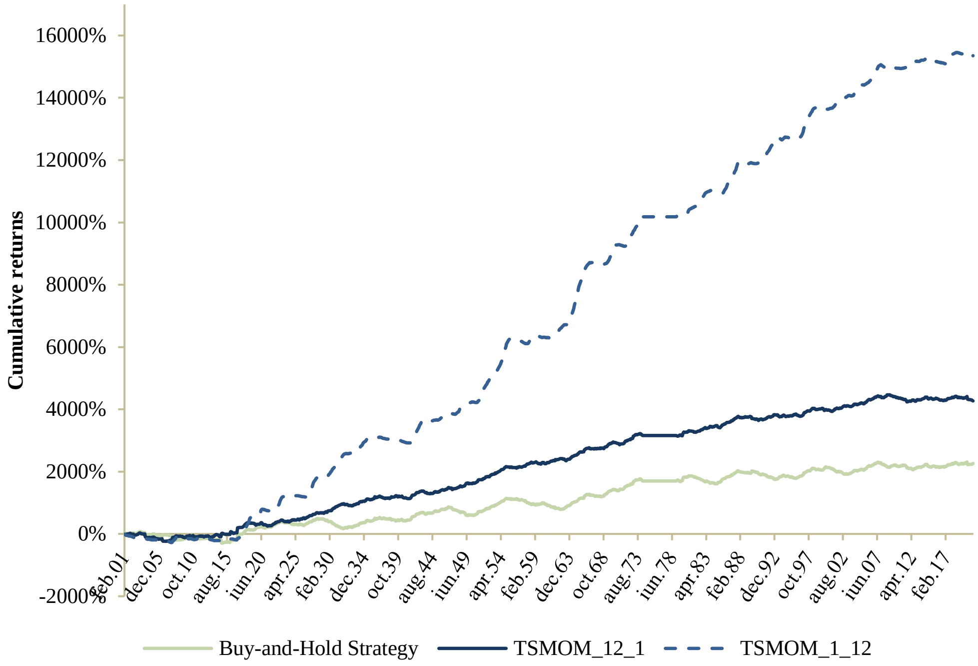
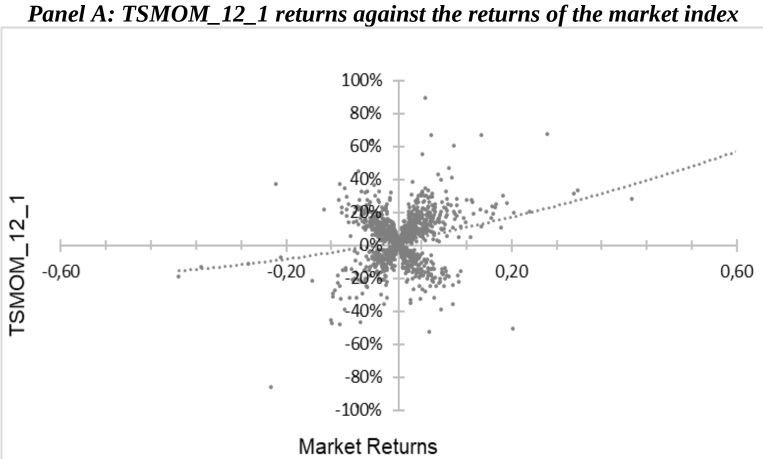


Figure no. 5 – Cumulative excess returns of the TSMOM_12_1, TSMOM_1_12, and the buy-and-hold strategy

The TSMOM_12_1 and TSMOM_1_12 strategies generated monthly mean returns of 0.93% and 4.31%, respectively, during the whole sample period. Time-series momentum effects seem to have remained robust over the most recent decades. In fact, whereas in the period 1900-1974 the TSMOM_12_1 and TSMOM_1_12 strategies yielded monthly mean returns of 0.83% and 3.72%, respectively, in the subsequent period, that goes from the reopening of the Portuguese stock exchange after the Carnation Revolution in 1978 until the end of 2020, the observed returns were even higher, reaching 1.10% and 5.33%, respectively. Finally, we investigate the cyclicality of the time-series momentum effects. In this regard, Figure no. 6 shows the returns generated by the TSMOM_12_1 and TSMOM_1_12 strategies plotted against the returns of the stock market in the period 1900-2020.

Panel A: TSMOM_12_1 returns against the returns of the market index



Panel B: TSMOM_1_12 returns against the returns of the market index

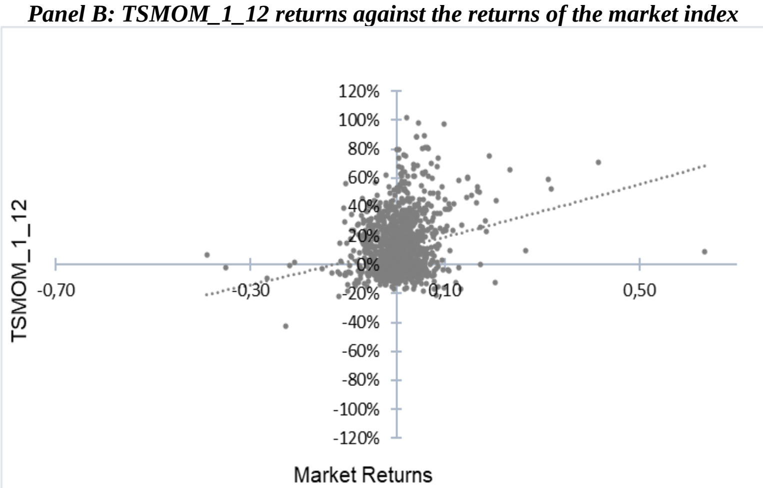


Figure no. 6 – TSMOM_12_1 and TSMOM_1_12 returns in extreme market conditions[5]

The positive slope of the quadratic trend indicates that both strategies have performed particularly well in extreme up years for the stock market. These findings suggest that the time-series momentum strategies are not especially valuable from a diversification perspective.

5. DISCUSSION

In this paper, we document strong time-series momentum effects in the Portuguese stock market during the last 120 years. The positive return continuation seems to last for a period of 12 months and is shown to be heavily concentrated at the first month. At longer investment horizons, returns tend to revert to the mean. The strategy that considers the returns on the previous month and holds the market portfolio for a period of 12 months provides the highest risk-adjusted return among the strategies under scrutiny, with an annualized Sharpe ratio of 1.99.

Our finding of a significant return continuation over a period of 12 months contrasts with the results reported by Moskowitz *et al.* (2012) for the US stock market since in this market a strategy with a look-back period of 12 months and a holding period of just 1 month is shown to present the highest significance from all the strategies under study. However, it should be noted that the results reported by Moskowitz *et al.* (2012) also indicate that a TSMOM_1_12 strategy would be profitable in the futures and forward contracts traded in the US as the respective alphas are found to be positive and statistically significant at the conventional levels (the reported *t*-statistics considering as underlying assets the equity indexes and all assets are 3.24 and 5.12, respectively). The greater persistence of price continuation observed in the Portuguese stock market corroborates similar results regarding the cross-sectional momentum effect in this market (Soares & Serra, 2005; Lobão & Lopes, 2014; Lobão & Azeredo, 2018). We conjecture that this phenomenon may be attributed to the slower diffusion of information in the Portuguese stock market, in line with the arguments asserted by H. Hong and Stein (1999). The reasons for this slow reaction of prices can be found in some institutional factors that have characterized the Portuguese stock market throughout its history (Mata *et al.*, 2017; OECD, 2020). The scarce liquidity of the market goes together with a country's economic structure inhabited mainly by very small firms that are not interested in accepting the fixed costs and the loss of control resulting from going public. In addition, institutional investors have historically played a relatively minor role in market transactions, which tends to slow down the impact of information on stock prices. In this context, it is understandable to find fairly persistent price trends in the Portuguese stock market.

The signs of strong time-series momentum that have been found in such dissimilar geographies as the US, China (Moskowitz *et al.*, 2012; Ham *et al.*, 2019), and now in an unexplored Portuguese historical dataset, are highly suggestive that the phenomenon is not a spurious pattern resulting from data mining.

The pattern described in our study of an initial underreaction and a delayed overreaction reflected into a reversion to the mean is consistent with the predictions of several sentiment theories. In this context, under-reaction could be caused by self-attribution or conservatism biases and the delayed overreaction might be the result of overconfidence or representativeness biases (Barberis *et al.*, 1998; Daniel *et al.*, 1998), for example.

The returns of time-series momentum strategies seem to be positively correlated with the performance of the market portfolio. That means that those strategies tend to perform best during extreme up-market periods and to deliver the worst returns during down markets. Consequently, time-series strategies do not seem to be a good fit for investors in the Portuguese stock market who value portfolios with a counter-cyclical profile. In this regard, our results differ significantly from those obtained in the US market by Moskowitz *et al.* (2012) as these authors concluded that time-series momentum in that country realized its largest gains during extreme negative-or-positive market conditions. Differences in the characteristics of the samples under scrutiny may explain this discrepancy. In fact, Moskowitz *et al.* (2012) analyzed equity futures, among other assets, while our study focuses on the evolution of the stock market. Furthermore, Moskowitz *et al.* (2012) considered a more limited period (1965-2009) while our analysis covers a period of about 120 years. Lastly, and probably most importantly, there are very significant institutional differences between the two markets, as it was mentioned above.

Our findings also carry relevant implications for investors as they suggest that a simple strategy of going long (short) in a well-diversified stock portfolio when the market as recently gone up (down) is able to outperform the standard buy-and-hold strategy. The existence of derivatives on the Portuguese stock index as well as the recent emergence of low-cost online brokers is likely to facilitate the exploitation of the strategies based on the time-series momentum effect.

Overall, our results add to the evidence that time-series effects are not a product of data mining and seem difficult to reconcile with the assertion that stock markets follow a random walk.

6. CONCLUSION, LIMITATIONS, AND SUGGESTIONS FOR FURTHER RESEARCH

In this study, we examined for the first time the Portuguese stock market for indication of time-series momentum effects. For that purpose, we used a new historical financial dataset that covers about 120 years of data.

We report strong time-series momentum effects that cannot be subsumed by the conventional risk factors. The positive return continuation lasts for a period of 12 months, being heavily concentrated at the first month. At longer investment horizons, returns tend to revert to the mean. A strategy with a 1-month look-back period and a 12-month holding period yields a Sharpe ratio roughly 5.4 times that generated by a passive strategy. Time-series momentum strategies present a procyclical profile.

A limitation of our study stems from the fact that we did not consider in our analysis the transaction costs that an investor would have to bear to explore strategies based on time-series momentum effects. Unfortunately, given the restrictions on the availability of historical data on the Portuguese stock market, it was not possible to take such factor into account.

The anomaly of momentum, in its different varieties, is one of the main challenges to the market efficiency hypothesis. Further avenues of research on this topic may include examining the relationship between time-series momentum and other investment strategies, including the traditional cross-sectional momentum; augmenting the robustness tests with macroeconomic risk factors; and examining the impact of trading costs on the profitability of time-series momentum strategies.

Acknowledgements

This research has been financed by Portuguese public funds through FCT - Fundação para a Ciência e a Tecnologia, I.P., in the framework of the project with reference UIDB/04105/2020.

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Notes

[1] Figure no. 1 shows the geometric mean annual returns of the national stock markets of the US, the UK, Germany, France, and Portugal in several historical periods. The initial source of the data referring to the Portuguese stock market is Mata *et al.* (2017). This database, covering the period 1900-2013, was subsequently completed with the values of the stock index PSI Geral for the period 2014-2020 obtained from Datastream. Data referring to the stock markets of the US, the UK, Germany, and France were collected from the Asset Allocation Database of Global Financial Data. The data for the markets of the US, Germany, France, and Portugal cover the entire period under analysis (1900-2020) while the data for the UK is only available from 1933 onwards.

[2] Figure no. 2 shows the results of the regression of the monthly excess returns on its lagged excess return over several horizons. The reported t-statistics are computed using the lagged monthly excess

returns as independent variables for lags h=1, 2, ..., 60 months, and returns are scaled by their respective ex-ante volatility to make them comparable. The dashed lines represent the significance level at 5%. The sample covers the period from February 1900 to December 2020.

[3] Figure no. 3 shows the results of the regression of the monthly excess returns on its lagged excess return over several horizons. The reported t-statistics were computed using the signs of the lagged monthly excess returns as independent variables for lags h = 1, 2, ..., 60 months, and returns are scaled by their respective ex-ante volatility to make them comparable. The dashed lines represent the significance level at 5%. The sample covers the period from February 1900 to December 2020.

[4] Table no. 2 reports the t-statistics of the alphas from regressing the time-series excess returns with different look-back and holding periods (1, 3, 6, 9, 12, 24, 36, or 48 months) against the standard risk factors of the Fama-French three-factor model. Due to the unavailability of risk factors referring to the Portuguese market, the risk factors of the European stock market were used as a proxy. The sample period spans from July 1990 to December 2020.

[5] Figure no. 6 presents the scatterplot of the non-overlapping TSMOM_1_12 and TSMOM_12_1 monthly returns against the corresponding non-overlapping monthly returns of the stock market index. The dashed line represents the quadratic fit. The sample covers the period from February 1900 to December 2020. Panel A plots the TSMOM_12_1 returns against the returns of the stock market index. Panel B plots the TSMOM_1_12 returns against the returns of the stock market index..