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Abstract: Momentum trading strategies assume that past winners, i.e. the best performing equity securities over the past up to 12 months tend to continue to perform well over the subsequent short-term period. This paper examines the momentum effect for the New York Stock Exchange over a period of more than 20 years. Although this issue is extensively studied, the volatility structure of momentum profits is still unexplored. Therefore, our main goal is to shed light on the hidden temporal patterns in the raw profits generated by winners trading strategies. For this purpose, we use continuous wavelet analysis so as to decompose the observed volatility of raw profit series over a range of investment horizons. We discover clearly pronounced patterns in times of turmoil that could not be explained by application of time domain filtering. Furthermore, we identify which investment horizons impact most heavily the dynamics in momentum profits during the Dot-com bubble and during the Great Recession. We consider this breakdown as particularly useful when studying changes in crowd investors' behavior and beliefs.

INTRODUCTION

Cross-sectional momentum effect has been a topic of significant research interest ever since the seminal paper of (1). They find that holding a long position in the past winner stocks and going short on the past losers turns out to be a profitable short-term investment strategy on the U.S. stock markets (NYSE and AMEX) in every five-year period between 1965 and 2009 except in the last one due to negative impact of the Great Recession (2). Eugene Fama qualifies momentum effect as one of the most challenging evidences to reconcile with the Efficient Market Hypothesis and expresses hope, that the market anomaly will sooner or later disappear (3). Although a huge amount of research literature is focused on the U.S. equity markets and the time variation in momentum profits during severe market turmoil, still the necessity to further deepen the research exists, especially by employing non-traditional analytical tools that could shed additional light on the issue.

Our ultimate goal is to examine volatility term structure of momentum profits both in tranquil and in crisis times. In particular, we form time series of averaged raw profits generated by winners' portfolios at the New York Stock Exchange. Traditional statistical analysis suggests significant increase in the volatility of these profits during periods of crises that might even cause momentum effect disappear. Therefore, we believe that further deepening of this analysis might provide useful insights on the momentum phenomenon. Keeping up with this research objective, we decompose the observed volatility of winners' portfolios raw profits over a range of investment horizons through application of the continuous wavelet transform. This breakdown enables visual identification of the investment horizons impacting most heavily the dynamics of momentum effect.

Such a representation is particularly useful when studying changes in investors' behavior and beliefs therefore we consider it as a major contribution of our research. Furthermore, wavelet transform has some important applications in empirical finance and this paper proposes one such application in the field of behavioral finance. The utilized

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procedure is replicable and provides empirical behaviorists with a fresh new look at the documented periodic changes in momentum effect, that occur in times of high market volatility, when momentum investment strategies turn out to be highly losing (see for example the findings in (4) and (5)).

In order to achieve our goal we analyze the wavelet power spectrum of the adjusted weekly profits on the winners-only portfolios with a formation period of 39 weeks and a holding period of 13 weeks. The choice of holding and formation period length is justified empirically. Five different sub-periods are closely inspected – the technological boom period (Jan/1995 – Dec/1999), the Dot-com burst period (Jan/2000 – Dec/2002), the economic boom period (Jan/2003 – Dec/2006), the Great Recession period (Jan/2007 – Dec/2009), the market rebound period (Jan/2010 – Apr/2018). The sub-period segregation refers to the research and conclusions of (6). We build on the results obtained by (7). In particular, the authors find that winners-only momentum investment strategies deliver higher profits in the technological boom period (Jan/1995 – Dec/1999) than the traditional winner-minus-loser-portfolios.

The rest of the paper is organized as follows. Section 2 present a literature review, Section 3 outlines the methodology. Section 4 presents the data and the major research results, followed by a discussion.

LITERATURE REVIEW

Asness and co-authors (8) study the profitability of value and cross-sectional momentum strategies across eight different asset classes and markets, including equity markets in the USA, the U.K., Europe and Japan, country index futures, government bonds, currencies and commodity futures. The contributed to existing literature through the seminal documentation of momentum effect in government bonds and value in government bonds, currencies and commodities. According to the conclusion of (8) momentum profits are positive in each of the four equity markets.

Foltice and Langer (9) question the proposition of momentum trading, regarding short selling of stocks, because it is not feasible for individual investors due to the following practical reasons: capability of undertaking these positions, the severe risk of uprising prices, fees and margin requirements. That is why, the authors propose a simplified momentum trading strategy in taking only long positions in past 6-month best performing one to 50 stocks on NYSE for a 12-month holding period. Transaction costs and risk are accounted for as initial investment amounts range between $5,000 to $1,000,000 and sample period covers the years from 1991 to 2010. The authors conclude that such a strategy is profitable for individual investors, measured monthly.

According to (5) profits of momentum strategies are severely negative in times of high market volatility and in abrupt market rebounds following market downturns. Negative profits are persistent due to their negative skewness and to some extent forecastable. Following market declines and when quick market rebound occurs momentum strategies crash due to conditionally large negative beta of the momentum portfolio, consisting of low-beta past winner stocks and high-beta past loser stocks. That is why momentum portfolios gain a little in market declines and lose a lot in market rebounds. In addition, (4) use a combination of self-collected historical data set of the Victorian London Stock Exchange (1867 to 1907) and existing data from CRSP United States (1926 to 2012). The researchers find that momentum investing strategy earned abnormal returns across both eras: a three-factor alpha of 0.5 percent per month in Victorian London and 1 percent per month in CRSP era. However, momentum trading undergoes rare periodic crashes in both eras, exposing investors to severe losses, where momentum effect disappears, only to reappear later. According to the authors the occurrence of crashes predetermines the persistence of momentum strategy. The variables that predict momentum crashes in both periods are similar: times when there is an easier access to blind capital. Thus, capital scarcity restrains investors to arbitrage out momentum profits to zero, letting momentum effect alive.

Jagadeesh & Titman (1) study the possible drivers, underlying momentum profits. The researchers conclude that abnormal momentum profits may not be attributed to compensation for bearing systematic risk, but to market inefficiency. Thus, research literature has focused primarily on behavioral explanations of the market anomaly. Momentum effect is driven by positive serial correlations of idiosyncratic components of individual stock returns, i.e. stock prices underreact to firm-specific information. Although most of the behavioral models share this view, they differ as to whether serial correlation is caused by under-reaction or delayed over-reaction to firm-specific information. If positive abnormal profits are followed by normal (negative) returns in the post-holding period, then momentum effect is caused by underreaction (delayed overreaction). Jegadeesh & Titman (2) find that on US stock markets (NYSE and AMEX) short-term positive momentum returns are sometimes followed by long-run return reversals, but sometimes not. Therefore, behavioral models do not unambiguously explain the underlying drivers of momentum, but provide a profound understanding of the anomaly in comparison to traditional risk-based models.

METHODOLOGY

We apply wavelet analysis on a time series of average profits on portfolios that exploit momentum trading strategy for the New York Stock Exchange. For the construction of the time series we replicate the procedure outlined by (10), with regard to the major research results of (7). The time-frequency characteristics of the average portfolio profits are studied through application of the continuous wavelet transform. The following text summarizes the idea behind the utilized momentum trading strategy and provides a brief introduction of the continuous wavelet transform.

Construction of Momentum Strategy

We have automatically downloaded data for all companies, traded on the NYSE and Amex for the period between the Jan-1995 – Apr-2018. As a result, we have obtained daily adjusted close prices for 3302 public companies altogether. We use only weekly adjusted close prices as of each Friday. As a research methodology we employ the one, suggested by Alphonse & Nguyen (10) for the Vietnamese Stock Exchange. After applying different criteria like avoiding companies with more than 5% missing historical prices between their first and last trading day on NYSE or Amex, excluding companies with less than 105 historical adjusted weekly prices and studying all companies, that have been traded on the two auction markets, no matter if they have been delisted or not . Then we transform the available adjusted weekly prices into simple returns.

Following the procedure developed by Alphonse & Nguyen (10) in week t we divide stocks into quantiles according to their average lagged returns over the past K weeks (K = 1, 2, 4, 8, 13, 26, 39 and 52 weeks – formation period). The stocks in the highest and lowest quantile are called respectively "winners" and "losers". We weight all component stocks in both portfolios equally. As in the classical approach, transaction costs are not allowed for.

For the reasons outlined in (9) and in (7) we would analyze further only the winners portfolios. Consequently, $R_{k,t}^{W}$ $(k = 1, \dots, J)$ denotes the raw profits for winners-only portfolios in a given week t, whereas the subscript k stands for the fact, that we calculate the profit of a given portfolio $(K; J)$, held in a particular week k within the holding period of J weeks. As broadly applied in research literature, we evaluate the performance of overlapping portfolios, since at week t there should be exactly J portfolios – the one, formed at the beginning of week t and the other $J - 1$ portfolios, constructed in week $t - 1, t - 2, \dots, t - J$. In a given calendar week t their profits are equally averaged:

$$OR_{J,\,t}^{W} = \frac{1}{J} \sum_{k=1}^{J} R_{k,\,t}^{W} \tag{1}$$

Afterwards, for each winners-only strategy $(K; J)$ we compute the average profit of all overlapping weekly profits $OR_{J,t}^{W}$. Thus, this aggregate measure is used as a metric for testing the availability of momentum effect on the NYSE. If the value of the metric is positive, momentum occurs, otherwise it is not present.

Wavelet Analysis

As argued by Aguirar-Conrara and Soares (11), the application of wavelets provides the possibility to trace transitional changes across time. For the empirical part of the paper, we take use of this property in order to shed light on the change of average winners portfolio profits that took place with the beginning of the burst of the Dot-com bubble and the 2008 Financial crisis. For this purpose we analyse the wavelet spectrum of the time series obtained through application of eq. (1). The text that follows explains briefly the idea behind wavelet spectrum while the reader might find an exhaustive discussion on the issue in (11).

The function $\psi(t) \in L^2(\mathbb{R})$, called mother wavelet is chosen for the continuous wavelet analysis. It should satisfy a decay condition, which ensures the function is well localized both in time and frequency. For functions with sufficient decay the admissibility condition is equivalent to requiring that $\Psi(0) = \int_{-\infty}^{\infty} \psi(t)dt = 0$, where $L^2(\mathbb{R})$ denotes the set of square integrable functions and $\Psi(\omega)$ denotes the Fourier transform of $\psi(t)$. A family $\psi_{\tau,s}$ of wavelet daughters can be obtained by scaling and translating the mother wavelet ψ: $\psi_{\tau,s} = \frac{1}{\sqrt{|s|}} \psi\left(\frac{t-\tau}{s}\right)$, $s, \tau \in \mathbb{R}, s \neq 0$, where s is a scaling factor controlling the width of the wavelet and τ is a translation parameter controlling its location. Given a time series $x(t) \epsilon L^2(\mathbb{R})$ its continuous wavelet transform with respect to the wavelet ψ is defined as follows:

$$W_{x;\psi}(\tau, s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{|s|}} \psi^* \left(\frac{t-\tau}{s}\right) dt, \tag{2}$$

where the asterisk denotes complex conjugate. For simplicity of notation the wavelet transform $W_{x;\psi}(\tau, s)$ will be denoted by W_x in the text that follows. If complex valued wavelet is used for the transform, then the wavelet spectrum as defined below might be viewed as the amplitude of the transform. A common choice is the Morlet wavelet which is utilized in the current paper as well. The wavelet power spectrum that is subject to our further analysis is defined by eq. (3):

$$WPS_x = |W_x|^2. \tag{3}$$

We use the freely available toolbox that is referenced in the article of (11) in order to apply eq. (3) to the time series delivered through eq. (1)

EMPIRICAL RESULTS AND DISCUSSION

For the purpose of our study, we take historic stock price records on weekly basis for all companies listed at NYSE and NYSE American for the period Jan-1995 – Apr-2018. The raw data is downloaded via the R library 'BatchGetSymbols'. Thus, the initial sample consists of the weekly stock prices of 3302 companies. After data cleaning and data preparation1 the number of retained stocks amounts to 2445. The next step of our analysis comes down to application of the procedure described by eq. (1) for a particular couple $\{K, J\}$. We apply eq. (1) over the following couples of formation and holding periods $\{(K, J);\ K = 1,2,4,8,13,26,39,52;\ J = 1,2,4,8,13,26,39,52\}$. As a result, we obtain 64 time series consisting of the weekly raw profits on winners portfolios for the period Jan-1995 – Apr-2018. As might be expected the average raw profit depends on the choice of formation and holding period.

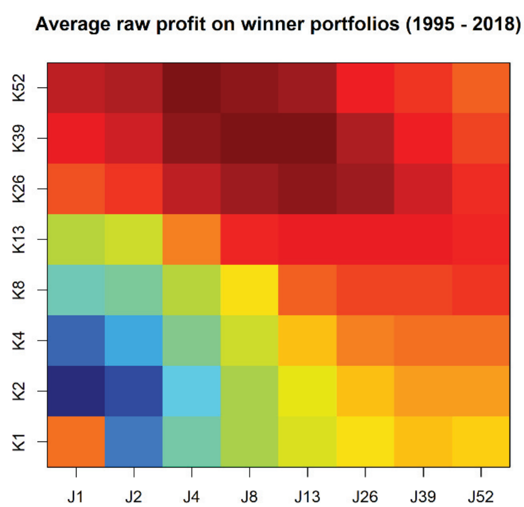

FIGURE 1. Raw profits on winner portfolios averaged over the entire period under study. The x-axis represents a grid of holding periods and the y-axis is a grid of formation periods.

Figure 1 presents the average raw profit for every strategy (K, J) generated over the period Jan-1995 – Apr-2018. Hotter colors indicate higher average raw profits while colder colors are used to code lower average performance. The figure suggests that highest raw profits are generated when the formation period is 26, 39, or 52 weeks and the holding period is 4, 8, 13, or 26 weeks. The worst performing strategy is with a formation period of 2 weeks and a holding period of just 1 week and it results in 0.17% weekly raw profit averaged over the period under study. The top performance of 0.47% average weekly raw profit over the period under study is achieved for the strategy with a

[1] During the process of data cleaning we remove stocks with price history of less than 105 weeks as this is the minimum length of price series required for transforming it to returns and applying (52,52) strategy. Furthermore, we remove stocks with more than 5% missing values between the first and the last trading date in order to make sure that the selected interpolation technique does not affect results. In addition, we assure robustness of results to presence of outliers by removing prices series that have registered a weekly increase (decrease) greater (less) than 100%.

formation period of 39 weeks and a holding period of 13 weeks. Therefore, we would further study the temporal patterns and cyclical changes observed for the series of raw profits generated by the strategy (39,13).

TABLE 1. Descriptive statistics of the time series of raw profits generated by the simple winners strategy (39,13).

	Jan-1995 Apr-2018	**Jan-1995 Dec-1999**	**Jan-2000 Dec-2002**	**Jan-2003 Dec-2006**	**Jan-2007 Dec-2009**	**Jan-2010 Apr-2018**
Num. of obs.	1175	221	156	209	156	433
Mean	0.47%	0.67%	0.44%	0.81%	0.16%	0.32%
SE Mean	0.09%	0.16%	0.26%	0.18%	0.36%	0.13%
Minimum	-17.65%	-7.96%	-14.29%	-7.94%	-17.65%	-12.52%
Maximum	16.29%	9.81%	11.46%	6.41%	16.29%	8.14%
Median	0.83%	0.66%	1.11%	0.63%	0.53%	0.70%
1. Quartile	-0.96%	-0.53%	-1.36%	-0.61%	-2.12%	-0.83%
3. Quartile	2.20%	2.11%	2.12%	2.51%	2.79%	1.84%

Table 1 provides some of the descriptive statistics of this series over the entire period under study (Jan-1995 – Apr-2018) as well as over five distinguished periods2. These are the technological exuberance (Jan-1995 – Dec-1999), the Dot-com burst period (Jan-2000 – Dec-2002), the economic boom period (Jan-2003 – Dec-2006), the Great Recession (Jan-2007 – Dec-2009), and the market rebound period (Jan-2010 – Apr-2018). The table suggests considerably higher raw profits during the periods of economic boom, while the lowest average raw profit is registered during the Great Recession. This period is also characterized by the highest minimum and maximum values in absolute terms. Overall, the figures reported in TABLE are consistent with findings documented in the literature on momentum behavior in times of turmoil. This paper aims to study further this behavior through an in-depth analysis of the volatility structure of the time series corresponding to the highest average raw profit over the period under study.

The upper panel of Figure 2 presents the plot of this time series. It might be seen that it is characterized by significant volatility especially during periods of turmoil. The bottom panel of Figure 2 presents the same time series smoothed exponentially over a window of 13 weeks. Overall, the observed volatility pattern suggests long periods of consecutive positive values interrupted by instances of large negative raw profits. Furthermore, the exponential filtering provides a clear visual summary of the dynamics in momentum effect.

The periods of negative reversals are of particular interest. We need to analyse them from a different angle in order to deepen our understanding on the processes behind momentum disappearance and re-emergence. For this purpose, we apply continuous wavelet analysis. Results from the application of Eq.(3) to the time series of raw profits on the winners portfolios with a formation period of 39 weeks and a holding period of 13 weeks are summarized visually at Figure 3.

Figure 3 is a colour map where each pixel corresponds to a particular value of WPS_x. Hotter colours represent greater values of the spectrum, while colder colours are used to denote lower values. The x-axis stands for the time line and the y-axis corresponds to the utilized frequencies, which are converted into time units in order to ease interpretation of results. The highest frequency is of one week and the lowest frequency corresponds to 15 years. The cone of influence represents the region in which the transform suffers from edge effects and it is plotted with tick black line. In this region the results should be interpreted with special care. The white lines indicate local maxima of the wavelet power spectrum.

This color map provides a breakdown of the volatility of the analyzed time series by investment horizons ranging from 1 week to 15 years. Therefore, we could analyze the structure of negative reversals observed at the bottom panel of Figure 2. The first significant reversal is noted at the end of 1998. The wavelet spectrum suggests that the observed increased volatility is due to concentrated investment activities at horizons of less than an year. This might be interpreted as follows. The most important driving force behind momentum disappearance is short-term investment activity which might be due to overreaction to bad news and fear. The same conclusions might be drawn for the subsequently observed negative fluctuations.

[2] We use the suggested sub-period segregation as suggested in (Nedev & Bogdanova, 2018).

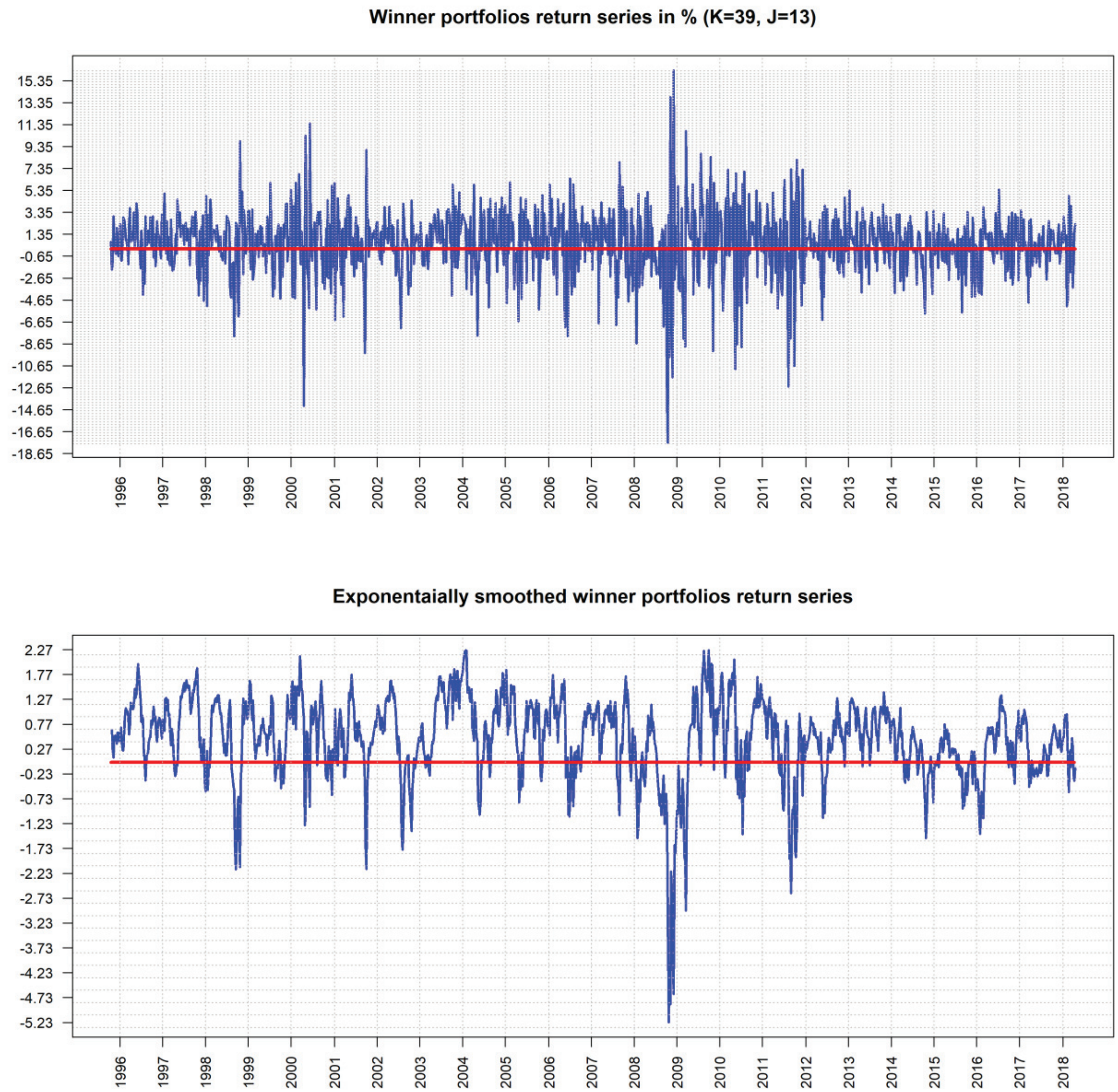

FIGURE 2. The upper panel presents the time series of raw profits on the winners portfolios with a formation period of 39 weeks and a holding period of 13 weeks. The bottom panel presents the same time series smoothed exponentially over a three-month window. The null level is indicated by the red line.

However, the patterns at Figure 3 corresponding to the period 2008 – 2013 suggest different picture. During that time, the observed volatility is caused by concentration of activity at both shorter and longer investment horizons. Apart from the higher frequency fluctuations that might be explained by investors' reactions to bad news, we could also note a clearly pronounced 3~4 year cyclical component that dictates the volatility of the analyzed raw profits. This component might be interpreted as a structural change in the momentum effect that is due to the Great Recession. Indeed, as suggested by the bottom panel of Figure 3 the average raw profits observed after 2012 are lower than those in earlier rebound periods.

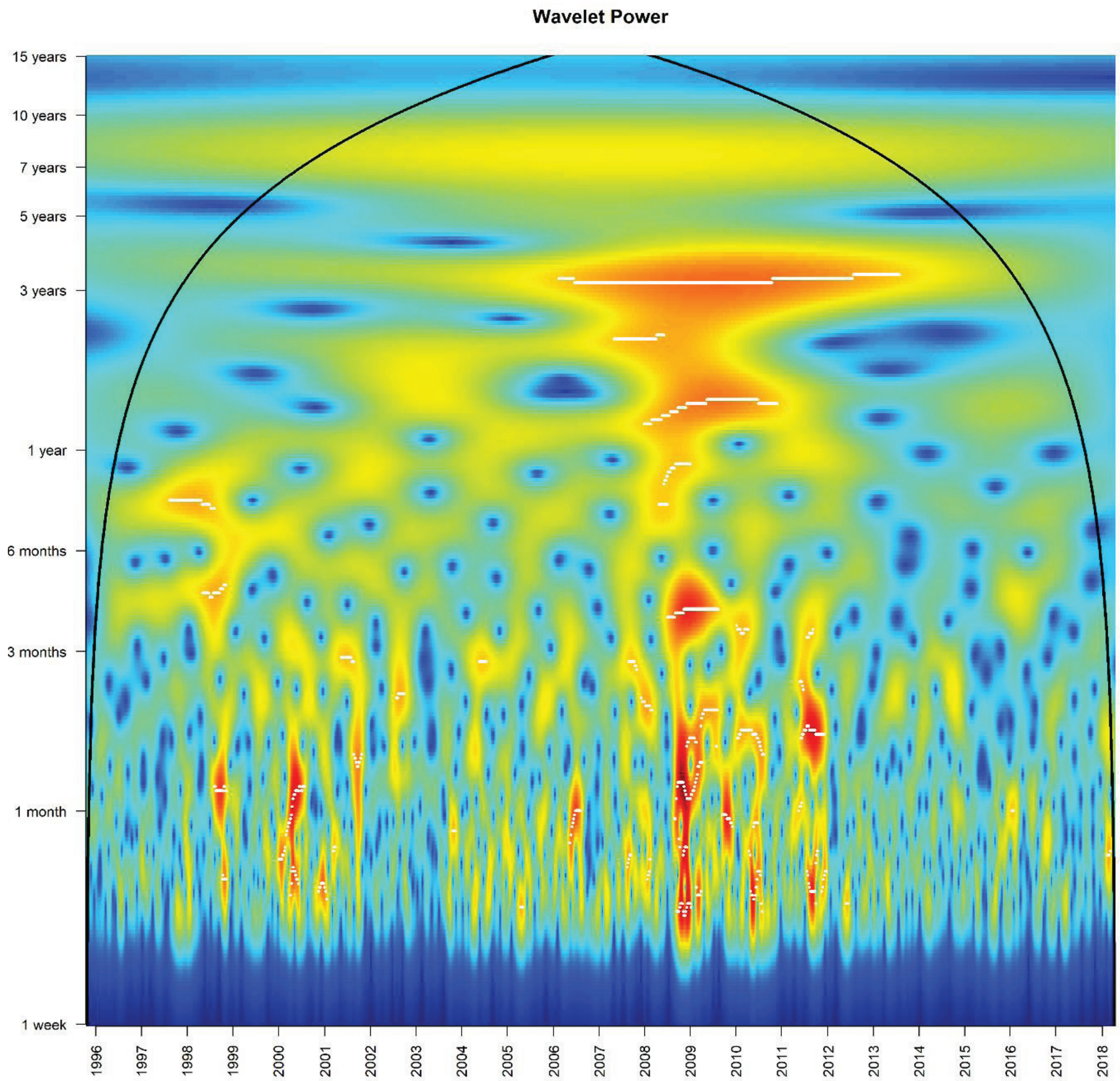

FIGURE 3. Wavelet power spectrum of the time series of raw profits on the winners portfolios with a formation period of 39 weeks and a holding period of 13 weeks.

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