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A generalised seasonality test and applications for cryptocurrency and stock market seasonality

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A B S T R A C T

This study develops a novel generalised seasonality test that utilises sequential dummy variable regressions for seasonality periodicity equal to prime numbers. It allows to test for existence of any seasonal patterns against the broad null hypothesis of no seasonality and to isolate most prominent seasonal cycles while using harmonic mean p-values to control for multiple testing. The proposed test has numerous applications in time series analysis. As an example, it is applied to identify seasonal patterns in 76 national stock markets and 772 cryptocurrency markets to detect trading cycles, determine their length, and test the weak-form efficient market hypothesis. Cryptocurrency markets are shown to be less efficient than national stock markets, with predominantly irregular seasonality periodicity that cannot be reduced to conventional weekly, monthly, or annual cycles.

1. Introduction and literature review

The study of seasonal patterns in time series for economic and financial datasets spans at least a century. Kondratieff (1925) is possibly the most famous early piece of research on identifying short-, medium-, and long-term cyclical patterns in macroeconomic aggregates. In finance, seasonality has been thoroughly investigated at least since the 1970 s, with calendar anomalies such as weekend effect (Cross, 1973), turn-of-the-month effect (Ariel, 1987), holiday effect (Ariel, 1990), and January effect (Keim, 1983) being discovered in stock price movements.[1] International evidence on calendar anomalies has been accumulating steadily, with mixed results from various national stock markets, suggesting seasonality patterns might differ substantially across similar datasets (Cadsby & Ratner, 1992; Gultekin & Gultekin, 1983; Kunkel et al., 2003). Most recently, weekly and monthly seasonality has been shown to contribute to abnormal returns of factor portfolios (Long et al., 2020; Zaremba, 2017).

Nevertheless, the statistical and econometric tools used by researchers to mine for seasonal effects are still fragmented and largely depend on the pre-assumed cyclical patterns, highlighting the need for the development of a general and robust procedure that would allow to test for existence of *any* seasonality in data against a broad null hypothesis of no seasonality. For example, to ensure that a stock return time series is not affected by calendar anomalies, a researcher must undertake a separate test for each of the suspected seasonality types. This is problematic for two reasons: first, it raises multiple testing concerns, and second, the nature of seasonality might differ from the commonly established weekly, monthly, or annual patterns. The multiple testing issue in empirical finance research led scholars to suggest that most calendar (Sullivan et al., 2001) and accounting-based (Linnainmaa & Roberts, 2018) anomalies are statistical artifacts or results of data mining, with McLean and Pontiff (2016) estimating that 26% of anomaly magnitude can be explained by sample selection bias, and Shanaev and Ghimire (2021) showing data-snooping bias is instrumental in understanding the Friday effect. Therefore, a generalised seasonality test that would encompass a broad null hypothesis of no seasonal patterns would be useful in preventing data-snooping and controlling the family-wise error rate in conventional calendar anomaly literature.

Furthermore, contemporary research has shown that even well-established financial markets cannot be fully described with

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[1] For a more detailed survey of calendar anomalies on financial markets as well as an overview of multiple testing and data mining concerns associated with conventional seasonality tests, see Shanaev and Ghimire (2021).

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conventional calendar anomalies alone. As such, Seif et al. (2017) find that December effect is more prominent than January effect for selected emerging markets; Chatzitzisi et al. (2019) document day-of-the-week patterns different from conventional Monday and Friday effects; Alves and Reis (2020) identify half-year and quarterly seasonality in ETF returns that does not correspond to the “classical” calendar anomalies; while Tse (2018) and Alves and Reis (2020) also detect an April effect in foreign exchange and ETF returns, respectively. Further, there exist various country- and market-specific seasonal phenomena that do not necessarily fall within the established calendar anomaly paradigm, such as the Hajj effect in Saudi Arabia (Wasiuzzaman, 2018) or cyclical reaction to macroeconomic variables in the United States (Parnes, 2020).

Another gap in the literature on seasonality methodology is the inapplicability of conventional anomaly detection tests onto novel cryptocurrency markets that are being open without any weekends and holidays and operate across jurisdictions, rendering generalisations of weekend and holiday effects as well as of tax-based explanations for January and April effects problematic. Kaiser (2019) demonstrates this empirically, showing that none of the well-documented patterns from the stock market literature, apart from the reverse January effect, are prominent in cryptocurrencies. Further, Aharon and Qadan (2019), Catania and Sandholdt (2019), Caporale and Plastun (2019), Qadan et al. (2021), and Kinateder and Papavassiliou (2021) show conventional day-of-the-week and holiday effects are mostly absent from cryptocurrency return dynamics, with Aharon and Qadan (2019) and Caporale and Plastun (2019) finding a reverse Monday effect, Kinateder and Papavassiliou (2021) supporting the reverse January effect, and Catania and Sandholdt (2019) reinforcing intraday rather than daily seasonality. One of the few studies to date arguing conventional seasonal anomalies are present on cryptocurrency markets is Kumar (2022) who document a positive turn-of-the-month effect in Bitcoin, Ethereum, and Litecoin. Nevertheless, Aharon and Qadan (2019), Catania and Sandholdt (2019), and Kinateder and Papavassiliou (2021) all agree that conventional seasonality tests generate more robust results for cryptocurrency volatility rather than returns. Mbanga (2019) and Haferkorn and Diaz (2014) further demonstrate the nuanced nature of calendar anomalies in cryptocurrency markets, documenting day-of-the-week effects in price clustering and trading activity, respectively, but not in coin price dynamics itself. This is perhaps what has stalled the seasonality studies on cryptocurrency markets, as market efficiency literature for cryptoassets still predominantly utilises time series dependence tests, and, while this subdiscipline of blockchain research reached comparative maturity (Ante, 2020), seasonality research remains underrepresented in it. Existing meta-analyses of trading strategies for cryptocurrencies also enforce the sparsity of seasonality research and lack of decisive consensus in it (Kyriazis, 2019). Notably, the most comprehensive piece of research on cryptocurrency seasonality to date, Long et al. (2020), uses the factor portfolio methodology and not the standard anomaly literature to inform their tests.

This study seeks to address the aforementioned issues and proposes a generalised seasonality test that does not require any strong presumptions regarding potential seasonal patterns. It utilises sequential regressions with dummy variables representing all possible prime cycle periodicities and uses Wilson (2019) harmonic mean p-values to control for the family-wise error rate. Such a design allows for degrees of freedom preservation and near-zero multicollinearity, even when testing for long-term seasonality in reasonably small datasets. The results of the test can be easily visualised and related to the common cyclical patterns (weekly, monthly, or annual) using prime factorisations.

The rest of the paper is organised as follows. In the next section, the testing procedure is outlined and elaborated upon. Next, the applicability of the test is showcased on an example of seasonality detection in daily data for 76 national stock market indices and an exhaustive sample of 772 cryptocurrency markets. The final section concludes, suggesting further potential applications of the developed test where some limitations of the proposed tests are also discussed.

2. Methodology

To test for seasonality in a time series of n observations one should start with choosing the maximum period $m \le n$. The number of explanatory dummy variables is calculated as $k = \pi(m)$, where π is the prime counting function equal to the quantity of prime numbers (i.e., natural numbers greater than one that are divisible only by one or themselves) not exceeding m. For example, $\pi(8) = 4$, as there are four primes (namely, 2, 3, 5, and 7) that do not exceed eight. As $\pi(m) \to \frac{m}{\ln m}$ for large m (Elliott, 2021), it allows for degrees of freedom preservation while also enabling the test to detect seasonality of cycle periodicity equal to any compound number representable as a product of primes $\pi \le m$. For example, if $m = 7$, the test will be able to detect any seasonal cycles of lengths 2, 3, 5, 7 and their products. Therefore, cycles of length $3 \times 7 = 21$ and $2 \times 2 \times 3 \times 3 \times 7 = 252$ (typical number of trading days in a month and in a year on stock markets, respectively) will also be identifiable. For cryptocurrency markets open for trading 24 h a day seven days a week without holidays, $m = 7$ allows to intuitively identify weekly seasonalities, $m = 5$ corresponds to a typical average calendar month length ($2 \times 3 \times 5 = 30$), while for annual patterns one has to include $m = 73$, as $365 = 5 \times 73$. Alternatively, one can select $m \to n$ and test for all possible prime cycle lengths in a less restrictive specification. This study shows both approaches for stock market and cryptocurrency applications.

Next, the set of explanatory dummy variables for $i \le n$ and $j \le k$ is constructed according to the procedure $X_{ij} = I(i \bmod \pi_j = 0)$. Therefore, the elements of the jth column are equal to one if the observation index i is wholly divided by the prime π_j and zero otherwise, or, equivalently, for column X_j corresponding to prime π_j, every π_jth entry is one and the rest are zeroes. An example of explanatory dummy variable construction for $n = 15$, $m = 7$, and $k = \pi(7) = 4$ can be seen in Table 1 below. A useful side property of this approach is the absence of multicollinearity by design, as any two prime numbers are coprime, which preserves the validity of the test for large m.

Next, multiple linear regressions are fitted sequentially for j ranging from 1 to $k = \pi(m)$, with the jth regression including explanatory variables X from 1 to j. Therefore, in this example, four regressions will be fitted, each testing for seasonality of cycle periodicity up to π_j. For every regression j, a regular F-test for joint

Table 1
Explanatory variable construction (example).

prime number prime index (π_j) observation index (i)	2 π_1 X_1	3 π_2 X_2	5 π_3 X_3	7 π_4 X_4
1	0	0	0	0
2	1	0	0	0
3	0	1	0	0
4	1	0	0	0
5	0	0	1	0
6	1	1	0	0
7	0	0	0	1
8	1	0	0	0
9	0	1	0	0
10	1	0	1	0
11	0	0	0	0
12	1	1	0	0
13	0	0	0	0
14	1	0	0	1
15	0	1	1	0

Table 2
Generalised seasonality test output for $m = 7$.

Market	Wilson p-value	most significant		Market	Wilson p-value	most significant	
		p-value	Cycle			p-value	cycle
Argentina	0.9647	0.8766	7	Malaysia	0.8159	0.6552	2
Australia	0.9853	0.9715	2	Mauritius	0.3403	0.2049	3
Austria	0.5254	0.2999	2	Mexico	0.6738	0.4926	3
Bahrain	0.1797	0.1089	3	Morocco	0.3395	0.2088	2
Bangladesh	**0.0053**	**0.0021**	5	Netherlands	0.4375	0.2307	2
Belgium	**0.0720**	**0.0435**	3	New Zealand	0.2454	0.1751	3
Bosnia and Herzegovina	0.4068	0.2925	2	Nigeria	0.5352	0.3676	7
Botswana	0.1536	0.1038	3	Norway	0.6875	0.5996	3
Brazil	0.5841	0.3580	2	Oman	0.6684	0.4622	2
Bulgaria	0.6084	0.5266	3	Pakistan	0.5945	0.4461	2
Canada	0.9611	0.9061	2	Peru	0.6426	0.5349	3
Chile	0.7064	0.5037	5	Philippines	0.5600	0.3587	5
China	0.9567	0.9080	2	Poland	0.7343	0.5377	2
Colombia	0.7840	0.6064	3	Portugal	0.5465	0.4175	5
Croatia	0.6992	0.4566	2	Qatar	0.1677	0.1361	7
Czechia	0.1499	**0.0673**	5	Romania	0.6711	0.5145	2
Denmark	**0.0324**	**0.0192**	7	Russia	0.6829	0.5854	3
Egypt	0.3006	0.1600	2	Saudi Arabia	0.5868	0.4926	7
Estonia	0.5473	0.4536	2	Serbia	0.7634	0.5924	2
Finland	0.2214	0.1430	2	Singapore	0.8756	0.7407	3
France	0.3982	0.2609	2	Slovenia	0.2250	0.1114	5
Germany	0.1733	0.1090	2	South Africa	0.8090	0.5958	2
Greece	0.4127	0.2436	7	South Korea	0.4983	0.2782	5
Hong Kong	0.7827	0.6295	2	Spain	0.4700	0.3582	2
Hungary	0.1147	**0.0524**	5	Sri Lanka	0.3546	0.2021	2
India	0.6118	0.4518	2	Sweden	0.3310	0.1923	2
Indonesia	0.9637	0.9023	7	Switzerland	0.1355	**0.0837**	2
Ireland	**0.0050**	**0.0025**	5	Taiwan	0.3668	0.2069	3
Israel	**0.0206**	**0.0092**	2	Thailand	0.3952	0.2212	2
Italy	0.9242	0.8617	3	Trinidad and Tobago	0.2416	0.1204	5
Jamaica	0.3779	0.1908	7	Tunisia	0.3987	0.2257	2
Japan	0.1323	**0.0619**	2	Turkey	0.5577	0.4091	3
Jordan	0.2809	0.1707	5	Ukraine	0.5484	0.4285	7
Kazakhstan	0.5220	0.2741	7	United Arab Emirates	0.7897	0.7359	2
Kenya	0.7102	0.6465	2	United Kingdom	0.3476	0.3086	3
Kuwait	0.8425	0.8185	3	United States	0.2119	**0.0973**	2
Lebanon	0.7196	0.5049	2	Vietnam	0.9077	0.8542	7
Lithuania	**0.0611**	**0.0184**	7	Zimbabwe	0.3377	0.1684	2

Notes: significant (at 10%) p-values are reported **in bold**.

significance is performed and a p-value p_j is calculated from the F-statistic F_j and degrees of freedom $(j, n - j - 1)$. Hence, every test returns an array of k p-values. As the F-tests cannot be assumed independent, the harmonic mean p-value is computed as in Wilson (2019) to control for multiple testing as per the formula:

$$p^* = \frac{k}{\sum_{j=1}^{k} 1/p_j}$$

If the harmonic mean p-value (Wilson p-value) p^* is below the selected threshold, the null hypothesis of no seasonality in the time series must be rejected in favour of the alternative hypothesis that seasonality is present.[2] Then, one can examine individual p_js and isolate the cycle periodicity with the lowest p-values to determine which prime number cycles contributed to seasonal patterns the most. In the next section, the test is applied to detect seasonal effects on daily frequency in 76 national stock market indices and 772 cryptocurrency markets.

3. Findings and discussion

3.1. Data

To showcase the applicability of the test, this study seeks to apply it to daily data on all 76 country-specific stock market index returns provided by Morgan Stanley Capital International (MSCI) for the five-year observation period 24/12/2014 – 25/12/2019 and an exhaustive sample of 772 cryptocurrency daily returns from coinmarketcap.com for the 29/04/2013 – 25/12/2019 period.[3] The test is applied for $m = 7(k = \pi(7) = 4)$ and $m = 499(k = \pi(499) = 95)$ to illustrate its ability to successfully capture both short-term and long-term trading cycles. The former arrangement ($m = 7$) allows to determine whether the stock market seasonality is weekly, monthly, annual, or of other form by using prime factorisations of the number of trading days in a month ($21 = 3 \times 7$) and a year ($252 = 2 \times 2 \times 3 \times 3 \times 7$) as well as the fact that a typical week consists of a prime number of trading days (5) itself. For cryptocurrency markets, the $m = 5$

[2] Monte Carlo simulation with white noise and GARCH(1,1) processes has confirmed the harmonic mean p-value procedure successfully controls for family-wise error rate, particularly for $\alpha < 0.2$, consistent with Wilson (2019). Data and code for the Monte Carlo simulation as well as the testing procedure are available upon request.

[3] All cryptocurrencies that have at least 100 price observations throughout the period are considered for sample selection. 29/04/2013 corresponds to the start of data collection by Coinmarketcap. The reliability of Coinmarketcap for market efficiency studies has been highlighted in Vidal-Tomas (2022). As for MSCI indices, all available value-weighted dollar-denominated indices were selected, and the start of the sample periods reflects data availability for the newer frontier markets.

Table 3
Seasonal effects detected on stock markets for $m = 7$.

Market	Seasonality				p-value				
	Overall	Weekly	Monthly	Annual	Wilson	2	3	5	7
Israel	Yes	Yes	Yes	Yes	**0.0206**	**0.0092**	**0.0236**	**0.0344**	**0.0682**
Denmark	Yes	Yes	Yes	No	**0.0324**	0.2105	**0.0409**	**0.0238**	**0.0192**
Ireland	Yes	Yes	Yes	Yes	**0.0050**	**0.0057**	**0.0164**	**0.0025**	**0.0063**
Lithuania	Yes	No	No	No	**0.0611**	0.3379	0.4155	0.1710	**0.0184**
Bangladesh	Yes	Yes	No	No	**0.0053**	0.5489	0.5747	**0.0021**	**0.0038**
Belgium	Yes	Yes	No	No	**0.0720**	0.1089	**0.0435**	**0.0663**	0.1202
Hungary	No	Yes	No	No	0.1147	0.7229	0.3188	**0.0524**	**0.0886**
Czechia	No	Yes	No	No	0.1499	0.9133	0.3420	**0.0673**	0.1281

Notes: significant (at 10%) p-values are reported **in bold**.

arrangement naturally tests monthly effects, $m = 7$ further captures weekly effects, and $m = 73$ is additionally considered for annual effects. The latter setup ($m = 499$) seeks to detect seasonality periodicity directly by observing the dynamics of p_j as 499 is a prime that is close to the number of stock market trading days in two years.

3.2. Results for national stock market indices

For $m = 7$, the generalised seasonality test output is reported in Table 2 below. The null hypothesis had to be rejected for six out of 76 countries (Bangladesh, Belgium, Denmark, Ireland, Israel, and Lithuania). Some individual F-tests for cycle length 2 (notably for Japan, Switzerland, and the United States) returned significant p-values, however, the results were not significant after the adjustment for multiple testing. Among the significant results, seasonal patterns varied notably, with Israel being the case for the most short-term trading cycles, while Denmark and Lithuania demonstrated more long-term cyclical behaviour.

Next, for results significant as per the Wilson harmonic mean p-value, the individual p-values for cycle lengths can be examined to generate inferences regarding the nature of established seasonality. The significance of a 5-cycle would imply weekly seasonality, similar to Monday and Friday effects (Cross, 1973) or average same weekday dependence (Long et al., 2020). The joint significance of 3-cycle and

Table 4
Generalised seasonality test output for stock markets for $m = 499$.

Market	Wilson p-value	most significant		Market	Wilson p-value	most significant	
		p-value	cycle			p-value	cycle
Argentina	0.2103	**0.0479**	59	Malaysia	0.8060	0.4802	43
Australia	0.7922	0.4542	73	Mauritius	0.5008	0.2002	479
Austria	0.5363	0.2794	173	Mexico	0.4831	**0.0841**	491
Bahrain	0.3970	**0.0906**	13	Morocco	0.6651	0.2034	29
Bangladesh	**0.0468**	**0.0021**	5	Netherlands	0.4562	0.1278	401
Belgium	0.2420	**0.0435**	3	New Zealand	0.3500	**0.0520**	491
Bosnia and Herzegovina	**0.0552**	**0.0077**	53	Nigeria	**0.0001**	**0.0000**	389
Botswana	0.2684	**0.0470**	47	Norway	0.6549	0.3464	41
Brazil	0.7862	0.3580	2	Oman	0.7738	0.4622	2
Bulgaria	0.8997	0.5266	3	Pakistan	0.5956	0.2674	89
Canada	0.6755	0.3796	283	Peru	**0.0965**	**0.0225**	359
Chile	0.1710	**0.0250**	89	Philippines	0.4843	0.2706	59
China	0.5583	0.2371	401	Poland	0.6724	0.3677	439
Colombia	0.7531	0.5002	311	Portugal	0.7789	0.4161	11
Croatia	0.2983	0.1140	47	Qatar	0.6365	**0.0974**	13
Czechia	0.4023	**0.0673**	5	Romania	**0.0108**	**0.0011**	353
Denmark	**0.0345**	**0.0017**	19	Russia	0.8624	0.5806	43
Egypt	**0.0000**	**0.0000**	487	Saudi Arabia	0.4439	0.1308	71
Estonia	0.5851	0.3597	167	Serbia	0.8389	0.5472	59
Finland	0.3058	0.1320	281	Singapore	0.2875	**0.0922**	439
France	0.4619	0.1560	401	Slovenia	0.6554	0.1114	5
Germany	0.5033	0.1090	2	South Africa	0.4895	0.1775	331
Greece	0.6927	0.2331	17	South Korea	0.6953	0.2782	5
Hong Kong	0.5456	0.2528	463	Spain	0.3440	0.1935	401
Hungary	0.5506	**0.0524**	5	Sri Lanka	0.4576	0.2021	2
India	0.5519	0.2075	11	Sweden	0.1860	**0.0322**	401
Indonesia	0.7734	0.5473	53	Switzerland	0.3743	0.0837	2
Ireland	**0.0053**	**0.0012**	281	Taiwan	0.7782	0.2069	3
Israel	**0.0535**	**0.0092**	2	Thailand	0.6243	0.2212	2
Italy	0.4187	0.2082	151	Trinidad and Tobago	0.4460	0.1204	5
Jamaica	0.7031	0.1908	7	Tunisia	0.7372	0.2257	2
Japan	0.4870	**0.0619**	2	Turkey	0.8911	0.4091	3
Jordan	**0.0906**	**0.0067**	13	Ukraine	0.7845	0.3629	47
Kazakhstan	0.4857	0.2741	7	United Arab Emirates	0.8012	0.4517	47
Kenya	0.3693	0.1230	131	United Kingdom	0.4670	0.1669	401
Kuwait	0.7690	0.4263	59	United States	0.2525	**0.0584**	283
Lebanon	**0.0000**	**0.0000**	269	Vietnam	0.8055	0.4873	197
Lithuania	**0.0799**	**0.0181**	61	Zimbabwe	0.3516	**0.0288**	79

Notes: significant (at 10%) p-values are reported **in bold**.

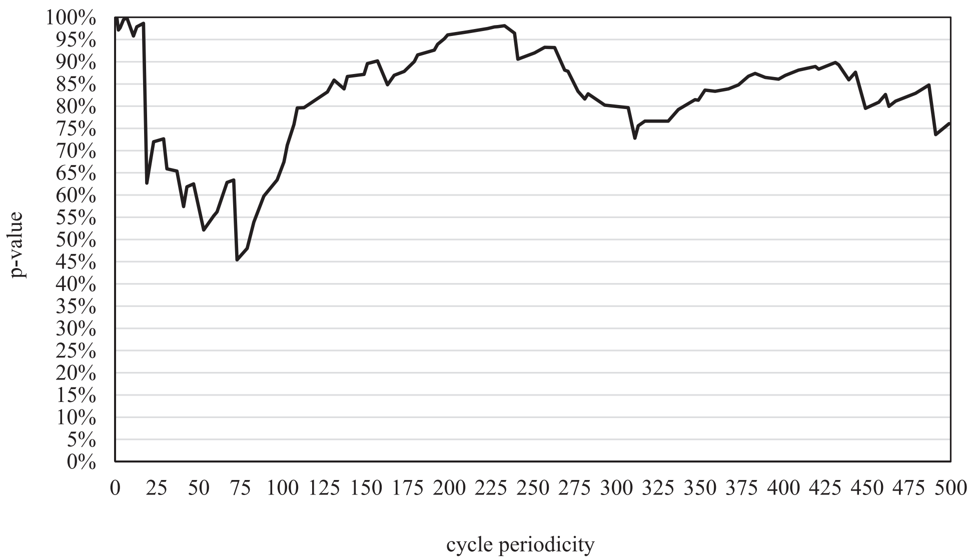

Fig. 1. An example of no seasonality (Australia). **Notes:** p-value does not drop below 10% for any cycle length, hence the Australian stock market is shown to have no seasonality.

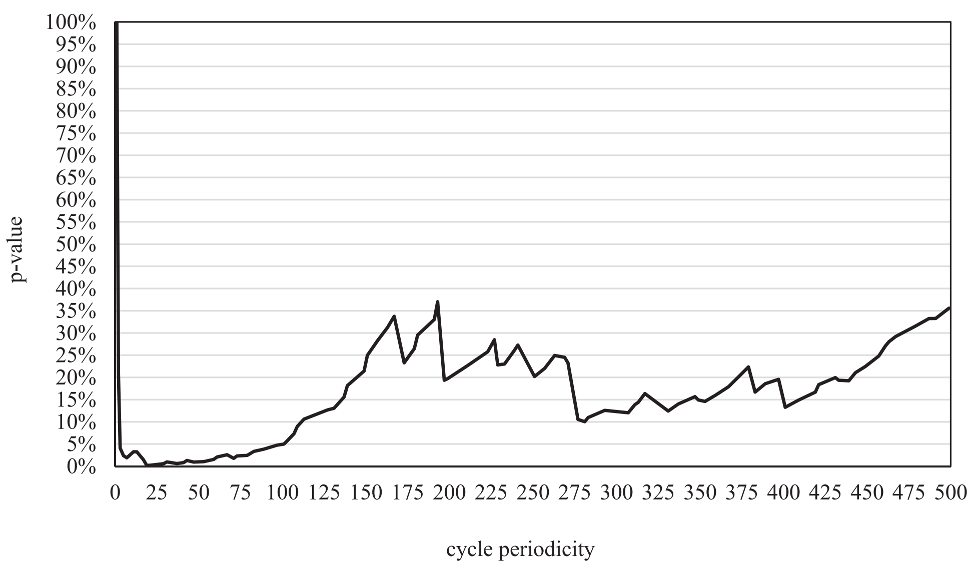

Fig. 2. An example of short-term seasonality (Denmark). **Notes:** p-value drops the lowest (below 1%) at cycle periodicity 19, while the harmonic mean p-value equals 3.24%, hence the Danish stock market is demonstrating short-term seasonality significant at 5%.

7-cycle would signal for monthly seasonal patterns as in turn-of-the-month effect (Ariel, 1987; Lakonishok & Smidt, 1988), or average same day of the month dependence (Zaremba, 2017). Annual effects, including the January effect (Keim, 1983), varying average monthly returns throughout the year (Gultekin & Gultekin, 1983; Tse, 2018), or holiday effect (Ariel, 1990) would be manifested in significance for 2-cycle, 3-cycle, and 7-cycle simultaneously. Table 3 below relates the significance of individual prime length cycles to prominent seasonal patterns (weekly, monthly, or annual).

Among the six markets with seasonal effects identified to be significant as per the Wilson harmonic mean p-value, Bangladesh and Belgium demonstrate weekly seasonality only, while monthly cycles are also present for Denmark, and annual patterns are manifested in Israel and Ireland. For Lithuania, the nature of seasonality does not fall under either of the three prominent periodicities. Hungary and Czechia have individually significant p-values for some of the estimations, however, the result ceases to be significant when controlled for multiple testing.

Table 4 above reports the generalised seasonality test results for $m = 499$. In this setting, the null hypothesis is rejected for 12 out of 76 (15.8%) markets (Bangladesh, Bosnia and Herzegovina, Denmark, Egypt, Ireland, Israel, Jordan, Lebanon, Lithuania, Nigeria, Peru, and Romania). Bangladesh, Denmark, and Israel persist as markets with strong short-term seasonality, while significant results that were not

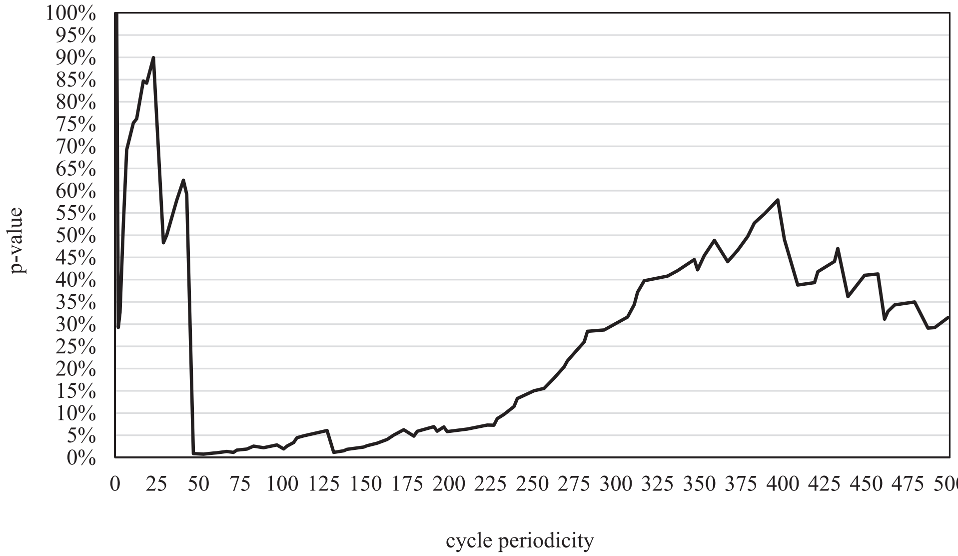

Fig. 3. An example of medium-term seasonality (Bosnia and Herzegovina). **Notes:** p-value drops the lowest (below 1%) at cycle periodicity 53, while the harmonic mean p-value equals 5.52%, hence the Bosnian stock market is demonstrating medium-term seasonality significant at 10%.

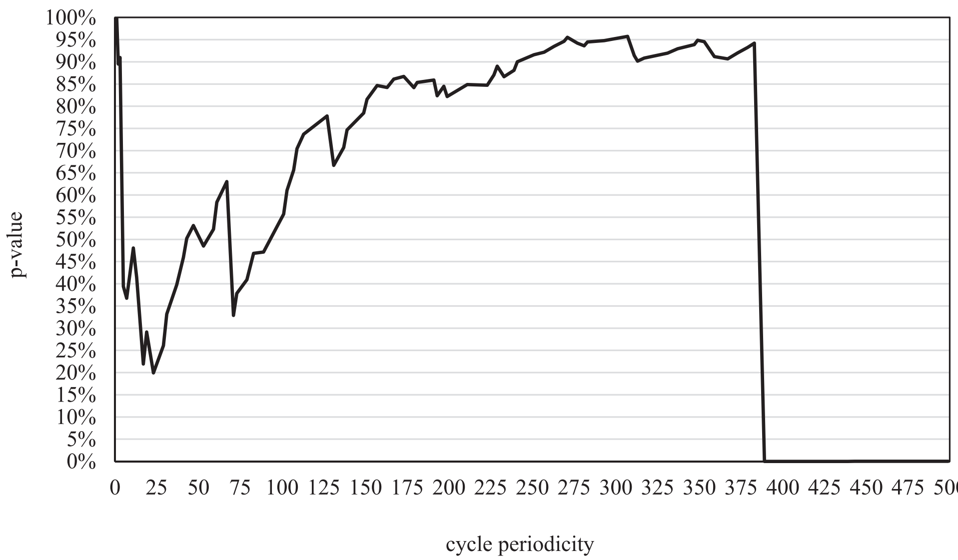

Fig. 4. An example of long-term seasonality (Nigeria). **Notes:** p-value drops the lowest (below 1%) at cycle periodicity 389, while the harmonic mean p-value equals 0.01%, hence the Nigerian stock market is demonstrating long-term seasonality significant at 1%.

detected by the test with $m = 7$ stem from more complicated longer-term cyclical patterns on these markets, such as Bosnia and Herzegovina (periodicity of 53), Lebanon, Nigeria, Peru, and Romania (periodicities of longer than one year). For Ireland, long-term seasonality is prominent in addition to short-term effects identified previously.

The results of the generalised seasonality test for large values of m can be visualised with a dynamic p-value graph, which allows to illustrate where p-values for individual cycle periodicities decrease below the significance threshold. Note that a drop in the p-value at a particular cycle length can signal the existence of seasonal effects of such periodicity, however the harmonic mean p-value needs to be consulted to determine whether the effect exists when multiple testing is accounted for. As such, Figs. 1–6 below show examples of no seasonality (Australia, Fig. 1), short-term seasonality (Denmark, Fig. 2), medium-term seasonality (Bosnia and Herzegovina, Fig. 3), long-term seasonality (Nigeria and Romania, Figs. 4 and 5), and both short- and long-term seasonality (Ireland, Fig. 6).

3.3. Results for cryptocurrency markets

Table 5 below presents seasonal effects detected for the m = 2, 3, 5, 7, and 73 specification. In this test, 171 out of 772 cryptocurrencies demonstrate varying seasonality patterns. 104, 44,

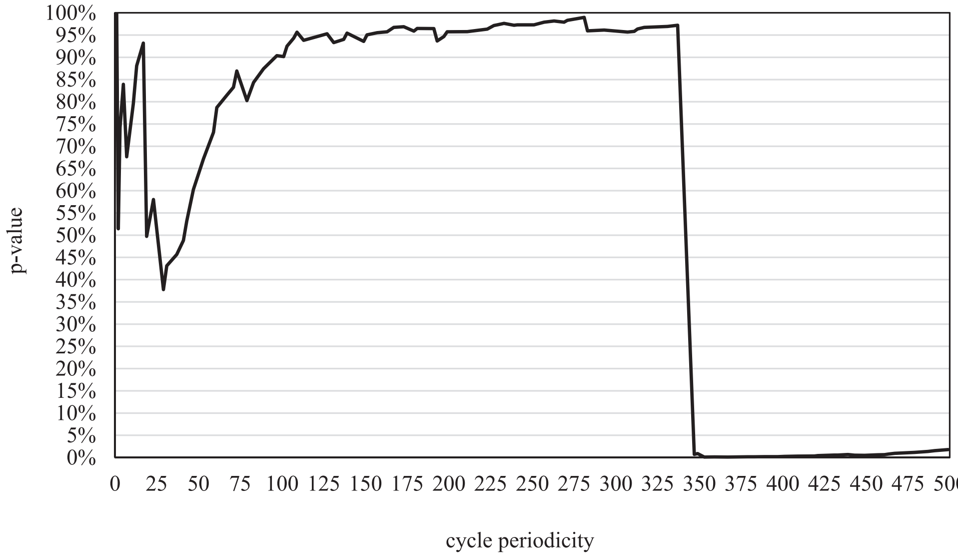

Fig. 5. An example of long-term seasonality (Romania). **Notes:** p-value drops the lowest (below 1%) at cycle periodicity 353, while the harmonic mean p-value equals 1.08%, hence the Romanian stock market is demonstrating long-term seasonality significant at 5%.

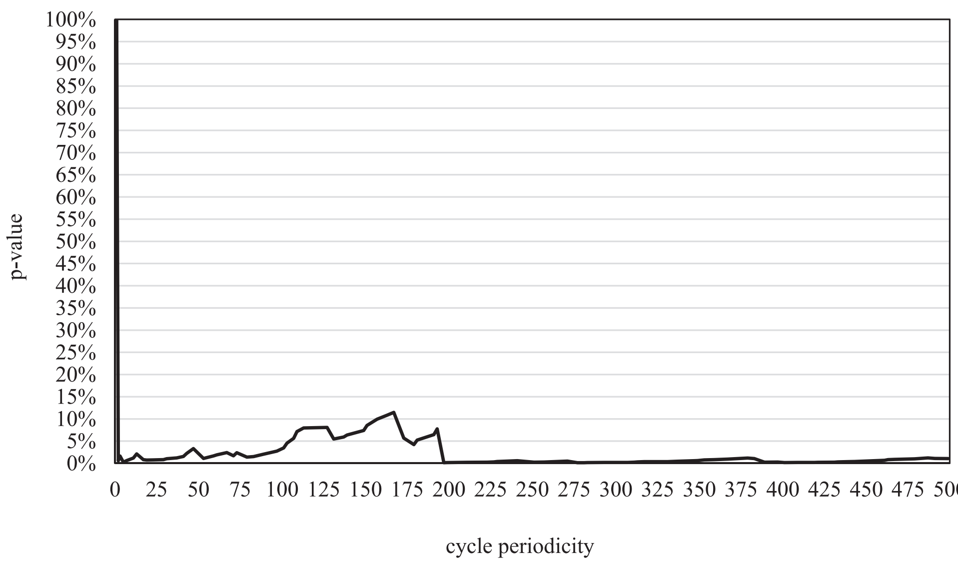

Fig. 6. An example of short- and long-term seasonality (Ireland). **Notes:** p-value drops the lowest (below 1%) at cycle periodicities 5 and 281, while the harmonic mean p-value equals 0.53%, hence the Irish stock market is demonstrating short- and long-term seasonalities significant at 1%.

and 32 coins show weekly, monthly, and annual patterns, respectively, with harmonic mean p-value being significant for 143 estimations. Among the largest (top 50) cryptocurrencies, XRP, Lisk, Bitcoin Gold, and Verge demonstrate weekly seasonality, Verge shows monthly return regularities, while Digibyte and Aeternity establish annual patterns. For Monacoin and Bitcoin Diamond returns, unconventional seasonality patterns that cannot be reduced to weekly, monthly, or annual effects are pronounced.

Table 6 below reports the aggregated results for the $m = 499$ test across the whole sample and quartiles based on size. Overall, significant seasonal patterns can be detected in 220 coins (28.5% of the sample), demonstrating a much more pronounced effect than for stock markets investigated in the previous subsection. Furthermore, seasonal effects are more characteristic of smaller coins (3rd and 4th quartile), than for the larger coins, highlighting the prominent size-efficiency and liquidity-efficiency nexuses in cryptoassets (Noda, 2021; Vidal-Tomas et al., 2019; Wei, 2018). Seasonal patterns in larger coins adhere to established weekly, monthly, and annual cycles to greater extent, while seasonal effects in smaller coins tend to be more unconventional. Long-term (cycle periodicity of greater than 90 days) seasonality is most prominent across size quartiles, while mid-term (one month to three months) is most often

Table 5
Seasonal effects detected on cryptocurrency markets for m = 2, 3, 5, 7, and 73.

Market	Seasonality				p-value					
	Overall	Weekly	Monthly	Annual	Wilson	2	3	5	7	73
XRP	Yes	Yes	No	No	**0.0734**	**0.0340**	**0.0768**	0.1574	**0.0623**	0.2996
LSK	No	Yes	No	No	0.1544	0.8964	0.4063	0.6035	**0.0449**	0.2044
BTG	Yes	Yes	No	No	**0.0977**	0.3660	0.6476	**0.0402**	**0.0543**	0.2728
BCD	Yes	No	No	No	**0.0049**	0.7540	0.6400	0.8068	0.5911	**0.0010**
MONA	Yes	No	No	No	**0.0876**	0.3637	0.6613	0.8255	0.9008	**0.0198**
DGB	No	No	No	Yes	0.1023	0.1127	0.1875	**0.0825**	0.1369	**0.0655**
XVG	Yes	Yes	Yes	No	**0.0412**	**0.0507**	**0.0195**	**0.0342**	**0.0664**	0.1721
AE	No	No	No	Yes	0.1248	0.8091	0.2736	**0.0989**	0.1730	**0.0519**
ARDR	Yes	No	No	No	**0.0901**	0.9211	**0.0420**	**0.0601**	0.1162	0.1866
STRAT	Yes	Yes	No	Yes	**0.0813**	0.7933	0.7697	**0.0423**	**0.0612**	**0.0527**
SERO	No	Yes	No	No	0.1080	0.6886	**0.0853**	0.1710	**0.0416**	0.3087
PAI	Yes	Yes	No	No	**0.0561**	**0.0463**	0.1043	0.1000	**0.0221**	0.3707
RDD	No	Yes	No	No	0.2001	0.2744	0.2456	0.2095	**0.0923**	0.5990
DIVI	Yes	Yes	No	Yes	**0.0539**	**0.0845**	0.1784	**0.0715**	**0.0874**	**0.0201**
PIVX	No	Yes	No	No	0.1003	0.7492	0.1774	**0.0405**	**0.0594**	0.7571
NULS	No	Yes	No	No	0.1077	0.9694	0.4489	0.6592	**0.0249**	0.7155
GRS	Yes	Yes	No	No	**0.0491**	0.2560	**0.0291**	**0.0262**	**0.0498**	0.1913
EMC2	Yes	No	Yes	No	**0.0789**	**0.0292**	**0.0927**	**0.0957**	0.1663	0.5339
VITAE	Yes	Yes	Yes	No	**0.0425**	**0.0209**	**0.0631**	**0.0310**	**0.0499**	0.6514
BHD	Yes	Yes	No	No	**0.0774**	0.6492	0.8818	0.4167	**0.0431**	**0.0275**
CVCC	Yes	No	No	No	**0.0001**	0.1466	0.1228	0.2417	0.3182	**0.0000**
APL	Yes	Yes	No	No	**0.0959**	**0.0550**	**0.0949**	0.1490	**0.0680**	0.5053
GRN	Yes	Yes	No	No	**0.0776**	0.5654	0.3200	0.4961	**0.0180**	0.5051
NYE	Yes	No	No	No	**0.0782**	0.3288	**0.0564**	0.1172	0.1612	**0.0351**
FO	Yes	Yes	No	No	**0.0362**	0.1292	0.1175	**0.0133**	**0.0226**	0.4767
BURST	Yes	Yes	No	No	**0.0825**	0.8530	**0.0448**	**0.0532**	**0.0853**	0.1525
NMC	Yes	Yes	No	No	**0.0769**	0.3716	**0.0334**	**0.0784**	**0.0806**	0.1382
DERO	Yes	No	Yes	No	**0.0384**	**0.0117**	**0.0389**	**0.0867**	0.1584	0.7730
POLIS	Yes	Yes	No	No	**0.0458**	**0.0574**	0.1422	**0.0187**	**0.0373**	0.2344
COTI	Yes	No	Yes	No	**0.0880**	**0.0975**	**0.0433**	**0.0954**	0.1432	0.1673
SFT	Yes	Yes	No	Yes	**0.0351**	0.8842	**0.0148**	**0.0320**	**0.0331**	**0.0826**
FLO	Yes	Yes	Yes	No	**0.0643**	**0.0488**	**0.0900**	**0.0833**	**0.0319**	0.3614
TTN	Yes	Yes	Yes	Yes	**0.0164**	**0.0056**	**0.0201**	**0.0288**	**0.0420**	**0.0553**
XCP	Yes	No	No	No	**0.0757**	0.2447	0.2332	0.3174	0.4293	**0.0192**
NIM	Yes	Yes	Yes	No	**0.0159**	**0.0099**	**0.0343**	**0.0084**	**0.0166**	0.1869
LBC	Yes	Yes	No	No	**0.0039**	0.9688	0.7978	**0.0864**	**0.0008**	0.1048
COLX	Yes	Yes	No	No	**0.0615**	0.6556	**0.0899**	**0.0678**	**0.0208**	0.1722
LCC	Yes	Yes	No	No	**0.0438**	0.2223	0.3105	**0.0224**	**0.0168**	0.4305
PCX	No	Yes	No	No	0.1992	0.3634	0.6546	0.1522	**0.0849**	0.4057
VEO	Yes	No	Yes	Yes	**0.0000**	**0.0241**	**0.0328**	**0.0777**	0.1021	**0.0000**
RSTR	Yes	Yes	Yes	No	**0.0290**	**0.0678**	**0.0149**	**0.0263**	**0.0205**	0.2652
FLASH	Yes	Yes	No	No	**0.0546**	0.2370	**0.0228**	**0.0425**	**0.0548**	0.6005
AXE	Yes	Yes	Yes	Yes	**0.0149**	**0.0111**	**0.0084**	**0.0153**	**0.0317**	**0.0335**
BBR	Yes	Yes	Yes	Yes	**0.0308**	**0.0519**	**0.0182**	**0.0383**	**0.0666**	**0.0212**
ECC	Yes	Yes	Yes	Yes	**0.0081**	**0.0403**	**0.0043**	**0.0102**	**0.0083**	**0.0072**
FTC	Yes	No	No	No	**0.0571**	0.4872	0.7678	0.4816	0.6509	**0.0124**
XST	Yes	Yes	No	Yes	**0.0491**	0.5205	0.2573	**0.0419**	**0.0836**	**0.0166**
XSPEC	Yes	Yes	No	Yes	**0.0658**	0.2619	0.4622	**0.0521**	**0.0862**	**0.0255**
VEX	Yes	No	No	No	**0.0006**	0.4786	0.4719	0.6235	0.7302	**0.0001**
CRON	Yes	No	No	No	**0.0031**	0.4671	0.7335	0.7332	0.8556	**0.0006**
TELOS	Yes	Yes	Yes	Yes	**0.0608**	**0.0968**	**0.0820**	**0.0729**	**0.0815**	**0.0297**
ADS	Yes	Yes	Yes	No	**0.0468**	**0.0426**	**0.0213**	**0.0504**	**0.0655**	0.8294
VEIL	Yes	No	No	No	**0.0185**	0.1565	0.2280	0.3915	0.5521	**0.0039**
PAC	Yes	No	No	No	**0.0000**	0.3341	0.2389	0.3736	0.5067	**0.0000**
RBTC	Yes	No	No	No	**0.0889**	0.6794	0.8920	0.8998	0.9563	**0.0194**
CLOAK	No	Yes	No	No	0.1345	0.9863	0.4368	0.6349	**0.0364**	0.2086
VIT	Yes	No	No	No	**0.0916**	0.3303	0.1417	0.2527	0.3404	**0.0266**
XPM	Yes	Yes	Yes	No	**0.0179**	**0.0055**	**0.0211**	**0.0321**	**0.0574**	0.7858
MUE	No	Yes	No	No	0.1397	0.6016	0.1816	**0.0723**	**0.0753**	0.6657
42	Yes	No	No	No	**0.0000**	0.3713	0.4785	0.6743	0.8161	**0.0000**
SMLY	Yes	Yes	Yes	No	**0.0578**	**0.0277**	**0.0525**	**0.0654**	**0.0864**	0.2177
NOTE	Yes	No	No	No	**0.0099**	0.4240	0.7260	0.7637	0.8595	**0.0020**
DEEX	No	No	No	Yes	0.1296	0.5393	0.6262	**0.0933**	0.1676	**0.0542**
BCA	No	No	Yes	No	0.1044	**0.0889**	**0.0828**	**0.0816**	0.1490	0.1792
SAFE	Yes	No	Yes	No	**0.0592**	**0.0212**	**0.0510**	**0.0956**	0.1748	0.6380
CCX	Yes	Yes	No	No	**0.0651**	**0.0491**	**0.0987**	0.1302	**0.0277**	0.4141
XSG	Yes	Yes	No	No	**0.0375**	0.8575	**0.0607**	**0.0134**	**0.0296**	0.1408
QAC	Yes	Yes	No	No	**0.0821**	0.8371	0.5222	**0.0457**	**0.0303**	0.3392
BTCZ	Yes	Yes	No	Yes	**0.0653**	0.7867	0.6553	**0.0294**	**0.0424**	**0.0618**
ZPT	Yes	No	No	No	**0.0640**	0.4461	**0.0220**	**0.0542**	0.1017	0.4709

(*continued on next page*)

Table 5 (*continued*)

Market	Seasonality				p-value					
	Overall	Weekly	Monthly	Annual	Wilson	2	3	5	7	73
IXC	Yes	Yes	No	No	**0.0067**	0.5930	**0.0028**	**0.0036**	**0.0088**	0.4143
ORB	No	Yes	No	No	0.1017	0.3741	**0.0796**	**0.0467**	**0.0926**	0.5848
DCY	Yes	Yes	Yes	Yes	**0.0004**	**0.0040**	**0.0009**	**0.0001**	**0.0002**	**0.0145**
TCC	No	Yes	No	No	0.2994	0.6472	0.8528	0.6789	**0.0983**	0.4283
AYA	Yes	No	No	No	**0.0178**	0.7725	0.9566	0.9135	0.8689	**0.0036**
NBAI	Yes	No	No	No	**0.0802**	**0.0271**	**0.0795**	0.1630	0.1760	0.9037
BTCP	Yes	No	No	No	**0.0066**	0.2539	0.4349	0.4605	0.6235	**0.0013**
ACM	Yes	No	No	No	**0.0469**	0.3778	0.6510	0.5377	0.1072	**0.0110**
XLR	Yes	No	No	No	**0.0003**	0.2506	0.3774	0.5115	0.6250	**0.0001**
XBI	No	Yes	No	No	0.2031	0.1521	0.3567	0.5344	**0.0846**	0.6464
BBP	Yes	No	No	No	**0.0152**	0.2653	0.4092	0.4842	0.5166	**0.0031**
RPD	Yes	No	Yes	Yes	**0.0271**	**0.0115**	**0.0398**	**0.0920**	0.1617	**0.0181**
UPX	No	Yes	No	No	0.1123	**0.0882**	0.1923	**0.0726**	**0.0910**	0.3082
MIB	Yes	Yes	Yes	Yes	**0.0247**	**0.0322**	**0.0930**	**0.0126**	**0.0271**	**0.0227**
XNV	Yes	No	No	No	**0.0882**	0.8209	**0.0331**	**0.0723**	0.1280	0.2765
DOPE	Yes	Yes	Yes	No	**0.0660**	**0.0552**	**0.0446**	**0.0609**	**0.0584**	0.5940
MONK	Yes	Yes	Yes	No	**0.0982**	**0.0972**	**0.0752**	**0.0795**	**0.0846**	0.3410
CXP	Yes	No	No	No	**0.0217**	0.9100	0.4340	0.4616	0.5529	**0.0045**
MSR	Yes	Yes	Yes	No	**0.0144**	**0.0056**	**0.0101**	**0.0241**	**0.0446**	0.1501
MAX	Yes	Yes	Yes	Yes	**0.0036**	**0.0375**	**0.0044**	**0.0013**	**0.0028**	**0.0360**
KEK	Yes	No	No	No	**0.0592**	0.4306	0.1679	0.1279	0.1740	**0.0160**
BLAST	Yes	Yes	Yes	Yes	**0.0071**	**0.0253**	**0.0029**	**0.0080**	**0.0162**	**0.0074**
MANNA	Yes	No	No	No	**0.0098**	0.6048	0.8693	0.7347	0.7620	**0.0020**
ZENI	Yes	No	No	No	**0.0262**	0.5438	**0.0953**	0.1548	0.2541	**0.0059**
SINS	Yes	Yes	Yes	Yes	**0.0037**	**0.0575**	**0.0043**	**0.0121**	**0.0027**	**0.0016**
NETKO	No	Yes	No	No	0.2396	0.4104	0.6439	0.8250	**0.0683**	0.9632
RUP	Yes	No	No	No	**0.0023**	0.1345	0.3233	0.5136	0.5436	**0.0005**
GZRO	Yes	Yes	No	No	**0.0222**	0.1303	0.2286	**0.0072**	**0.0134**	0.8419
NCP	Yes	No	No	No	**0.0008**	0.7340	0.5477	0.2935	0.4434	**0.0002**
PENG	No	Yes	No	No	0.1214	0.2691	0.3541	**0.0804**	**0.0784**	0.1058
XDNA	Yes	Yes	Yes	No	**0.0055**	**0.0622**	**0.0016**	**0.0050**	**0.0119**	0.2083
SSC	Yes	Yes	Yes	Yes	**0.0019**	**0.0010**	**0.0010**	**0.0027**	**0.0042**	**0.0496**
LANA	No	No	No	Yes	0.1049	0.6609	0.1383	**0.0917**	0.1561	**0.0463**
KZC	Yes	Yes	Yes	Yes	**0.0145**	**0.0123**	**0.0105**	**0.0098**	**0.0201**	**0.0584**
ZCR	Yes	No	No	No	**0.0897**	0.2816	**0.0725**	0.1162	0.2045	**0.0402**
GIN	No	Yes	No	No	0.1890	0.1984	0.2793	0.2903	**0.0899**	0.3066
PHO	Yes	No	No	No	**0.0376**	0.9369	0.1917	0.3280	0.4719	**0.0082**
BEN	Yes	Yes	No	No	**0.0590**	**0.0688**	0.1512	**0.0319**	**0.0371**	0.1906
GALI	Yes	No	No	No	**0.0041**	0.2790	0.3128	0.2122	0.1375	**0.0008**
UNIT	Yes	No	No	No	**0.0497**	0.8758	0.7538	0.8657	0.9426	**0.0104**
GCN	Yes	Yes	No	Yes	**0.0799**	0.2688	**0.0859**	**0.0480**	**0.0897**	**0.0657**
CROAT	Yes	Yes	Yes	No	**0.0781**	**0.0853**	**0.0390**	**0.0863**	**0.0811**	0.3673
ANC	Yes	No	No	No	**0.0013**	0.2990	0.2187	0.2885	0.4226	**0.0003**
KOBO	Yes	Yes	No	No	**0.0457**	0.1562	**0.0381**	**0.0278**	**0.0309**	0.1202
FRST	Yes	Yes	No	No	**0.0080**	0.6874	0.3747	0.1640	**0.0017**	**0.0262**
LTHN	Yes	Yes	Yes	No	**0.0432**	**0.0161**	**0.0511**	**0.0571**	**0.0698**	0.4736
ANON	Yes	Yes	Yes	No	**0.0071**	**0.0137**	**0.0028**	**0.0053**	**0.0128**	0.1177
GTM	Yes	Yes	Yes	No	**0.0052**	**0.0017**	**0.0043**	**0.0115**	**0.0229**	0.3858
XCN	No	Yes	No	No	0.1555	**0.0901**	0.2327	0.2586	**0.0888**	0.6151
CTX	No	Yes	No	No	0.2044	0.9109	0.9833	0.4007	**0.0575**	0.4071
MCPC	Yes	Yes	No	Yes	**0.0427**	0.8691	**0.0197**	**0.0486**	**0.0906**	**0.0300**
BTK	Yes	Yes	Yes	No	**0.0572**	**0.0292**	**0.0389**	**0.0644**	**0.0925**	0.8072
ARC	Yes	Yes	No	No	**0.0746**	0.6160	0.8780	**0.0275**	**0.0390**	0.4487
EVT	Yes	Yes	Yes	Yes	**0.0004**	**0.0388**	**0.0003**	**0.0002**	**0.0002**	**0.0280**
MOIN	Yes	No	No	No	**0.0984**	**0.0373**	0.1140	0.2138	0.1874	0.1916
PNY	Yes	No	No	No	**0.0000**	0.3389	0.5186	0.6614	0.7665	**0.0000**
PLURA	Yes	Yes	No	No	**0.0582**	0.1927	**0.0212**	**0.0509**	**0.0992**	0.2664
ICR	Yes	No	No	No	**0.0025**	0.1177	**0.0967**	0.1918	0.2922	**0.0005**
SUPER	Yes	Yes	No	No	**0.0908**	0.4649	0.6746	**0.0387**	**0.0432**	0.4089
SWIFT	Yes	No	No	No	**0.0236**	0.8690	0.6328	0.1882	0.3053	**0.0050**
EDRC	Yes	Yes	Yes	No	**0.0231**	**0.0073**	**0.0210**	**0.0494**	**0.0972**	0.6487
FBN	Yes	No	No	No	**0.0011**	0.2905	0.4415	0.6018	0.7280	**0.0002**
STEEP	Yes	Yes	No	No	**0.0867**	0.4593	0.7164	**0.0322**	**0.0601**	0.1574
CPC	Yes	Yes	Yes	No	**0.0285**	**0.0112**	**0.0312**	**0.0317**	**0.0556**	0.2192
ELE	Yes	Yes	No	No	**0.0794**	0.9633	0.1283	**0.0342**	**0.0612**	0.1163
SPR	Yes	No	No	No	**0.0927**	0.2874	0.4187	0.4373	0.5808	**0.0227**
XRA	Yes	No	No	No	**0.0778**	**0.0249**	**0.0786**	0.1652	0.2545	0.7590
IQ	No	Yes	No	No	0.2075	0.8123	0.1807	0.1744	**0.0945**	0.9873
DMB	Yes	No	No	No	**0.0938**	**0.0610**	**0.0558**	0.1020	0.1458	0.4238
BTAD	Yes	No	No	No	**0.0990**	**0.0745**	**0.0491**	0.1106	0.1656	0.6122

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Table 5 (*continued*)

Market	Seasonality				p-value					
	Overall	Weekly	Monthly	Annual	Wilson	2	3	5	7	73
CTL	Yes	No	No	No	**0.0059**	0.2756	0.5513	0.5131	0.4337	**0.0012**
YTN	Yes	No	No	No	**0.0000**	0.3292	0.4769	0.1411	0.2275	**0.0000**
KTS	Yes	Yes	Yes	No	**0.0051**	**0.0105**	**0.0348**	**0.0017**	**0.0039**	0.3725
GSR	Yes	Yes	No	No	**0.0046**	0.6169	**0.0442**	**0.0014**	**0.0029**	0.3108
GPKR	Yes	Yes	No	No	**0.0862**	0.5679	**0.0525**	**0.0648**	**0.0563**	0.2495
XUEZ	Yes	Yes	No	Yes	**0.0237**	0.1022	0.1432	**0.0305**	**0.0068**	**0.0731**
XIND	Yes	No	No	No	**0.0607**	0.7598	0.9325	0.5927	0.6042	**0.0131**
BLC	Yes	No	No	No	**0.0805**	0.1590	**0.0874**	0.1561	0.1571	**0.0317**
SMC	Yes	No	No	No	**0.0552**	0.8794	0.7058	0.7096	0.8456	**0.0117**
PEX	Yes	Yes	No	Yes	**0.0107**	0.3291	0.2005	**0.0035**	**0.0062**	**0.0919**
CF	Yes	No	No	Yes	**0.0097**	0.1314	**0.0460**	**0.0966**	0.1128	**0.0021**
EVOS	Yes	Yes	No	No	**0.0876**	0.2005	**0.0767**	**0.0669**	**0.0445**	0.6013
SONO	No	Yes	No	No	0.1409	0.1585	0.3664	0.5393	**0.0426**	0.8926
IMS	No	Yes	No	No	0.1328	0.7708	0.2264	**0.0911**	**0.0866**	0.1060
EGX	Yes	Yes	Yes	No	**0.0369**	**0.0432**	**0.0782**	**0.0153**	**0.0311**	0.4765
SPK	Yes	Yes	No	No	**0.0703**	0.1473	**0.0277**	**0.0618**	**0.0925**	0.7958
CONX	Yes	No	No	No	**0.0509**	0.5641	0.5693	0.7528	0.8243	**0.0109**
LBTC	Yes	Yes	Yes	No	**0.0730**	**0.0918**	**0.0460**	**0.0441**	**0.0821**	0.9385
CNNC	No	Yes	No	No	0.1039	**0.0883**	0.1973	**0.0796**	**0.0768**	0.1628
PXI	Yes	No	Yes	No	**0.0749**	**0.0419**	**0.0524**	**0.0695**	0.1233	0.7619
MRI	Yes	Yes	No	No	**0.0781**	0.6512	**0.0388**	**0.0812**	**0.0435**	0.7039
HWC	No	Yes	No	No	0.2138	0.7231	0.9381	0.3571	**0.0812**	0.1716
DASHG	Yes	No	No	No	**0.0089**	0.6715	0.8670	0.8818	0.1316	**0.0018**
DTEM	Yes	Yes	Yes	No	**0.0894**	**0.0931**	**0.0725**	**0.0588**	**0.0884**	0.3227
DOT	Yes	No	No	Yes	**0.0004**	0.1891	**0.0477**	**0.0925**	0.1700	**0.0001**
IOEX	Yes	No	No	No	**0.0168**	0.7366	0.1738	0.3088	0.3904	**0.0035**
GOD	Yes	No	No	No	**0.0827**	0.8173	0.9252	0.7038	0.7492	**0.0181**
RBBT	No	Yes	No	No	0.1224	0.2342	0.4061	0.1868	**0.0627**	**0.0780**
ACES	Yes	No	No	No	**0.0856**	**0.0274**	**0.0868**	0.1717	0.2811	0.9144
OC	Yes	No	No	No	**0.0798**	**0.0937**	0.2457	0.4191	0.3558	**0.0234**
OCUL	Yes	Yes	No	Yes	**0.0651**	0.9982	**0.0657**	**0.0458**	**0.0476**	**0.0565**

Notes: significant (at 10%) p-values are reported **in bold**.

Table 6
The structure of cryptocurrency seasonality across coin size and effect types.

Seasonality	overall	1st quartile	2nd quartile	3rd quartile	4th quartile
none	552	159	139	120	134
any	220	34	54	73	59
short-term	32	5	9	12	6
mid-term	54	9	19	15	11
long-term	134	20	26	46	42
weekly	103	30	25	28	20
monthly	44	10	15	13	6
annual	32	7	11	9	5
conventional	51	12	12	17	10
unconventional	169	22	42	56	49
total	772	193	193	193	193
% of total	overall	1st quartile	2nd quartile	3rd quartile	4th quartile
none	71.50	82.38	72.02	62.18	69.43
any	28.50	17.62	27.98	37.82	30.57
short-term	4.15	2.59	4.66	6.22	3.11
mid-term	6.99	4.66	9.84	7.77	5.70
long-term	17.36	10.36	13.47	23.83	21.76
weekly	13.34	15.54	12.95	14.51	10.36
monthly	5.70	5.18	7.77	6.74	3.11
annual	4.15	3.63	5.70	4.66	2.59
conventional	6.61	6.22	6.22	8.81	5.18
unconventional	21.89	11.40	21.76	29.02	25.39

Notes: statistical significance assessed at 10% and cryptocurrencies are split into quartiles based on market capitalisation. Unconventional seasonality is defined as seasonality not conforming to weekly, monthly, or annual patterns.

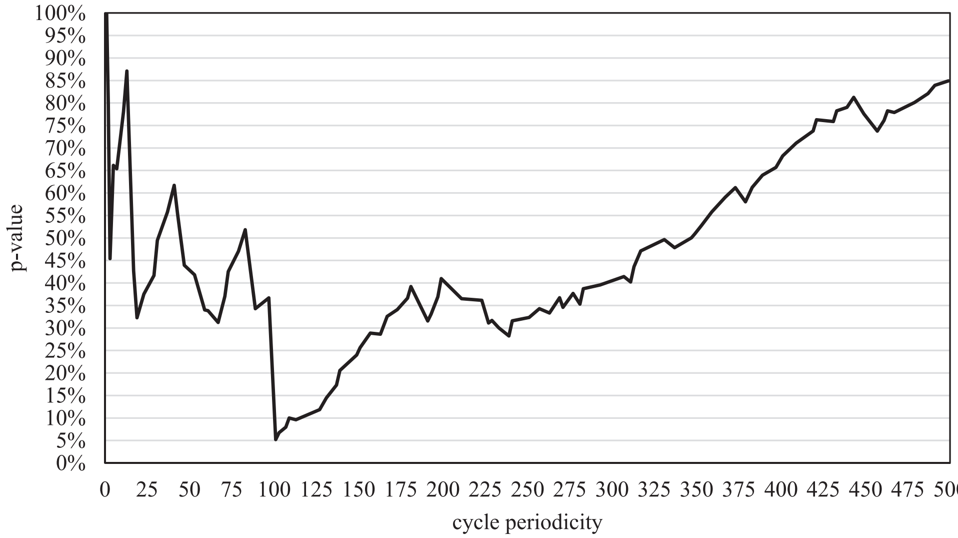

Fig. 7. The seasonality pattern of Bitcoin (no seasonality). **Notes:** p-value drops below 10% for cycle length 101, however the harmonic mean p-value exceeds 10%, hence Bitcoin is shown to have no seasonality when adjusted for multiple testing.

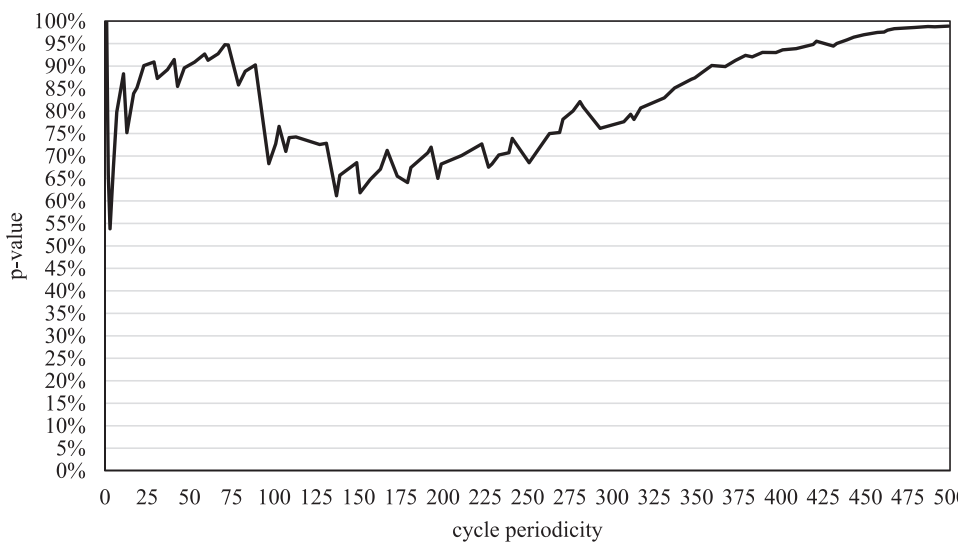

Fig. 8. The seasonality pattern of Ethereum (no seasonality). **Notes:** p-value never drops below 10% and the harmonic mean p-value exceeds 10%, hence Ethereum is shown to have no seasonality.

associated with the coins from the second quartile, and short-term (cycle periodicity of less than 30 days) is most typical for coins from the third quartile.

Figs. 7–12 below report the seasonality patterns for Bitcoin (Fig. 7), Ethereum (Fig. 8), and XRP (Fig. 9), as well as most prominent coins with long-term (Litecoin, Fig. 10), medium-term (Bitcoin Diamond, Fig. 11), and short-term (Groestlcoin, Fig. 12) seasonality as detected by the generalised test. Bitcoin and Ethereum show no robust seasonal patterns after adjusted for multiple testing, reflecting the relative efficiency of the largest cryptoassets and consistent with prior literature (Kaiser, 2019; Kinateder & Papavassiliou, 2021). XRP, Groestlcoin, Bitcoin Diamond, and Litecoin, however, demonstrate patterns of cycle length equal to roughly two days, two weeks, two months, and one year, respectively, showing both the prominence and the diversity of seasonal effects on cryptocurrency markets.

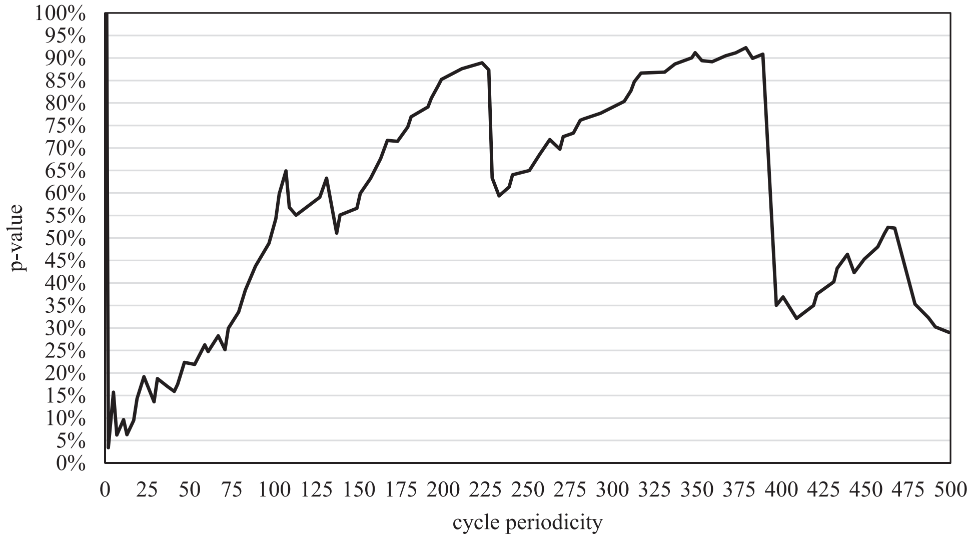

Fig. 9. The seasonality pattern of XRP (short-term seasonality). **Notes:** p-value drops the lowest (below 5%) at cycle periodicity 2, while the harmonic mean p-value equals 7.34%, hence XRP is demonstrating short-term seasonality significant at 10%.

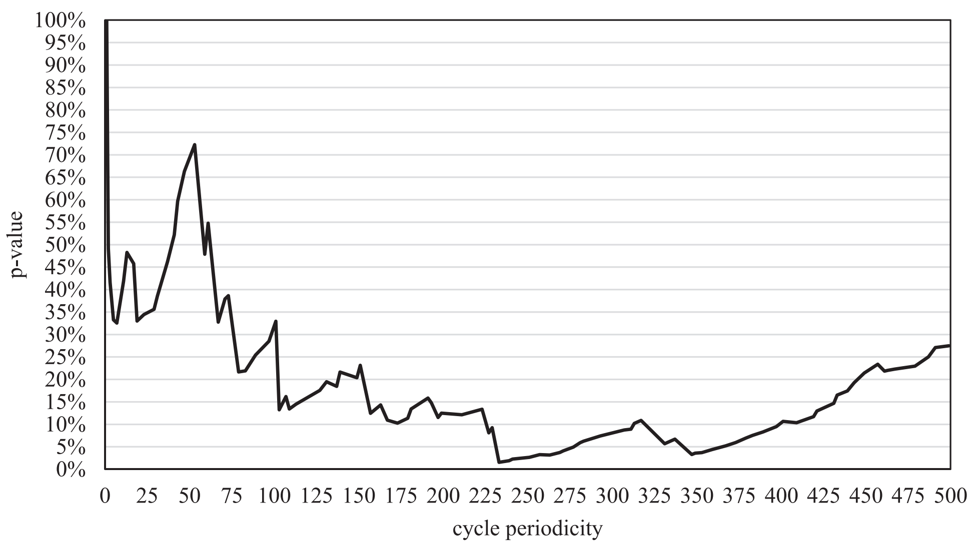

Fig. 10. The seasonality pattern of Litecoin (long-term seasonality). **Notes:** p-value drops the lowest (below 5%) at cycle periodicity 2, while the harmonic mean p-value equals 7.34%, hence XRP is demonstrating short-term seasonality significant at 10%.

3.4. Discussion

The findings of the test with regards to both stock and cryptocurrency markets have multi-faceted implications. First, testing for general seasonal patterns in asset returns is a powerful test for market efficiency, with cryptocurrencies showing more prominent patterns than national stock indices. The generalised seasonality test can thus augment the toolbox of efficiency tests that focus on time series dependence (such as runs test, variance ratio test, BDSL test, or Hurst exponent). Second, the proposed test generalises and formalises the testing for the existence of calendar anomalies, while allowing to detect patterns without pre-assuming their structure nearly as strongly as in existing research on seasonality, which is especially useful for emergent assets with unconventional trading times, such as cryptocurrencies. The test simultaneously addresses the multiple testing concerns in a conceptually and computationally simple way and enables to locate cyclicality that deviates from weekly, monthly, or annual structure commonly imposed on the data in the empirical literature. Finally, the test can inform trading strategies and help investors determine trading cycle lengths and exploit calendar anomalies with greater flexibility than usual tests allow. When applied to high-frequency data (e.g., 15-minute candles for most liquid instruments), the test can even assist intraday trading.

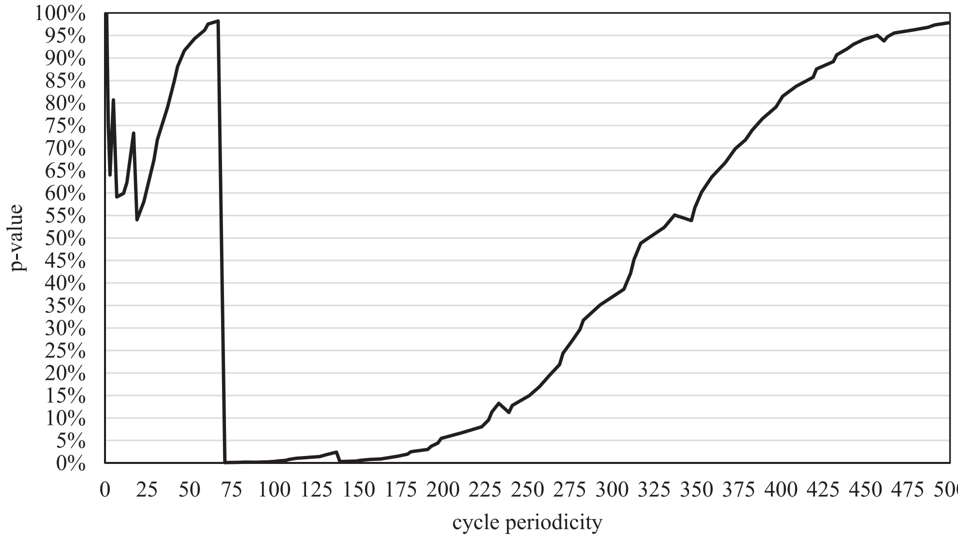

Fig. 11. The seasonality pattern of Bitcoin Diamond (medium-term seasonality). **Notes:** p-value drops the lowest (below 5%) at cycle periodicity 2, while the harmonic mean p-value equals 7.34%, hence XRP is demonstrating short-term seasonality significant at 10%.

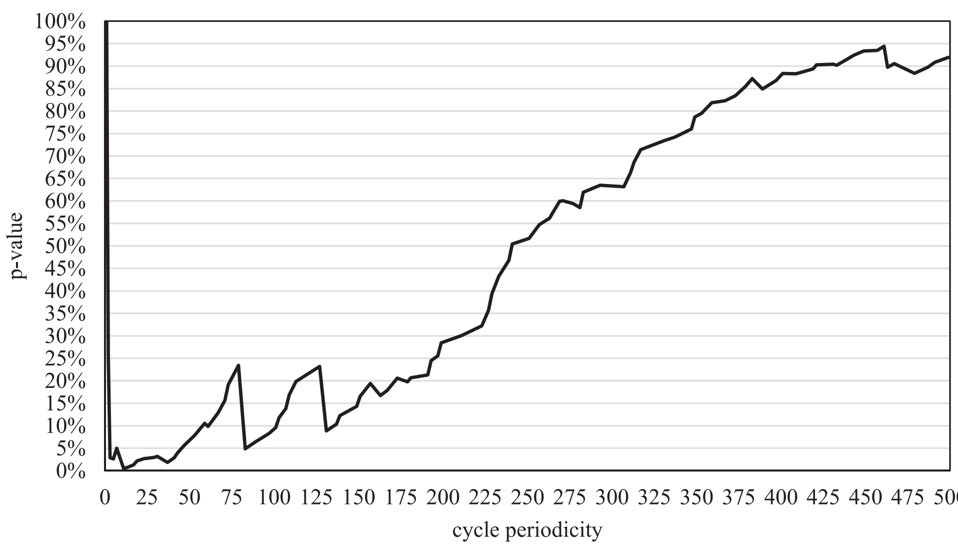

Fig. 12. The seasonality pattern of Groestlcoin (short-term seasonality). **Notes:** p-value drops the lowest (below 5%) at cycle periodicity 2, while the harmonic mean p-value equals 7.34%, hence XRP is demonstrating short-term seasonality significant at 10%.

4. Conclusion

The generalised seasonality test developed by this study is a conceptually and computationally simple yet powerful econometric tool that allows to test for existence of any seasonal patterns in time series against the general null hypothesis of no seasonality. It utilises sequential regressions with dummy variables for cycle periodicity equal to prime numbers and applies Wilson (2019) harmonic mean p-value to control for family-wise error rate. Such test design allows to identify long-term cycles in data without substantial degrees of freedom loss or multicollinearity concerns. The study has evidenced the applicability of the test to seasonal effect detection in daily stock returns for 76 national stock market indices and 772 cryptocurrencies. Cryptocurrency markets are shown to be more susceptible to seasonal anomalies and thus less efficient, with notably unconventional seasonal patterns that do not fall within the established calendar anomaly paradigm, which supports and augments the existing literature on cryptocurrency market efficiency (Khuntia & Pattanayak, 2018) and seasonality (Aharon & Qadan, 2019; Kaiser, 2019; Qadan et al., 2021). The existence and relative prevalence of unconventional seasonality for cryptocurrencies in comparison to stock markets highlights the global and idiosyncratic nature of cryptocurrency trading (Vidal-Tomas, 2021).

The limitations of the method can be mainly associated with the adaptive market hypothesis (Khuntia & Pattanayak, 2018; Lo, 2004), market learning (List, 2003), and the corresponding propensity of financial market anomalies to disappear or decay with time (McLean & Pontiff, 2016; Shanaev & Ghimire, 2021). Further research could therefore apply the developed test to other asset classes and investigate its performance in subsamples.

Potential further applications of the test are numerous. In finance, it can serve as an additional market efficiency test augmenting the existing battery of time series dependence tests or as a tool for intraday traders and investors exploiting calendar anomalies. As such, investors can apply the test to return time series as a convenient and reliable tool to detect seasonal patterns while limiting the risk of data-snooping biases subject to multiple testing. In economics, it can be used to detect business cycles or to generate seasonally adjusted data, for example for macroeconomic aggregates. For machine learning applications, the test can function as a pre-processing tool to identify outliers and anomalies or to smoothen the data.

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