Seasonality in the cross section of stock returns:

Advanced markets versus emerging markets

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Abstract

We extend the studies of stock return seasonality by Heston and Sadka (2008, 2010) to a comprehensive sample of 42 international markets, including 21 advanced markets and 21 emerging markets. The empirical results show a large variation in stock seasonality across markets and suggest that this phenomenon exists primarily in advanced markets. A winner-loser portfolio approach shows that return seasonality is economically significant in advanced markets but not in emerging markets. We conduct statistical, rational and behavioral analyses to explore the potential reasons for the seasonality observed in advanced markets and find that regression bias, the January effect, and the Fama-French-Carhart type risk premium all can partially explain this seasonality difference.

JEL Classification: G12, G14, G15

Keywords: Asset pricing; Market efficiency; Seasonality; International financial markets; Emerging market

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1. Introduction

Prior studies show that stock returns are serially correlated. For example, Jegadeesh and Titman (1993, 1995) document a negative first-order serial correlation and positive higher-order serial correlations in monthly stock returns. Buying stocks that have performed well in the past and selling stocks that have performed poorly generates significant positive returns over the subsequent three to 12 months. Moreover, according to Heston and Sadka (2008), stocks' relative performance in one month is related to their relative performance in the same month in previous 20 years. In other words, past winner stocks that outperformed the market in a given calendar month one, two, three or even 20 years ago will continue to outperform in current month and past loser stocks from the same calendar month will continue to underperform. Keloharju, Linnainmaa, and Nyberg (2016) report that a strategy selecting stocks based on their historical same-month returns generate an average return of 13% per year.

Existing studies of the same-month return pattern, however, mostly focus on the U.S. market (e.g. Heston and Sadka, 2008; Keloharju et al., 2016). Heston and Sadka (2010) extend their study to Canada, Japan, and 12 European countries, and find that firms that have outperformed their domestic market peers in a particular month of 1-5 years ago continue to outperform in the same calendar month, suggesting that international stock markets may exhibit similar patterns found in the U.S. stock market. However, the question of whether emerging markets exhibit similar return patterns has not yet been thoroughly investigated, [1] and the few existing studies on international markets focus on stock market indexes rather than individual stocks. We investigate whether the same-month return pattern exists in emerging markets and whether this pattern differs from that observed in advanced markets. We use a comprehensive dataset of 42 markets outside the U.S., including 21 advanced markets and 21 emerging markets. The dataset covers the main regions of international financial markets, including North America, South America, Europe, Asia-Pacific, and the Middle-East. To our knowledge, our dataset covers more international markets than any other study of stock return seasonality.

We test whether stock returns exhibit seasonality in both advanced and emerging markets using a procedure similar to that in Heston and Sadka (2008, 2010). The Fama-MacBeth regression results suggest that seasonal patterns are strong in advanced markets but weak in emerging markets (Table 2). Pooling all advanced markets together as a whole market, stock returns are statistically positively related to returns in the same-month one, two, three, four and five years ago. Pooling all emerging markets together, although stock returns are significantly positively related to returns in the same-month two years ago and marginally significantly related to same-month returns one year ago, they are not significantly positively related to the same-month returns in other years, and are actually negatively related to returns in the same-month five years ago, suggesting that return seasonality in these markets is weak.[2] We further test whether this difference is economically meaningful using a portfolio approach similar to DeBondt and Thaler (1985), Jegadeesh and Titman (2001), and Heston and Sadka (2008, 2010). We allocate stocks into 10 decile portfolios according to their historical same-month returns over various historical time intervals, and form a seasonality portfolio by longing the historical same-month winner stocks and shorting the historical same-month loser stocks. We then compute the next-month total returns as well as returns in excess of the local market returns for each portfolio. [3] We construct portfolios over all markets in the sample as well as for each international market separately.

The average excess return of the winner-minus-loser portfolio compromised of stocks of all advanced markets is as high as 0.53% (*t-stat* = 3.37) when the portfolio is formed on returns in the same month in the past year. The return becomes 0.27% (*t-stat* = 1.77) when the portfolio is formed on returns in the same month of 2-3 years ago, and 0.21% (*t-stat* = 1.10) when it is formed on returns in the same month of 4-5 years ago. In contrast, the average excess return of the winner-minus-loser portfolio compromised of stocks of all emerging markets is 0.11% (*t-stat* = 0.43) when it is formed on returns in the same month in the past year. The excess return further declines to -0.23% (*t-stat* = -0.75), and -0.24% (*t-stat* = -0.82) when the portfolio is formed on

[1] A few studies have been done on emerging markets: Ho (1990) studies the stock return seasonality in Asia Pacific markets; Fountas and Segredakis (2002) study the January anomaly in eighteen emerging stock markets over the period 1987–1995; Al-Saad and Moosa (2005) study the stock return seasonality in the Kuwait Stock Exchange and Pandey (2002) studies the Malaysian stock market.

[2] These results do not imply no seasonality in individual emerging markets, see Section 3.2.2.

[3] Local market return is the return on the value-weighted local market index.

returns in the same month of 2-3 years or 4-5 years ago, respectively. Buying the same-month winners and selling the same-month losers in past year is profitable (i.e. delivers significant positive returns) in nine of the 19 advanced economies but only in three of the 18 emerging markets.[4] Moreover, in several emerging markets, this strategy leads investors to lose money (Table 4). This pattern remains when the winner-minus-loser portfolio is formed on the same-month returns 2 or 3 years ago.

In sum, our results suggest that stock return seasonality is a statistically and economically significant phenomenon and is more common in advanced markets than in emerging markets. These findings build on those of Heston and Sadka (2010), who focus on 14 advanced markets. The literature proposes several potential explanations for this seasonality difference between advanced and emerging markets. Kamstra (2017) suggests that an implementation bias in the Fama-MacBeth test for seasonality may explain this difference, and proposes a fixed-effect procedure to fix such bias. Keloharju et al. (2016) show that the seasonality anomaly interacts with other return anomalies through shared systematic factors. Lewellen (2002) finds that stocks excess covariance rather than under- or over-reaction explains the anomaly in momentum portfolios. Cooper et al. (2006) document that returns in January have power to predict market returns over the next 11 months of the year. We test whether the above reasons can explain the difference in seasonality patterns between advanced and emerging markets and find that some of these explanations have partial explanatory power.

We implement the fixed-effect models proposed by Kamstra (2017) by controlling for firms' expected return level, and find that the implementation bias in the Fama-MacBeth procedure can partially explain the difference in seasonality patterns between advanced and emerging markets. After adjusting for this bias, the *t*-statistics of the coefficients on the same-month returns 2-5 years ago in advanced markets become insignificant or marginally significant (between 0.76 and 1.85). The *t*-statistics of the coefficients on the historical same-month returns in emerging markets, however, are almost unchanged, suggesting that the implementation bias in the Fama-MacBeth analysis may partially drive this seasonality difference.

The difference in return seasonality between advanced markets and emerging markets can be partly attributed to the differences in firm characteristics between the two types of markets. Specifically, there is a significant difference in seasonality between small firms in advanced markets and those in emerging markets, while seasonality patterns in large firms (Table 6) are similar across markets. The empirical results also suggest that the winner-loser strategy produces significantly positive returns in January and December in advanced markets, but not in emerging markets (Table 7). The performance difference in seasonal portfolios between the advanced markets and the emerging markets can also be partially explained by the local market risk factors including size, book-to-market and momentum formed following Fama and French (1993) and Carhart (1997) (Table 8). The winner-minus-loser portfolios based on the same-month returns in the past year are able to deliver significant positive risk-adjusted returns (alphas) in six of the 19 advanced markets and only in two of the 15 emerging markets. When the winner-loser portfolios are constructed on the same-month returns 2-3 years ago, and 4-5 years ago, the number of advanced markets with significant positive alphas, increases to 13 and 10, respectively. The number of emerging markets increases to four in both cases. In other words, the Fama-French-Carhart type risk factors have some explanatory power of the short-term return seasonality patterns. We also examine whether the global risk factors formed similarly to those in Fama and French (1993) and Carhart (1997) can explain the difference in the performance of the seasonal winner-loser portfolios between emerging and advanced markets and find that the local risk factors have more explanatory power than the global factors.[5]

In sum, we find that each of proposed statistical, rational and behavioral reasons may explain the existence of seasonality in many advanced markets and its absence in many emerging markets. However, all of their explanatory powers are partial; the fact that we do not find one perfect answer implies that other unknown reasons driving this phenomenon are worth investigating further. [6]

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[4] We drop several markets from the analyses due to data availability and reliability; see section 3 for details.

[5] These results are not reported, but are available upon request.

[6] Such reasons may include, for example, differences in investor's rationality and risk aversion across countries (Kamstra, Kramer, Levi and Wang, 2014; Hirshlerfer, Jiang and Meng,2017), difference in culture, regulation and law environments (Houston, Lin, Lin and Ma, 2010; Houston, Lin, and Ma, 2012; and Li, Griffin, Yue, and Zhao, 2013, among others).

The remainder of this paper is organized as follows. Section 2 introduces the methodology, variable definitions, and data sources. The main empirical findings are in Section 3, and Section 4 wraps up this paper.

2. Methodology and data

2.1 Methodology

Following Heston and Sadka (2008), the stock return seasonality test can be specified as the following two-step Fama-MacBeth (1973) regression:

$$r_{n,i,t} = \alpha_{n,t} + \beta_{k,t} r_{n,i,t-k} + \varepsilon_{n,i,t}, \tag{1}$$

where $r_{n,i,t}$ is the return on stock i from market n in month t, and the coefficient $\beta_{k,t}$ represents the cross-sectional response of returns in month t to returns in the lagged month t-k. For each lagged month $\beta_{k,t}$ is computed as the average of all stocks slope coefficients.

For the economic significance analysis, at the beginning of each month, stocks are sorted into ten equal groups based on their historical seasonal (raw or excess) returns, i.e. returns in the same month of 1, 2 and 3, or 4 and 5 years ago. We form a winner portfolio by buying all stocks in the top group (with the highest historical seasonal returns) and a loser portfolio by buying all stocks in the bottom group. We then compute the return spread between the winner portfolio and the loser portfolio in each month. The portfolios are formed for both individual markets and all markets in aggregate throughout all available lagged months. In addition to evaluating the raw returns, we calculate the risk-adjusted portfolio performance by following a Fama-French-Carhart type four-factor model to test whether the seasonality pattern can be explained by local and global risk factors:

$$r_{n,i,t} - r_{f,n,t} = \alpha_{n,t} + A_{n,t}\left(R_{n,M,t} - r_{n,f,t}\right) + B_{n,t} SMB_{n,t} + C_{n,t} HML_{n,t} + D_{n,t} WML_{n,t} + \varepsilon_{n,i,t}, \tag{2}$$

where $R_{n,M,t}$ is the monthly value-weighted return on the market portfolio in market n in month t and $r_{n,f,t}$ is the risk free rate for market n in month t and is approximated by the return on one-month U.S. Treasury Bills. $SMB_{n,t}$, $HML_{n,t}$ and $WML_{n,t}$ represent the return differences between the small size stock portfolio and the large size stock portfolio, between the high book-to-market (B/M) equity stock portfolio and the low B/M stock portfolio, and between the past winner stock portfolio and the past loser stock portfolio, respectively, for market n in month t.[7]

2.2 Data

The data in this paper, including stock prices for individual firms, market price indexes, trading volumes, market capitalizations, book-to-market values and the risk-free interest rates for all international markets, are collected from the Datastream International.[8] As noted by Ince and Porter (2006), the Datastream International data suffers from several problems in relation to data coverage, classification, and integrity for international markets. In addition, according to Brennan et al. (2013), extreme returns may generate large illiquidity and affect the validity of the model. Therefore, in compiling the data, we set a firm's observations over a given month to "missing" if its stock returns and trading volumes at the end of that month are in the top or the bottom 1% of the cross-section in each market. To fix the massive stale data issue, we follow Ince and Porter (2006) and drop observations with security prices and trading volumes that have zero variance for more than three months during our sample period. Moreover, we require five or more stocks for each market in each month to ensure meaningful analysis, which means the begin date of our sample varies across markets. Because the sample ends in June 2013, the data spans from January 1995 to June 2013.[9] We end up with 21 advanced markets and 21 emerging

[7] See Appendix for the details of Fama-French (1993) portfolio formation.
[8] We use monthly data for empirical analysis and daily data for some of the cleaning rules.
[9] Begin and end dates vary from market to market. Data for emerging markets tend to cover shorter periods.

markets.[10] Monthly data are used to construct Fama-French (1993) and Carhart (1997) risk factors.[11] Monthly return of stock *i* from market *n* in month *t* is defined as $R_{n,i,t} = (log(P_{n,i,t}) - log(P_{n,t,t-1})) \times 100$, where $P_{n,i,t}$ denotes the closing price at the end of month *t* and $P_{n,i,t-1}$ the closing price at the end of month *t*-1.

Table 1 reports summary statistics of the data, including begin date, average number of firms per month, average return per month, and total observations for each market. India's stock market has more stocks than any other market (on average 4,074 stocks per month) while stocks in Romania's stock market have delivered the highest average return: 4.55% per month over the past 18 years. Hungary's market, on the other hand, has the smallest number of stocks: 51 per month, on average; Italy's market delivered the worst performance, with an average return of only 0.10% per month during the sample period. In general, the average stock returns in emerging markets are higher than those in advanced markets over the past two decades. However, most advanced markets have longer sample periods, implying that the analysis on emerging market may suffer from small sample bias. For example, the begin date for both Bulgaria and Ukraine markets is May 2006.

3. Empirical analysis

3.1 Statistical analysis

We start with the Fama-MacBeth (1973) two-pass procedure to test the cross-sectional correlation between returns in the current month and returns in the same calendar month in previous years. We first conduct the empirical analysis for model (1) separately for each individual stock in our sample, using 16 lags of 1, 2, 3, … , 12, 24, 36, 48, and 60 months. To better understand the difference in seasonality patterns between advanced markets and emerging markets, we split the data into two groups (advanced and emerging) and then calculate the average $\beta_{k,t}$ for both groups. The estimation results are reported in Panel A of Table 2. The first column shows the time series averages of cross-sectional seasonal coefficients for all markets, the second column shows the time series averages for all advanced markets, and the third column shows the time series averages for all emerging markets.

For emerging markets, the seasonality coefficients are significant for lags of 1, 2, 9, 10, 12 and 24 months. The seasonality coefficient signs with lags of 1 and 2 months are negative (*t-stat* = -7.97 and -2.72, respectively), indicating that a short-term reversal pattern exists in emerging markets and consistent with short-term reversal literature (e.g. Lehmann, 1990; Lo and MacKinlay, 1990; and Jegadessh, 1990). More interestingly, although the signs of the coefficients of lags of 12, and 24 months are positive and statistically significant (*t-stat* = 1.70 and 2.71, respectively), the coefficients on lags of 36 and 48 months are small and insignificant and the coefficient on a lag of 60 months is negative, indicating that return seasonality is weak in emerging markets. For the advanced markets, the seasonality coefficients are significant for lags of 1, 3, 12, 24, 36, 48 and 60 months (*t-stat* = -7.14, 3.16, 3.06, 1.67, 2.62, 2.19 and 2.90, respectively), significant evidence of return seasonality in these markets and consistent with Heston and Sodka (2010). For the whole sample, the coefficients are significant for lags of 1, 9, 10, 12, and 24 months (*t-stat* = -9.47, 2.42, 1.98, 3.07 and 2.58, respectively), evidence of short-term reversal and seasonality.

To examine the difference across individual markets, we conduct the same regressions for each market. The average *t*-statistics of the same-month coefficients for advanced, emerging and all markets are plotted in Figure 1. The plots support the findings in Table 2 that the seasonality pattern at an annual frequency (longer annual

[10] The 21 advanced markets include Australia, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, the New Zealand, Norway, Portugal, Singapore, Spain, Switzerland, and the United Kingdom; the 21 emerging markets include Argentina, Brazil, Bulgaria, China, Egypt, Hungary, India, Indonesia, South Korea, Mexico, Malaysia, Morocco, the Philippines, Poland, Romania, Russia, South Africa, Saudi Arabia, Turkey, Taiwan, and Ukraine. According to the definition in the 2013 MSCI world index, we categorize South Korea as an emerging market and Greece as an advanced market.
[11] For detailed information on the data and Fama-French portfolio formation, please refer to the Appendix.

lags) is more significant in advanced markets and the short term momentum and return reversal (shorter lags) are more significant in emerging markets.

To address the misspecification concern inherent to relying on a single regression, we conduct multivariate analysis to examine the robustness of the above findings. Specifically, we test the following augmented Model:

$$r_{n,i,t} = \alpha_{n,t} + \sum_{k=1}^{12} \beta_{k,t} r_{n,i,t-k} + \beta_{24,t} r_{n,i,t-24} + \beta_{36,t} r_{n,i,t-36} + \beta_{48,t} r_{n,i,t-48} + \beta_{60,t} r_{n,i,t-60} + \varepsilon_{n,i,t}. \quad (1')$$

The independent and dependent variables are defined in Section 2, under Model (1). The estimation results of Model (1′) are reported in Panel B of Table 2, and are, in general, consistent with those in Panel A. The results suggest that the annual seasonality pattern, in aggregate, is more significant in advanced markets (seasonality coefficients are positive and significant for lags of 12, 36, 48, and 60 months) than in emerging markets (seasonality coefficients are positive and significant for lags of 12 and 36 months and negative and significant for lag of 60 months). For the short-term return reversal, the coefficients are more significant for emerging markets (negative and significant for lags of 1 to 5 months) than that for advanced markets (negative and significant for 1 month only). To sum up, the multivariate regression results suggest that our findings remain when more lagged returns are included.

3.2 Portfolio analysis

3.2.1 Whole market analysis

The presence of the return seasonality patterns identified in the previous section raises another interesting question of whether these patterns are economically meaningful. We investigate this economic significance by forming winner-loser portfolio strategies based on distinct annual intervals. Following Heston and Sadka (2008) and to separate our study from short-term momentum studies (Jegadeesh and Titman, 1993 and 2001), we form portfolios based on three same-month intervals: the past year (year1), 2 and 3 years ago (years 2-3), and 4 and 5 years ago (years 4-5). We create decile portfolios based on the average same-month raw returns over each lagged interval and evaluate the portfolio performance over the subsequent month. For example, for January 2013, the winner decile portfolio of years 2-3 would be an equally weighted combination of the 10% stocks that delivered the highest average returns in January 2010 and January 2011. Both decile portfolio raw returns and market excess returns are calculated.[12] To save space, we only report the time series means of the cross-sectional average returns of the winner (10% of stocks with the highest same-month returns) and the loser (10% of stocks with the lowest same-month returns) decile portfolios, as well as the time series average of return spread between the winners and losers (Table 3).[13]

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[12] Market excess return of firm *i* in market *k* in month *t* is defined as the difference between firm *i*'s return and the value-weighted returns of all stocks in market *k* in month *t*: $r_{excess,i,t} = r_{i,t} - r_{k,t}$.

[13] In an unreported table, we follow Heston and Sadka (2010) and conduct analyses of seasonal and non-seasonal spread portfolio. We find similar results as those in Heston and Sadka that economic values exists in seasonal (and momentum) spread portfolios in advanced markets but not in non-seasonal spread portfolios. However, we do not find economic value for seasonal spread portfolios in emerging markets. We thank an anonymous referee for suggesting this analysis.

Table 1. Summary statistics

This table reports summary statistics of stocks for each market and across all 42 markets. Markets are grouped into advanced and emerging markets. The former group includes Australia, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Israel, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Switzerland, and the United Kingdom, and the latter group includes Argentina, Brazil, Bulgaria, China, Egypt, Hungary, India, Indonesia, Korea, Mexico, Malaysia, Morocco, the Philippines, Poland, Romania, Russia, South Africa, Saudi Arabia, Turkey, Taiwan, and Ukraine. Number of stocks, number of observations and average monthly returns are reported. We require 5 or more stocks in each month for each market to be included in the sample. The begin month for each market is reported in the first column. The sample period is ended in June 2013.

Country	Starting date	Number of firms	Average returns (%)	Total Observations
Argentina	1995.01	85	1.45	15,794
Australia	1995.01	183	0.63	24,720
Belgium	1995.01	241	0.56	34,065
Brazil	1995.07	194	2.08	19,058
Bulgaria	2006.05	353	2.32	25,943
Canada	1995.01	995	1.75	135,773
China	1997.07	250	1.04	24,640
Denmark	1995.01	173	0.61	29,408
Egypt	1996.11	133	1.47	18,455
Finland	1995.01	215	0.58	34,303
France	1995.01	805	1.07	121,068
Germany	1995.01	959	0.85	139,768
Greece	1995.01	337	0.53	50,818
Hong Kong	1995.01	1,289	1.56	179,907
Hungary	2006.01	51	0.47	3,123
India	1995.01	4,074	2.44	584,896
Indonesia	1995.01	427	2.37	55,346
Ireland	1999.01	75	0.98	8,932
Israel	1995.01	479	1.14	80,813
Italy	1995.01	268	0.10	38,725
Japan	1995.01	2,529	0.45	463,767
Korea	1995.01	1,698	1.71	236,790
Mexico	1995.01	120	1.40	20,258
Malaysia	1995.01	902	0.78	138,333
Morocco	1998.09	77	0.30	9,312
Netherlands	1995.01	243	0.60	38,353
New Zealand	1995.01	123	0.58	17,665
Norway	1995.01	226	0.71	27,053
Philippine	1995.01	238	2.29	42,717
Portugal	1995.02	90	0.83	14,148
Poland	1997.09	793	0.62	49,315
Romania	1997.01	189	4.55	26,370
Russia	2003.05	244	1.93	17,105
South Africa	1995.01	247	1.65	38,632
Saudi Arabia	2002.08	158	1.02	24,508
Singapore	1995.01	480	0.92	61,083
Spain	1995.01	283	0.42	40,411
Switzerland	1995.01	435	0.72	64,631
Turkey	1995.01	383	3.34	56,839
Taiwan	1995.01	454	0.82	71,052
United Kingdom	1995.01	1,659	0.78	206,562
Ukraine	2006.05	249	3.22	15,809
Emerging	NA	12,861	1.72	1,680,623
Advanced	NA	10,545	0.79	1,612,782
Total	NA	23,406	1.28	3,293,405

Table 2. Statistical test of stock return seasonality

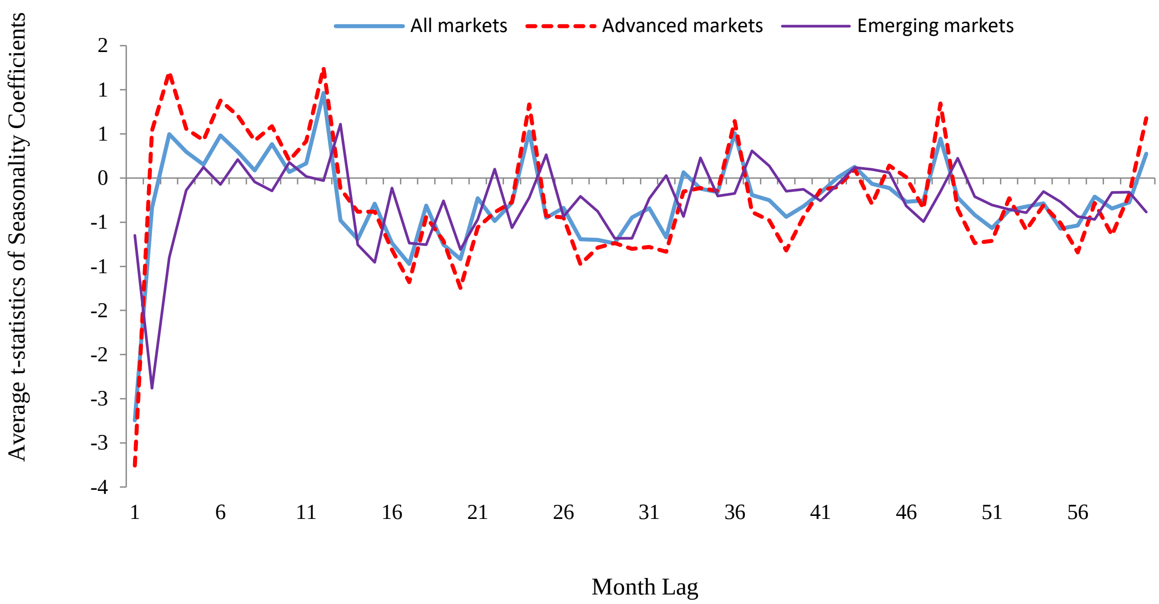
This table reports the results of stock return seasonality tests using the Fama-MacBeth two-pass approach. We conduct a cross-sectional linear regression in each month in the first pass and calculate (and report) the averages of the time series coefficients in the second pass. We conduct analyses for all, advanced and emerging markets, respectively. Panel A reports the results of seasonality test using a single regression specified as: $r_{n,i,t} = \alpha_{n,t} + \beta_{k,t} r_{n,i,t-k} + \varepsilon_{n,k,t}$ and Panel B reports the results using a multiple regression specified as: $r_{n,i,t} = \alpha_{n,t} + \sum_{k=1}^{12} \beta_{k,t} r_{n,i,t-k} + \beta_{24,t} r_{n,i,t-24} + \beta_{36,t} r_{n,i,t-36} + \beta_{48,t} r_{n,i,t-48} + \beta_{60,t} r_{n,i,t-60} + \varepsilon_{n,k,t}$ where $r_{n,i,t}$ is the return on stock i from market n in month t, and the slope coefficient $\beta_{k,t}$ represents the cross-sectional response of returns in a given month to returns in a previous month k. The t-statistics (in parentheses) are adjusted for heteroskedasticity and autocorrelation. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The sample period is from January 1995 to June 2013.

Return lag k	All markets		Advanced markets		Emerging markets	
Panel A. Single regression results						
1	-0.043***		-0.040***		-0.044***	
	(-9.47)		(-7.14)		(-7.97)	
2	-0.005		0.008*		-0.013***	
	(-1.29)		(1.67)		(-2.72)	
3	0.004		0.011***		0.002	
	(1.09)		(3.16)		(0.3)	
4	0.005		0.005		0.003	
	(1.32)		(1.04)		(0.68)	
5	0.001		0.002		0.000	
	(0.36)		(0.41)		(-0.1)	
6	0.006		0.004		0.007	
	(1.31)		(0.88)		(1.15)	
7	0.004		0.005		0.004	
	(1.22)		(1.22)		(1.11)	
8	0.002		0.004		0.001	
	(0.73)		(0.96)		(0.2)	
9	0.008**		0.002		0.011**	
	(2.42)		(0.49)		(2.26)	
10	0.006**		0.002		0.008**	
	(1.98)		(0.37)		(2.12)	
11	0.003		0.002		0.004	
	(1.03)		(0.65)		(0.89)	
12	0.008***		0.009***		0.006*	
	(3.07)		(3.06)		(1.70)	
24	0.007**		0.004*		0.012***	
	(2.58)		(1.67)		(2.71)	
36	0.003		0.007**		0.002	
	(1.39)		(2.62)		(0.68)	
48	0.009		0.012**		0.001	
	(1.59)		(2.19)		(0.23)	
60	0.001		0.007***		-0.006	
	(0.49)		(2.90)		(-1.18)	
Panel B. Multiple regression results						
1	-0.049***	-0.039***	-0.046***	-0.048***	-0.051***	-0.034***
	(-10.76)	(-8.67)	(-8.40)	(-7.63)	(-9.40)	(-5.41)
2	-0.009**	-0.014***	0.003	-0.001	-0.019***	-0.027***
	(-2.52)	(-3.78)	(0.64)	(-0.17)	(-4.47)	(-6.07)
3	0.001	0.004	0.009***	0.006*	-0.003	-0.010***
	(0.48)	(1.24)	(2.72)	(1.71)	(-0.75)	(-2.99)
4	0.003	-0.005*	0.003	0.004	0.000	-0.010***
	(0.85)	(-1.76)	(0.93)	(1.08)	(-0.02)	(-3.81)
5	0.002	0.003	0.001	0.001	0.000	-0.007***
	(0.77)	(1.09)	(0.35)	(0.45)	(-0.03)	(-2.39)
6	0.004	0.002	0.004	0.004	0.004	-0.002
	(1.17)	(0.53)	(1.01)	(0.92)	(0.87)	(-0.39)
7	0.003	0.000	0.004	0.001	0.004	-0.001
	(1.19)	(0.11)	(1.23)	(0.34)	(1.36)	(-0.32)
8	0.003	0.001	0.002	0.001	0.002	-0.002
	(0.95)	(0.42)	(0.63)	(0.18)	(0.74)	(-0.62)
9	0.008**	-0.002	0.001	0.003	0.011**	0.000
	(2.59)	(-0.92)	(0.38)	(0.70)	(2.59)	(-0.09)
10	0.006**	0.002	0.001	0.000	0.008***	-0.001
	(2.37)	(0.84)	(0.35)	(0.08)	(2.66)	(-0.34)
11	0.004	0.011***	0.005	0.007***	0.005	0.004
	(1.61)	(3.71)	(1.63)	(2.18)	(1.28)	(1.36)

12	0.008***	0.000	0.010***	0.011***	0.006**	0.007*
	(3.71)	(0.03)	(3.82)	(3.03)	(2.30)	(1.85)
24		0.002		0.002		0.003
		(1.26)		(1.01)		(1.40)
36		0.008***		0.006***		0.007***
		(4.05)		(3.32)		(2.78)
48		0.004***		0.010***		0.001
		(2.51)		(2.34)		(0.39)
60		0.001		0.008***		-0.007***
		(0.67)		(2.94)		(-2.20)

Figure 1. Statistical significance of seasonality tests.

This figure plots the distribution of the average *t-statistics* of time-serially averaged coefficients of cross-sectional averaged return response from one month to up to 60 months for all markets, advanced markets and emerging markets. In each month and for each country, return seasonal coefficient is estimated from the following specification: $r_{n,i,t} = \alpha_{n,t} + \beta_{k,t} r_{n,i,t-k} + \varepsilon_{n,k,t}, i = 1,2,..I, k = 1,2 \ldots 60; t = 1, 2, \ldots T$, where *i* denotes the i^{th} stock, *n* denotes the n^{th} country, and k denotes the k^{th} lag. The sample period is from January 1995 to June 2013.



Panel A of Table 3 reports the performance of the winner–loser strategy based on investing in stocks in all markets; Panels B and C report the performance of such strategy in advanced and emerging markets, respectively. In general, Table 3 shows that exploiting stock return seasonality is economically significant in advanced markets but not in emerging markets. The top 10% of same-month winner stocks in advanced markets (Panel B) significantly outperform the bottom 10% of same-month loser stocks by 53 basis points (*t-stat* = 3.37) when stocks are sorted on same-month returns in the past year, and 27 basis points (*t-stat* = 1.77) when stocks are sorted on returns in the same month of 2-3 years ago. The top 10% of stocks in advanced markets based on returns in the same month of 4-5 years ago still outperform the bottom 10% of stocks while this outperformance is not significant (*t-stat* = 1.10). The top 10% of same-month winner stocks in emerging markets (Panel C), however, fail to outperform the bottom 10% of same-month loser stocks regardless of the seasonal windows used for the portfolio formation. The results in Panel C may explain why the top 10% of same-month winner stocks with the entire sample (Panel A) do not outperform the bottom 10% of same-month loser stocks for any of the three time lags. Taking together, the results in Table 3 show that the economic value of stock return seasonality is, at a whole market level, significant in advanced markets but not in emerging markets, consistent with the results in the previous section.[14]

3.2.2 Individual market analysis

We next investigate whether a few individual markets mainly drive the observed differences in the success of the winner-loser strategy in advanced and emerging markets. Particularly, it is important to know whether the differences are not common in most markets in which stock return seasonality may not exist as documented in the literature.[15] Existing studies show that the differences in cultures, legal systems, and information environments across emerging markets are substantial[16], which imply that strong heterogeneity across emerging markets may weaken the economic value of seasonality when we pool all stocks. To address these concerns, we first repeat our analysis for each individual market to test whether the differences in the return spreads between same-month winner and loser stocks across individual markets lead to the significant aggregate difference in return seasonality observed in the previous section. Given the fact of short sample periods for some emerging markets, we form same-month portfolios based on three shorter time intervals: 1 year ago, 2 years ago, and 3 years ago to include as many markets in the sample as possible. In total we can apply the winner-loser strategy in 19 advanced markets and 18 emerging markets using our current sample. The time series means of the cross-sectional average returns of the top (winner) and bottom decile (loser) portfolios in each individual market, as well as the differences between them are reported in Table 4.[17]

Panel A of Table 4 shows the winner-loser strategy performance in individual advanced markets and Panel B shows the performance for individual emerging markets. The average return, standard deviation and fraction of positive returns across all individual markets are reported at the end of each panel. It is evident that the winner-loser strategy generates significant positive returns in more advanced markets than in emerging markets. The results also indicate that stock returns are more likely to respond to recent same-month returns than to distant ones, which is consistent with our findings in Section 3.2.1. Specifically, when stocks are sorted on the same-month returns in the past year, winners outperform losers in nine of 19 advanced markets, including Belgium, Finland, Japan, the Netherlands, New Zealand, Norway, Spain, Switzerland, and the United Kingdom. However, only 3 of 18 emerging markets (Poland, Romania, and South Africa) show this pattern. Although the winner-loser strategy delivers positive returns in 79% of advanced markets and in 72% of emerging markets, the average return of the winner-loser strategy is 0.61% and significant across all individual advanced market, and is 0.36% and insignificant across all emerging market. When stocks are sorted on the same-month returns 2 years ago, winners outperform losers in six advanced markets and in one emerging market, respectively. The winner-loser strategy can generate positive returns in 74% of advanced markets but only in 67% of emerging markets. The

[14] As we show next, at individual market level, return seasonality exists in some emerging markets and does not exist in some advance markets.
[15] For example, Fountas and Segredakis (2002) and Ratner and Leal (1999).
[16] For example, Millar et al. (2005).
[17] We drop several markets because they either do not have three-year data to form portfolios or have too many stale data. We only report the portfolio raw returns to save space. The excess returns show similar patterns, and are available upon request.

average return of the winner-loser strategy across all advanced market is 0.39% and statistically significant and it becomes 0.05% and insignificant across emerging markets. Winners outperform losers in five advanced markets but in none of emerging markets when portfolios are formed on the same-month returns 3 years ago. The fraction of advanced markets in which the winner-loser strategy can generate positive returns is 84% and this fraction is 61% in emerging markets. The average return of the winner-loser strategy across all advanced market is 0.54% and statistically significant and it becomes 0.30% and insignificant across emerging markets.

In sum, the above results suggest that stock return seasonality does not exist in every market in our sample and stock returns show much more significant seasonal patterns in advanced markets pooled as a whole market than in emerging markets. The difference in stock return seasonality between the pooled advanced markets and the pooled emerging markets is both statistically and economically significant. In the following analyses, we explore the underlying explanations for this difference and focus on the ones for the seasonal pattern in advanced markets.

3.3 Potential explanations for seasonality difference

Previous studies have proposed several explanations for the existence of stock return seasonality in the U.S. from both a statistical and an economic perspective. Kamstra (2017) shows that statistical bias exists in the seasonality regressions. Keloharju et al. (2016) suggest that seasonality may be explained by multiple risk factors. Studies by Bouman and Jacobsen, (2002), Kamstra, Kramer, and Levi, (2003), and Cooper, McConnell and Ovtchinnikov (2006) suggest that stock return seasonality can be partially driven by the calendar effect on stock prices. In addition, Bogousslavsky (2016) show that the variation in expected returns is correlated with the frequency of the trader's rebalancing horizon, which generates seasonality in the cross-section of stock returns.[18] In this section, we test the above explanations with our data, focusing on return seasonality in advanced markets.

3.3.1 Fama-MacBeth implementation bias and seasonality

Kamstra (2017) argues that stock return momentum and the time-series autocorrelation from Fama-MacBeth regressions have been exaggerated due to a common implementation bias. Specifically, he shows via simulations that the findings in Heston and Sadka (2008, 2010) may be problematic because the lagged returns can be spuriously correlated with current returns. Since our research follows Heston and Sadka (2008, 2010), we turn Model 1 and Model 1′ into fixed effect models by splitting stocks into deciles by the firm expected return (average historical returns are used as the proxy) as suggested by Kamstra (2017). We re-run the following fixed-effect models:[19]

$$r_{n,i,t} = \sum_{j=1}^{10} \alpha_{0,j} D_{i,j} + \beta_{k,t} r_{n,i,t-k} + \varepsilon_{n,i,t}, \tag{3}$$

$$r_{n,i,t} = \sum_{j=1}^{10} \alpha_{0,j} D_{i,j} + \sum_{k=1}^{12} \beta_{k,t} r_{n,i,t-k} + \beta_{24,t} r_{n,i,t-24} + \beta_{36,t} r_{n,i,t-36} + \beta_{48,t} r_{n,i,t-48} + \beta_{60,t} r_{n,i,t-60} + \varepsilon_{n,i,t,} \tag{3′}$$

where j represents the decile of firm i's expected return, which is calculated using the average of the firm's returns over the past 12 months, and $D_{i,j}$ equals 1 when firm i is in expected return decile j, and 0 otherwise. All other variables are defined in Section 2, under Model (1).

[18] We do not investigate this explanation because we do not have access to trading data.
[19] We also tested an alternative model by including average past returns in the equation as proposed by Kamstra (2017), and the results are similar with the fixed effect model. The results are available upon request.

Table 3. Economic significance of stock return seasonality

This table reports the economic value of stock return seasonality. In each month, we allocate all stocks into decile groups based on historical seasonal return over three rolling windows: the past year, 2-3 years ago, or 4-5 years ago and calculate the equal-weighted portfolio returns over the subsequent month for each decile. We report the time series average portfolio returns of winner stocks (highest historical seasonal return decile) and loser stocks (lowest historical seasonal return decile) and the spread between the two groups. Panel A reports the results using the whole sample; Panel B reports the results for stocks in advanced markets, and Panel C reports the results for stocks in emerging markets. The associated Newey-West *t*-statistics with 4 lags are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The sample period is from January 1995 to June 2013.

	Panel A: All markets		Panel B: Advanced markets		Panel C: Emerging markets	
	Total ret (%)	Excess ret (%)	Total ret (%)	Excess ret (%)	Total ret (%)	Excess ret (%)
Seasonality basis: year 1						
Winners	1.94***	0.43***	1.55***	0.57***	2.46***	0.42***
	(5.31)	(4.31)	(4.32)	(4.97)	(5.46)	(3.08)
Losers	1.83***	0.16	1.04***	0.03	2.51***	0.32*
	(4.63)	(1.33)	(2.75)	(0.28)	(5.01)	(1.72)
Winners-losers	0.11	0.27	0.51***	0.53***	-0.06	0.11
	(0.63)	(1.59)	(3.14)	(3.37)	(-0.22)	(0.43)
Seasonality basis: year 2-3						
Winners	2.17***	0.33***	1.81***	0.50***	2.31***	0.10
	(5.81)	(3.04)	(4.80)	(4.36)	(4.65)	(0.38)
Losers	2.11***	0.15	1.63***	0.24*	2.64***	0.33**
	(5.58)	(1.32)	(4.06)	(1.84)	(5.74)	(1.96)
Winners-losers	0.05	0.18	0.18	0.27*	-0.34	-0.23
	(0.36)	(1.34)	(1.14)	(1.77)	(-1.06)	(-0.75)
Seasonality basis: year 4-5						
Winners	1.76***	0.08	1.25***	0.27**	2.34***	-0.05
	(4.37)	(0.81)	(3.14)	(2.29)	(4.75)	(-0.26)
Losers	1.96***	0.10	1.11***	0.06	2.72***	0.19
	(4.77)	(0.86)	(2.89)	(0.49)	(5.15)	(0.93)
Winners-losers	-0.21	-0.02	0.140	0.21	-0.38	-0.24
	(-1.11)	(-0.11)	(0.72)	(1.10)	(-1.29)	(-0.82)

Table 4. Economic significance of stock return seasonality by stock market

This table reports the economic value of stock return seasonality for each stock market. In each month and for each market we sort stocks into decile groups based on historical seasonal return over three rolling windows: the past year, 2 years ago, or 3 years ago and calculate the equal-weighted portfolio returns over the subsequent month for each decile. We report the time series average portfolio returns of the winner stocks (highest historical seasonal return decile) and loser stocks (lowest historical seasonal return decile) and the spread between the two groups for each market. Panel A shows the results for each individual advanced market, and Panel B shows the results for each individual emerging market. The average return across markets, the corresponding standard deviation and the fraction of positive returns are reported at the end of each panel. The associated Newey-West *t*-statistics with 4 lags are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	Year 1			Year 2			Year 3		
Seasonality	Winners	Losers	WML	Winners	Losers	WML	Winners	Losers	WML
Panel A: Advanced markets									
Australia	2.23**	1.45*	0.78	0.54	0.28	0.26	0.65	-0.47	1.12
	(1.94)	(1.94)	(0.67)	(0.64)	(0.35)	(0.32)	(0.53)	(-0.55)	(0.93)
Belgium	0.94*	0.02	0.92*	1.37**	0.69	0.68	1.14	0.94	0.20
	(1.93)	(0.03)	(1.64)	(2.41)	(1.10)	(1.14)	(1.61)	(1.46)	(0.24)
Canada	3.25***	3.17***	0.09	3.18***	2.28***	0.89*	2.46***	2.82***	-0.36
	(4.68)	(4.59)	(0.18)	(4.88)	(3.16)	(1.70)	(3.16)	(3.69)	(-0.71)
Denmark	1.08**	0.64	0.44	0.87	1.20**	-0.34	1.46**	0.47	0.99
	(2.41)	(1.10)	(0.84)	(1.55)	(2.33)	(-0.57)	(2.25)	(0.83)	(1.57)
Finland	0.78	-0.15	0.93*	1.38**	0.56	0.82*	1.69***	-0.33	2.03***
	(1.28)	(-0.25)	(1.67)	(2.39)	(0.89)	(1.83)	(2.93)	(-0.59)	(4.75)
France	2.14***	1.55***	0.59	2.04***	2.27***	-0.23	1.90***	1.49***	0.40
	(5.00)	(3.15)	(1.53)	(4.96)	(4.18)	(-0.45)	(4.18)	(3.12)	(0.83)
Germany	1.58***	0.96*	0.62	1.59***	1.58***	0.01	1.37***	1.00**	0.37
	(3.48)	(1.87)	(1.43)	(3.76)	(3.17)	(0.02)	(3.02)	(2.17)	(0.84)
Greece	0.81	1.37	-0.56	-0.13	-0.49	0.36	0.18	-0.28	0.47
	(0.91)	(1.35)	(-0.76)	(-0.15)	(-0.59)	(0.64)	(0.22)	(-0.37)	(0.85)
Hong Kong	2.15***	2.01**	0.14	1.95**	2.40***	-0.45	2.15***	2.71***	-0.56
	(2.70)	(2.29)	(0.31)	(2.28)	(2.62)	(-0.91)	(2.77)	(2.93)	(-1.25)
Israel	1.58***	1.78***	-0.20	1.14**	1.54**	-0.40	1.70***	1.34**	0.37
	(2.82)	(2.97)	(-0.38)	(2.04)	(2.57)	(-0.89)	(2.60)	(2.38)	(0.78)
Italy	-0.05	0.15	-0.20	-0.01	-0.34	0.33	0.19	-0.63	0.82**
	(-0.10)	(0.21)	(-0.35)	(-0.01)	(-0.54)	(0.80)	(0.32)	(-1.15)	(2.24)
Japan	0.95***	0.26	0.69***	1.18**	0.38	0.80***	1.15**	0.33	0.82***
	(2.17)	(0.53)	(3.11)	(2.45)	(0.78)	(3.80)	(2.45)	(0.75)	(4.35)
Netherlands	1.14*	-0.03	1.17*	1.24**	0.09	1.15**	1.83***	0.48	1.34**
	(1.73)	(-0.05)	(1.83)	(2.06)	(0.14)	(2.22)	(2.80)	(0.80)	(2.38)
New Zealand	1.34*	-0.40	1.74*	2.41***	1.34	1.07	1.81**	1.69	0.12
	(1.67)	(-0.49)	(1.78)	(3.43)	(1.01)	(0.74)	(2.11)	(1.03)	(0.07)
Norway	1.17	-0.13	1.30*	0.72	0.14	0.59	1.30	0.96	0.34
	(1.44)	(-0.15)	(1.82)	(0.85)	(0.13)	(0.81)	(1.28)	(1.11)	(0.40)
Singapore	1.62**	1.78*	-0.15	0.98	1.55**	-0.57	2.09**	1.50*	0.58
	(2.03)	(1.91)	(-0.26)	(1.41)	(1.96)	(-1.22)	(2.48)	(1.80)	(0.89)
Spain	1.19**	0.21	0.98**	0.97*	0.20	0.77**	0.81	0.47	0.34
	(2.26)	(0.35)	(2.16)	(1.84)	(0.36)	(2.04)	(1.36)	(0.77)	(0.76)
Switzerland	1.76***	0.52	1.24***	1.78***	0.55	1.22***	1.57**	0.57	1.00**
	(3.90)	(1.06)	(3.26)	(3.61)	(1.21)	(3.62)	(2.58)	(1.42)	(2.10)
United Kingdom	1.84***	0.73	1.11***	1.45***	1.07**	0.38	1.38***	1.50***	-0.11
	(4.54)	(1.49)	(2.99)	(3.27)	(2.41)	(1.19)	(3.25)	(2.75)	(-0.27)
Average	1.45***	0.84***	0.61***	1.30***	0.91***	0.39***	1.41***	0.87***	0.54***
Std. Dev.	0.69	0.92	0.60	0.77	0.85	0.56	0.61	0.94	0.59
Positive ratio	94.74%	78.95%	78.95%	89.47%	89.47%	73.68%	100.00%	78.95%	84.21%
Panel B: Emerging markets									
Brazil	0.27	1.97	-1.69*	-1.18	0.62	-1.79	-2.08	-3.74**	1.66
	(0.21)	(1.44)	(-1.66)	(-1.11)	(0.42)	(-1.50)	(-1.49)	(-2.18)	(0.75)
Bulgaria	2.63***	1.63*	1.00	2.68***	1.74*	0.95	4.78 **	3.02*	1.76
	(2.86)	(1.77)	(1.17)	(2.60)	(1.91)	(0.71)	(2.28)	(1.71)	(0.59)
China	1.66*	0.91	0.74	1.77	2.33*	-0.55	0.67	0.05	0.61
	(1.67)	(0.88)	(1.30)	(1.45)	(1.91)	(-0.84)	(0.48)	(0.04)	(0.88)
Egypt	0.40	-0.54	0.94	0.15	-0.13	0.27	0.99	2.02	-1.03
	(0.27)	(-0.39)	(0.80)	(0.11)	(-0.09)	(0.44)	(0.50)	(0.88)	(-0.90)
India	3.29***	3.12***	0.17	3.69***	3.61***	0.09	3.32***	3.52***	-0.20

	(4.48)	(3.99)	(0.44)	(5.09)	(4.39)	(0.24)	(4.24)	(4.42)	(-0.47)
Indonesia	2.42***	2.96***	-0.54	2.43***	2.41***	0.02	2.71***	3.53***	-0.81
	(3.31)	(3.26)	(-0.69)	(3.39)	(2.86)	(0.03)	(3.35)	(4.30)	(-1.40)
Korea	1.84**	1.74*	0.10	2.01**	1.38*	0.63	1.99***	1.73**	0.26
	(2.51)	(1.94)	(0.17)	(2.53)	(1.78)	(1.62)	(2.96)	(2.39)	(0.73)
Mexico	1.99	0.87	1.12	1.98***	0.90	1.08	1.19	2.60	-1.41
	(1.61)	(0.87)	(0.97)	(2.80)	(1.20)	(1.25)	(0.85)	(1.57)	(-0.75)
Malaysia	0.93	0.64	0.29	1.10	0.55	0.55	1.51**	0.93	0.57
	(1.39)	(0.83)	(0.79)	(1.52)	(0.64)	(1.58)	(2.46)	(1.54)	(1.89)
Philippine	3.09***	2.05***	1.03	2.27**	2.30***	-0.03	2.69***	2.33***	0.36
	(3.73)	(2.74)	(1.58)	(2.55)	(2.71)	(-0.05)	(3.08)	(3.34)	(0.53)
Poland	2.90***	1.47	1.44**	2.15**	1.76**	0.38	1.14	2.72**	-1.58**
	(3.48)	(1.71)	(2.25)	(2.52)	(2.12)	(0.60)	(1.28)	(2.34)	(-2.45)
Romania	5.95***	3.52***	2.43*	3.31***	3.15**	0.16	4.35**	3.04**	1.32
	(5.09)	(3.66)	(1.94)	(2.93)	(2.44)	(0.13)	(2.59)	(2.30)	(0.75)
Russia	3.71*	3.40**	0.31	-1.34	-1.09	-0.25	-2.44***	-3.54**	1.10
	(1.90)	(2.40)	(0.15)	(-1.40)	(-1.39)	(-0.28)	(-3.50)	(-2.25)	(0.84)
South Africa	3.32***	1.94***	1.38*	3.72***	3.25***	0.47	1.93***	2.29***	-0.37
	(5.65)	(3.28)	(1.91)	(5.36)	(5.40)	(0.59)	(3.49)	(3.85)	(-0.57)
Saudi Arabia	0.20	1.29	-1.09	1.19	1.65	-0.46	1.45	0.40	1.05
	(0.20)	(0.89)	(-1.11)	(1.11)	(1.33)	(-0.46)	(1.31)	(0.46)	(1.38)
Turkey	3.78***	2.82***	0.96	3.48***	3.08***	0.41	2.95***	3.09***	-0.13
	(4.05)	(3.05)	(1.90)	(3.67)	(3.05)	(0.98)	(3.03)	(3.14)	(-0.31)
Taiwan	0.46	0.94	-0.48	1.31*	0.55	0.76*	1.06	0.52	0.54
	(0.71)	(1.48)	(-1.31)	(1.89)	(0.82)	(1.90)	(1.49)	(0.73)	(1.76)
Ukraine	0.27	1.97	-1.69*	-1.18	0.62	-1.79	-2.08	-3.74**	1.66
	(0.21)	(1.44)	(-1.66)	(-1.11)	(0.42)	(-1.50)	(-1.49)	(-2.18)	(0.75)
Average	2.17***	1.82***	0.36	1.64***	1.59***	0.05	1.45***	1.15*	0.30
Std. Dev.	1.54	1.04	1.08	1.58	1.25	0.78	1.97	2.39	1.02
Positive ratio	100.00%	94.44%	72.22%	83.33%	88.89%	66.67%	83.33%	83.33%	61.11%

The empirical estimations are reported in Table 5, in which Panel A presents the results of regressions with single lags and Panel B shows the results of regressions with multiple lags. First, the results show that seasonality patterns still exist in both advanced and emerging markets, especially for shorter time horizon (12-month and 24-month). Regardless, the results also suggest that the model implication bias proposed by Kamstra (2017) has a significant impact on stock return seasonality, especially for advanced markets. Comparing with the results in Panel A of Table 2, there are fewer significant lag coefficients in Panel A of Table 5. Specifically, only the coefficients of 12- and 36-month lags in Table 5 are positive and significant for advanced markets (and the latter is only marginally significant at 10%); in contrast, the coefficients of the 12-, 24-, 36-, 48-, and 60-month lags in Table 2 are all positive and significant for advanced markets. The results for all markets and the emerging markets in Table 5 are similar to those in Table 2; for both groups, the coefficients of two of the seasonal lags (12- and 24-month) are significant in Table 2 and the coefficients of three of the seasonal lags (12-, 24- and 36-month) are significant in Table 5. The results in Panel B of Table 5 are similar to those in Panel A. The seasonality patterns in the multiple regressions still exist, but the difference between advanced markets and emerging markets declines substantially. In sum, the results in Table 5 imply that the estimation bias suggested by Kamstra (2017) might be one of the reasons for the significant seasonality patterns in advanced markets.

3.3.2 Size and seasonality

Another potential explanation for the differences in seasonality between advanced markets and emerging markets is the difference in firm characteristics between the two types of markets. Since emerging markets tend to have weaker legal environment than advanced markets and less stringent requirements for companies going public,[20] public firms in emerging markets might be smaller and more diverse compared to those in advanced markets. Therefore, in this section, we split all firms in each market into two groups at the beginning of each month based on firm size, which is defined as the market capitalization of common stock outstanding. We then form decile portfolios within each size group based on three time intervals: the past year, 2-3 years ago, and 4-5

[20] For example, Klapper and Love (2004) and Fan, Wei, and Xu (2011).

years ago. The time series average of the cross-sectional mean excess returns for the top decile portfolio (winner) and the bottom decile (loser) portfolio, as well as differences between them are reported in Table 6.

Panel A of Table 6 reports the respective performance of the winner-loser strategy for large firms in all markets, advanced markets, and emerging markets and Panel B reports the corresponding performance of the winner-loser strategy for small firms. The results suggest that the difference in stock return seasonality between advanced and emerging markets is more pronounced in small firms than in large firms. For the large firm group, stock returns are significantly related to returns in the same month in the past year but not related to returns in the same month in other lagged years for both advanced and emerging markets, and there is little difference between the two groups of markets (Panel A). The winner-loser strategy generates positive and significant returns (52 basis points for advanced markets and 54 basis points for emerging markets) based on the same-month returns in the past year but not based on the same-month returns in more distant time intervals. The differences in return seasonality between the advanced markets and the emerging markets, however, are clearly observable in small firms (Panel B). For advanced markets, the excess returns delivered by past same-month winners in all three time intervals are positive, while those delivered by past same-month losers are negative. In emerging markets, the excess returns delivered by both past same-month winners and past same-month losers are negative. The winner-loser strategy on the same-month returns 2-3 years ago generates positive and marginally significant (at the 10% level) returns in advanced markets, but negative and insignificant returns in emerging markets. Although some differences in small firms' return seasonality do exist between advanced markets and emerging markets, most of them are insignificant or marginally significant. To conclude, Table 6 suggests that size effect can partly explain the difference in return seasonality between advanced and emerging markets.

3.3.3 Calendar effect and seasonality

Gultekin and Gultekin (1983), Bouman and Jacobsen (2002), and Kamstra, Kramer, and Levi (2003) show that the seasonality of stock returns in advanced markets tends to be different in January from other months.[21] In this section, we test whether such calendar effect can partially explain the difference in return seasonality between advanced and emerging markets. We expect that the difference exists in some calendar months but disappears in other months if calendar effect matters.

At the beginning of each calendar month, we equally sort stocks into ten groups based on their historical same-month returns in the past year, 2-3 years ago, or 4-5 years ago, respectively. Winner stocks are the stocks in the top group (10% of stocks with the highest historical same-month returns) and losers are stocks in the bottom group. Table 7 presents the portfolio returns for both the winner and loser groups, as well as the performance of the winner-loser strategy (longing winner stocks and shorting loser stocks) in each calendar month. Panel A reports the results for advanced markets and Panel B reports the results for emerging markets.[22]

The calendar effect on stock returns is pronounced in advanced markets, especially in January and December. In January, the average returns delivered by the winner-loser strategy based on all three time intervals are significantly positive: 82 basis points (*t-stat* = 1.77) for the strategy formed on the same-month return in the past year, 125 basis points (*t-stat* = 2.13) for the strategy based on the same-month return 2-3 years ago, and 184 basis points (*t-stat* = 3.93) for the strategy based on the same-month return 4-5 years ago. In December the same-month winner-loser strategy delivers returns of 160 basis points (*t-stat* = 3.36), 147 basis points (*t-stat* = 2.60) , and 86 basis points (*t-stat* = 1.77) when the strategy is constructed on same-month returns in the past year, 2-3 years ago, and 4-5 years ago, respectively. In contrast, no obvious pattern exists among emerging markets. When formed on the same-month returns in the past year, the winner-loser strategy produce significant positive returns in March and significant negative returns in May. The average return is significantly positive in February when

[21] These papers do not just focus on January returns but rather on a multi-month seasonality and the results in January are more profound than those in other months.

[22] We dropped several markets because either they do not have three years of data to form portfolios or have too many stale data.

the winner-loser strategy is formed based on same-month returns 2-3 years ago, and in August when it is formed on same-month returns 4-5 years ago.

Table 5. Implementation bias and seasonality

This table reports the empirical results of whether the implementation bias in the two-stage Fama-MacBeth analysis can explain the seasonality patterns in advanced markets. We conduct a cross-sectional linear regression in each month in the first stage and calculate (and report) the averages of time series coefficients in the second stage. We conduct analyses for all, advanced, and emerging markets, respectively. Panel A reports the results of seasonality tests using single regressions, specified as: $r_{n,i,t} = \sum_{j=1}^{10} \alpha_{0,j} D_{i,j} + \beta_{k,t} r_{n,i,t-k} + \varepsilon_{n,i,t}$, and Panel B reports the results of seasonality tests using multivariate regressions, specified as: $r_{n,i,t} = \sum_{j=1}^{10} \alpha_{0,j} D_{i,j} + \sum_{k=1}^{12} \beta_{k,t} r_{n,i,t-k} + \beta_{24,t} r_{n,i,t-24} + \beta_{36,t} r_{n,i,t-36} + \beta_{48,t} r_{n,i,t-48} + \beta_{60,t} r_{n,i,t-60} + \varepsilon_{n,i,t}$, where j represents the decile of firm i's expected return, calculated using firm's averaged returns over the past 12 months. $D_{i,j}$ equals 1 when firm i is in expected return decile j, and 0 otherwise. $r_{n,i,t}$ is the return on stock i from market n in month t, and the slope coefficient $\beta_{k,t}$ represents the cross-sectional response of returns in a given month to returns in a previous month k. The t-statistics (in parentheses) are adjusted for heteroskedasticity and autocorrelation. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The sample period is from January 1995 to June 2013.

Return lag k	All markets		Advanced markets		Emerging markets	
Panel A. Single regression results						
1	-0.029***		-0.037***		-0.03***	
	(-7.79)		(-7.88)		(-6.13)	
2	-0.005		-0.002		-0.008	
	(-1.25)		(-0.46)		(-1.58)	
3	0.006		0.011**		0.006	
	(1.65)		(3.18)		(1.18)	
4	0.006		-0.002		-0.002	
	(1.38)		(-0.30)		(-0.30)	
5	0.002		-0.0003		0.002 **	
	(0.57)		(-0.11)		(0.48)	
6	0.006		0.005		0.003	
	(1.39)		(1.62)		(0.60)	
7	0.005		0.006		0.007	
	(1.52)		(1.54)		(1.58)	
8	0.004		0.001		0.006	
	(1.26)		(0.32)		(1.46)	
9	0.01***		0.002		0.02*	
	(2.60)		(0.56)		(2.73)	
10	0.003		-0.003		0.006	
	(1.06)		(-0.99)		(1.45)	
11	0.005		-0.001		0.008	
	(1.46)		(-0.35)		(1.63)	
12	0.007**		0.011***		0.008*	
	(2.22)		(2.85)		(1.80)	
24	0.010***		0.003		0.012**	
	(2.84)		(1.25)		(2.58)	
36	0.009***		0.006*		0.01***	
	(3.33)		(1.70)		(3.03)	
48	0.001		0.002		-0.0002	
	(0.31)		(0.76)		(-0.07)	
60	0.002		0.004		0.0005	
	(0.42)		(1.25)		(0.12)	
Panel B. Multiple regression results						
1	-0.029***	-0.043***	-0.039***	-0.042***	-0.031***	-0.044***
	(-7.89)	(-9.12)	(-8.70)	(-8.70)	(-6.73)	(-7.76)
2	-0.006	-0.013***	-0.004	-0.004	-0.010**	-0.030***
	(-1.36)	(-4.18)	(-1.02)	(-0.98)	(-2.42)	(-4.65)
3	0.005	-0.000	0.009**	0.006	0.003	-0.005
	(1.58)	(-0.15)	(2.51)	(0.16)	(0.74)	(-1.01)
4	0.005	-0.006*	-0.001	0.003	0.005	-0.009**
	(1.83)	(-1.76)	(-0.28)	(0.60)	(1.39)	(-2.43)
5	0.004	-0.005	-0.001	-0.002	0.006	-0.007
	(1.14)	(-1.10)	(-0.32)	(-0.58)	(1.29)	(-1.40)
6	0.006*	0.002	0.003	0.004	0.005	-0.002
	(1.83)	(0.55)	(0.83)	(1.22)	(1.03)	(-0.42)
7	0.006**	0.002	0.004	0.002	0.008**	0.003
	(2.18)	(0.85)	(1.06)	(0.73)	(2.36)	(0.76)
8	0.006**	0.005	0.001	-0.001	0.008**	0.004

	(2.07)	(1.32)	(0.44)	(-0.29)	(2.23)	(0.87)
9	0.001***	0.005*	0.000***	0.005	0.017***	0.004
	(2.76)	(1.23)	(0.18)	(1.23)	(2.99)	(0.87)
10	0.006**	0.007**	-0.004	0.002	0.009**	0.004
	(2.08)	(2.28)	(-1.19)	(0.62)	(2.26)	(1.04)
11	0.007**	0.007**	0.000	0.006*	0.009**	0.004
	(2.22)	(2.32)	(0.46)	(1.79)	(2.16)	(0.93)
12	0.009**	0.011***	0.011**	0.013***	0.011**	0.007*
	(2.96)	(3.11)	(3.28)	(3.14)	(2.58)	(1.70)
24		0.006**		0.002		0.007**
		(2.21)		(0.67)		(2.08)
36		0.008***		0.006*		0.010**
		(2.24)		(1.84)		(2.48)
48		0.003		0.007*		-0.002
		(0.79)		(1.78)		(-0.58)
60		0.000		0.005*		-0.002
		(0.12)		(1.85)		(-0.53)

Table 6. Economic significance of stock return seasonality and firm size

This table reports the economic value of stock return seasonality for large firms (Panel A) and small firms (Panel B). In each month we first sort stocks into two groups based market capitalization, and then sort them into decile groups based on historical seasonal return over three time windows: the past year, 2-3 years ago, or 4-5 years ago and calculate the equal-weighted portfolio returns over the subsequent month for each decile. We report the portfolio returns of winner stocks (highest historical seasonal return decile) and loser stocks (lowest historical seasonal return decile) and the spread between the two portfolios. Panel A reports results for the large firm group and Panel B reports results for the small firm group. The associated Newey-West *t*-statistics with 4 lags are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The sample period is from January 1995 to June 2013.

Portfolios excess return (%)	All markets	Advanced markets	Emerging markets
Panel A. Large firms			
		Seasonality basis: year 1	
Winners	0.92***	0.93***	0.90***
	(11.9)	(11.82)	(6.70)
Losers	0.39***	0.42***	0.37**
	(4.46)	(4.33)	(2.45)
Winners-losers	0.53***	0.52***	0.54***
	(4.52)	(4.18)	(2.68)
		Seasonality basis: year 2-3	
Winners	0.67***	0.65***	0.68***
	(7.03)	(5.91)	(4.37)
Losers	0.79***	0.73***	0.86***
	(8.78)	(8.09)	(5.40)
Winners-losers	-0.13	-0.08	-0.17
	(-0.96)	(-0.55)	(-0.79)
		Seasonality basis: year 4-5	
Winners	0.52***	0.56***	0.48***
	(7.02)	(6.98)	(3.79)
Losers	0.75***	0.61***	0.88***
	(7.89)	(7.02)	(5.18)
Winners-losers	-0.23*	-0.06	-0.41**
	(-1.92)	(-0.47)	(-1.96)
Panel B. Small firms			
		Seasonality basis: year 1	
Winners	-0.01	0.11	-0.14
	(-0.16)	(0.94)	(-1.00)
Losers	-0.17	-0.01	-0.34**
	(-1.57)	(-0.08)	(-2.21)
Winners-losers	0.16	0.12	0.20
	(1.13)	(0.64)	(0.95)
		Seasonality basis: year 2-3	
Winners	-0.31***	0.00	-0.64***
	(-3.67)	(0.03)	(-5.22)
Losers	-0.35***	-0.31**	-0.40***
	(-3.70)	(-2.38)	(-2.84)
Winners-losers	0.04	0.31*	-0.24
	(0.32)	(1.77)	(-1.34)
		Seasonality basis: year 4-5	
Winners	-0.12	0.03	-0.28
	(-1.04)	(0.21)	(-1.48)
Losers	-0.29***	-0.25**	-0.32**
	(-3.06)	(-2.07)	(-2.25)
Winners-losers	0.17	0.28	0.05
	(1.09)	(1.49)	(0.19)

Table 7. Stock return seasonality and calendar effect

This table reports the economic value of stock return seasonality across calendar months for advanced and emerging markets, respectively. In each month and for each market we sort stocks into decile groups based on historical seasonal return over three time windows: the past year, 2-3 years ago, or 4-5 years ago and calculate the equal-weighted portfolio returns over the subsequent month for each decile. We report the portfolio returns of winner stocks (highest historical seasonal return decile) and loser stocks (lowest seasonal return decile) and the spread between the two portfolios in each calendar month. Panel A shows the results for advanced markets, and Panel B shows the results for emerging markets. The associated Newey-West *t*-statistics with 4 lags are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The sample period is from January 1995 to June 2013.

	Year 1			Year 2-3			Year 4-5		
	Winners	Losers	WML	Winners	Losers	WML	Winners	Losers	WML
Panel A: Advanced markets									
January	1.88	1.06	0.82*	2.04	0.78	1.25**	1.90	0.06	1.84***
	(5.17)	(3.72)	(1.77)	(4.68)	(1.63)	(2.13)	(5.82)	(0.15)	(3.93)
February	0.63	0.45	0.18	1.01	1.26	-0.25	1.23	-0.28	1.51
	(1.22)	(1.12)	(0.29)	(1.67)	(2.18)	(-0.50)	(2.11)	(-0.43)	(1.33)
March	0.59	-0.25	0.84*	0.14	0.49	-0.35	0.46	0.17	0.29
	(2.08)	(-0.72)	(1.80)	(0.42)	(1.46)	(-0.64)	(1.18)	(0.47)	(0.44)
April	1.06	0.53	0.53	0.57	0.48	0.09	0.18	0.15	0.02
	(2.64)	(1.13)	(1.15)	(1.81)	(0.92)	(0.21)	(0.78)	(0.32)	(0.04)
May	0.53	0.32	0.21	0.41	0.99	-0.57	-0.34	0.63	-0.97
	(1.49)	(0.74)	(0.40)	(0.93)	(1.76)	(-1.21)	(-0.72)	(1.40)	(-1.28)
June	0.21	-0.59	0.81*	0.24	-0.44	0.68	-0.18	0.10	-0.28
	(0.95)	(-1.52)	(1.91)	(0.48)	(-1.12)	(1.62)	(-0.38)	(0.30)	(-0.45)
July	-0.12	-0.13	0.01	-0.02	-0.40	0.38	0.13	-0.19	0.31
	(-0.44)	(-0.32)	(0.02)	(-0.12)	(-1.09)	(1.47)	(0.35)	(-0.57)	(0.68)
August	0.34	0.04	0.30	-0.30	0.08	-0.38	-0.30	-0.01	-0.29
	(1.11)	(0.08)	(0.56)	(-1.26)	(0.2)	(-0.86)	(-0.76)	(-0.02)	(-0.52)
September	-0.04	-0.17	0.13	0.04	-0.05	0.09	0.66	-0.03	0.69
	(-0.11)	(-0.35)	(0.21)	(0.10)	(-0.09)	(0.11)	(1.46)	(-0.05)	(0.87)
October	0.82	0.24	0.58	0.46	-0.35	0.81	-0.02	0.59	-0.61
	(1.96)	(0.57)	(1.15)	(1.83)	(-0.72)	(1.55)	(-0.04)	(1.15)	(-0.70)
November	0.47	0.57	-0.10	0.51	0.69	-0.17	0.15	0.12	0.02
	(0.94)	(1.21)	(-0.18)	(0.95)	(1.12)	(-0.23)	(0.49)	(0.37)	(0.05)
December	0.58	-1.02	1.60***	0.30	-1.17	1.47**	0.40	-0.46	0.86*
	(1.92)	(-2.60)	(3.36)	(0.93)	(-3.34)	(2.60)	(2.04)	(-1.03)	(1.77)
Panel B: Emerging markets									
January	4.11	2.43	1.69	4.33	2.98	1.35	1.17	1.08	0.10
	(2.12)	(1.41)	(1.10)	(2.90)	(1.50)	(0.88)	(0.87)	(0.42)	(0.04)
February	2.00	1.82	0.18	4.31	1.30	3.01**	0.45	1.43	-0.97
	(1.62)	(1.51)	(0.12)	(3.04)	(1.27)	(2.73)	(0.38)	(1.54)	(-0.89)
March	2.54	-1.00	3.54**	-2.23	-0.90	-1.34	1.55	-1.02	2.57
	(1.85)	(-0.64)	(2.68)	(-0.72)	(-0.57)	(-0.47)	(1.12)	(-0.59)	(1.54)
April	4.31	3.89	0.42	5.70	5.44	0.26	4.94	4.56	0.38
	(2.81)	(1.77)	(0.22)	(3.24)	(3.1)	(0.19)	(2.99)	(3.21)	(0.36)
May	1.61	3.81	-2.20*	1.71	3.35	-1.64	1.81	2.80	-0.99
	(0.88)	(1.56)	(-1.66)	(0.88)	(1.77)	(-0.98)	(0.65)	(1.60)	(-0.60)
June	2.14	1.90	0.25	1.04	1.26	-0.21	-0.34	2.65	-2.99**
	(1.12)	(0.92)	(0.17)	(0.8)	(0.74)	(-0.25)	(-0.19)	(1.25)	(-2.41)
July	1.92	3.42	-1.51	3.76	3.24	0.51	3.07	3.55	-0.48
	(1.48)	(2.29)	(-1.53)	(2.63)	(2.65)	(0.56)	(2.53)	(2.26)	(-0.46)
August	3.09	0.11	2.98	3.38	0.67	2.71	4.10	1.89	2.21**
	(1.47)	(0.07)	(1.56)	(1.86)	(0.51)	(2.29)	(2.38)	(1.54)	(1.98)
September	-0.19	-0.34	0.15	1.03	0.19	0.85	-0.05	0.94	-0.99
	(-0.14)	(-0.17)	(0.12)	(0.61)	(0.13)	(1.05)	(-0.02)	(0.59)	(-0.82)
October	0.37	0.46	-0.09	0.53	0.44	0.10	1.27	0.42	0.86
	(0.20)	(0.26)	(-0.09)	(0.28)	(0.21)	(0.13)	(0.64)	(0.22)	(1.60)
November	3.01	6.11	-3.10	4.04	2.09	1.96	4.38	5.56	-1.18
	(1.54)	(1.81)	(-1.04)	(2.43)	(1.37)	(1.50)	(2.15)	(3.18)	(-0.94)
December	6.26	4.13	2.13	5.24	4.23	1.01	7.13	4.16	2.97
	(3.18)	(2.04)	(1.43)	(2.34)	(2.03)	(0.41)	(2.43)	(1.87)	(0.91)

Table 8. Seasonality returns adjusted by local risk factors

This table reports the risk-adjusted returns of winner and loser seasonal stock portfolios and the return spread between the two groups. In each month and for each market we sort stocks into decile groups based on historical seasonal returns over three time windows: the past year, 2 years ago, or 3 years ago and calculate the equal-weighted risk-adjusted returns over the subsequent month for each decile. We construct the four Fama-French-Carhart risk factors for each market and apply the following model to adjust stock returns: [23] $r_{n,i,t} - r_{n,f,t} = \alpha_{n,t} + A_{n,t}(R_{n,M,t} - r_{n,f,t}) + B_{n,t}SMB_{n,t} + C_{n,t}HML_{n,t} + D_{n,t}WML_{n,t} + \varepsilon_{n,i,t}$ where $R_{n,M,t}$ is the equal-weighted market monthly return for market *n* in month *t* and $r_{n,f,t}$ is the risk free rate for market *n* in month *t*. $SMB_{n,t}$, $HML_{n,t}$ and $WML_{n,t}$ denote the size, book-to-market (B/M) and momentum factors. We report the risk-adjusted portfolio returns (alpha) of winner stocks (highest historical seasonal return decile) and loser stocks (lowest seasonal return decile) and the spread between the two portfolios in each calendar month. Panel A shows the results for advanced markets, and Panel B shows the results for emerging markets. The associated Newey-West *t*-statistics with 4 lags are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The sample period is from January 1995 to June 2013.

	Year 1			Year 2			Year 3		
	Winners	Losers	WML	Winners	Losers	WML	Winners	Losers	WML
Panel A: Advanced countries									
Australia	-0.93	-0.93	-0.00	-0.30	-0.63	0.32	-0.12	-0.78	0.66
	(-1.22)	(-1.63)	(0.00)	(-0.57)	(-1.10)	(0.36)	(-0.27)	(-0.88)	(0.60)
Belgium	-0.65	-1.17**	0.52	-0.11	-0.70	0.59	0.20	-0.91**	1.11
	(-1.57)	(-2.25)	(1.15)	(-0.38)	(-1.41)	(0.99)	(0.39)	(-2.03)	(1.55)
Canada	-1.23***	-0.99**	-0.24	0.22	-2.15***	2.37***	-0.58**	-1.77***	1.20**
	(-2.68)	(-1.96)	(-0.55)	(0.82)	(-4.91)	(4.71)	(-2.19)	(-4.03)	(2.41)
Denmark	0.09	0.032	0.06	-0.07	0.06	-0.13	0.53*	-0.42	0.95
	(0.22)	(0.05)	(0.15)	(-0.25)	(0.11)	(-0.22)	(1.78)	(-0.82)	(1.63)
Finland	-0.59	-1.09***	0.50	0.22	-1.39***	1.61***	0.55***	-1.47***	2.02
	(-1.24)	(-2.31)	(1.31)	(1.12)	(-3.12)	(3.19)	(3.18)	(-3.67)	(4.37)
France	-0.22	-0.73	0.51	0.10	-0.85*	0.95*	-0.04	-0.62	0.58
	(-0.55)	(-1.48)	(1.51)	(0.51)	(-1.88)	(1.82)	(-0.19)	(-1.35)	(1.09)
Germany	-1.31***	-2.38***	1.06***	-0.06	-1.43***	1.37***	-0.42**	-1.35***	0.93**
	(-3.61)	(-5.73)	(2.83)	(-0.30)	(-4.00)	(3.22)	(-2.00)	(-3.55)	(2.00)
Greece	-1.94***	-2.15***	0.21	0.14	-2.07***	2.20***	-0.34	-2.18***	1.84**
	(-3.54)	(-3.49)	(0.39)	(0.47)	(-3.42)	(3.01)	(-1.25)	(-3.43)	(2.46)
Hong Kong	-1.78***	-2.26***	0.48	-0.47**	-1.86***	1.39**	-0.22	-1.70***	1.48**
	(-3.68)	(-4.22)	(1.30)	(-2.11)	(-3.61)	(2.63)	(-0.97)	(-2.72)	(2.16)
Israel	-0.57	-0.69	0.11	0.03	-0.63	0.65	0.14	-0.35	0.49
	(-1.06)	(-1.00)	(0.27)	(0.12)	(-1.07)	(1.10)	(0.51)	(-0.63)	(0.83)
Italy	-1.520***	-1.82***	0.30	0.14	-1.79***	1.93***	0.06	-1.67***	1.74***
	(-3.53)	(-3.67)	(1.12)	(0.83)	(-3.68)	(3.75)	(0.36)	(-3.62)	(3.54)
Japan	-0.54**	-1.17***	0.64***	0.23**	-1.38***	1.61***	0.16	-0.98***	1.14***
	(-1.97)	(-3.66)	(3.28)	(2.28)	(-4.35)	(4.92)	(1.55)	(-3.30)	(3.54)
Nether land	-0.24	-0.40	0.16	0.24	-0.47	0.71	0.14	-0.34	0.48
	(-0.53)	(-0.79)	(0.39)	(1.05)	(-0.94)	(1.27)	(0.69)	(-0.68)	(0.86)
New Zealand	0.40	-0.45	0.86*	0.19	-0.11	0.30	-0.36	-0.01	-0.35
	(0.85)	(-1.03)	(1.72)	(0.50)	(-0.21)	(0.42)	(-0.96)	(-0.01)	(-0.46)
Norway	-0.56	-1.05*	0.49	0.75**	-1.32**	2.07***	0.34	-1.43	1.77***
	(-1.01)	(-1.69)	(0.93)	(2.13)	(-2.36)	(3.18)	(0.80)	(-2.62)	(2.69)
Singapore	-1.26***	-1.92***	0.66*	-0.08	-1.94***	1.86***	0.06	-1.60	1.67***
	(-2.64)	(-3.47)	(1.75)	(-0.35)	(-3.65)	(3.05)	(0.22)	(-3.00)	(2.81)
Spain	-0.07	-0.23	0.17	0.12	-0.78*	0.90*	-0.25	-0.46	0.21
	(-0.14)	(-0.44)	(0.47)	(0.55)	(-1.67)	(1.79)	(-1.28)	(-0.95)	(0.41)
Switzer land	-0.65	-1.49***	0.85**	0.032	-1.23***	1.26***	0.10	-1.32***	1.42***
	(-1.54)	(-2.89)	(2.39)	(0.19)	(-2.90)	(3.04)	(0.39)	(-3.25)	(3.15)
United Kingdom	-0.90***	-1.59***	0.70**	0.060	-1.13***	1.19***	-0.07	-1.25***	1.18**
	(-2.88)	(-3.98)	(2.53)	(0.37)	(-3.02)	(2.91)	(-0.46)	(-2.87)	(2.42)
Average	-0.76***	-1.18***	0.42***	0.07	-1.15***	1.22***	-0.01	-1.08***	1.08***
Std. Dev.	0.61	0.68	0.33	0.24	0.63	0.68	0.30	0.59	0.61
Positive fraction	10.53%	5.26%	89.47%	68.42%	5.26%	94.74%	52.63%	0.00%	94.74%

[23] See detailed explanation of the model in Section 3. For details on the formation of the Fama-French-Carhart factors, please see the Appendix.

	Year 1			Year 2			Year 3		
	Winners	Losers	WML	Winners	Losers	WML	Winners	Losers	WML
Panel B: Emerging markets									
Brazil	-0.63	0.24	-0.87	-0.26	0.11	-0.38	0.09	0.46	-0.37
	(-0.89)	(0.28)	(-1.12)	(-0.45)	(0.13)	(-0.35)	(0.13)	(0.72)	(-0.41)
Bulgaria	1.51	0.71	0.80	N/A	N/A	N/A	N/A	N/A	N/A
	(1.57)	(0.78)	(0.82)						
China	-0.54	-1.34**	0.80*	-0.28	-1.25**	0.97	0.03	-1.04	1.06
	(-0.91)	(-2.18)	(1.84)	(-1.34)	(-1.99)	(1.39)	(0.09)	(-1.5)	(1.43)
India	-0.51	-0.94*	0.43	-0.15	-0.78	0.63	-0.48**	-0.52	0.04
	(-1.08)	(-1.76)	(1.10)	(-0.75)	(-1.45)	(1.14)	(-2.41)	(-1.09)	(0.08)
Indonesia	1.65**	0.98	0.68	-0.28	1.52*	-1.80**	0.04	1.43*	-1.38*
	(1.97)	(1.18)	(1.11)	(-0.89)	(1.87)	(-2.04)	(0.11)	(1.92)	(-1.65)
Korea	-0.96	-1.92***	0.95	0.01	-1.76***	1.77***	0.11	-1.81***	1.92***
	(-1.72)	(-2.99)	(1.85)	(0.06)	(-3.02)	(2.94)	(0.6)	(-3.61)	(3.32)
Malaysia	-1.94***	-2.38***	0.44	0.03	-2.49***	2.51***	0.31**	-1.99***	2.30***
	(-4.72)	(-6.02)	(1.35)	(0.16)	(-5.47)	(5.01)	(2.05)	(-5.24)	(5.4)
Philippine	0.07	-0.50	0.57	-0.23	-0.12	-0.11	0.10	-0.03	0.13
	(0.11)	(-0.75)	(1.00)	(-0.6)	(-0.2)	(-0.16)	(0.25)	(-0.05)	(0.20)
Poland	-0.90	-0.90	0.00	-0.07	-1.25*	1.18	0.68*	-1.12	1.80***
	(-1.43)	(-1.30)	(0.01)	(-0.19)	(-1.88)	(1.35)	(1.69)	(-1.72)	(2.48)
Romania	1.47*	-0.60	2.08*	-0.36	0.90	-1.25	-0.22	-0.08	-0.14
	(1.78)	(-0.64)	(2.16)	(-0.48)	(0.81)	(-0.86)	(-0.26)	(-0.09)	(-0.11)
Russia	2.19**	0.76	1.43	-1.05	2.06**	-3.10**	-0.11	0.62	-0.73
	(2.15)	(1.02)	(1.47)	(-1.54)	(2.41)	(-2.50)	(-0.35)	(1.18)	(-1.16)
South Africa	0.41	0.38	0.04	0.22	0.53	-0.31	N/A	N/A	N/A
	(0.92)	(0.71)	(0.07)	(0.57)	(1.07)	(-0.44)			
Saudi Arabia	0.14	0.06	0.08	N/A	N/A	N/A	N/A	N/A	N/A
	(0.25)	(0.08)	(0.13)						
Turkey	-0.98**	-1.38**	0.40	-0.02	-1.54***	1.52***	-0.17	-0.90	0.73
	(-2.15)	(-2.59)	(1.15)	(-0.14)	(-3.06)	(2.98)	(-0.77)	(-1.63)	(1.15)
Taiwan	-1.53***	-1.21**	-0.32	0.36*	-1.93***	2.29***	0.24	-2.03***	2.27***
	(-3.80)	(-2.47)	(-1.07)	(1.81)	(-4.26)	(4.57)	(1.40)	(-4.55)	(4.83)
Average	-0.04	-0.54*	0.50**	-0.16	-0.46	0.30	0.05	-0.58*	0.64*
Std. Dev.	1.21	0.99	0.68	0.33	1.36	1.60	0.28	1.05	1.18
Positive fraction	46.67%	40.00%	80.00%	30.77%	38.46%	53.85%	66.67%	25.00%	66.67%

These results are in line with the prior studies of the January effect (Gultekin and Gultekin, 1983; Bouman and Jacobsen, 2002; Kamstra, Kramer, and Levi, 2003). The results are also consistent with our previous findings that stock return seasonality is strong in advanced markets but weak in emerging markets. Moreover, existing studies show that the January effect is related to tax-loss selling. Gultekin and Gultekin (1983) examine stock market seasonality in a subset of advanced countries and find disproportionately large January returns in most countries, as well as large April returns in the U.K., corresponding with the beginning of the tax year in each country. For many emerging markets, however, accounting standards and tax laws have not been well developed or strictly enforced especially at the individual market level. For example, both Claessens et al. (1995), and Fountas and Segredakis (2002) find very limited evidence in favor of the turn-of-the-tax-year effect and the tax-loss selling hypothesis in emerging markets. Although it is beyond the scope of this study, these studies suggest that tax loss selling may be one of the major reasons for the difference in the calendar effect between advanced markets and emerging markets.

3.3.4 Risk-adjusted returns

Fama and French (1993) introduce a three-factor (market, size and book-to-market) model to price asset returns. Carhart (1997) proposes an additional momentum factor. In this section, we construct the four risk factors for each market and investigate whether the seasonality pattern remains after adjusting for these risk premiums.[24] Specifically, in each month we sort stocks into ten groups based on their historical returns in the same month of 1, 2, or 3 years ago, calculate portfolio returns for the subsequent month, and apply Model 2 to adjust the risk premiums in portfolio returns (alpha).[25] Table 8 presents the risk-adjusted portfolio returns of the

[24] Please refer to the Appendix for details on how the Fama-French-Carhart factors are formed.

[25] See detailed explanation of the model in Section 2. It may also be interesting to include other variables in the specification such as the weather in each market. While we do not have these data, we thank to an anonymous referee for making this point.

winner and loser portfolios and the winner-loser strategy (longing winner stocks and shorting loser stocks) in each market, as well as the mean, standard deviation, and fraction of positive adjusted-returns across all individual markets. Panel A reports the results for advanced markets and Panel B for emerging markets.[26]

The results in Table 8 are consistent with Table 4 that the seasonality patterns in terms of risk-adjusted portfolio returns exist mainly in advanced markets but not in emerging markets. In particular, the winner-loser strategy based on the same-month returns in the past year produces significantly positive risk-adjusted returns in six advanced markets (Germany, Japan, New Zealand, Singapore, Switzerland, and the United Kingdom), but only in two emerging markets (China and Romania). The winner-loser strategy based on the same-month returns 2 years ago works well in thirteen advanced markets and four emerging markets. The winner-loser strategy based on the same-month returns 3 years ago works well in 10 advanced markets and 4 emerging markets. The average risk-adjusted return of the winner-loser strategy over all advanced markets as a whole is positive and statistically significant at 1% level for all three portfolio formation time-lags. In emerging markets, the average risk-adjusted return of the winner-loser strategy over all markets is significantly positive when portfolios are formed on the same-month return in the past year but insignificantly or marginally significantly positive in other cases. We also note that, among emerging markets, seasonality patterns are more prominent in Asian markets. Regardless, the results indicate that the return seasonality patterns remain more prominent in advanced markets than in emerging markets after adjusting for risk premiums. More importantly, there is a significant difference between Table 8 and Table 4. Table 8 suggests that return seasonality exists in more advanced markets when portfolios are formed on returns in the same month of years that are more distant. In particular, the winner-loser strategy works well in 13 and 10 advanced markets when portfolios are formed on the same-month returns 2 and 3 years ago, respectively, and 6 advanced markets when they are formed on the same-month returns in the past year. For emerging markets, however, the counterpart numbers are 4, 4, and 2. This evidence indicates that risk factors might be able to partially explain the short-term seasonality patterns in international stock returns.

In an untabulated analysis, we replace the local Fama-French-Carhart risk factors with global Fama-French-Carhart risk factors to compute risk-adjusted returns. In contrast to Table 8, the risk-adjusted returns delivered by the winner-loser strategy are almost unchanged relative to the raw returns, indicating that global risk factors have less power to explain stock return seasonality than local risk factors.[27]

3.3.5 Mood beta-adjusted returns

Recent studies suggest that stock return seasonality exhibits different patterns under different investors' moods. For example, Kamstra et al. (2014) assume that investors' risk preferences differ between two semi-annual seasons (spring & summer vs. fall & winter): they are less risk averse during the former and more during the latter. The empirical results confirm that risky asset returns are higher during the seasons when risk-free returns are lower (fall & winter), and the opposite in the other seasons (spring & summer). Hirshleifer et al. (2017) find that stock returns with seasonality in past mood periods (e.g., the best-return month realized in the year) tend to persist in future periods with a congruent mood, but tend to reverse in periods with a non-congruent mood. They propose a mood beta variable and argue that these patterns are stronger for high-mood-beta stocks.

Following Hirshleifer et al. (2017), we construct the annually updated mood beta for all stocks in our sample using the equation below, and test whether stock seasonality exists in international markets after we control firms' mood beta, which is defined as:

$$\beta_i^{mood} = (\overline{XRET}_{i,Best} - \overline{XRET}_{i,Worst})/(\overline{XRET}_{A,Best} - \overline{XRET}_{A,Worst}) \tag{4}$$

where $XRET_{Best}$ denotes the month with the highest return in each year and $XRET_{Worst}$ denotes the month with the lowest return. The subscript i is for individual stocks and the subscript $_A$ is for the aggregate stock market. The variables with bars indicate the average excess returns using the previous 5-year window.[28]

[26] Several markets were dropped because they either do not have three years data to form portfolios or have too much stale data.
[27] The result is available upon requests.
[28] Hirshleifer et al. (2017) also propose other measures of mood beta such as the average stock return change in response to the aggregate return change in January and October. We confirm that the results remain using those alternative measures.

We replace the Fama-French risk factors by the mood beta variable to examine the mood-beta-adjusted portfolio returns (alpha) [29] for all three groups of markets: emerging markets, advanced markets, and all markets. Specifically, in each month we sort stocks into ten groups based on their historical same-month returns in the past year, 2-3 years ago, or 4-5 years ago, respectively, and calculate the mood-beta-adjusted portfolio returns (alpha) using the revised Model 2. Table 9 presents the mood-beta-adjusted portfolio returns of the winner and the loser groups as well as the winner-loser portfolio (longing winner stocks and shorting loser stocks) for each group of markets. Panel A reports the results based on the whole sample, Panel B reports the results for stocks in advanced markets, and Panel C reports the results for stocks in emerging markets.

The results in Table 9 are consistent with those in Table 3 that the seasonal winner-loser strategy is profitable in advanced markets but not in emerging markets. Specifically, after being adjusted by the mood-beta premium, the top 10% of stocks with the highest same-month returns significantly outperform the 10% of stocks with the lowest same-month returns in advanced markets when sorting on same-month returns in the past year and 2-3 years ago. In contrast, the seasonal winner-loser strategy does not generate significant profits in emerging markets for any of the three same-month intervals. These results indicate that the differences in seasonality between advanced markets and emerging markets cannot be explained by investors' mood beta.

4. Conclusion

This paper investigates stock return seasonality patterns in international markets. We collect data from 42 international markets, including 21 advanced markets and 21 emerging markets. Our sample covers the major financial markets of five main regions, including North America, South America, Europe, Asia-Pacific, and the Middle-East. The data span from January 1995 to June 2013. Following Heston and Sadka (2008), we apply the Fama-MacBeth (1973) two-pass methodology to estimate the seasonal coefficients of the cross-sectional response of returns in a given month to returns in the same month in previous years. The results reveal that stock returns show significant seasonality in advanced markets as a pooled market but not in emerging markets. The findings hold when we perform multivariate analyses by including multiple seasonal returns.

To test whether stock return seasonality is economically significant, we sort stocks into 10 decile groups based on returns in the same month of 1 year ago, 2-3 years ago and 4-5 years ago, respectively, and compute the decile portfolio returns as well as the winner-loser spread over the subsequent month. The results show that stock return seasonality is economically significant in advanced markets as a whole market but insignificant in emerging markets. Specifically, when sorted on the past year's seasonal return, winner stocks in advanced markets outperform loser stocks by 53 basis points in raw returns; the significance decreases when stocks are sorted on returns in more distant past seasonal months (2-5 years ago). We breakdown our data by market and find that winners outperform losers in nine, six, and five advanced markets when portfolios are formed based on the same-month returns 1, 2, or 3 years ago, respectively. In contrast, winners outperform losers in three, one, and zero emerging markets when portfolios are formed based on the same-month returns 1, 2, and 3 years ago, respectively.

We further explore the possible explanations for the differences in stock return seasonality patterns across international markets. We first test the Kamstra's (2017) argument that the difference in seasonality patterns between advanced and emerging markets may be partly attributed to the implementation bias in the Fama-MacBeth procedure and our results support this point. Second, we also find that the difference in seasonality patterns can be partly attributed to differences in firm characteristics such as size. Seasonality is more prominent in small stocks than in large stocks. Third, we find significant January and December effects on the returns of the seasonal portfolios formed on all three intervals (1 year ago, 2-3 years ago, and 4-5 years ago) in advanced markets, but no effect on the seasonal portfolios in emerging markets. Forth, we test whether the Fama-French-Carhart risk factors can explain stock return seasonality patterns, and find that these risk factors have partial power to explain the short-term seasonality patterns in international stock returns. Lastly, following Hirshleifer et al. (2017), we test whether the stock return seasonality pattern is affected by investors' mood. The results are similar to our base portfolio analysis: the winner-loser strategy generate significant profits for advanced markets

[29] See detailed explanation of the model in Section 2.

but not for emerging markets when winner and loser portfolios are formed on the same-month returns in the past year or 2-3 years ago.

In sum, we find significant differences in stock return seasonality between advanced and emerging markets, and these differences can be attributed to multiple reasons, including regression bias, firm size, risk premium and the calendar effect. In terms of future research, it is interesting to investigate other possible explanations for this seasonality pattern in advanced markets, including investor's sentiment, risk aversion, culture, regulation, and so on.

Table 9. Seasonality returns adjusted by investor mood beta

This table reports the mood-beta-adjusted returns of winner and loser seasonal stock portfolios and the return spread between the two groups. We construct investor mood beta according to Hirshleifer et al. (2017). In each month and for each market we sort stocks into decile groups based on historical seasonal returns over three time windows: the past year, 2-3 years ago, or 4-5 years ago and calculate the equal-weighted risk-adjusted returns over the subsequent month for each decile. We apply the following model to adjust stock returns (alpha):[30] $r_{n,i,t} - r_{n,f,t} = \alpha_t + A_{n,t}\beta^{Mood}_{n,i,t-k} + \varepsilon_{n,i,t}$ where $A_{n,M,t}$ is market loading for market n in month t and $r_{n,f,t}$ is the risk-free rate for market n in month t. $\beta^{Mood}_{n,i,t-k}$ denotes the investor mood beta for each individual stock in market n. We report the risk-adjusted portfolio returns (alpha) of winner stocks (highest historical seasonal return decile) and loser stocks (lowest seasonal return decile) and the spread between the two portfolios in each calendar month. Panel A reports the results for the whole sample, Panel B for stocks in advanced markets, and Panel C for stocks in emerging markets. The associated Newey-West t-statistics with 4 lags are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The sample period is from January 1995 to June 2013.

Portfolios	Panel A: All markets	Panel B: Advanced markets	Panel C: Emerging markets
	Seasonality basis: year 1		
Winners	1.14***	1.41**	1.49***
	(2.73)	(2.02)	(3.05)
Losers	-1.22	-0.21	-0.34
	(-1.10)	(-0.30)	(-0.23)
Winners-losers	2.36**	1.71**	1.83
	(2.21)	(2.03)	(1.30)
	Seasonality basis: year 2-3		
Winners	0.74	0.45	0.98
	(1.25)	(1.20)	(1.50)
Losers	0.79	-0.19	1.00
	(1.36)	(-0.39)	(1.52)
Winners-losers	-0.06	0.65*	-0.01
	(-0.10)	(1.80)	(-0.02)
	Seasonality basis: year 4-5		
Winners	0.58	0.61	0.97
	(1.06)	(1.54)	(1.60)
Losers	1.05*	0.06	1.35**
	(1.80)	(0.15)	(2.03)
Winners-losers	-0.47	0.54	-0.38
	(-0.79)	(1.56)	(-0.58)

[30] See detailed explanation of the model in Section 3.

Appendix. Data and Fama-French-Carhart portfolio formation

The data used in this study, including stock price, trading volume, market capitalization, and book-to-market value, is from Datastream International. Formation of size, book-to-market, and momentum portfolios follows the procedure in Fama and French (1993). Portfolios are rebalanced every month and evaluated over the subsequent month. To form portfolios, all firms at year t must have book-value data in December of year t and equity data (stock price and market capitalization) at the beginning of January of year t. Stocks are independently divided into five groups by size (large/small market capitalization), book-to-market ratios (High/Low), and momentum. The size portfolios are formed based on firm's capitalization at the end of June of year t-1. The book-to-market and momentum portfolios are formed at the end of December of year t-1. We then calculate the value-weighted returns for each portfolio, and construct the Fama-French and momentum factors as the return difference between the corresponding top and bottom portfolios.

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