Aalto University
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THE PREDICTIVE POWER OF SALES SEASONALITY OVER STOCK RETURNS IN THE ASIAN STOCK MARKETS

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Abstract

This paper examines the predictive power of sales seasonality over stock returns in the Asian stock markets from January 2004 to December 2019. I find that sales seasonality has predictive power over future stock returns because of time variation. A long-short portfolio, which buys the firms in their low-sales seasons and shorts the firms in their high-sales seasons produces an annual alpha of 4.08% - 6.49% with an equally-weighted portfolio and an annual alpha of 8.04% - 10.76% with a value-weighted portfolio. The results remain significant after controlling for other previously documented return predicting variables.

Keywords Sales seasonality, Seasonality, Asset pricing, Return predictability

Contents

1. Introduction

Sales seasonality is a measure that states how firms' sales (revenue) are divided between each quarter of the year. For some firms, these seasonal variations in supply and demand can mean a large change in firms' sales and for others, these variations might not produce as large a change, which means that they can produce steady sales throughout the year. One of the world's largest manufacturers of consumer and professional electronics products, SONY, is an example of a firm with steady sales since they are split evenly (approximately 25% per quarter) between the fiscal quarters. In contrast, a Chinese sugar manufacturer, Nanning Sugar, produces almost 50% of its revenue in their high-seasons and 11% in their low-sales seasons, which means that they have high variation in their sales. For most firms, the variations in quarterly sales are highly predictable and can be foreseen well in advance.

Seasonality in stock returns has been an extensively researched question and it has a long history in the financial environment. Samuelson (1965) was the first to present the idea that prices should not change to expected seasonal "news". The studies on seasonality were continued by Beaver (1968), Frazzini and Lamont (2006), Savor and Wilson (2016), and Barber et al. (2013), who found seasonalities in excepted earnings announcement months. Chang (2017) continued this by founding seasonality based on the measurement of the earnings announcement, which was presented earlier by Bernard and Thomas (1990). Heston and Sadka (2008) found that firms show comparatively high (or low) abnormal returns in the same month every year and as an answer to this, research by Keloharju et al. (2016) showed that returns in seasonality are driven primarily by the seasonality in systematic factors.

Despite the fact that seasonality in stock returns has received a considerable amount of attention, the seasonality in firms' economic activities excluding net profit has not been as well documented. Only the recent research by Grullo et al. (2020) studies the important relationship between firms' economic activities (i.e. sales) and future stock returns. Using sales as a measurement for seasonality, they find evidence that seasonal patterns generate time variation, which indicates that stock returns are counter-seasonal. However, it is not clear what produces this seasonality anomaly and hence, additional studies of sales seasonality over future stock returns are needed.

The sales seasonalities' predictive power over future stock returns is an intriguing topic since it cannot be explained by the known seasonalities in literature, which were mentioned above. Additionally, since the sales seasonality was brought up to conversation by Grullo et al. (2020), there has not been enough research to investigate, why these seasonal patterns produce time variation in stock returns.

Even though the results by Grullo et al. (2020) seem to violate the efficient market hypothesis and cannot be explained by the known seasonalities, some indicators might rationally explain where the sales seasonality derives from. Sales seasonality could be explained by the predictions of the real options theories by Berk et al. (1999), where firms invest more during their high seasons, which is why their excepted return should be counter-seasonal. Another explanation pointed out by Grullo et al. (2020), could be the effect of leverage on expected returns. If firms reduce their leverage during high seasons, these seasonal patterns in financing policies could produce time variation in stock returns. Lastly, sales seasonality could be explained by the model of Merton (1987), where time variation is produced by the level of investor attention towards the stock since if the stock becomes neglected during low seasons, the returns in these periods should be higher.

In this paper, I continue the research around the sales seasonalities' predictive power over the future stock returns inspired by the research of Grullo et al. (2020), since it is new to financial research and not well documented. Their research finds that sales seasonality has predictive power over stock returns in the US stock markets. Especially, low-sales season firms tend to significantly outperform high-sales season firms. A long-short portfolio of buying low-sales season firms and shorting high-sales season firms produces an annual alpha of 8.4%. To continue their research, I will test if this effect can be found in other large markets. I will test the following hypothesis in Asian stock markets since Asia represents the largest stock markets after the US:

H0: *Firms in their low-sales seasons produce higher returns than firms in their high-sales seasons*

Using a sample of data from January 2004 to December 2019 I find that there is a significant relationship between sales seasonality and future stock returns, which derives mostly from the long leg of the portfolios in the Asian stock markets. I test the predictive power of sales seasonality by a decile portfolio test, where I divide my sample of firms into ten decile portfolios by measurement of sales seasonality to examine Capital asset pricing model excess returns (Sharpe, 1964; Lintner, 1965), Fama-French three-factor alphas (Fama and French, 1993) and Fama-French five-factor alphas (Fama and French, 2015). A long-short portfolio that buys the low-sales season firms and shorts the firms in their high-sales season produces an annual alpha of 4.08% - 6.49% with an equally-weighted portfolio and an annual alpha of 8.04% - 10.76% with a value-weighted portfolio, and the results are mostly statistically significant. Additionally, I test the relationship of sales seasonality with factors presented in earlier literature. Moreover, I test for differences between small and large firms.

The rest of the paper proceeds as follows. Section 2 describes the data and methodology. Section 3 discusses the main results. Section 4 addresses the robustness of the main results. Section 5 concludes the paper.

2. Data and methodology

I use data from the Thomson Reuters Eikon to construct my sample. I begin by gathering annual and quarterly accounting data (e.g. sales data) and monthly stock returns to construct my dataset. I start gathering my sample with all common stocks traded in Asian Stock markets from January 2004 to December 2019. Following the approach of Grullo et al. (2020), I exclude all financial firms from this sample. The sample of Asian stock markets consists of exchanges in these countries as it is defined by Eikon: China, Hong Kong, India, Indonesia, Israel, Japan, Kuwait, Malaysia, Pakistan, Saudi Arabia, Singapore, Sri Lanka, Taiwan, Thailand, and United Arabic Emirates.

For the measurement of sales seasonality, I construct a quarterly variable (SEA), which is equal to sales in quarter q of a year t divided by the annual sales.

$$SEA_{qt} = \frac{SALES_{qt}}{ANNUALSALES_t} \tag{1}$$

The data used for this variable is the accounting data taken from Eikon. The sales data for each firm are taken on a quarterly level and annual level. Like Grullo et al. (2020), I remove all observations with negative quarterly sales or negative annual sales. Firms are required to have non-missing sales data for all four quarters during any given year and for all the years in the dataset. If the sum of quarterly sales taken from the Eikon differs from the total sales, I only include firm-year observations if the sum of quarterly sales is between 95% and 105% of total annual sales. To prevent any possible outlier impact, I form a new variable $AVGSEA_{qt}$, which is equal to the average of SEA_{qt} in the years $t-2$ and $t-3$. I use $AVGSEA_{qt}$ to predict SEA_{qt} in year t to ensure that investors have the sales seasonality data available at the time of the portfolio construction. If a given firm produces steady sales throughout the year, SEA_{qt} would be equal to 25% for each quarter. For firms within their high-sales seasons, SEA_{qt} would be over 25% and under 25% for firms in their low-sales seasons.

The datasets used for the asset pricing models in this paper are from Kenneth French's website[1], including the Fama-French three-factor model (Fama-French, 1993), the Fama-French five-factor

[1] The datasets are available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

model (Fama-French, 2015), and the momentum factor used for the Carhart's four-factor alpha (Carhart, 1997). The datasets for asset pricing models are from developed countries excluding the US, since it has most of the Asian markets included which are in the sample.

The problem with the sample construction is that the data for Asian markets is not available for as long a time as it is for the US stock markets since Chinese firms started reporting their quarterly numbers in 2003. This limits the sample sizes quite heavily. For example, Grullo et al. (2020) used a sample from 1970 to 2017 and observed 14 008 firms, whereas my sample observed 1400 firms from January 2004 to December 2019. A small change of adding even two years to the length of my sample could half the firms available for the sample in the given period. This problem also biases the sample size, since it is more likely that larger firms have the data available straight after the year 2003 which makes the sample slightly biased towards larger firms, but this is limited by the fact that the sample begins in the year 2004.

3. Main results

3.1. Decile portfolio test

My main test to measure the predictive power of sales seasonality is performed with a decile portfolio test. In the decile portfolio test, I allocate stocks at the beginning of each month, from January 2004 to December 2019, into ten decile portfolios based on their level of the sales seasonality, $AVGSEA_{qt}$ in year $t-2$. The portfolios are held for one month and then rebalanced at the beginning of the next month. The portfolios are created so that the first portfolio (Low 1) contains the firms with the lowest $AVGSEA_{qt}$ in the given month and the last portfolio (High 10) contains the firms with the highest $AVGSEA_{qt}$. For each month I calculate average returns for both the equally- and value-weighted portfolios. Following the approach of Grullo e al. (2020), I use three asset pricing models to control for the effect of prominent factors: Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965), Fama-French three-factor alpha (Fama and French, 1993) and Fama-French five-factor alpha (Fama and French, 2015)

In Table 1, I report the excess returns, alphas and in parenthesis, I report the t-statistic. Panel A represents the results for the equally-weighted portfolio and Panel B for the value-weighted portfolio. As shown in the results by Grullo et al. (2020) and in line with my hypothesis, I anticipate the excess returns and alphas to decline when moving from the low sales seasonality portfolio to the high sales seasonality portfolio (i.e from left to right in Table 1). Additionally, I examine if value-weighted portfolios produce higher excess returns and alphas than the equally-weighted as was shown by Grullo et al. (2020).

The last column in Table 1 shows the excess returns, alphas, and t-statistics for a long-short (L – H) portfolio, which buys the firms in the first decile (Low 1) and shorts the firms in the last decile (High 10). This represents buying stocks in their low-sales seasons and shorting stocks in their high-sales seasons. The return of this portfolio is the difference between the first decile (Low 1) and the last decile (High 10).

3.1.1. Equally-weighted

The results of the equally-weighted portfolios indicate that there is not a clear pattern in the excess returns of the ten portfolios. A difference can be found when comparing the extreme portfolios since the low-sales season portfolio produces higher returns than the high-sales season. The return of the long-short portfolio, which is the spread between low-sales and high-sales, is notable with an annual excess return of 4.08%. However, it is not significant at the 5% level or 10% with the t-statistic of 1.274. The Fama-French three-factor alpha produces similar results with no clear pattern but the difference between low and high-seasons is still notable with an annual alpha of 4.08% with a t-statistic of 1.266, which is not significant even at the 10% level. The Fama-French five-factor model produces similar results with no clear pattern in returns, but it has the highest return between low and high sales seasonality with an annual alpha of 6.49%, which is significant at the 10% level with a t-statistic of 1.818.

The results from the decile portfolio test with equally-weighted portfolios show that sales seasonality has some predictive power regarding stock returns in the sample period. In line with my hypothesis, low-sales season firms are able to outperform high-sales season firms. The excess returns and alphas are economically significant with results between 4.08% - 6.49% on the annual level but only Fama-French five-factor alpha is statistically significant at the 10% level. In addition, any of the factors by Fama-French cannot explain the excess returns and alphas. The results found are similar to what was found by Grullo et al. (2020), but the excess returns and alphas are slightly higher than what was found in the US markets. However, they are not as statistically significant. The returns of the long-short portfolios seem to be mainly driven by the good performance of low-sales season firms since the excess return and alphas of the lowest deciles are highest, whereas the high-sales season portfolio does not stand out from the other deciles. This differs from Grullo et al. (2020), where the high-sales season portfolio stands out from other portfolios with negative returns. The difference could be due to the fact that the sample is biased towards larger firms.

3.1.2. Value-weighted

In value-weighted portfolios, as in the equally-weighted, there cannot be found a clear pattern in the excess returns. However, the long-short portfolio produces a notable annual excess return of 8.16% which is significant at the 5% level with a t-statistic of 2.036, which was not the case with the equally-weighted portfolios. The Fama-French three-factor and five-factor models produce similar returns as the excess returns since there cannot be found a clear decreasing pattern from low to high. However, the difference between the returns of extremes is yet notable. The Fama-French three-factor produces annual alpha of 8.04%, which is significant at the 5% level with a t-statistic of 1.997, and the five-factor model annual alpha of 10.76%, which is significant at the 5% level with a t-statistic of 2.408. The t-statistic of the five-factor model is also the highest of all excess returns and alphas regarding both equally and value-weighted portfolios.

Overall, the results from the decile portfolio test with value-weighted portfolios show that sales seasonality has predictive power over stock returns in the sample period. In line with my hypothesis, low-sales season firms are able to significantly outperform high-sales season firms. The excess returns and alphas are economically significant with results between 8.04% - 10.76% with a significance level of 5%. The results are driven by the good performance of low-sales season firms over the high-sales season firms and cannot be explained by Fama-French factors as was with the equally-weighted. The major difference is that value-weighted returns are higher and stronger than the equally-weighted returns, as was found in the US stock market by Grullo et al. (2020). The returns are also significant at the 5% level, which they were not in the equally-weighted portfolios. To conclude, the results from the equally and value-weighted portfolios show that the predictive power of sales seasonality is economically significant but only unanimously statistically significant with value-weighted portfolios, which propose that sales seasonality is more a big firm phenomenon.

Table 1

The predictive power of sales seasonality

This table reports the performance of decile portfolios sorted by the sales seasonality (SEA). SEA is equal to sales in quarter q of a year t divided by the annual sales in year t. To prevent any possible outlier impact, I form variable AVGSEA, which is equal to the average of SEA over the years t-2 and t-3. I then use AVGSEA in year t-2 to predict SEA in the year t to ensure that all the data is available to the investors when formatting the portfolio. This table reports the excess returns of Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965), Fama-French three-factor alpha (Fama and French, 1993), Fama-French five-factor alpha (Fama and French, 2015), and t-statistics in parenthesis. The last column reports the excess returns and alphas of a long-short (L-H) portfolio, which buys firms in the Low 1 decile and shorts firms in the High (10) decile. The sample consists of all nonfinancial firms in the Asian markets from January 2004 to December 2019. Panel A represents the results for monthly balanced equally-weighted portfolio returns and Panel B for value-weighted returns.

Panel A: Equally-weighted											
	Low (1)	2	3	4	5	6	7	8	9	High (10)	L - H
Capital Asset Pricing Model											
Alpha	1.540	0.980	0.894	0.976	1.018	0.896	1.018	1.097	0.997	1.200	0.340
	(3.570)	(2.690)	(2.740)	(3.182)	(3.439)	(3.217)	(3.526)	(3.613)	(3.063)	(3.154)	(1.274)
Market	0.665	0.654	0.629	0.670	0.598	0.597	0.656	0.584	0.652	0.625	0.040
	(7.401)	(8.623)	(9.263)	(10.503)	(9.705)	(10.300)	(10.919)	(9.250)	(9.621)	(7.886)	(0.719)
Fama-French three-factor model											
Alpha	1.505	0.950	0.867	0.949	0.988	0.870	0.993	1.070	0.969	1.160	0.340
	(3.539)	(2.658)	(2.711)	(3.159)	(3.435)	(3.190)	(3.495)	(3.598)	(3.027)	(3.124)	(1.266)
Market	0.702	0.694	0.655	0.704	0.633	0.624	0.680	0.616	0.681	0.660	0.040
	(7.743)	(9.097)	(9.763)	(10.978)	(10.326)	(10.738)	(11.236)	(9.721)	(9.981)	(8.318)	(0.712)
SMB	0.709	0.640	0.588	0.559	0.623	0.525	0.490	0.548	0.567	0.700	0.001
	(2.622)	(2.817)	(2.893)	(2.926)	(3.408)	(3.029)	(2.731)	(2.899)	(2.785)	(2.988)	(0.004)
HML	-0.006	-0.094	-0.090	-0.059	-0.040	0.003	0.019	-0.058	0.006	0.007	-0.013
	(-0.024)	(-0.435)	(-0.462)	(-0.323)	(-0.231)	(0.018)	(0.110)	(-0.322)	(0.032)	(0.030)	(-0.079)
Fama-French five-factor model											
Alpha	2.213	1.590	1.382	1.458	1.402	1.239	1.399	1.401	1.219	1.672	0.541
	(4.880)	(4.251)	(4.107)	(4.653)	(4.647)	(4.233)	(4.621)	(4.320)	(3.449)	(4.139)	(1.818)
Market	0.412	0.395	0.407	0.445	0.421	0.442	0.462	0.459	0.560	0.451	-0.039
	(3.554)	(4.131)	(4.741)	(5.553)	(5.394)	(5.917)	(6.010)	(5.537)	(6.200)	(4.369)	(-0.516)
SMB	0.363	0.312	0.316	0.288	0.396	0.331	0.275	0.377	0.437	0.460	-0.097
	(1.325)	(1.381)	(1.553)	(1.522)	(2.147)	(1.873)	(1.511)	(1.926)	(2.045)	(1.883)	(-0.537)
HML	-0.112	-0.047	0.016	0.060	0.029	0.067	0.176	-0.019	0.044	-0.059	-0.053
	(-0.316)	(-0.161)	(0.060)	(0.242)	(0.120)	(0.290)	(0.748)	(-0.075)	(0.158)	(-0.188)	(-0.227)
RMW	-1.445	-1.949	-0.911	-0.955	-0.780	-0.662	-0.645	-0.606	-0.452	-1.027	-0.418
	(-2.814)	(-2.821)	(-2.390)	(-2.506)	(0.026)	(-1.998)	(-1.892)	(-1.649)	(-1.130)	(-2.246)	(-1.241)
CMA	-1.202	-1.330	-1.186	-1.197	-0.964	-0.830	-1.045	-0.712	-0.552	-0.878	-0.325
	(-3.050)	(-4.092)	(-4.058)	(-4.394)	(-3.627)	(-3.263)	(-3.996)	(-2.527)	(-1.797)	(-2.501)	(-1.255)

Panel B: Value-weighted											
	Low (1)	2	3	4	5	6	7	8	9	High (10)	L - H
Capital Asset Pricing Model											
Alpha	1.913	1.358	0.916	1.142	1.306	0.764	0.745	1.351	0.921	1.233	0.680
	(3.856)	(3.769)	(2.578)	(3.946)	(4.403)	(2.627)	(2.396)	(3.857)	(2.257)	(2.664)	(2.036)
Market	0.672	0.776	0.784	0.763	0.682	0.632	0.660	0.759	0.713	0.819	-0.147
	(6.510)	(10.346)	(10.601)	(12.672)	(11.047)	(10.434)	(10.207)	(10.408)	(8.396)	(8.496)	(-2.108)
Fama-French three-factor model											
Alpha	1.885	1.337	0.902	1.130	1.302	0.764	0.741	1.343	0.903	1.215	0.670
	(3.820)	(3.744)	(2.568)	(3.895)	(4.399)	(2.610)	(2.398)	(3.818)	(2.219)	(2.634)	(1.997)
Market	0.709	0.809	0.823	0.770	0.706	0.625	0.690	0.752	0.744	0.856	-0.147
	(6.744)	(10.624)	(10.998)	(12.449)	(11.189)	(10.019)	(10.472)	(10.022)	(8.575)	(8.704)	(-2.051)
SMB	0.613	0.485	0.410	0.206	0.184	-0.026	0.205	0.078	0.431	0.464	0.149
	(1.955)	(2.134)	(1.835)	(1.116)	(0.978)	(-0.139)	(1.043)	(0.350)	(1.664)	(1.583)	(0.699)
HML	-0.080	-0.120	-0.293	0.062	-0.230	0.086	-0.301	0.179	-0.126	-0.207	0.128
	(-0.265)	(-0.549)	(-1.368)	(0.351)	(-1.274)	(0.484)	(-1.599)	(0.836)	(-0.507)	(-0.737)	(0.624)
Fama-French five-factor model											
Alpha	2.569	1.781	1.195	1.502	1.609	0.990	0.964	1.473	1.228	1.671	0.897
	(4.833)	(4.657)	(3.136)	(4.865)	(5.169)	(3.104)	(2.820)	(3.755)	(2.788)	(3.316)	(2.408)
Market	0.402	0.563	0.623	0.557	0.473	0.470	0.587	0.692	0.508	0.624	-0.223
	(2.960)	(5.766)	(6.404)	(7.059)	(5.949)	(5.774)	(6.725)	(6.911)	(4.512)	(4.849)	(-2.339)
SMB	0.267	0.239	0.231	-0.003	-0.013	-0.164	0.091	0.012	0.226	0.222	0.045
	(0.831)	(1.036)	(1.004)	(-0.015)	(-0.071)	(-0.851)	(0.440)	(0.051)	(0.849)	(0.727)	(0.202)
HML	-0.079	0.060	-0.025	0.231	0.142	0.295	-0.293	0.183	0.224	-0.105	0.025
	(-0.191)	(0.201)	(-0.083)	(1.005)	(0.582)	(1.179)	(-1.093)	(0.595)	(0.647)	(-0.265)	(0.087)
RMW	-1.318	-0.718	-0.359	-0.577	-0.306	-0.275	-0.424	-0.247	-0.360	-0.802	-0.517
	(-2.190)	(-1.658)	(-0.832)	(-1.651)	(-0.867)	(-0.762)	(-1.096)	(-0.556)	(-0.721)	(-1.404)	(-1.225)
CMA	-1.338	-1.175	-1.029	-1.035	-1.233	-0.797	-0.450	-0.260	-1.232	-1.068	-0.271
	(-2.897)	(-3.534)	(-3.109)	(-3.859)	(-4.558)	(-2.876)	(-1.515)	(-0.763)	(-3.218)	(-2.436)	(-0.836)

3.2. Relationship between size and sales seasonality

The results from the decile portfolio test reported a notable difference between equally and value-weighted returns. Therefore, my second test will study the relationship between size (market value of equity, ME) and the sales seasonality premium more closely similar to Grullo et al. (2020). To assess this relationship, I perform a decile portfolio test in the same way as in the main test, but by dividing my data first into five different quintiles by size so that the first quintile represents the smallest market value of equity (ME) and the fifth quintile the largest market value of equity (ME). After dividing the data into quintiles, I calculate alphas for both equally and value-weighted long-short portfolios for each quintile using the Fama-French five-factor model (Fama and French, 2015). As the results shown by Grullo et al. (2020) and the decile portfolio test, I expect the alphas to increase when moving from the first quintile to the last quintile.

Figure 1 shows the alphas for both equally and value-weighted portfolios for each quintile. The results show that the sales seasonality premium increases from the first quintile (2.0% annual alpha) to 10.39% in quintile 4 and then decline to 4.92% in quintile 5. Similar to Grullo et al. (2020), these results indicate that the sales seasonality premium is more a big firm phenomenon and not driven by a small firm effect since the premium increases when the firm's market value of equity increase as well. The main difference when comparing the results with Grullo et al. (2020) is that the first quintiles do not produce negative returns. I believe that is due to the sample being slightly biased towards the large market capitalization firms. The results state that the bias itself is not massive because a clear difference can be found between the first and last quintile.

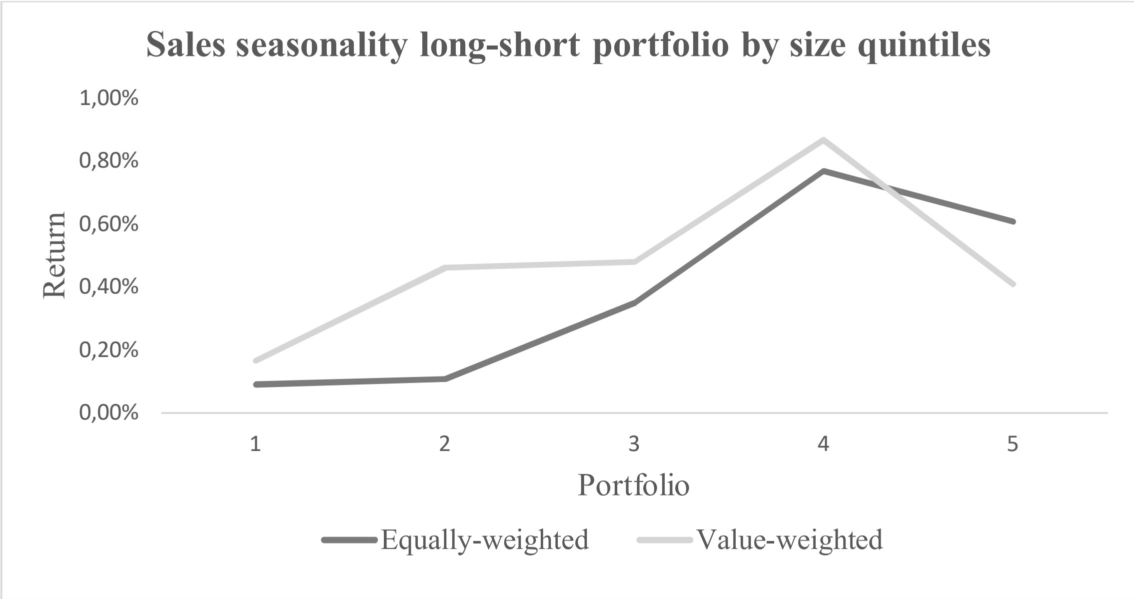

Figure 1
Sales seasonality within size quintiles

This figure shows the alphas of the Fama-French five-factor model for the long-short portfolios for each size quintile. Size (ME) is defined as the market value of equity in January of the year t to January of the year t +1. Size quintiles are formatted by dividing the firms in the sample into five different quintiles by their size. Quintile 1 holds the firms with the lowest market values of equity and quintile 5 the firms with the highest market values of equity. For each quintile, I calculate both equally and value-weighted long-short portfolios, which are then regressed by the Fama-French five-factor model (Fama and French, 2015). The sample consists of all nonfinancial firms in the Asian markets from January 2004 to December 2019.

3.3. Correlation with other asset pricing factors

My third test is to research how existing asset pricing factors correlate with the sales seasonality effect. I perform this test because, in the decile portfolio test and in the results from Grullo et al. (2020), none of the known factors by Fama-French could explain the returns. It is important to examine if the sales seasonality effect correlates with existing asset pricing factors. In the test, I produce a factor based on the sales seasonality strategy (SEAF) to estimate Pearson's correlation between the SEAF and existing asset pricing factors. SEAF is equal to the returns of a low-sales season portfolio minus the returns of a high-sales season portfolio. The factor is produced by the method of the Fama-French convention[2].

In Panel A, I report the correlations between the sales seasonality factor (SEAF) and the following six factors by Fama-French: (i) market excess return (Mkt-rf), (ii) size's small minus big (SMB), (iii) book to market's high minus low (HML), (iv) investment's conservative minus aggressive (CMA), (v) profitability's robust minus weak (RMW), and (vi) momentum's up minus down (UMD). Panel A confirms that the SEAF is mainly uncorrelated with the existing asset pricing factors by Fama-French. The only correlation can be found between SEAF and UMD which is known as the momentum factor. This relationship will be investigated later on.

In Panel B, I compare means, standard deviations, and means divided by standard deviations which produce a measure similar to Sharpe ratios. This is done to analyze the performance of SEAF over the Fama-French factors. The highest mean is by UMD (0.531%), followed by SEAF (0.487%) and Mkt-rf (0.433%). When divided by the standard deviation to a Sharpe-like measurement, the factor with the highest mean by standard deviation is RMW with 0.969, followed by UMD (0.566) and SEAF (0.508). The high numbers by RMW and UMD may be explained by a time span too short, with unusually low volatility or high mean. If these factors are taken out of consideration, SEAF produces the highest numbers in mean and mean divided by standard deviation which means that it can produce higher returns than Mkt-rf during the given time span. This supports my earlier findings from the decile portfolio test and the tests by Grullo et al. (2020), which state that the sales seasonality effect can produce excess returns and alphas over the market return.

[2]The information for the development of the factor is available at Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 2

Pearson correlations and Sharpe ratios

Panel A reports the Pearson's correlations between asset pricing factors. Panel B reports Sharpe ratios, which are calculated by dividing the mean with standard deviation. MKTRF is the excess return of the market, SMB is size's small minus big, HML is book-to-market's high minus low, UMD is momentum's up minus down, CMA is investment's conservative minus aggressive, RMW is profitability's robust minus weak, and SEAF is a factor based on sales seasonality (low season minus high season) using the Fama-French factor approach. The sample consists of all nonfinancial firms in the Asian markets from January 2004 to December 2019.

Panel A: Pearson correlations

Variable	MKTRF	SMB	HML	UMD	CMA	RMW	SEAF
MKTRF		-0.156	0.178	-0.015	-0.479	-0.320	-0.077
SMB			-0.165	-0.197	-0.123	-0.055	0.043
HML				0.076	0.390	-0.633	0.009
UMD					0.053	0.339	-0.375
CMA						-0.138	0.048
RMW							-0.072
SEAF							1.000

Panel B: Sharpe ratios

Variable	Mean %	Std. Dev.	Annualized Sharpe ratio
MKTRF	0.433	4.800	0.313
SMB	0.027	1.605	0.058
HML	0.048	1.682	0.099
UMD	0.531	3.251	0.566
CMA	0.100	1.439	0.242
RMW	0.309	1.104	0.969
SEAF	0.487	3.319	0.508

3.3.1. Carhart Four Factor – model

As an additional test to the correlation between the sales seasonality effect and other asset pricing factors, I test the relationship between sales seasonality premium and momentum. In this test, I am going to regress my equally and value-weighted long-short portfolios from the decile portfolio test with Carhart's Four Factor-alpha -model (Carhart, 1997) to see if excess return and alphas could be explained by the momentum factor since there could be found some correlation between momentum and the sales seasonality in the Pearson's correlation. In Table 3, I report the alphas of Carhart's four-factor model and t-statistics in parenthesis. The table will include the Fama-French three-factor model (Fama and French, 1993), Carhart four-factor alpha (Carhart, 1997), and Fama-French five-factor model (Fama and French, 2015) (from left to right), to ease the comparison between results.

The results imply that a clear relationship cannot be found between sales seasonality premium and momentum factor. When regressing the equally-weighted portfolio with Carhart's four factor-alpha, the coefficient of the UMD is 0.075 with a t-statistic of 0.805, which is insignificant. The outline of the results is the same when regressing the value-weighted portfolio since the coefficient of the UMD is 0.029 with a t-statistic of 0.244. This implies that the excess returns cannot be explained by the momentum factor. The momentum factor still has an impact on the returns, since both equally and value-weighted returns decrease when adding the momentum factor to the regression compared to the Fama-French three-factor model. As table 3 shows, alpha from the equally-weighted decreases from 0.340 to 0.292 on a monthly level with a t-statistic of 1.058. Value-weighted alpha decreases from 0.670 to 0.651 on a monthly level with a t-statistic of 1.889, which decreases its significance from the 5%-level to the 10%-level.

Overall, there is no clear pattern between sales seasonality premium and momentum factor, since it cannot explain the excess returns and alphas of the decile portfolio test. Yet, it cannot be fully excluded since it has a decreasing effect on the returns when added to the asset pricing models. To further research the sales seasonality's relationship with the momentum factor is an interesting topic but it is out of the scope of this study.

Table 3

Carhart four-factor alpha

This table reports the results of the Carhart four-factor alpha regression. From left to right, Fama-French three-factor alpha (Fama and French, 1993), Carhart four-factor alpha (Carhart, 1997), Fama-French five-factor alpha (Fama and French, 2015), and t-statistics in parenthesis. The long-short portfolios constructed in the decile portfolio test are regressed with the Carhart four-factor alpha model to see how the momentum factor affects the results. The sample consists of all nonfinancial firms in the Asian markets from January 2004 to December 2019. Panel A reports the results of the regressions with the equally-weighted portfolios and Panel B reports the results of value-weighted portfolios.

Panel A: Equally-weighted

	Fama-French three-factor model	Carhart four-factor alpha	Fama-French five-factor model
Alpha	0.340	0.292	0.541
	(1.266)	(1.058)	(1.818)
Market	0.040	0.057	-0.039
	(0.712)	(0.938)	(-0.516)
SMB	0.001	-0.096	-0.097
	(0.004)	(-0.056)	(-0.537)
HML	-0.013	0.025	-0.053
	(-0.079)	(0.180)	(-0.227)
RMW			-0.418
			(-1.241)
CMA			-0.325
			(-1.255)
UMD		0.075	
		(0.805)	

Panel B: Value-weighted

	Fama-French three-factor model	Carhart four-factor alpha	Fama-French five-factor model
Alpha	0.670	0.651	0.897
	(1.997)	(1.889)	(2.408)
Market	-0.147	-0.140	-0.223
	(-2.051)	(-1.849)	(-2.339)
SMB	0.149	0.145	0.045
	(0.699)	(0.677)	(0.202)
HML	0.128	0.142	0.025
	(0.624)	(0.665)	(0.087)
RMW			-0.517
			(-1.225)
CMA			-0.271
			(-0.836)
UMD		0.029	
		(0.244)	

4. Robustness

4.1. Fama-MacBeth test

Motivated by Grullo et al. (2020), I test the robustness of the predictive power of sales seasonality by running a cross-sectional asset-pricing test, the Fama-MacBeth test (Fama and MacBeth, 1973). I test if the results of sales seasonality predictive power from the decile portfolio test hold when I control for other return predicting variables. This approach allows me to control multiple variables at the same time. I perform the test in two main phases by the example of Grullo et al. (2020). In the first phase, I regress the monthly excess returns on the measure of sales seasonality (SEA), to access the relationship between returns and sales seasonality more closely. In the second phase, I run a Fama-MacBeth regression of monthly excess returns on all the following variables similar to Grullo et al. (2020): (i) measure of sales seasonality (SEA), (ii) the log of the market value of equity (LogME), (iii) book-to-market (BM), (iv) gross profits divided by assets (GPA), (v) momentum (MOM), (vi) return seasonality (HS36). In Appendix A, I define each of the variables used.

In Table 4, I report the coefficients from the Fama-MacBeth test and t-statistics in parenthesis. The results are divided into three different entities, including Full sample, Small firms, and Big firms (from left to right). The split between small and big firms is done by identifying companies above and below the median of my sample. As in the results shown by Grullo et al. (2020) and in line with my hypothesis, I expect the SEA coefficient to be negative.

The results presented in Table 4 indicate that my previous findings from the decile portfolio test are robust to other return predicting variables and that the seasonality of the sales is negatively correlated with the future stock returns. In all of the cross-sectional regressions presented, the SEA has a negative and statistically significant coefficient. In the first regression with the SEA as the only variable in the full sample, the coefficient of the SEA is -0.080 with a t-statistic of -7.457. Full sample results with all the variables included show that sales seasonality remains statistically significant when all the variables are included in the regression with a t-statistic of -7.267 and SEA coefficient of -0.083. Comparing the results from tests with small and big firms verifies my earlier findings of sales seasonality being more of a big firm phenomenon since the effect is stronger among larger films. Big firms -sample results show that when regressed with all the variables, SEA produces a coefficient of -0.118 with a t-statistic of -7.992 compared to small firms with a SEA coefficient of -0.075 with a t- statistic of -6.022.

Table 4
Fama-MacBeth regressions
This table reports coefficients from Fama and MacBeth (1973) regressions of monthly excess returns on sales seasonality and other variables. Variables used are the log of the market value of equity (LogME), book-to-market (BM), gross profits divided by assets (GPA), and momentum (MOM) calculated from t – 12 to t – 2. HS36 is the three-month's average of the previous same month returns. SEA is equal to sales in quarter q of a year t divided by the annual sales in year t. To prevent any possible outlier impact, I form variable AVGSEA, which is equal to the average of SEA over the years t-2 and t-3. I then use AVGSEA in year t-2 to predict SEA in the year t to ensure that all the data is available to the investors when forming their portfolio. Under the label, Full sample, are all the observations that are included. Under the label, Small firms, are all the observations below the sample median and under the label, Big firms, are all the observations above the sample median. Model 1 represents the regression between excess returns and the measure of SEA. Model 2 represents the regression between excess returns and all the variables mentioned above. The sample consists of all nonfinancial firms in the Asian markets from January 2004 to December 2019.

	Full sample		Small firms		Big firms	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Intercept	0.596	0.595	0.660	0.694	0.560	0.562
	(2.127)	(1.832)	(2.081)	(1.811)	(2.238)	(1.873)
SEA	-0.080	-0.083	-0.070	-0.075	-0.120	-0.118
	(-7.457)	(-7.267)	(-6.462)	(-6.022)	(-8.268)	(-7.992)
LogME		-0.005		-0.003		-0.012
		(-0.202)		(-0.196)		(-0.217)
BM		-0.002		-0.003		-0.002
		(-0.286)		(-0.326)		(-0.371)
GPA		0.792		0.652		0.794
		(0.898)		(0.862)		(0.928)
MOM		-0.029		-0.032		-0.032
		(-0.733)		(-0.621)		(-0.416)
HS36		0.151		0.210		0.178
		(0.254)		(0.265)		(0.223)

4.2. Alternative measures of firms' economic activity

I perform a robustness check to the results from the decile portfolio test by using alternative measures of firms' economic activity, including the cost of goods sold (COGS), sales and administrative expenses (SGA), gross profits (GP), and net income (NI). In the main test, sales are used to identify seasonal patterns since they are always nonnegative and are not that sensitive to any changes in the firm's capital structure or to the presence of unusual and nonrecurring items. This robustness check allows me to see how seasonality in firms' other economic activities affects the results.

This test is performed the same way as the decile portfolio test by grouping firms into ten different deciles based on their seasonality measure. The measure is constructed the same way as in the main test, but the variable used for identifying seasonality is different (i.e. cost of goods sold, sales and administrative expenses, gross profits, and net income)[3]. For variables that might have negative values, I divide the quarterly values by the absolute value of the annual sum of the quarterly level to generate the measure of seasonality. For example, if quarterly gross profits are 2, -4, 5, and -10, the annual absolute value is 21. This is the reason why I used, following the example of Grullo et al. (2020), the sales as the measurement of seasonality since firms with negative gross profits or net profit could be distributed to low-season portfolio several times within a year if they produced negative values in more than one season.

In table 5, I report the excess returns and alphas, and t-statistics for the robustness check. To save space, I only report the returns from the long-short portfolio, and in Appendix B, the full table with every coefficient for each measurement of economic activity. Panel A represents the results for the equally-weighted portfolio and Panel B for the value-weighted portfolio. The results from the decile portfolio for both equally and value-weighted seem to be robust to a change in measure used for firms' economic activity as the results from this robustness check are mostly similar to the results when using sales as a measurement. The results are not surprising since most of the firms' economic activities correlate with sales. Measures as the cost of goods sold and, sales and administrative expenses produce results similar to those by sales as a seasonality since they are usually nearly perfectly correlated with sales. Whereas, gross profit and net income produce weaker results since they might have the impact of accruals and nonrecurring items on financial variables included.

[3] In Appendix A, I describe in detail how each variable is constructed

Table 5

Robustness check with alternative measures for firms' economic activity

This table reports the results for the robustness check by changing the measurement for firms' economic activity. From left to right, excess returns of Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965), Fama-French three-factor alpha (Fama and French, 1993), Fama-French five-factor alpha (Fama and French, 2015), Carhart four-factor alpha (Carhart, 1997), and t-statistics in parenthesis. Measures used are sales seasonality (SEA), Cost of goods sold (COGS), sales and administrative expenses (SG&A), gross profits (GP), and net income (NI). The sample consists of all nonfinancial firms in the Asian markets from January 2004 to December 2019. Panel A reports the results for the equally-weighted portfolio and Panel B for the value-weighted portfolios.

Panel A: Equally-weighted

	Capital Asset Pricing Model	Fama-French three-factor model	Fama-French five-factor model	Carhart four-factor alpha
SEA	0.340	0.340	0.541	0.292
	(1.274)	(1.266)	(1.818)	(1.058)
COGS	0.103	0.297	0.250	0.153
	(1.255)	(1.213)	(1.611)	(1.591)
SGA	0.478	0.229	0.212	0.059
	(1.230)	(1.141)	(1.496)	(1.281)
GP	0.140	0.238	0.653	0.160
	(0.730)	(0.710)	(1.303)	(1.385)
NI	0.414	0.398	0.402	0.413
	(1.094)	(2.050)	(1.862)	(1.068)

Panel B: Value-weighted

	Capital Asset Pricing Model	Fama-French three-factor model	Fama-French five-factor model	Carhart four-factor alpha
SEA	0.680	0.670	0.897	0.651
	(2.036)	(1.997)	(2.408)	(1.889)
COGS	0.892	0.902	1.174	0.961
	(2.251)	(2.264)	(2.682)	(2.352)
SGA	0.778	0.777	0.863	0.785
	(1.874)	(1.860)	(1.853)	(1.827)
GP	0.794	0.797	0.987	0.933
	(2.548)	(2.543)	(2.858)	(2.932)
NI	0.442	0.509	0.601	0.611
	(1.126)	(1.144)	(1.310)	(1.313)

4.3. Different regression data

To test the robustness of the results from the decile portfolio test, I regress the portfolios with different regression datasets. In this test, I will regress the portfolios assembled in the decile portfolio test with datasets of Japanese data, Asia ex-Japan, and Developed countries retrieved from Kenneth French's website[4]. This robustness check is important since although stock market data was taken from the Asian stock markets, different platforms used in this study (e.g. Thomson Reuters Eikon, Kenneth French) have different definitions for the Asian markets.

In table 6, I report the excess returns and alphas, and t-statistics for the long-short portfolios from the decile portfolio test regressed with the Japanese, Asia ex-Japan, and Developed countries data. Panel A represents the results for the equally-weighted portfolio and Panel B for the value-weighted portfolio. The results from the decile portfolio for both equally and value-weighted seem to be robust to the changes in the data used for the regressions as the results from this robustness check are mostly similar to the results from the decile portfolio test.

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

Table 6

Robustness check for regression data

This table reports the results of the robustness check to the decile portfolio test by changing the data used for the regressions. The returns are the excess returns of Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965), Fama-French three-factor alpha (Fama and French, 1993), Fama-French five-factor alpha (Fama and French, 2015), and t-statistics in parenthesis. The data used for the regressions are taken from the Fama-French website. The sample consists of all nonfinancial firms in the Asian markets from January 2004 to December 2019. Panel A reports the results for the equally-weighted portfolio and Panel B reports for the value-weighted portfolios.

Panel A: Equally-weighted			
	Japan	Asia ex-Japan	Developed
Capital asset pricing model	0.340	0.327	0.339
	(1.279)	(1.225)	(1.263)
Fama-French three-factor model	0.352	0.363	0.343
	(1.308)	(1.340)	(1.267)
Fama-French five-factor model	0.421	0.377	0.705
	(1.542)	(1.338)	(2.433)
Panel B: Value-weighted			
	Japan	Asia ex-Japan	Developed
Capital asset pricing model	0.648	0.679	0.707
	(1.932)	(2.018)	(2.105)
Fama-French three-factor model	0.589	0.687	0.710
	(1.753)	(2.005)	(2.121)
Fama-French five-factor model	0.606	0.848	1.094
	(1.769)	(2.413)	(3.026)

4.4. Chaining portfolio sizes

To further test the robustness of the results from the decile portfolio test, I change the portfolio sizes used in the test to see whether this has a significant effect on the results. In the main test, I constructed ten portfolios based on the AVGSEA, and for the robustness check, I produce only five portfolios to double the number of firms in each portfolio. After constructing the portfolios, I form the long-short portfolio for equally and value-weighted, which buys the firms in the first decile (Low 1) and shorts the firms in the last decile (High 5) as it was done in the main test.

In Table 7, I report the excess returns and alphas, and t-statistics for the long-short portfolios from the robustness check. Panel A represents the results for the equally-weighted portfolio and Panel B for the value-weighted portfolio. To save space, I only report the returns from the long-short portfolio and the full tables in Appendix B.

Panel A shows that results from the decile portfolio test are robust to changes in portfolio sizes when examined the equally-weighted portfolios as the results are similar to the results from the decile portfolio test. Panel B shows that results from the decile portfolio test are not as robust to changes in portfolio sizes when comparing results from value-weighted to equally-weighted. Fama-French five-factor alpha decreases from a t-statistic of 2.408 to 1.705 when changing the portfolio sizes. This decrease is significant since it drops the significance level from 5% to 10%. The results are the same with excess returns and Fama-French three-factor alpha since there can be found a clear change in significance level.

This decrease in returns seems to be driven by the poor performance of low sales seasonality firms which might be due to an increase in portfolio sizes which have decreased the effect of low-sales seasonality. Additionally, doubling the portfolio sizes, the long-short portfolio now consists of almost 1/3 of the firms in the sample. For this reason, the results of this robustness check should be taken with caution.

Table 7

Robustness check for portfolio sizes

This table reports the results of the robustness check to decile portfolio test by changing the portfolio sizes from ten to five. The returns are the excess returns of Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965), Fama-French three-factor alpha (Fama and French, 1993), Fama-French five-factor alpha (Fama and French, 2015), and t-statistics in parenthesis. Panel A reports the results for the equally-weighted portfolio and Panel B for the value-weighted portfolios. The sample consists of all nonfinancial firms in the Asian markets from January 2004 to December 2019.

Panel A: Equally-weighted

	Five deciles			Ten deciles		
	Capital asset pricing model	Fama-French three-factor model	Fama-French five-factor model	Capital asset pricing model	Fama-French three-factor model	Fama-French five-factor model
Alpha	0.164	0.163	0.472	0.340	0.340	0.541
	(0.741)	(0.733)	(1.964)	(1.274)	(1.266)	(1.818)
Market	0.018	0.023	-0.110	0.040	0.040	-0.039
	(0.391)	(0.474)	(-1.798)	(0.719)	(0.712)	(-0.516)
SMB		0.033	-0.120		0.001	-0.097
		(0.236)	(-0.829)		(0.004)	(-0.537)
HML		-0.044	-0.067		-0.013	-0.053
		(-0.328)	(-0.355)		(-0.079)	(-0.227)
RMW			-0.613			-0.418
			(-2.250)			(-1.241)
CMA			-0.566			-0.325
			(-2.706)			(-1.255)

Panel B: Value-weighted

	Five deciles			Ten deciles		
	Capital asset pricing model	Fama-French three-factor model	Fama-French five-factor model	Capital asset pricing model	Fama-French three-factor model	Fama-French five-factor model
Alpha	0.495	0.490	0.631	0.680	0.670	0.897
	(1.498)	(1.479)	(1.705)	(2.036)	(1.997)	(2.408)
Market	0.001	-0.003	-0.033	-0.147	-0.147	-0.223
	(0.013)	(-0.047)	(-0.347)	(-2.108)	(-2.051)	(-2.339)
SMB		0.047	-0.009		0.149	0.045
		(0.224)	(-0.041)		(0.699)	(0.202)
HML		0.108	-0.025		0.128	0.025
		(0.533)	(-0.085)		(0.624)	(0.087)
RMW			-0.374			-0.517
			(-0.892)			(-1.225)
CMA			-0.051			-0.271
			(-0.157)			(-0.836)

5. Conclusions

In this paper, I study the predictive power of sales seasonality over stock returns in the Asian stock markets. The sample period is from January 2004 to December 2019 and it includes over 1400 firms. I use the decile portfolio test to test the predictive power of sales seasonality (SEA). In the decile portfolio test, I divide the sample of firms into ten decile portfolios based on the AVGSEA, which is equal to the average of SEA over the years t - 2 and t - 3. This is done to ensure that all the data is available to the investors when formatting the portfolio. After constructing the portfolios, I examine differences in returns between the decile portfolios and compare the differences between equally and value-weighted portfolios.

I find economically and statistically significant results that low-sales season firms produce higher returns than the high-sales season firms. A long-short portfolio that buys the low-sales season firms and shorts the firms in their high-sales season produces an annual alpha of 4.08% - 6.49% with an equally-weighted portfolio and 8.04% - 10.76% with a value-weighted portfolio. Results from additional testing indicate that the sales seasonality premium is stronger among big firms and not driven by the small firm effect, and that a factor based on sales seasonality (SEAF) is uncorrelated with the known factors by Fama-French. These results hold when testing the robustness of the predictive power of sales seasonality by running a cross-sectional asset pricing test, the Fama-MacBeth test (Fama and MacBeth, 1973), and when controlling for other return predicting variables. I perform multiple other robustness checks and find that the results are robust to changes in portfolio sizes, data used for the regressions, and changes in the measure of firms' economic activities.

The research done in this paper provides further evidence on the predictive power of sales seasonality over stock returns: the effect can be found in the Asian stock markets. In the Asian stock markets, the size of the effect is slightly larger than what was found by Grullo et al. (2020) but it is not as significant. My findings provide support for the earlier findings of the sales seasonality being derived from the long-leg of the portfolios and that the effect is uncorrelated with the known factors by Fama-French. Even though the results were similar to what was found before, there are still points of concern that could be researched further on. The main concern is the size of the sample since data was only available from the year 2003 and not for as many firms as would be appropriate. A small sample size with an insufficient amount of data could mean the possible emergence of outliers. Further research could try to find evidence in other large markets where there would be more data available. Furthermore, the research with Asian markets should be revised in the future when there is a longer time period available.

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APPENDIX A

This appendix defines the variables used in this paper.

Variable code	Database	Description
AVGSEA	Thomson Reuters	AVGSEA is equal to the average of SEA in the years t -2 and t - 3
BE	Thomson Reuters	BE is the book value of equity in January of the year t
BM	Thomson Reuters	BE of fiscal year divided by ME in December of year t - 1
GPA	Thomson Reuters	GPA is equal to sales minus cost of goods sold divided by total assets in calendar year t - 1
HS36	Thomson Reuters	HS36 is the average returns for month t -12, month t - 24 and t - 36
LogME	Thomson Reuters	LogME is the logarithm of ME
ME	Thomson Reuters	Shares outstanding times the absolute value of price in January of the year t
MOM	Thomson Reuters	The cumulative return from month t – 12 to t -2
SEA	Thomson Reuters	SEA is equal to sales in quarter q of a year t divided by the annual sales
CGSEA	Thomson Reuters	CGSEA is equal to cost of goods sold (COGS) in quarter q of the year divided by the annual cost of goods sold (COGS) in year t
GPSEA	Thomson Reuters	GPSEA is equal to gross profit (GP) in quarter q of the year divided by the annual gross profit (GP) in year t
NISEA	Thomson Reuters	NISEA is equal to net income (NI) in quarter q of the year divided by the annual net income (NI) in year t
SGASEA	Thomson Reuters	SGASEA is equal to selling, general, and administrative expenses (SGA) in quarter q of the year divided by the annual selling, general, and administrative expenses (SGA) in year t
SEAF	Thomson Reuters	SEAF is constructed using the method described in the Kenneth French website for factor construction. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data _ library.html

APPENDIX B

Tabel B1

Robustness check for portfolio sizes

This table reports the results of the robustness check to decile portfolio test by changing the portfolio sizes from ten to five. The results are the excess returns of Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965), Fama-French three-factor alpha (Fama and French, 1993), Fama-French five-factor alpha (Fama and French, 2015), and t-statistics in parenthesis. The last column reports the excess returns and alphas of a long-short (L-H) portfolio, which buys firms in the Low 1 decile and shorts firms in the High (5) decile. The sample consists of all nonfinancial firms in the Asian markets from January 2004 to December 2019. Panel A reports the results for the equally-weighted portfolio and Panel B reports the results for the value-weighted portfolios.

Panel A: Equally-weighted						
	Low (1)	2	3	4	High (5)	L-H
Capital asset pricing model						
Alpha	1.265	0.932	0.965	1.058	1.101	0.164
	(3.281)	(3.000)	(3.432)	(3.630)	(3.226)	(0.741)
Market	0.660	0.652	0.595	0.620	0.642	0.018
	(8.218)	(10.090)	(10.163)	(10.220)	(9.031)	(0.391)
Fama-French three-factor model						
Alpha	1.234	0.906	0.938	1.032	1.070	0.163
	(3.252)	(2.976)	(3.420)	(3.610)	(3.197)	(0.733)
Market	0.697	0.687	0.626	0.649	0.674	0.023
	(8.617)	(10.587)	(10.715)	(10.649)	(9.449)	(0.474)
SMB	0.657	0.565	0.567	0.535	0.624	0.033
	(2.724)	(2.918)	(3.250)	(2.941)	(2.930)	(0.236)
HML	-0.047	-0.081	-0.026	-0.009	-0.003	-0.044
	(-0.204)	(-0.438)	(-0.156)	(-0.053)	(-0.013)	(-0.328)
Fama-French five-factor model						
Alpha	1.905	1.424	1.331	1.409	1.433	0.472
	(4.477)	(4.478)	(4.552)	(4.593)	(3.913)	(1.964)
Market	0.401	0.428	0.431	0.457	0.511	-0.110
	(3.928)	(5.275)	(5.766)	(5.836)	(5.468)	(-1.798)
SMB	0.320	0.291	0.359	0.334	0.440	-0.120
	(1.325)	(1.515)	(2.032)	(1.802)	(1.991)	(-0.829)
HML	-0.068	0.020	0.047	0.078	-0.001	-0.067
	(-0.217)	(0.081)	(0.207)	(0.326)	(-0.004)	(-0.355)
RMW	-1.310	-0.920	-0.702	-0.659	-0.697	-0.613
	(-2.894)	(-2.556)	(-2.119)	(-1.898)	(-1.681)	(-2.250)
CMA	-1.277	-1.186	-0.894	-0.886	-0.711	-0.566
	(-3.676)	(-4.290)	(-3.519)	(-3.324)	(-2.235)	(-2.706)

Panel B: Value-weighted						
	Low (1)	2	3	4	High (5)	L-H
Capital asset pricing model						
Alpha	1.550	1.032	0.976	1.060	1.055	0.495
	(4.246)	(3.658)	(3.877)	(3.642)	(2.668)	(1.498)
Market	0.743	0.794	0.665	0.737	0.742	0.001
	(9.780)	(13.524)	(12.691)	(12.174)	(9.017)	(0.013)
Fama-French three-factor model						
Alpha	1.526	1.019	0.976	1.055	1.036	0.490
	(4.226)	(3.628)	(3.854)	(3.608)	(2.641)	(1.479)
Market	0.777	0.817	0.673	0.748	0.780	-0.003
	(10.093)	(13.664)	(12.468)	(12.005)	(9.330)	(-0.047)
SMB	0.525	0.314	0.047	0.131	0.478	0.047
	(2.288)	(1.758)	(0.294)	(0.706)	(1.917)	(0.224)
HML	-0.103	-0.100	-0.085	-0.064	-0.210	0.108
	(-0.467)	(-0.584)	(-0.554)	(-0.359)	(-0.881)	(0.553)
Fama-French five-factor model						
Alpha	2.031	1.304	1.225	1.264	1.400	0.631
	(5.278)	(4.379)	(4.579)	(3.901)	(3.296)	(1.705)
Market	0.517	0.609	0.482	0.658	0.550	-0.033
	(5.257)	(8.010)	(7.049)	(7.955)	(5.065)	(-0.347)
SMB	0.255	0.134	-0.114	0.027	0.264	-0.009
	(1.096)	(0.747)	(-0.705)	(0.139)	(1.029)	(-0.041)
HML	0.026	0.209	0.223	-0.781	0.051	-0.025
	(0.086)	(0.894)	(1.064)	(-0.305)	(0.152)	(-0.085)
RMW	-0.876	-0.313	-0.244	-0.413	-0.502	-0.374
	(-2.009)	(-0.929)	(-0.804)	(-1.126)	(-1.043)	(-0.892)
CMA	-1.208	-1.085	-1.014	-0.390	-1.157	-0.051
	(-3.611)	(-4.190)	(-4.359)	(-1.364)	(-3.135)	(-0.157)

Table B2

The predictive power of cost of goods sold seasonality

This table reports the results from the robustness check for the decile portfolio test, where the cost of goods sold are used to measure the seasonality (CGSEA). CGSEA is equal to sales in quarter q of a year t divided by the annual sales in year t. To prevent any possible outlier impact, I form the variable AVGCGSEA, which is equal to the average of CGSEA over the years t-2 and t-3. I then use AVGCGSEA in year t-2 to predict CGSEA in the year t to ensure that all the data is available to the investors when formatting the portfolio. The results are the excess returns of Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965), Fama-French three-factor alpha (Fama and French, 1993), Fama-French five-factor alpha (Fama and French, 2015), Carhart four-factor alpha (Carhart, 1997), and t-statistics in parenthesis. The sample consists of all nonfinancial firms in the Asian markets from January 2004 to December 2019. Panel A reports the results for the equally-weighted portfolio and Panel B reports the results for the value-weighted portfolios.

Panel A: Equally-weighted

	Capital asset pricing model	Fama-French three-factor model	Fama-French five-factor model	Carhart four-factor alpha
Alpha	0.103	0.297	0.250	0.153
	(1.255)	(1.213)	(1.611)	(1.591)
Market	0.034	0.043	-0.042	0.024
	(0.854)	(1.070)	(-0.789)	(0.574)
SMB		0.136	0.051	0.148
		(1.128)	(0.403)	(1.226)
HML		-0.041	0.020	-0.084
		(-0.351)	(0.126)	(-0.706)
RMW			-0.251	
			(-1.067)	
CMA			-0.406	
			(-1.249)	
UMD				-0.087
				(-1.325)

Panel B: Value-weighted

	Capital asset pricing model	Fama-French three-factor model	Fama-French five-factor model	Carhart four-factor alpha
Alpha	0.892	0.902	1.174	0.961
	(2.251)	(2.264)	(2.682)	(2.352)
Market	-0.079	-0.089	-0.261	-0.109
	(-0.963)	(-1.051)	(-1.332)	(-1.211)
SMB		-0.193	-0.352	-0.180
		(-0.760)	(-1.332)	(-0.707)
HML		-0.005	0.187	-0.052
		(-0.020)	(0.545)	(-0.204)
RMW			-0.378	
			(-0.761)	
CMA			-0.860	
			(-1.260)	
UMD				-0.093
				(-0.668)

Table B3

The predictive power of sales and general administrative expenses seasonality

This table reports the results from the robustness check for the decile portfolio test, where sales and general administrative expenses are used to measure the seasonality (SGASEA). SGASEA is equal to sales in quarter q of a year t divided by the annual sales in year t. To prevent any possible outlier impact, I form variable AVGSGASEA, which is equal to the average of SGASEA over the years t-2 and t-3. I then use AVGSGASEA in year t-2 to predict SGASEA in the year t to ensure that all the data is available to the investors when formatting the portfolio. The results are the excess returns of Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965), Fama-French three-factor alpha (Fama and French, 1993), Fama-French five-factor alpha (Fama and French, 2015), Carhart four-factor alpha (Carhart, 1997), and t-statistics in parenthesis. The sample consists of all nonfinancial firms in the Asian markets from January 2004 to December 2019. Panel A reports the results for the equally-weighted portfolio and Panel B reports the results for the value-weighted portfolios.

Panel A: Equally-weighted				
	Capital asset pricing model	Fama-French three-factor model	Fama-French five-factor model	Carhart four-factor alpha
Alpha	0.478	0.229	0.212	0.059
	(1.230)	(1.141)	(1.496)	(1.281)
Market	0.075	0.096	0.037	0.086
	(1.731)	(1.208)	(0.642)	(1.862)
SMB		0.390	0.339	0.397
		(2.014)	(1.481)	(3.049)
HML		-0.008	0.075	-0.032
		(-0.067)	(0.424)	(-0.247)
RMW			-0.096	
			(-0.377)	
CMA			-0.305	
			(-1.554)	
UMD				-0.047
				(-0.660)
Panel B: Value-weighted				
Alpha	0.778	0.777	0.863	0.785
	(1.874)	(1.860)	(1.853)	(1.827)
Market	-0.036	-0.038	-0.105	-0.040
	(-0.412)	(-0.423)	(-0.882)	(-0.424)
SMB		0.000	-0.056	0.002
		(0.000)	(-0.200)	(0.006)
HML		0.034	0.145	0.028
		(0.132)	(0.398)	(0.104)
RMW			-0.080	
			(-0.152)	
CMA			-0.359	
			(-0.886)	
UMD				-0.011
				(-0.079)

Table B4

The predictive power of gross profit seasonality

This table reports the results from the robustness check for the decile portfolio test, where gross profits are used to measure the seasonality (GPSEA). GPSEA is equal to sales in quarter q of a year t divided by the annual sales in year t. To prevent any possible outlier impact, I form variable AVGGPSEA, which is equal to the average of GPSEA over the years t-2 and t-3. I then use AVGGPSEA in year t-2 to predict GPSEA in the year t to ensure that all the data is available to the investors when formatting the portfolio. The results are the excess returns of Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965), Fama-French three-factor alpha (Fama and French, 1993), Fama-French five-factor alpha (Fama and French, 2015), Carhart four-factor alpha (Carhart, 1997), and t-statistics in parenthesis. The sample consists of all nonfinancial firms in the Asian markets from January 2004 to December 2019.. Panel A reports the results for the equally-weighted portfolio and Panel B reports the results for the value-weighted portfolios.

	Capital asset pricing model	Fama-French three-factor model	Fama-French five-factor model	Carhart four-factor alpha
Panel A: Equally-weighted				
Alpha	0.140	0.238	0.653	0.160
	(0.730)	(0.710)	(1.303)	(1.385)
Market	0.076	0.083	0.057	0.062
	(0.895)	(1.011)	(1.029)	(1.426)
SMB		0.039	0.012	0.052
		(0.319)	(0.090)	(0.427)
HML		-0.080	-0.068	-0.128
		(-0.677)	(-0.403)	(-1.053)
RMW			-0.091	
			(-0.371)	
CMA			-0.120	
			(-0.644)	
UMD				-0.096
				(-1.444)
Panel B: Value-weighted				
Alpha	0.794	0.797	0.987	0.933
	(2.548)	(2.543)	(2.858)	(2.932)
Market	0.036	0.038	-0.088	-0.008
	(0.550)	(0.562)	(-0.998)	(-0.114)
SMB		-0.040	-0.154	-0.012
		(-0.203)	(-0.740)	(-0.058)
HML		-0.065	0.092	-0.172
		(-0.341)	(0.339)	(-0.874)
RMW			-0.245	
			(-0.627)	
CMA			-0.639	
			(-1.129)	
UMD				-0.211
				(-1.962)

Table B5

The predictive power of net income seasonality

This table reports the results from the robustness check for the decile portfolio test, where net income is used to measure the seasonality (NISEA). NISEA is equal to sales in quarter q of a year t divided by the annual sales in year t. To prevent any possible outlier impact, I form variable AVGNISEA, which is equal to the average of NISEA over the years t-2 and t-3. I then use AVGNISEA in year t-2 to predict NISEA in the year t to ensure that all the data is available to the investors when formatting the portfolio. The results are the excess returns of Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965), Fama-French three-factor alpha (Fama and French, 1993), Fama-French five-factor alpha (Fama and French, 2015), Carhart four-factor alpha (Carhart, 1997), and t-statistics in parenthesis. The sample consists of all nonfinancial firms in the Asian markets from January 2004 to December 2019. Panel A reports the results for the equally-weighted portfolio and Panel B reports the results for the value-weighted portfolios.

	Capital asset pricing model	Fama-French three-factor model	Fama-French five-factor model	Carhart four-factor alpha
Panel A: Equally-weighted				
Alpha	0.414	0.398	0.402	0.413
	(1.094)	(2.050)	(1.862)	(1.068)
Market	-0.017	0.004	-0.031	-0.001
	(-0.407)	(0.099)	(-0.562)	(-0.018)
SMB		0.334	0.327	0.347
		(1.786)	(1.509)	(1.796)
HML		-0.046	0.084	-0.058
		(-0.389)	(0.494)	(-0.466)
RMW			0.092	
			(0.376)	
CMA			-0.229	
			(-1.220)	
UMD				-0.023
				(-0.336)
Panel B: Value-weighted				
Alpha	0.442	0.509	0.601	0.611
	(1.126)	(1.144)	(1.310)	(1.313)
Market	0.215	0.222	0.248	0.202
	(1.937)	(1.953)	(1.455)	(1.522)
SMB		-0.061	-0.031	-0.048
		(-0.273)	(-0.129)	(-0.213)
HML		-0.172	-0.159	-0.221
		(-0.798)	(-0.513)	(-0.985)
RMW			0.132	
			(0.295)	
CMA			0.102	
			(0.297)	
UMD				-0.097
				(-0.789)