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The seasonality in sell-side analysts' recommendations

Yury O. Kucheev[a,b], Tomas Sorensson[b,c,*]

[a] Department of Industrial Management, Business Administration and Statistics, School of Industrial Engineering, Technical University of Madrid (UPM)/Universidad Politécnica de Madrid, c/ José Gutiérrez Abascal, 2, Madrid 28006, Spain

[b] Department of Industrial Economics and Management, School of Industrial Engineering and Management, KTH Royal Institute of Technology, SE-100 44, Stockholm, Sweden

[c] Swedish House of Finance, Stockholm School of Economics, Stockholm, Sweden

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ABSTRACT

We examine whether highly reputed sell-side analysts (Stars) account for stock market seasonality in their forecasts. Extensive research has documented that seasonality exists in the stock market, and in their quest to become Stars, analysts may consider seasonality when they issue recommendations. We find that both Star and Non-Star analysts are highly optimistic in May, which contradicts the adage "Sell in May and go away". Detailed analyses reveal that optimism cycles are related to the calendar of companies' earnings announcements rather than market-specific effects. When they issue recommendations, analysts tend not to consider three well-known seasonal effects that we investigate.

1. Introduction

Investors and researchers are interested in whether seasonal patterns exist in analysts' recommendations and whether such patterns represent one of the differences between Star and Non-Star analysts. Although we assume market efficiency, empirical research documents significant seasonal anomalies for a number of financial markets (see, e.g., Baker and Wurgler (2006), Kelly and Meschke (2010), Keloharju et al. (2016)). Well-documented seasonal market anomalies include Monday, Friday, turn of the month, January, September, and "Sell in May" (returns are close to zero from May through October) effects (Bouman and Jacobsen, 2002; Dowling and Lucey, 2008), which are broadly covered by practitioners (Klement, 2016; Fidelity, 2017). Seasonality has also been reported for sell-side analysts' earnings forecasts and pricing of IPOs (Dolvin and Pyles, 2007; Doeswijk, 2008), as well as for recommendation changes (Kliger and Kudryavtsev, 2014). Although the true cause of seasonal anomalies is highly debated, all of these papers conclude that seasonal patterns exist in financial markets and affect the majority of market players.

Ratings of so-called Star analysts can help market participants identify analysts with an advanced ability to produce valuable information. Groysberg et al. (2011) find that recognition as a Star is very important for analysts because it significantly influences their compensation. Other important determinants of compensation include generating trading commissions and receiving favourable broker votes, which lead to well-documented conflicts of interests in sell-side research. Bradshaw (2011) summarizes the literature on financial analysts and argues that analysts' forecasts are believed to be persistently over-optimistic. At the same time, analysts are motivated to issue accurate earnings forecasts because these forecasts are inputs in their stock recommendations and, if accurate and profitable, could lead to an increase in analysts' credibility with investing clients. Lim (2001) develops a model showing that rational analysts may optimally report optimistically biased forecasts to gain access to private information from the covered firm's

* Corresponding author at: Department of Industrial Economics and Management, School of Industrial Engineering and Management, KTH Royal Institute of Technology, SE-100 44, Stockholm, Sweden.

E-mail address: tomas.sorensson@indek.kth.se (T. Sorensson).

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management.

Although academic researchers, managers of listed companies, and investors have long been interested in the value of analysts' reports (Brav and Lehavy, 2003), there are fewer studies on the context of analysts' decision making. For this reason, Ramnath et al., (2008), Bradshaw (2011), and Fang and Yasuda (2014, p. 236) call for more research on the "black box" of analysts' decision-making processes, which we address in our study.

Based on earlier findings, we expect to observe seasonal patterns in analysts' target prices and recommendations. However, if Star analysts indeed outperform Non-Stars, they may be more aware of seasonality and consider these anomalies in their forecasts. We hypothesize that well-known seasonal anomalies could be used strategically by analysts to time the market. Using the US market data for 2003–2014, combined with analysts' target prices and recommendations, we test for any difference in the seasonality patterns for Star and Non-Star analysts and determine how analysts' optimism varies over time depending on a number of seasonal factors. We then discuss the potential source of such a bias. Given the relatively few number of studies on analysts' target prices (Bonini et al., 2010; Bilinski et al., 2013; Bradshaw et al., 2013), our study contributes to this literature by providing a detailed analysis of the expected returns on analysts' target prices and their link to analysts' recommendations, as well as to overall market performance and companies' reporting activities.

Our results show that neither the Stars nor Non-Stars group of analysts follows well-known seasonal effects. Analysts are most optimistic in May and issue more optimistic target prices in the summer than in winter, which contradicts the "Sell in May and go away" adage. In particular, Non-Stars are more optimistic than Stars in their Buy and Hold recommendations and less pessimistic than Stars in their Sell recommendations. Further investigation revealed that the optimism in target prices is related to the calendar of companies' earnings announcements rather than to the seasonality of market returns. Previous studies conclude that seasonality in aggregated market returns is independent of earnings announcements (see, e.g., Barber et al., 2013; Fang et al., 2018; Heston and Sadka, 2008). We contribute to this debate by showing that earnings announcements, however, are correlated with another market seasonal pattern, namely with optimism cycles in analysts' target prices.

2. Data

Analysts' recommendations and target prices come from the Thomson Financial Institutional Brokers' Estimate System (I/B/E/S). Monthly market returns and risk factors come from the Fama–French and CRSP database. Manually collected lists of Star analysts from *Institutional Investor* magazine (October 2003 – October 2013), *The Wall Street Journal* (May 2003 – April 2013), and *StarMine* (October 2003 – August 2013) were matched with I/B/E/S by analysts' names and broker affiliations and double-checked for any possible inconsistencies (typos, affiliation changes, etc.). Earnings announcement dates come from the *Compustat* database (*RDQ* variable).

The sample of analysts is divided into groups of Stars (1,924 non-repeating names) and Non-Stars (7,658 unique names of analysts not listed as Stars in a given year). When a particular analyst is rated as a Star in two different rankings or industries, the analyst is included only once in the group of Stars. On average, our sample consists of approximately 15 percent of the analysts listed as Stars every year. Out of 9,582 analysts overall, 20 percent have been selected at least once as Stars.

We omit "penny stocks" and only retain target prices for companies that have a stock price of more than one dollar on the preceding trading day. Similarly to Huang et al. (2009), we define the target price expected return, *TPER*, as $TP_t/P_{t-1}-1$, where TP_t is the analysts target price with a 12-month horizon issued on day t; and P_{t-1} is the stock price on the previous trading day before t. To avoid influence of outliers, we cut 5 percent of target price observations from both sides of the distribution.[1] Our recommendation dataset contains only recommendation changes, as previous studies show that the changes have significant investment value relative to the levels (Boni and Womack, 2006). We merge the *TPER* and recommendation changes datasets using analysts' identification numbers and announcement dates (variables AMASKCD and ANNDATS in I/B/E/S) and omit those observations that do not match.

Our final database contains 67,973 target prices for 5,142 companies listed on the NYSE, AMEX and NASDAQ markets that were announced between November 2003 and November 2014 (we exclude October 2003 because of its incompleteness). The final sample of *TPER* has a mean value of 10.12 percent, minimum of −45.65 percent, and maximum of 59.58 percent. Table 1 reports the number of target prices conditional on recommendation categories. Non-Stars issued 3.6 times more target prices (53,239) than Stars (14,734). Both Stars and Non-Stars have similar distributions of target prices among the recommendation categories, with 47 percent of target prices on the Buy level, 41 percent on Hold, and 12 percent on Sell. For both groups, target prices were evenly distributed between the summer and winter seasons.

3. Methods

We employ an OLS regression analysis similar to Bouman and Jacobsen (2002) and the Carhart four-factor model (Carhart, 1997) with seasonal dummy variables:

$$Rm_m = \mu + \gamma DT_m + \varepsilon_m, \tag{1}$$

$$R_{j,m} - Rf_m = \alpha_m + \gamma DT_m + \beta(Rm_m - Rf_m) + sSMB_m + hHML_m + mUMD_m + \varepsilon_m, \tag{2}$$

[1] Descriptive statistics for our initial and final samples are available upon request. The results of our study are qualitatively the same if we repeat our tests on the sample limited to TPER of (-1;1) and with a 1% cut of outliers.

Table 1
Number of target prices for each recommendation category for Stars (Panel A) and Non-Stars (Panel B) from November 2003 – November 2014.

Portfolio	Number of *TPER* and % from All						
	Total (Winter + Summer)		Winter		Summer		Winter, % from Total
	No. *TPER*	% from All	No.	%	No.	%	
Panel A. Stars							
Buy	6866	47%	3439	46%	3427	47%	50%
Hold	6079	41%	3085	41%	2994	41%	50%
Sell	1789	12%	910	13%	879	12%	51%
All:	14734	100%	7434	100%	7300	100%	50%
Panel B. Non-Stars							
Buy	25035	47%	12598	47%	12437	47%	50%
Hold	22010	41%	10909	41%	11101	42%	50%
Sell	6194	12%	3067	12%	3127	12%	50%
All:	53239	100%	26574	100%	26665	100%	50%

Target price expected return, *TPER*, is defined as TP_t/P_{t-1}–1, where TP_t is the analyst's target price with a 12-month horizon issued on day *t*; and P_{t-1} is the share price on the previous trading day before *t*. The Buy portfolio includes Strong Buy and Buy recommendations; Sell includes Strong Sell and Sell; Hold includes Holds. *Winter* season is from November until April, as in Bouman and Jacobsen (2002). Star analysts are those listed in *The Wall Street Journal, Institutional Investor*, and Thomson Reuters' *StarMine* "Top Stock Pickers" and "Top Earnings Estimators". Analysts in the group of Non-Stars are those who are not listed in any of the mentioned Star rankings during a particular evaluation year. Ratings are published from May 2003 to November 2013.

where:

Rm_m is the market return on month *m* (value-weighted portfolio of all stocks with share code 10 or 11 in CRSP).
DT_m is a seasonal dummy: equal to 1 for *winter* (the period from November to April) and zero otherwise (Bouman and Jacobsen, 2002); or equal to 1 for the month of January, May, or September (all regressions run separately),
Rf_m is the risk-free rate,
SMB_m, HML_m, UMD_m are the monthly risk factors representing the differences in returns on small versus big stocks, high versus low book-to-market stocks, and high versus low recent returns, respectively.

The coefficients in the model are interpreted as follows. To study seasonal anomalies, such as the difference between *summer* and *winter*, coefficient μ will return a mean value during the summer and γ will show the difference between seasons and the statistical significance of this difference.

4. Results

4.1. Seasonality in market returns

Table 2 reports the regression coefficients of the returns of the aggregated market (columns 1–3 for different sample periods) and of individual stocks (column 4 for unadjusted and column 5 for risk-adjusted returns) on the seasonal dummy variables. The aggregated market returns during 1970–2014 had a significant winter and September seasonality (column 1 in Table 2), with 0.98 pp higher returns in winter than in summer, and 1.44 pp lower returns in September than in other months. From 1970–2003 (column 2), which immediately precedes our sample of target prices, only September had a significant seasonality, with 2.29 pp lower returns in that month than in other months. During 2003–2014 (column 3), none of the seasonal effects had a significant coefficient. However, all seasonal effects on the level of individual stocks (columns 4 and 5) were statistically significant, both unadjusted and adjusted for the risk factors. Considering the observed significant seasonality for individual stocks and for the extended sample period as well as the broad coverage of seasonality in the extant literature and periodic news, we assume that analysts are aware of market seasonality.

4.2. Seasonality in target prices

Table 3 reports the average target price expected return for Stars (Panel A) and Non-Stars (Panel B) in different seasons as well as the difference between Non-Stars and Stars (Panel C). Both groups of analysts issue more optimistic target prices in summer than in winter. Non-Stars have 1.06 pp more optimistic *TPER*s than Stars, regardless of recommendation. Conditional on recommendation categories, Non-Stars are more optimistic on Buy and Hold levels and less pessimistic in their Sell recommendations. For the group of Non-Stars, the differences between seasons are statistically significant for all recommendation levels. For the Stars, only the Buy and Hold levels show a significant increase in optimism in summer, while their *TPER*s on the level of Sell recommendations are insignificantly different between seasons.

Fig. 1 plots the average *TPER* over a calendar year and reveals a clear time-varying dependence, with three peaks in March, May/June, and August. Both Stars and Non-Stars show similar patterns, with Non-Stars having systematically more optimistic *TPER*s in all

Table 2
Seasonal effects in CRSP market returns.

	Market Value-Weighted Returns (Rm_m), %			Returns on Individual Stocks ($R_{j,m}$), %	
	1970–2014 (1)	1970–2003 (2)	2003–2014 (3)	2003–2014 (4)	Carhart-4F 2003–2014 (5)
Winter	0.98**	0.85	0.89	1.42***	0.41***
	(2.49)	(1.56)	(1.22)	(45.49)	(13.94)
January	0.59	0.99	−1.22	1.19***	1.90***
	(0.82)	(1.00)	(−0.92)	(20.98)	(34.88)
May	−0.14	0.78	−0.64	−0.63***	−0.09*
	(−0.19)	(0.79)	(−0.48)	(−11.15)	(−1.67)
September	−1.44**	−2.29**	0.09	−0.26***	−0.09*
	(−2.02)	(−2.34)	(0.07)	(−4.61)	(−1.67)

The reported values correspond to the γ coefficients obtained from the following regressions.
Columns 1–3: for monthly (geometrically compounded) value-weighted returns of the market Rm_m (CRSP index) regressed as in Eq. (1): $Rm_m = \mu + \gamma DT_m + \varepsilon_m$.
Column 4: for monthly returns on individual stocks, $R_{j,m}$ (return on stock j on month m).
Column 5: monthly returns on individual stocks adjusted for the four risk factors in the Carhart four-factor model (Carhart, 1997) with fifth time dummy variable (Carhart-4F):
$R_{j,m} - Rf_m = \alpha_m + \gamma DT_m + \beta(Rm_m - Rf_m) + sSMB_m + hHML_m + mUMD_m + \varepsilon_m$.
In all regressions, DT_m is the seasonal dummy variable, which is equal to 1 during either winter (from November to April), January, May, or September, and 0 otherwise. Regressions for different dummy variables are run separately.
t-statistics in parentheses
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$.

Table 3
Average target price expected return, *TPER*, conditional on the season for each recommendation category for Non-Stars and Stars.

Portfolio	Average *TPER*, %			Diff: Summer-Winter	
	Total	Winter	Summer	Diff.	*t*-stat
Panel A. Stars					
Buy	19.44	19.14	19.78	0.65*	(1.35)
Hold	4.62	4.49	4.75	0.26	(0.79)
Sell	−13.76	−14.13	−13.37	0.76	(1.24)
All:	9.3	8.98	9.62	0.64**	(1.95)
Panel B. Non-Stars					
Buy	20.51	19.94	21.09	1.15***	(4.67)
Hold	5.27	5.03	5.51	0.49***	(2.63)
Sell	−12.66	−13.44	−11.91	1.53***	(4.19)
All:	10.35	9.97	10.74	0.77***	(4.44)
Panel C. Diff. Non-Stars – Stars					
Buy	1.07***	0.08**	1.33***	–	–
	(4.01)	(2.18)	(3.51)	–	–
Hold	0.65***	0.53**	0.86***	–	–
	(3.30)	(1.91)	(2.74)	–	–
Sell	1.10***	0.70*	1.47***	–	–
	(2.90)	(1.31)	(2.74)	–	–
All:	1.06***	0.99***	1.12***	–	–
	(5.66)	(3.75)	(4.24)	–	–

Target price expected return, *TPER*, is defined as TP_t/P_{t-1}–1, where TP_t is the analyst's target price with a 12-month horizon issued on day *t*; and P_{t-1} is the share price on the previous trading day before *t*. The Buy portfolio includes Strong Buy and Buy recommendations; Sell includes Strong Sell and Sell; Hold includes Holds. *Winter* season is from November until April, as in Bouman and Jacobsen (2002).
t-statistics in parentheses
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$.

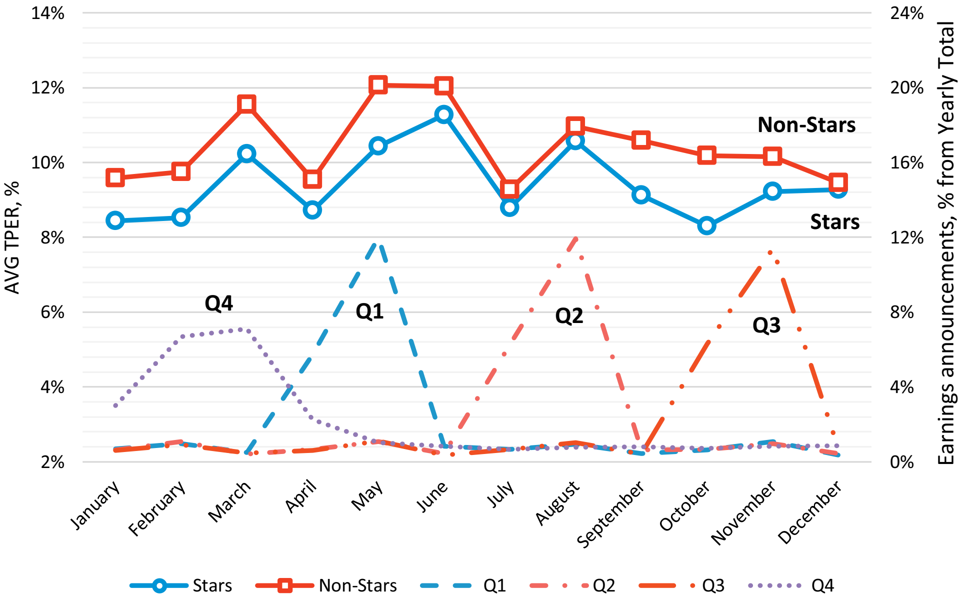

Fig. 1. Average monthly *TPER* (%) for Stars and Non-Stars and calendar of earnings announcements.
Target price expected return, *TPER*, is defined as $TP_t/P_{t-1}-1$, where TP_t is the analyst's target price with a 12-month horizon issued on day *t*; and P_{t-1} is the share price on the previous trading day before *t*. The fraction of EAs is the number of EAs issued by companies in a given month divided by the total number of EAs that year.

Table 4
Seasonality in expected returns on target prices.

	$TPER_m$, %			$TPER_m$ (%) regressed on Carhart-4F		
	All Analysts (1)	Stars (2)	Non-Stars (3)	All Analysts (4)	Stars (5)	Non-Stars (6)
Winter	−0.75***	−0.64*	−0.77***	−0.66***	−0.51	−0.70***
	(−4.86)	(−1.95)	(−4.44)	(−4.28)	(−1.54)	(−3.96)
January	−0.90***	−0.97*	−0.86***	−0.95***	−0.93*	−0.95***
	(−3.73)	(−1.93)	(−3.12)	(−3.85)	(−1.80)	(−3.36)
May	1.73***	1.24**	1.86***	1.69***	1.30**	1.79***
	(6.20)	(2.06)	(5.91)	(6.02)	(2.16)	(5.65)
September	0.12	−0.19	0.25	0.12	−0.20	0.24
	(0.41)	(−0.30)	(0.72)	(0.40)	(−0.33)	(0.71)

The reported coefficients γ are obtained by regressing the expected return on target price for firm *j* by analyst *i* on day *t* in month *m*, $TPER_{i,j,t}$, in the following models:
Columns 1–3: $TPER_{i,j,t} = \mu + \gamma DT_m + \varepsilon_m$,
Columns 4–6: adjusted for the four risk factors in the Carhart four-factor (Carhart-4F) model (Carhart, 1997) with fifth time dummy variable: $TPER_{i,j,t} = \alpha_m + \gamma DT_m + \beta(Rm_m - Rf_m) + sSMB_m + hHML_m + mUMD_m + \varepsilon_m$.
In all regressions, DT_m is the seasonal dummy variable, which is equal to 1 during either winter (from November to April), January, May, or September. Regressions for different dummy variables are run separately.
t-statistics in parentheses
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$.

months. The biggest difference between the groups is in January and October, while the smallest difference is in July and August.

Table 4 reports the results of testing the seasonality in *TPER* unadjusted for risk (columns 1–3)[2] as well as adjusted for Carhart risk factors (columns 4–6). The *May* dummy variable is included, as Fig. 1 displayed the highest target prices for both groups of analysts in May. All analysts, a joint group of Stars and Non-Stars, issue 1.73 pp more optimistic target prices in May than in other months, and 0.75 pp more optimistic target prices in winter than in summer. Analysts are 0.90 pp more pessimistic in January than in other months of the year. Surprisingly, none of the September seasonal coefficients was significantly different from zero, showing that

[2] The coefficients in the first row in columns 2 and 3 correspond to those reported in Table 3 for the difference between winter and summer periods for Stars and Non-Stars.

Table 5
The dependence of the average monthly target price expected returns, *TPER*, on monthly market returns for the total sample of analysts (Non-Stars and Stars), monthly values.

	Dependent variable					
Regressor	$TPER_m$ (1)	$TPER_m$ (2)	$TPER_m$ (3)	*Diff.* $TPER_m$ (4)	*Diff.* $TPER_m$ (5)	*Diff.* $TPER_m$ (6)
Rm_m	−0.08			−0.15***		
	(−1.48)			(−3.33)		
$L.Rm_m$		−0.09			0.00	
		(−1.52)			(0.05)	
$F.Rm_m$			0.07			−0.00
			(1.28)			(−0.04)
Constant	0.10***	0.10***	0.10***	0.00	0.00	0.00
	(40.20)	(40.01)	(40.53)	(0.98)	(0.35)	(0.20)
Adj. R^2, %	0.9	0.9	0.5	7.2	0.8	0.8

Target price expected return, $TPER_{i,j,t}$, is defined as TP_t/P_{t-1}–1, where TP_t is the analyst's target price with a 12-month horizon issued on day *t;* P_{t-1} is the *i*'s share price on the previous trading day before *t.* $TPER_m$ is the average target price for all analysts in month *m*. Reported values correspond to the coefficients of the regression: $TPER_m = \mu + \beta Rm_m + \varepsilon_m$, where Rm_m is the geometrically compounded value-weighted return on the CRSP index in month *m; L.* and *F.* in front of the independent variables correspond to Lag and Lead operators, respectively. *Diff.* in front of the dependent variable $TPER_m$ corresponds to the difference operator. The time period is from November 2003 to November 2014.
t-statistics in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

analysts are neutral in their September forecasts, despite the market returns displaying strong negative September seasonal trends (see Table 2). However, the Stars' risk-adjusted *TPER* forecasts in winter are not significantly different from their summer forecasts. Overall, we interpret the higher *TPER* in May and subsequent summer optimism as analysts acting against the "Sell in May" effect by issuing more optimistic target prices immediately before the low-return period in summer.

4.3. Earnings announcements and optimism cycles in target prices

We tested two hypotheses. First, we assessed whether analysts' optimism as reflected in *TPER* is associated with current or expected market returns. Table 5 reports the results of the regression analysis of *TPER* on simultaneous as well as future and lagged returns that show whether overall market conditions predict changes in analysts' optimism and reversed dependence of whether market returns can be predicted from changes in analysts' optimism. Almost all of the coefficients are statistically insignificant, which indicates that the target prices are not correlated with market returns. However, model 4, which considers differenced *TPER*, shows that a change in *TPER* has some predictive power for current market returns. Because all of the regressions have a very low model fit (R^2), we conclude that there is no correlation between market returns and the optimism of analysts for both the simultaneous and lagged variables.

Second, we tested whether analysts' optimism is related to the calendar of companies' earnings announcements (EAs). The fraction of EAs is the number of EAs issued by companies in a given month divided by the total number of EAs that year. Plotting monthly *TPER* and EAs on one graph reveals a correlation between *TPER* and quarterly EAs (see Fig. 1), with simultaneous peaks in *TPER* and the number of announcements for the fourth (in March for the previous calendar year), the first (in May) and second (in August) quartile EAs. The third quartile EAs correlate with the Stars' *TPER* but not with those of the Non-Stars. The optimism in analysts' *TPER* increases each time the number of quarterly reports increases. However, there is a strong decline in optimism each month before the majority of companies publish their EAs.[3] Thus, the analysts who issue reports one month before the majority of EAs are published do not have very optimistic forecasts. This result could be explained by the fact that most companies do not disclose much information one month prior to their EAs. In contrast, the highest optimism is observed for those *TPER* that are issued in the same month as when the majority of EAs are published. This explanation is similar and complementary to that of Doeswijk (2008), who investigates earnings forecasts and IPOs. We use more recent data and found similar patterns in target prices.

5. Conclusions

Our results show that analysts have a reversed pattern of optimism compared to the famous market adage "Sell in May and go away". Analysts are the most optimistic in May immediately before the low-return period of the market and issue more optimistic target prices in summer than in winter. On average, Non-Stars are more optimistic than Stars, forecasting higher expected returns on all three levels of recommendations. We find no significant correlation between target prices and market returns (both simultaneous

[3] Our findings are confirmed by regressing TPER and the log of TPER on the lagged percentage of EAs (monthly number divided by the total yearly number of EAs), with the coefficients positive and significant in both regressions. These results are available upon request.

and lagged values) and propose an alternative explanation for the observed seasonality.

We document that the pattern of optimism over the year, which is reflected in target prices, has a strong correlation with the calendar of companies' earnings announcements. The optimism increases every quarter with the number of published quarterly reports, peaking in the month when the number of reports is highest before subsequently declining. The lowest optimism for analysts is reported for the month preceding those with the highest number of earnings announcements. Our results therefore reveal that an optimism cycle exists, but it is related to the activities of corporations and the amount of information provided by corporations, rather than to changes in the seasons.

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