Journal of Neuroscience, Psychology, and Economics
2012, Vol. 5, No. 3, 131–151

© 2012 American Psychological Association
1937-321X/12/$12.00 DOI: 10.1037/a0029473

When Chronobiology Met Economics: Seasonal Affective Disorder and the Demand for Initial Public Offerings

Doron Kliger, Gregory Gurevich, and Abraham Haim
University of Haifa

Standard economic theory presumes invariant preferences. We refute this presumption on chronobiological grounds, documenting the impact of seasonal affective disorder on investors' demand for initial public offerings (IPOs). We found that seasonal mood substantially influences short- and long-run IPO performance: (a) examining IPO first trading days indicates that, in the short run, stocks issued in short, decreasing, photoperiods (i.e., days associated with depressing daylight conditions), earn lower returns than stocks issued in long, increasing, photoperiods (i.e., cheerful days); (b) by a quarter of a year, the stocks' cum-initial-returns are equated, implying that the short-run initial excess returns of the stocks issued in the cheerful periods are fully absorbed by subsequent performance; and (c) in the long run, the stocks issued in the cheerful periods continue to underperform (until about a year and a half) and subsequently (up to 3 years) possibly revert to the grand average of IPO underperformance. The average initial return differential between the IPOs issued in depressing and cheerful days is in the sizable order of between 5 and 10% of the offering, approaching 15−25% for the relatively less publicly exposed firms, as assessed using a database of 1,526 IPOs with average gross proceeds of $15 million.

Keywords: behavioral finance, chronobiology, chronoeconomics, initial public offerings, seasonal affective disorder

According to expected utility theory (Von Neumann & Morgenstern, 1944), the main building block in economic modeling of choice under risk, rational decision-makers are endowed with invariant preferences, referred to as their *types*. Here we show that this notion of type is insufficient for describing and predicting investors' behavior in financial markets, most prominently when the considered investments lack long history, to wit, when pricing initial public offerings (IPOs). Specifically, we demonstrate that season-related mood, emerging from photoperiod conditions, exerts substantial influence on short- and long-run IPO market prices. The initial return differential between the IPOs issued in depressing and cheerful days is in the sizable order of 5−10% of the offering, approaching 15−25% for relatively less publicly exposed firms, as assessed using a database of 1,526 IPOs with average gross proceeds of $15 million.

A rapidly growing body of research has demonstrated that psychological factors play an important role in investors' decision-making process. For instance, a range of studies has examined psychological impact on asset pricing. A comprehensive review of these and related developments can be found in Hirshleifer (2001). Among other factors, seasonal mood fluctuations are shown to exert nonnegligible influence on stock market performance (see, e.g., Kamstra, Kramer, & Levi, 2000, 2003); Kliger and Levy (2008) employed option prices to show that seasonal mood effects distort investors' probability perceptions, while Kliger and Levy (2003) demonstrated that investors' risk preferences are affected by the same factors; Kaplanski and Levy (2008) reported systematical seasonal fluctuations of the Volatility Index (VIX) calculated by the Chicago Board of

Doron Kliger and Gregory Gurevich, Department of Economics, University of Haifa, Haifa Israel; and Abraham Haim, The Israeli Center for Interdisciplinary Research in Chronobiology, University of Haifa, Haifa, Israel.

We are grateful to Jay Ritter for providing us with the initial public offering data and for clarifying technical issues.

Correspondence concerning this article should be addressed to Doron Kliger, Department of Economics, University of Haifa, Haifa 31905, Israel. E-mail: kliger@econ.haifa.ac.il

Options Exchange (CBOE); and Reimann and Bechara (2010) reviewed and discussed the accumulated evidence relating economic decision making to emotions and their neurological correlates. In the present study, we addressed the following question: Do related mood conditions influence the pricing of IPOs? Kamstra et al. (2003) sketched the relevant literature and explained that "Through the links between SAD [seasonal affective disorder] and depression and between depression and risk aversion, seasonal variation in length of day can translate into seasonal variation in equity returns" (p. 324). We presumed that, in the case of IPOs, mood might play a key role in forming investors' behavior, due to the lack of pricing anchors that are provided in other cases by the stocks' trading history.

The two main issues dealt with in the IPO literature are the short- and long-run stock performance, both of which are associated with some nontrivial phenomena. In the short run, IPO first-day (or initial) returns are abnormally high (cf. Ritter, 1991; Ritter & Welch, 2002), a short-run effect commonly known as IPO *underpricing* (see, e.g., Stoll & Curley, 1970; Reilly, 1973; Ibbotson, 1975, for early research of the issue; see Ljungqvist, 2007, for a review of recent developments). The high initial return surmises that issuers could have achieved a much higher price for their security from the initial investors, and their failure to do so earned the label of *leaving money on the table* (see Loughran & Ritter, 2002). Long-run behavior is known as IPO *underperformance*, because post-IPO returns are often found to be considerably below benchmarks of comparable securities for a period as long as up to several years (see Ma & Shen, 2003, for a recent example of research on this issue). Although both IPO underpricing and underperformance are commonly observed in large data sets, within-sample analysis usually reveals considerable firm heterogeneity, with different securities manifesting the described effects to different extent: some IPOs seem to be more underpriced than others as well as exhibit various degrees of underperformance. In this study, we delve into possible reasons for this variability. Addressing this issue may shed light on possible sources of these widely observed effects. In particular, we suggest that investors' mood may exert substantial influence on the extent of IPO underpricing and subsequently poor long-run performance.

The investors' mood-related behavior we have detected is corroborated by accumulated knowledge in chronobiology, the scientific discipline in charge of the study of rhythmicity, biological clocks, and seasonality. Seasonality in anatomical, physiological, and behavioral aspects is well documented in many mammalian species, with photoperiod being the main environmental signal for seasonal acclimatization in mammal species existing out of the tropics photoperiod (Nelson, 2005; Haim, Shanas, Zubidat, & Scantelbury, 2005). Humans, just like other mammals, are seasonal, as manifested for instance by their birth rates, mortality, and suicide rates (Roenneberg & Aschoff, 1990). The brain-located pineal gland acts as a clock and as a calendar by employing melatonin secretion level and duration to signal the time of the day and the season of the year to other brain parts and tissues (Reiter, 1991, 1993). Seasonal acclimatization of various systems is crucial for the survival of animals because mammals in their natural habitats and changes in photoperiod are the environmental signal for the entrainment of the biological clock and for adjusting the function of the various systems and behavioral patterns to the approaching season (Nelson, 2005).

The discoveries of non-image-forming photoreceptors in the retina and the new visual protein melanopsin located in the bipolar cells of the retina can better explain the transfer of the environmental light−dark signals and the photoperiod (as a relation between photophase and scotophase) to the pineal gland via the hypothalamic suprachiasmatic nuclei, which form the main oscillator (Berson, Dunn, & Takao, 2002). In addition, the seasonal increase in the dark hours during autumn and winter are accompanied by an increase in the pineal melatonin production. A question to be asked is: Can these changes in melatonin be connected to human seasonal behavioral patterns? The rhythmic nature of behavior has been revealed in learning, perception, memory function, and social conduct, up to extreme behavior such as suicide. We hypothesized, therefore, that changes in hormone secretion have a significant effect on mood and decision making in the financial arena as well. The best-known negative effect of melatonin hyperproduction on hu-

man behavior is SAD, a type of seasonal depression affecting numerous people each year, especially in higher latitudes as the northern parts of United States and Western Europe. SAD is caused by a biochemical imbalance in the hypothalamus due to the shortening of daylight hours and the lack of sunlight (e.g., Rosenthal et al., 1984) that results in an increased level of plasma melatonin, secreted from the pineal gland for a longer duration (Reiter, 1993). A less debilitating form is known as the *subsyndromal SAD* or *winter blues*. Common SAD symptoms comprise of sleep difficulties, drowsiness, listlessness, lack of energy, social and communicative problems, anxiety, fatigue, focusing problems, and restlessness. According to studies documenting the prevalence of SAD, roughly five percent of the population suffers from seasonal depression, up to 20% endures subsyndromal features, and about half of the rest possess some mild symptoms.[1]

A number of economic studies have employed seasonal and mood-related factors. Kamstra et al. (2000) were the first to address the chronobiological consequences of daylight conditions for financial markets; furthermore, Kamstra et al. (2003) documented a seasonal pattern in stock market returns and attributed it to SAD. Garrett, Kamstra, and Kramer (2005) found that a conditional capital asset pricing model, which allows the price of risk to vary in relation to seasonal variation in the length of day, is able to capture the "SAD effect." Dolvin and Pyles (2007) investigated one of the issues in which we are interested, namely, seasonality in short-run IPO performance, using a somewhat different viewpoint and data set, on which we elaborate in the Short-Run Results section. Kliger and Levy (2008) integrated considerations of mood into nonexpected utility theories. An important element in many nonexpected utility theories is the probability weighting functions (PWFs) that nonlinearly weight physical probabilities. Using U.S. market price data, they established an empirical relation between SAD and the shape of the PWFs, pointing that bad mood causes investors to systematically distort their PWFs. Kaplanski and Levy (2008) employed the VIX calculated by the CBOE, finding that SAD factors increase contemporaneous VIX levels, and that that increase is not validated by the corresponding levels of the subsequently realized stock market volatility.

To explore the potential influence of mood on IPO pricing, we employed a large data set of 1,526 IPOs that was previously analyzed in a long-run performance context (see Ritter, 1991). Sorting the IPOs according to their issuing dates enabled us to compare their short- and long-run performance under the different seasonal mood conditions.

In the rest of the study, we provide a general review of the season- and mood-related psychological impact on decision making, describe the employed data, and discuss our results.

Mood Impact on Decision Making

Psychological factors potentially exert influence on security market prices, especially in the case of IPOs, due to the lack of trading history, presumably serving as an anchor in the valuation process. To date, however, there seems to be no conclusive explanation for the observed IPO mispricing. We suggest that investors' mood, as related to seasonal effects of daylight exposure, is to be included in the endeavor toward such an explanation, because it correlates with a considerable part of the observed price variation.

To assess investors' valuation of IPOs, we performed horizon-dependent analysis. In particular, we distinguished between short- and long-run IPO performance, in line with the existing IPO literature (cf. Ritter & Welsh, 2002). In addition, we analyzed the IPO *first season* performance, which is motivated by (a) dealing with behavioral phenomena and checking for within-year reversals, and (b) employing seasons in accordance with the SAD-related effects mentioned above, so 3 months, the approximate duration of each season, is potentially relevant for the analysis. We discovered that within 3 months, the cum-initial-return stock performance is approaching similar levels, implying that the short-run initial excess returns of the stocks issued in cheerful seasons are fully absorbed by subsequent performance. Below, we suggest testable hypotheses about seasonal mood effects on short- and long-run IPO performance.

[1] Compare Rosen et al. (1990), Oren and Rosenthal (1992), Dam, Jakobsen, & Mellerap (1998), Saeed and Bruce (1998), and Keller et al. (2005).

Short-Run Analysis

With respect to the short run, we hypothesized that investors' mood, as related to seasonal effects of photophase exposure, would affect IPO pricing and, thus, initial returns. In particular, we posed the following testable hypothesis and alternative:

> H_0 *(short run):* IPO underpricing is unrelated to seasonal mood effects.
>
> H_1 *(short run):* IPO underpricing is more salient in positive than in negative mood periods, in accordance with seasonal photophase exposure of the investors.

Testing the hypothesis is important for two reasons. First, in general, it may provide additional evidence for the role psychological factors play in economic decision making. Second, more specifically, it may shed light on the as-yet unresolved issues of IPO mispricing.

We employed two photophase-related mood proxies. The first and presumably more influential proxy is the *change* in and the second is the *level* of daylight duration (Nelson, 2005). The higher relative sensitivity of human perception to changes, as opposed to absolute levels, of stimuli is a basic behavioral feature of the human perceptual apparatus (cf., e.g., Kahneman & Tversky, 1979, p. 277). To wit, shortening the photophase is associated with bad mood, and lengthening the photophase with good mood; and, though maybe to a lesser extent, a short photophase is associated with bad mood, while a long photophase with good mood. With respect to the latter, the question of a cutoff point, that is, the specific photophase duration splitting between "short" and "long" days, should be addressed. To that end, we explored the cutoff splitting the sample by the average daylight duration, also reporting results generated by the cutoff endogenously inferred by the data. Finally, in addition to separately analyzing each of the abovementioned mood proxies, we combined them into one variable, comparing IPOs issued in short, photophase-decreasing days to those issued in long, photophase-increasing days.

Figure 1 shows the level and the gradient of the annual daylight duration cycle, the two features we used to proxy investors' mood. Each IPO was associated with a specific locus on the two curves, in accordance with the calendar date of the issue, in the following sense: (a) in accordance with photophase duration *changes* mood proxy, IPOs belonging to the negative part of the gradient graph are associated with SAD-onset effects and correspondingly negative mood condition, while those belonging to the positive part are associated with SAD remission and correspondingly positive mood condition; and (b) in accordance with the daylight *level* mood proxy, IPOs belonging to the lower part of the daylight level graph are associated with worse mood, as compared to the IPOs belonging to the higher part of the graph.

We attributed the hypothesized seasonal mood-related effects on IPO underpricing to the lack of trading history, which presumably serves as an anchor in the valuation process. Moreover, we expected the relatively less publicly exposed offerings to manifest more salient mood-related effects, because the lack of an explicit pricing anchor may be even more consequential when the issuing firm is also generally less familiar to the public. Note also that, in Kamstra et al. (2003), the SAD impact was shown to be mediated by risk aversion, while the less publicly exposed firms are also likely to be the riskier. Closely related issues are addressed by Kamstra et al. (2000), who pointed out that ". . . [weekend anomaly] like other anomalies, is generally stronger for small firms" (p. 1006), and that "The daylight-saving effect would appear to be particularly pronounced for small firms . . ." (p. 1008); furthermore, Kamstra, Kramer, and Levi (2012) explained that "smaller, riskier stocks . . . are more likely to exhibit seasonally varying returns due to time-varying investor risk aversion" (p. 940). Accordingly, we posed the following testable hypothesis and alternative:

> H_0 *(public exposure):* The IPOs' mood-related effects are unrelated to the firm's degree of public exposure.
>
> H_1 *(public exposure):* The IPOs' mood-related effects are more salient the less publicly exposed the firm is.

We proxied the IPOs' lack of public exposure, or degree of asymmetric information, by measures of the firm's size and activity history.

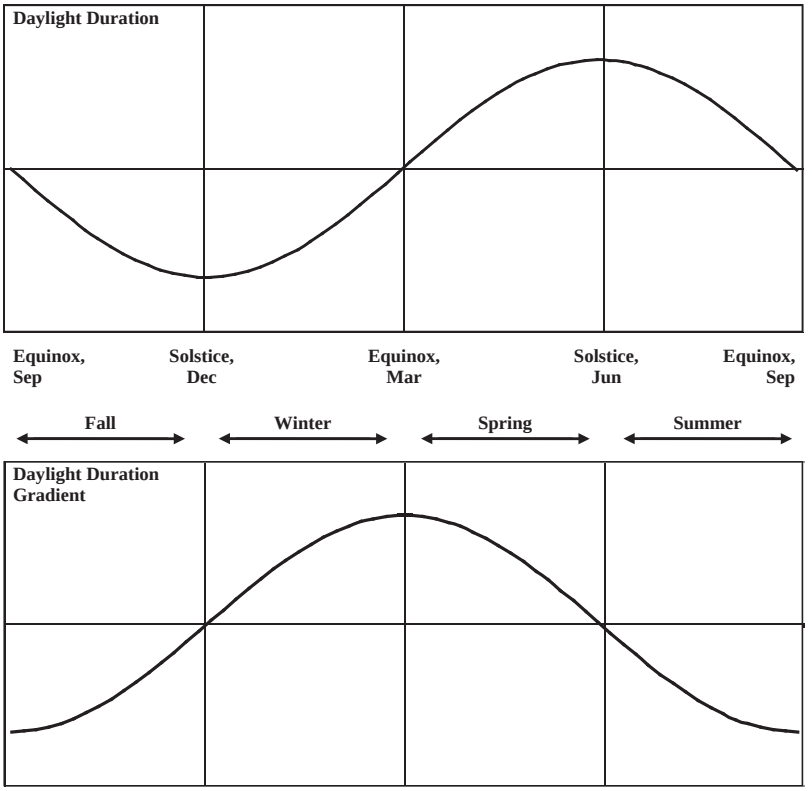

Figure 1. Annual photoperiod cycle. Note that the calendar dates of the fall and spring equinoxes are September 22 or 23 and March 20 or 21, respectively; calendar dates of the winter and summer solstices are December 21 or 22 and June 21 or 22, respectively. In our study, increasing photoperiod is defined as after December 22 and not later than June 22; photoperiods of more than 12 hr are defined as after March 21 and before September 22.

Specifically, firms with lower sales turnover, smaller offering gross proceeds, and younger firms are less well known to the market participants and they are followed less strictly by professionals and the media. Detecting a more salient effect for smaller and younger firms would corroborate the public exposure argument we have raised.

Long-Run Analysis

The seasons' cycle resulting from photoperiodicity imposes changing conditions four times a year. We therefore posed the following testable hypothesis and alternative:

> H_0 *(Long Run 1):* The seasonal mood−related component of IPO underpricing is not offset within subsequent quarter-of-year performance.
>
> H_1 *(Long Run 1):* The seasonal mood−related component of IPO underpricing is offset within subsequent quarter-of-year performance.

In the long run, IPO stocks are known to underperform as compared to benchmarks. We, therefore, kept tracking them according to the seasonal mood partition for several years from the offering date. Hence, we posed the following testable hypothesis and alternative:

> H_0 *(Long Run 2):* The long-run IPO underperformance may not be differentiated by seasonal mood factors.
>
> H_1 *(Long Run 2):* The extent of long-run IPO underperformance is differentiated by seasonal mood factors.

Table 1
Descriptive Statistics of Data, Seasonally Partitioned

Descriptive statistics	Fall	Winter	Spring	Summer	All
No. of observations	491	250	392	393	1526
Percentage of sample	32.18	16.38	25.69	25.75	100.00
Initial returns (mean percent)	11.55	15.54	18.18	12.13	14.06
Cumulative returns (mean percent at 36 months, excluding initial)	−26.46	−32.13	−33.45	−23.66	−28.44
Average sales (12-month revenues, in thousands)	$46,019	$33,722	$40,551	$48,006	$43,112
t statistic (*p*)	0.73 (47%)	1.51 (13%)	0.55 (58%)	1.05 (29%)	
25th percentile	1,840	2,261	1,361	1,312	1,579
Median	14,031	11,775	10,398	10,329	11,681
75th percentile	37,345	36,733	35,003	36,061	36,140
Average gross proceeds (offering price times shares sold, in thousands)	$13,952	$14,114	$17,372	$15,213	$15,182
t statistic (*p*)	1.30 (19%)	0.73 (47%)	1.98 (5%)	0.03 (98%)	
25th percentile	4,144	3,653	4,082	3,956	4,058
Median	7,827	8,178	7,480	7,333	7,620
75th percentile	15,015	15,859	18,043	16,440	16,260
Standard Industrial Classification group (%)					
1. Computer manufacturing	9.0	10.8	8.9	9.7	9.4
2. Communications and electronic equipment	9.4	10.0	9.7	7.4	9.0
3. Oil and gas	6.1	8.0	10.0	9.7	8.3
4. Financial institutions (banks and savings and loans)	8.2	12.8	6.6	6.9	8.2
5. Computer and data processing services	6.9	5.6	8.9	7.6	7.4
6. Optical, medical, and scientific instruments	7.5	7.2	6.9	7.4	7.3
7. Retailers	4.3	2.4	5.4	5.6	4.6
8. Wholesalers	4.1	3.2	5.4	3.6	4.1
9. Restaurant chains	5.3	2.8	2.0	3.3	3.5
10. Health care and health maintenance organizations	2.6	3.2	2.3	5.1	3.3
11. Drugs and genetic engineering	2.6	2.0	3.1	3.5	2.9
12. Miscellaneous business services	3.7	2.8	2.8	1.5	2.8
13. Airlines	1.4	3.2	1.0	1.5	1.7
14. All other firms	28.9	26.0	27.0	27.2	27.5
Total	100.0	100.0	100.0	100.0	100.0
χ^2 (*p*)	10.31 (67%)	16.49 (22%)	10.58 (65%)	10.95 (62%)	
Firm age in years (%)					
0−1 (AGE1)	18.1	14.0	15.8	16.8	16.5
2−4 (AGE2)	23.6	25.6	25.0	26.2	25.0
5−9 (AGE3)	21.4	23.6	19.6	22.1	21.5
10−19 (AGE4)	18.8	20.8	21.7	21.1	20.4
20 and up (AGE5)	18.1	16.0	17.9	13.8	16.6
Total	100.0	100.0	100.0	100.0	100.0
χ^2 (*p*)	2.54 (64%)	1.58 (81%)	1.42 (84%)	2.33 (67%)	
Year of issue (%)					
1975−1979	10.4	9.2	8.7	8.9	9.4
1980	10.4	7.2	5.4	9.9	8.5
1981	13.4	19.2	29.8	17.6	19.7
1982	9.2	6.0	4.8	3.6	6.0
1983	45.2	22.0	34.0	45.5	38.6
1984	11.4	36.4	17.3	14.5	17.8
Total	100.0	100.0	100.0	100.0	100.0
χ^2 (*p*)	36.88 (0%)	66.74 (0%)	28.61 (0%)	13.46 (1%)	

Note. Gross proceeds and sales are expressed in terms of 1984 dollars purchasing power, using the gross national product index data from the Federal Reserve Bank of St. Louis; total values vary only slightly from those reported in Ritter (1991); reported *p* values are for tests comparing each season's subsample to the whole sample properties; and (d) cumulative 36-month returns are calculated by averaging excess returns across the monthly data available for each partition.

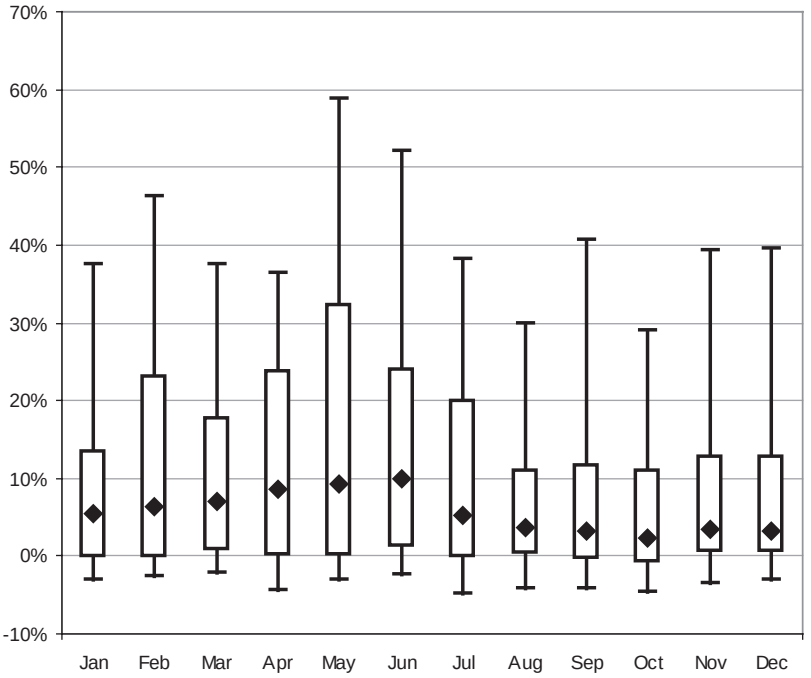

Figure 2. Initial public offering initial returns statistics, depicting the 10, 25, 50, 75, and 90th percentiles of initial excess returns partitioned by the offering month.

Below, we provide a brief data description and then turn to the empirical results obtained with respect to each of the aforementioned hypotheses.

Data

To test our hypotheses, we employed the IPO data set used in Ritter (1991).[2] The data contain 1,526 IPOs issued from 1975–1984, initially traded on NASDAQ (most of the sample), or the American or New York Stock Exchanges. These IPOs comprised 85.1% of the aggregate gross proceeds of all IPOs issued during this period. For each IPO, the data included the offering date, initial market return and 36 subsequent monthly returns, Standard Industrial Classification (SIC) code, and additional issuing firm−related information. We sorted the data according to the calendar date of the offering and corresponding photophase conditions. Subsequently, we compared the short- and long-run performance of the IPOs issued in the course of positive versus negative seasonally related mood periods. As a benchmark for the IPOs' performance, we employed the matching firm data, which were used in Ritter (1991), and analyzed the IPO returns in excess of their matching firms.[3] Table 1 provides a general description of the employed data, by seasonal dates of the offering, according to the annual photophase duration cycle in Figure 1.

The data are suitably distributed for seasonal comparison, with each season hosting at least 16% (250 IPOs) of the whole sample. Moreover, the seasons' subsample properties have common qualities, to wit, the IPOs issued in each season possess very similar sales and gross-proceeds distributions, as well as scatter profiles over the different SIC groups and firms' ages. Statistical tests comparing the subsamples' properties with those

[2] See Ritter (1991) for the comprehensive data description.

[3] See Ritter (1991) for an appendix describing the matching firms' selection procedure, which was generally based on choice according to Standard Industrial Classification and firm market value criteria.

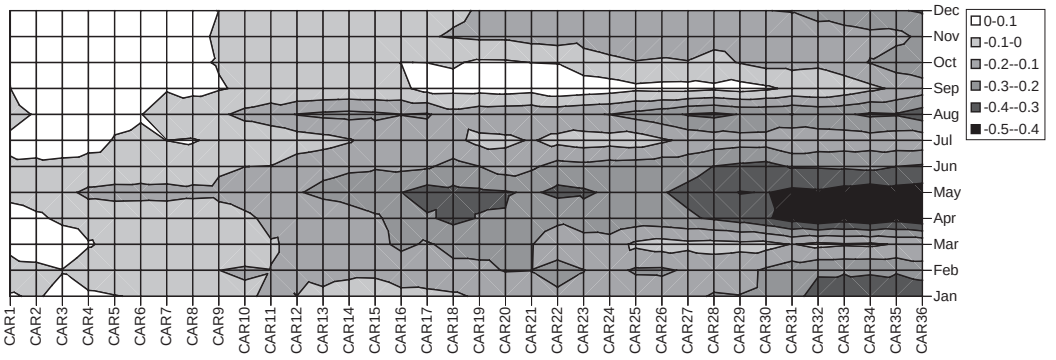

Figure 3. Monthly partition surface of cumulative excess returns, initial excess returns excluded, using matching firms as benchmark. CAR = Cumulative Abnormal Return.

of the whole sample generally did not reject identity: the *t* statistics comparing the means of sales and gross proceeds were not significant in all cases except gross proceeds in the spring, and the chi-square statistics comparing the SIC and age distributions were not significant. The issuing years of the 1,526 IPOs were distributed over the 10-year sample period, with the majority in the last 2 years, and fewer than 10% in first 5 years of data. Although these distributional properties suitably represent the seasons' subsamples, the chi-square statistics indicated that their distributions differed from the total sample.

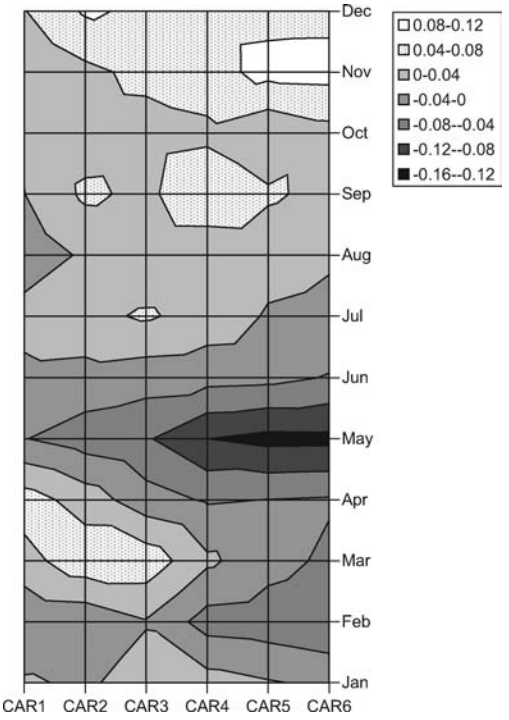

Figure 4. Monthly partition surface for first half year, initial excess return excluded, using matching firms as benchmark. CAR = Cumulative Abnormal Return.

Short-run IPO performance manifested considerable variation. Figure 2 portrays the 10, 25, 50, 75, and 90th percentiles of initial excess returns partitioned by the month of the offering. The IPO initial excess returns over the whole data set of 1,526 IPOs averaged about 14%, while ranging from about −50% to more than 300%. The median monthly initial excess returns varied from about 2−10%, and the 10th and 25th percentiles from −4% to −2% and from 0−1%, with highest and lowest values accruing in May/June and October, respectively.

The long-run IPO performance manifested considerable variation as well. Figure 3 presents the monthly partition surface of cumulative excess returns, up to 3 years after the offering. Lastly, considering the intermediate, semiannual, return pattern yields a similar observation (Figure 4).

Comparing the short- and long-run excess returns presented above indicates that IPO performance may be related to the calendar date of the offering. For instance, a closer look at extreme excess returns reveals that offerings from April to June (increasing photophase) end up with the lowest, and from October to December with the highest cumulative excess returns, that is, the opposite of the picture portrayed by the initial excess returns.

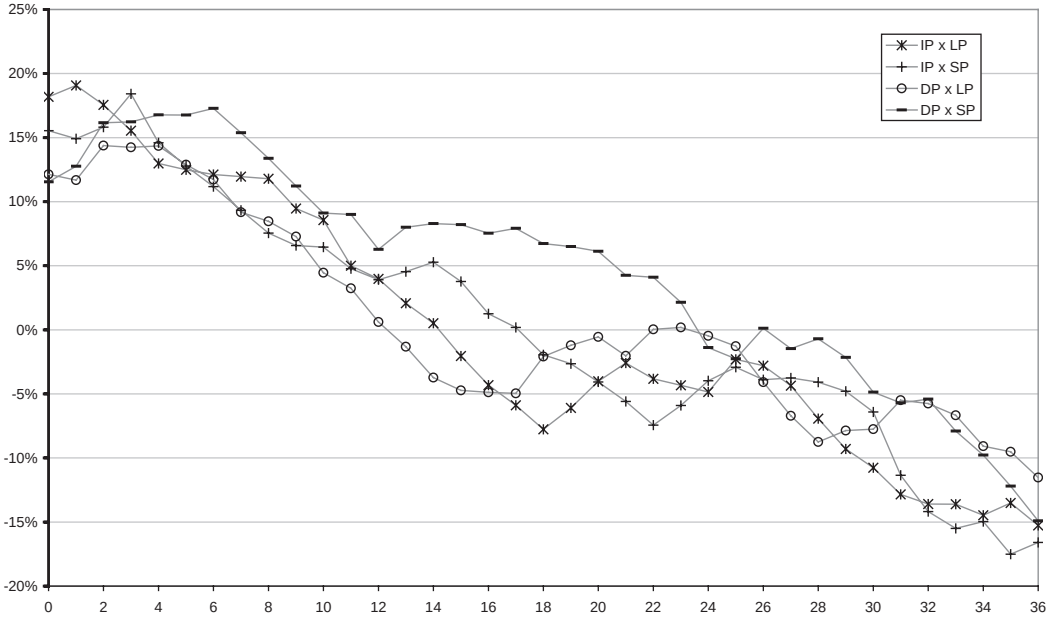

Figure 5. Quarterly partition of returns using matching firms as benchmark, initial excess returns included. IP = increasing photoperiod; LP = long photoperiod; DP = decreasing photoperiod; SP = short photoperiod.

To test the hypotheses presented in the Short-Run and the Long-Run Analysis sections, we partitioned the IPOs in the database by each of the following indicators (cf. Figure 1):[4]

> Increasing photoperiod (IP) versus decreasing photoperiod (DP) indicates IPOs issued during periods of positive daylight duration gradient, that is, increasing photophase, versus IPOs issued in periods of negative photophase gradient, that is, decreasing photophase; and
>
> Long photoperiod (LP) versus short photoperiod (SP) indicates IPOs issued during periods of more than12-hr of photophase versus IPOs issued in periods of less than 12 hr of photophase.

To get a comprehensive picture of IPO performance variation related to the above-mentioned indicators, we employed a four-way partition of the sample (Figure 5). This representation refers simultaneously to the photophase duration and its gradient, thereby dividing the sample into four IPO cohorts with offering days that are: (a) less than 12 hr and decreasing (DP $\times$ SP); (2) more than 12 hr and decreasing (DP $\times$ LP); (3) less than 12 hr and increasing (IP $\times$ SP); and (4) more than 12 hr and increasing (IP $\times$ LP).

Figure 5 permits identifying the basic effects mentioned earlier with respect to the long-run monthly performance. For instance, for the IP $\times$ LP subsample, average initial returns are the highest, followed by a sharp decline over the following months. In contrast, the average initial returns of the DP $\times$ SP subsample are the lowest and followed by the highest cumulative returns in most of the period. Actually, about 3 months after the offering date, these two subsamples' cum-initial-returns are approaching similar levels, after which their initial relative performance is overturned. The two other subsamples (IP $\times$ SP and DP $\times$ LP) manifested intermediate performance, consistent with their daylight duration and gradient properties. The overall picture of the aftermarket performance becomes even clearer when inspecting

[4] Results based on raw initial returns (not reported) led to essentially the same conclusions as the results based on the excess initial returns.

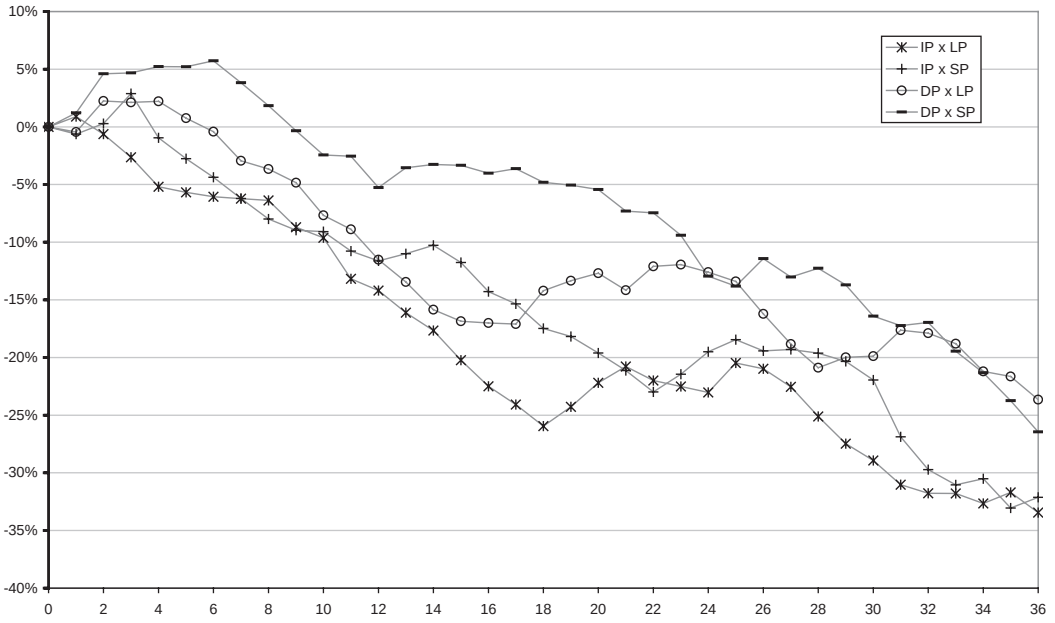

Figure 6. Quarterly partition of returns using matching firms as benchmark, initial excess returns excluded. IP = increasing photoperiod; LP = long photoperiod; DP = decreasing photoperiod; SP = short photoperiod.

the series' cumulative returns excluding the initial returns, as shown in Figure 6.

Excluding the initial excess returns, the long-run difference between the subsamples DP × SP and IP × LP is quite pronounced, corroborating the observation that the initial excess return tendency seems to be reversed during the months after the offering. On the whole, all presented partitions of the data suggest a relation between the IPO's calendar date of issue and its initial and subsequent performance. Henceforth, we turn to the results obtained from a systematic analysis of the substantial variation in short- and long-run IPO performance.

Results

Short-Run Results

The results presented below suggest that the initial return variability is strongly related to the gradient and level of photophase duration within-year periodicity. Figures 7 and 8 depict the cumulative distribution functions (CDFs) of the IPO excess returns partitioned by each of the two seasonally related mood indicators. The subsamples' CDFs differ significantly from each other according to the Kolmogorov–Smirnov test, with the IP and LP CDFs being uniformly lower than their respective counterparts, DP and SP, with p values less than 1%.[5] Henceforth, we will demonstrate that the mood-partitioned subsample pairs also differ fundamentally, as determined by their mean and their median return performance.

Table 2 compares the means and medians of the short-run IPO excess returns partitioned by the two indicators. Dividing the data set into two IPO cohorts, according to the photophase duration gradient of the calendar offering date (the IP and DP indicators), yielded 642 and 884

[5] Note that using excess returns (return differences between the initial public offerings [IPOs] and their matching firms) as the measured variable mitigated possible clustering-induced within-sample dependence. As an even stricter test, taking into account only the number of nonoverlapping observations, resulted in p values smaller than 2.5% for the difference between the increasing photoperiod and decreasing photoperiod cumulative distribution functions (CDFs), and 1% for the difference between the long photoperiod and short photoperiod CDFs.

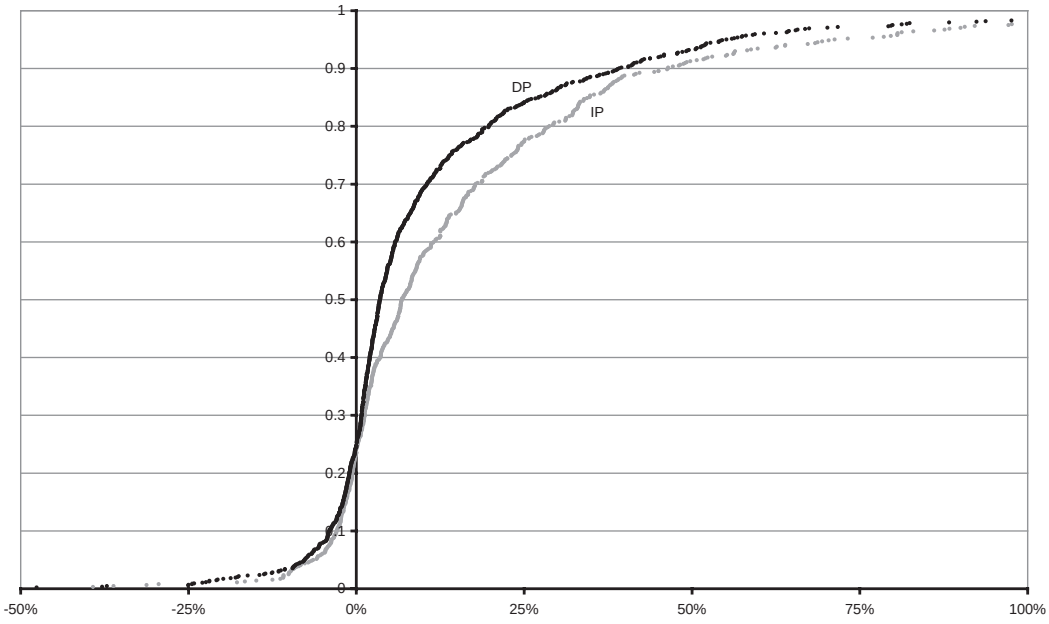

Figure 7. Cumulative distribution functions of initial public offering excess returns by decreasing photoperiod (DP) versus increasing photoperiod (IP).

observations in the day-increasing and day-decreasing subsamples, with respective mean initial excess returns of 17.15% and 11.81%, respectively. The difference between the mean excess returns (5.34%) was statistically significant ($p <$ .1%) according to the mean comparison t test. Moreover, comparing the median excess returns of the two subsamples, 6.77% and 3.52%, using the Mann–Whitney test, pointed to a highly significant difference ($p <$ .1%).

The second partition we performed was according to the photophase duration (i.e., level) in the calendar offering date (the LP and SP indicators); this partition generated 785 and 741 observations in the long- and short-days subsamples, with mean returns of 15.15% and 12.90%. According to a two-tailed p value, the between-subsample difference of 2.25% was not significant ($p >$ 10%), but, taking a directional hypothesis, it was significant with a one-tailed p value of about 7%. The median excess returns in the two subsamples (5.94% and 3.61%) provided a sharper result, with a highly significant difference ($p <$ 1%) according to the Mann–Whitney test.[6]

Finally, we restricted the analysis to the IPOs issued in the long and increasing, as opposed to short and decreasing, photophase periods (see Table 2). Combining the indicators (i.e., comparing the subsamples IP $\times$ LP and DP $\times$ SP) yielded 392 and 491 observations, respectively. The respective mean initial excess returns were 18.18% and 11.55%; the difference of 6.63% was highly statistically significant ($p <$ 1%) and the respective median excess returns (8.33% vs. 3.06%) differed significantly ($p <$ .01%) as well.

Overall, the foregoing results indicate that IPOs issued on days associated with depressing photophase conditions earned lower initial excess returns than securities issued on cheerful periods. In particular, the photophase duration gradient seemed to exert a more substantial influence compared to the level indicator, and the combined analysis using the two proxies

[6] Recall that the photophase duration (level) partition hinges on a somewhat arbitrary cutoff splitting the sample by the average photophase duration. We also searched for a cutoff splitting the data into two groups with the maximal, most significant, initial excess return difference. Interestingly, this endogenously generated cutoff point turned out to be located at photophase duration of 12.5 hr, that is, slightly higher than the average duration.

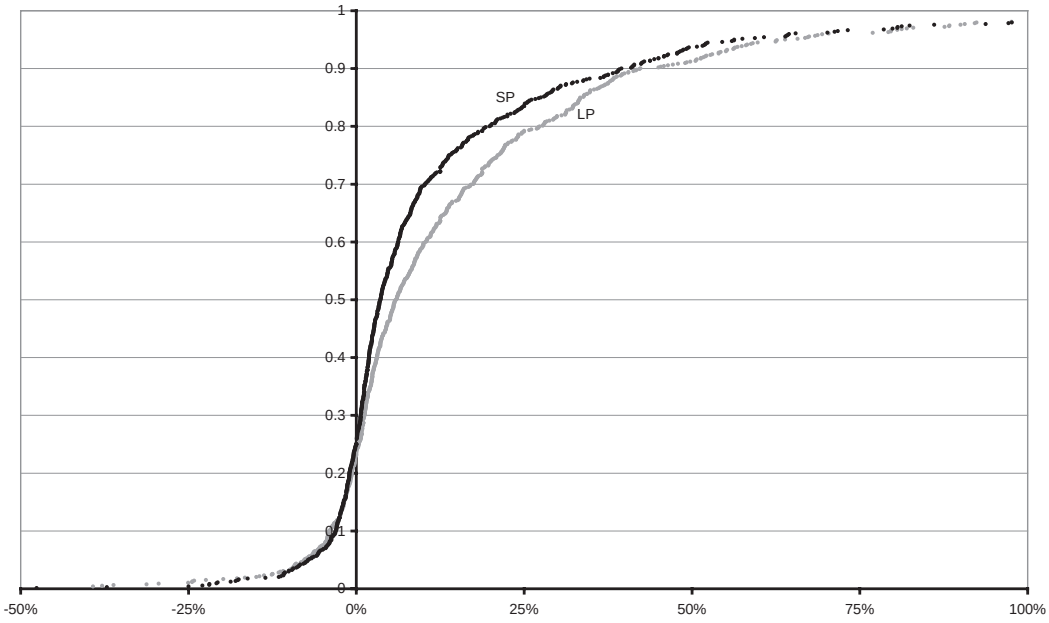

Figure 8. Cumulative distribution functions of initial public offering excess returns by short photoperiod (SP) versus long photoperiod (LP).

yielded significant results as well. To eliminate the possibility that subsample heterogeneity generated the results, we conducted multiple regressions of the initial returns on the photophase condition indicators, controlling for various IPO characteristics.

Table 3 presents the results of the multiple ordinary least squares regressions, controlling for the firms' sales, offering gross proceeds, industry affiliation, age, and year of issue.[7] In Specifications a and b, the IPOs' initial excess returns were regressed on each of the daylight condition variables, namely, the daylight changes indicator (IP vs. DP) and the daylight level indicators (LP vs. SP), respectively. The reported estimates captured the difference between the initial excess returns in the two daylight conditions. The results manifested the considerable influence of the photophase conditions on IPO initial excess returns, that is, the effect remained prominent after controlling for the IPO features. Corroborating our presumption, the effect was more prominent for the daylight changes than for levels.

As an additional way of assessing the SAD impact, we used the account of SAD incidences onset and recovery developed by Lam (1998) and employed by Kamstra, Kramer, Levi, and Wermers (2011) as a proxy for the SAD influence on market participants.[8] It is worth noting that onset and recovery correlated highly with the photophase levels and even more so with the changes in photophase. For the regression, we normalized the variable to range from 0−1, such that the estimated coefficient would measure the effect on the initial excess returns between March and September (the months with the lowest and highest onset and recovery values, respectively). Specification c of Table 3 shows the impact of the normalized onset and recovery on the initial excess returns while controlling for the firms' characteristics; the regres-

[7] The information used for constructing the control variables is depicted in Table 1. The dummy variables of sales and gross proceeds partition the data according to the quartiles reported in the table; industry affiliation dummy variables represent the Standard Industrial Classification groups; firms' age dummies and year of issue are constructed according to the partition appearing in the table. All regression covariance matrices are heteroscedasticity consistent (White, 1980).

[8] The onset and recovery values, from September to August, are: 38, 30, 8, 1, –5, –21, – 42, –21, –5, 0, 3, and 15 (cf. Kamstra, Kramer, Levi, & Wermers, 2011, for details).

Table 2
Short-Run Analysis: Mean and Median Returns by Photophase Conditions

Indicator	Value	No. obs.	*M* (%)	*SD* (%)	Median (%)
IP	1	642	17.15	34.31	6.77
DP	0	884	11.81	28.50	3.52
	Difference		5.34		3.25
	p		0.09		0.01
LP	1	785	15.15	30.53	5.94
SP	0	741	12.90	31.83	3.61
	Difference		2.25		2.33
	p		15.79		0.21
	Total	1,526	14.06	31.18	4.61
IP × LP	1	392	18.18	35.42	8.33
DP × SP	0	491	11.55	31.43	3.06
	Difference		6.63		5.27
	p		0.33		<0.01
	Total	883	14.49	33.40	4.27

Note. For mean comparison, *p* value of *t* test is reported; for median comparison, Mann−Whitney *p* value is reported; Kolmogorov−Smirnov tests comparing the cumulative distribution functions indicate significance at $p < .001$ level for all partitions. No. obs. = number of observations; IP = increasing photoperiod; DP = decreasing photoperiod; LP = long photoperiod; SP = short photoperiod.

sion results indicate a substantial (11.68%) and highly significant ($p < .01$%) influence.

In addition to the separate analysis of photophase duration changes and levels, we also measured their combined effect, first, by regressing the initial excess returns jointly on the photophase duration changes and levels explanatory variables (IP vs. DP and LP × SP, Specification d) and, second, by regressing the excess returns on the product of the two measures, using only the extreme observations of short-and-decreasing, or long-and-increasing, photophase duration (IP × LP vs. DP × SP, Specification e). In support of the analysis thus far, the effect was

Table 3
Multiple Regression Analysis Controlling for Sales, Gross Proceeds, Industry Affiliation, Year of Issue, and Firm's Age

	(a)	(b)	(c)	(d)	(e)
Regression specification					
IP vs. DP	8.04			7.88	
p (%)	<0.01			<0.01	
LP vs. SP		2.20		0.95	
p (%)		13.43		50.98	
Normalized onset and recovery			11.68		
p (%)			<0.01		
IP × LP vs. DP × SP					9.57
p (%)					<0.01
R^2 (%)	17.89	16.51	17.22	17.92	18.55
Adjusted R^2 (%)	16.08	14.66	15.39	16.04	15.39
Controls					
Sales	Yes	Yes	Yes	Yes	Yes
Gross proceeds	Yes	Yes	Yes	Yes	Yes
Standard Industrial Classification	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes	Yes
No. obs.			1,526		883

Note. Regression covariance matrices are heteroscedasticity consistent (White, 1980). IP = increasing photoperiod; DP = decreasing photoperiod; LP = long photoperiod; SP = short photoperiod; No. obs. = number of observations.

Table 4
Public Exposure Regression Analysis: Daylight Condition Effects on the Initial Returns Using the Firms' Sales as a Proxy for the Public Exposure

Public exposure indicators	Sa1	Sa2	Sa3	Sa4	Sa1	Not Sa1	Difference
IP vs. DP (1,526 observations)	16.39	2.48	7.14	6.00	16.35	5.30	11.05
p (%)	0.11	35.09	0.02	<0.01	0.11	<0.01	1.49
LP vs. SP (1,526 observations)	1.43	2.17	1.70	3.46	1.21	2.61	−1.40
p (%)	77.91	39.60	34.58	1.00	81.11	1.99	NA
IP × LP vs. DP × SP (883 observations)	15.83	5.57	8.49	8.30	15.66	7.67	7.99
p (%)	2.80	13.60	0.03	0.01	2.90	<0.01	13.96

Note. Gross proceeds and sales are expressed in terms of 1984 dollars purchasing power, using the gross national product index data from the Federal Reserve Bank of St. Louis; regression covariance matrices are heteroscedasticity consistent (White, 1980); two-tailed *p* values are reported below the public exposure indicator estimates; one-tailed *p* values, for the directional hypotheses that the least publicly exposed firms manifest higher mood-related effects, are reported below the estimated difference (Difference). IP = increasing photoperiod; DP = decreasing photoperiod; LP = long photoperiod; SP = short photoperiod; NA = Not Available (for the one-tailed hypothesis).

significant, being most prominent when comparing the performance of IPOs issued on long-and-increasing, as opposed to short-and-decreasing, photophase conditions.

To conclude, the evidence indicates that the extent of IPO underpricing is related to seasonal mood effects, being higher in positive (long or increasing photophase) than in negative mood (short or decreasing photophase) periods.

Recall that we attributed the prominence of the seasonal mood-related effect on IPO pricing to the lack of trading history, that is, the absence of anchoring information for the valuation process. To test the validity of this argument, we estimated the photophase condition effects on the initial excess returns conditioned on the firms' sales, offering gross proceeds, and age, presumed to serve as proxies for the public exposure. We expected the relatively less publicly exposed offerings to manifest more salient mood-related effects. Tables 4−6 display the multiple regression results of the IPOs' initial excess returns on the battery of public exposure indicators, controlling for the IPO characteristics (cf. footnote 7 and Table 1). Tables 4−6 describe regression results, which partition the daylight effect by one of the three proxies: the firms' sales (see Table 4), offering gross proceeds (see Table 5), and age (see Table 6). Specifically, Sa1−Sa4 partition the IPO sample into quarters (see Table 4), according to the firms' 12-month revenues, Sa1 indicating the lowest, and Sa4 the highest, sales groups; GP1−GP4 partition the firms in a similar man-

Table 5
Public Exposure Regression Analysis: Daylight Condition Effects on the Initial Returns Using the Firms' Offering Gross Proceeds as a Proxy for the Public Exposure

Public exposure indicators	GP1	GP2	GP3	GP4	GP1	Not GP1	Difference
IP vs. DP (1,526 observations)	14.98	6.17	4.28	6.49	15.06	5.78	9.28
p (%)	0.15	4.16	3.18	0.02	0.14	<0.01	2.78
LP vs. SP (1,526 observations)	4.49	−1.21	2.95	2.45	4.52	1.55	2.97
p (%)	32.55	68.79	11.81	15.80	32.25	22.33	26.80
IP × LP vs. DP × SP (883 observations)	18.94	3.87	6.79	9.09	19.04	6.78	12.26
p (%)	0.66	30.10	3.39	0.02	0.62	0.02	4.35

Note. Gross proceeds and sales are expressed in terms of 1984 dollars purchasing power, using the gross national product index data from the Federal Reserve Bank of St. Louis; regression covariance matrices are heteroscedasticity consistent (White, 1980); two-tailed *p* values are reported below the public exposure indicator estimates; one-tailed *p* values, for the directional hypotheses that the least publicly exposed firms manifest higher mood-related effects, are reported below the estimated difference (Difference). IP = increasing photoperiod; DP = decreasing photoperiod; LP = long photoperiod; SP = short photoperiod.

Table 6
Public Exposure Regression Analysis: Daylight Condition Effects on the Initial Returns Using the Firms' Age as a Proxy for the Public Exposure

Public exposure indicators	Age1	Age2	Age3	Age4	Age5	Age1	Not Age1	Difference
IP vs. DP (1,526 observations)	23.46	6.04	6.07	2.88	4.98	23.43	5.04	18.39
p (%)	0.11	3.68	1.30	13.54	1.97	0.10	0.01	0.54
LP vs. SP (1,526 observations)	4.91	2.55	1.11	4.04	1.80	4.90	1.62	3.28
p (%)	46.67	38.05	63.17	2.76	36.05	46.68	16.86	31.67
IP × LP vs. DP × SP (883 observations)	24.26	8.41	7.22	6.99	2.88	24.19	6.48	17.71
p (%)	1.35	5.33	3.64	0.91	23.89	1.34	0.02	3.78

Note. Gross proceeds and sales are expressed in terms of 1984 dollars purchasing power, using the gross national product index data from the Federal Reserve Bank of St. Louis; regression covariance matrices are heteroscedasticity consistent (White, 1980); two-tailed *p* values are reported below the public exposure indicator estimates; one-tailed *p* values, for the directional hypotheses that the least publicly exposed firms manifest higher mood-related effects, are reported below the estimated difference (Difference). IP = increasing photoperiod; DP = decreasing photoperiod; LP = long photoperiod; SP = short photoperiod.

ner by their gross proceeds (see Table 5); and Age1−Age5 partition the sample by the firms' age (see Table 6). The conditions effects were measured by photophase duration changes (IP vs. DP), photophase duration levels (LP vs. SP), and the combined indicators (IP × LP vs. DP × SP, as defined above). The left-hand side of the tables' panels present the results of regressions employing full partitions, and the right-hand side the results obtained by differentiating the least publicly exposed firms (lower sales and gross proceeds, younger age) from the rest of the sample.

First, consistent with the previously presented results, the seasonally related mood effects were less prominent when measured by photophase level indicators alone, while the photophase changes and combined indicators

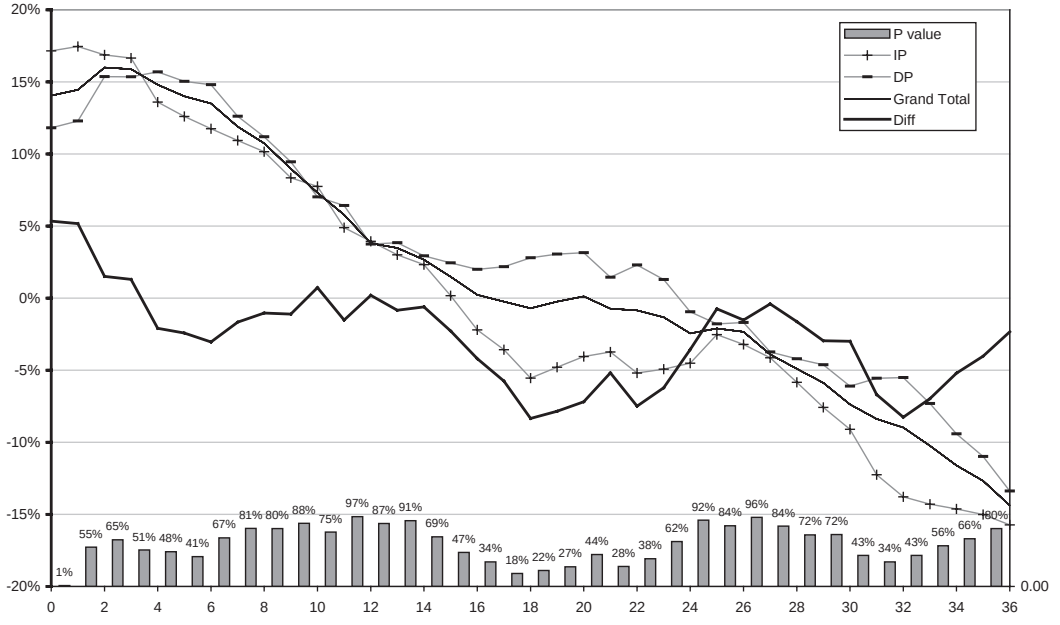

Figure 9. Increasing photoperiod (IP) versus decreasing photoperiod (DP), excess returns difference and average, using matching firms as benchmark, initial returns included. Diff = difference.

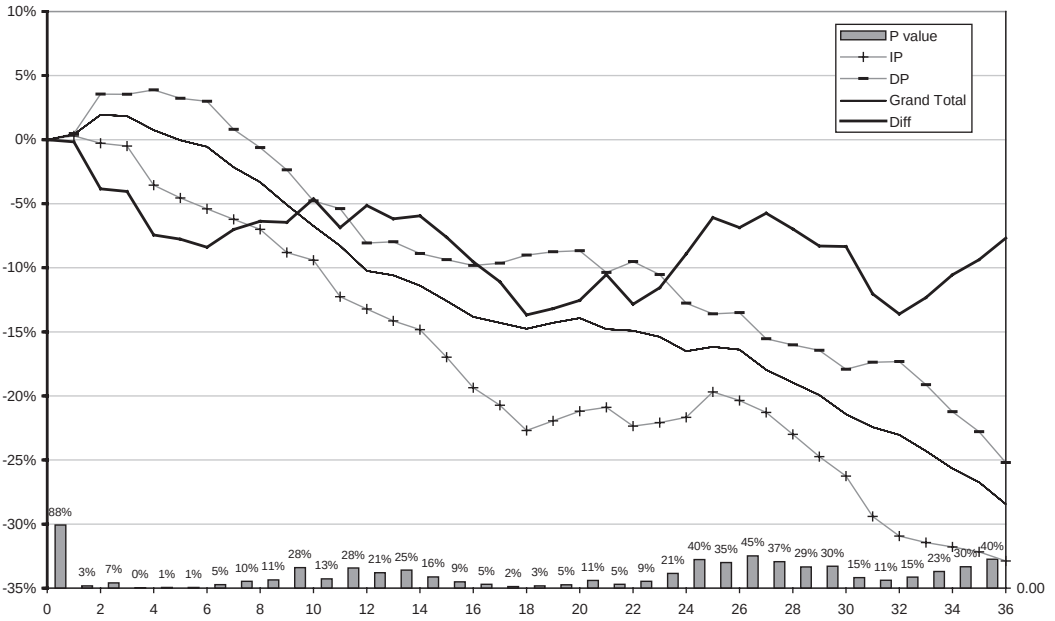

Figure 10. Increasing photoperiod (IP) versus decreasing photoperiod (DP), excess returns difference and average, using matching firms as benchmark, initial returns excluded. Diff = difference.

manifested prominent, significant evidence in support of the hypothesis we proposed. Henceforth, therefore, we focus on the coefficients of the photophase changes as the sole determinant (i.e., employ the IP vs. DP partition) and in combination with photophase levels (IP $\times$ LP vs. DP $\times$ SP). Turning to the public exposure hypothesis, using the fully spanned partition according to each of the three public exposure proxies (left-hand side of each panel), the photophase effect measured for the least publicly exposed group (i.e., Sa1, GP1, and Age1) was considerably higher than for the other groups, suggesting that smaller and younger firms are more susceptible to the seasonal mood effects. Specifically, the photophase effect on the returns of the lowest sales quartile (see Table 4) in all of the specifications involving photophase changes is slightly higher than 15%; the picture emerging from the gross proceeds analysis (see Table 5) yields similar results with effects of about 15% and approaching 20%; and the analysis using firms' age (see Table 6) points to an effect of around 25%. Consequently, we compared the least publicly exposed firms, according to each proxy, to the rest of the sample (the right-hand side of Tables 4−6). Testing the directional (i.e., one-tailed) hypothesis that the mood-related photophase effect on the least publicly exposed firms is stronger than the effect on the rest of the sample yielded significant results in most of the cases. Specifically, the photophase effect on the excess returns of the lowest sales quartile (see Table 4, rightmost column) points to a difference in the order of 8−11%, which is significant for the IP versus DP specification, but not significant for the other specifications; the results using the gross proceeds partition (see Table 5) yielded even stronger results, pointing to a difference in the order of about 9−13%, which is significant ($p < 5\%$) for all of specifications involving photophase changes; and the analysis employing the firms' age (see Table 6) yielded the strongest results of a significant ($p < 5\%$) difference between the least publicly exposed and the rest of the firms, around 18−19%. To sum, although the aggregate analysis showed a return differential between the IPOs issued in depressing and cheerful days in the order of 5−10% of the offering, the magnitude of the effect approached 15−25% for the least publicly ex-

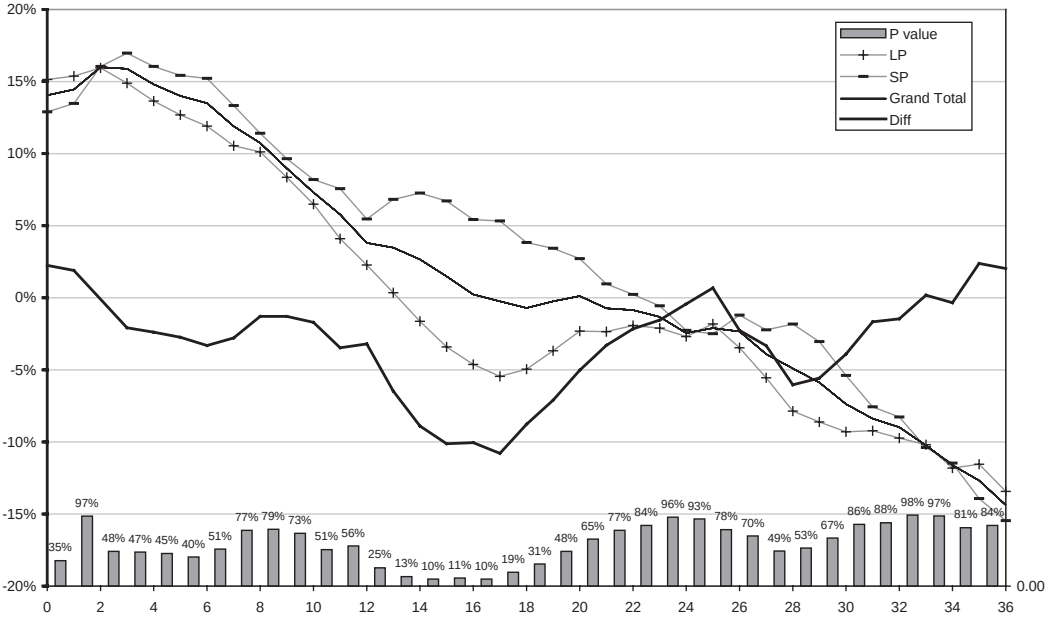

Figure 11. Long photoperiod (LP) versus short photoperiod (SP), excess returns difference and average, using matching firms as benchmark, initial returns included. Diff = difference.

posed firms. Thus, the results corroborate the existence of the mood effect, as well as its relation to the lack of trading history, normally serving as an anchor in the valuation process. In particular, as demonstrated by the results depicted in Tables 4−6, we found that knowing the firm's characteristics helped predict the size of the SAD impact. Dolvin and Pyles (2007), for comparison, reported higher underpricing under SP than under LP, but, within SP, they reported higher underpricing in the winter than in the fall. Although their finding is consistent with our SP versus LP results, their results are consistent with our DP versus IP results, to wit, Dolvin and Pyles's results are in line with ours on the photophase changes partition, for which our data also seem to manifest a more pronounced SAD impact.[9]

Long-Run Results

To assess the long-run IPO performance as related to the calendar date of the offering, we inspected the aftermarket monthly returns of the IPO cohorts, which were issued during the different photophase conditions. The returns were tracked for 3 years after the offering date. As with the short-run analysis, the IPO cohorts were defined according to the alternative photophase characteristics partitions. As above, we used matching firms as benchmarks and analyzed the IPO returns in excess of the returns of their matches. Hence we denote IPO excess returns as $AR_{it} = r_{it} - r_{mt}$, where r_{it} is the month t (raw) return of IPO i and r_{mt} is its matching firm contemporaneous return. Accordingly, the average excess return for an IPO cohort in month t is defined as the arithmetic average of all IPO excess returns in the cohort, that is, $AAR_t = \frac{1}{n_t}\sum_{i=1}^{n_t} AR_{it}$, where n_t is the cohort's number of IPOs in month t.[10] The Cumulative Abnormal Returns (CARs) up to month t are defined as summations of average excess returns over the given period, that is, $CAR_t = \sum_{j=i}^{t} AAR_j$. For the rest of this sec-

[9] Note also that Dolvin and Pyles (2007) employed a different data set, consisting of, inter alia, high technology and Internet firms going public during the Internet bubble of 1999–2000.

[10] To simplify the notation, we eliminated the cohort subscript.

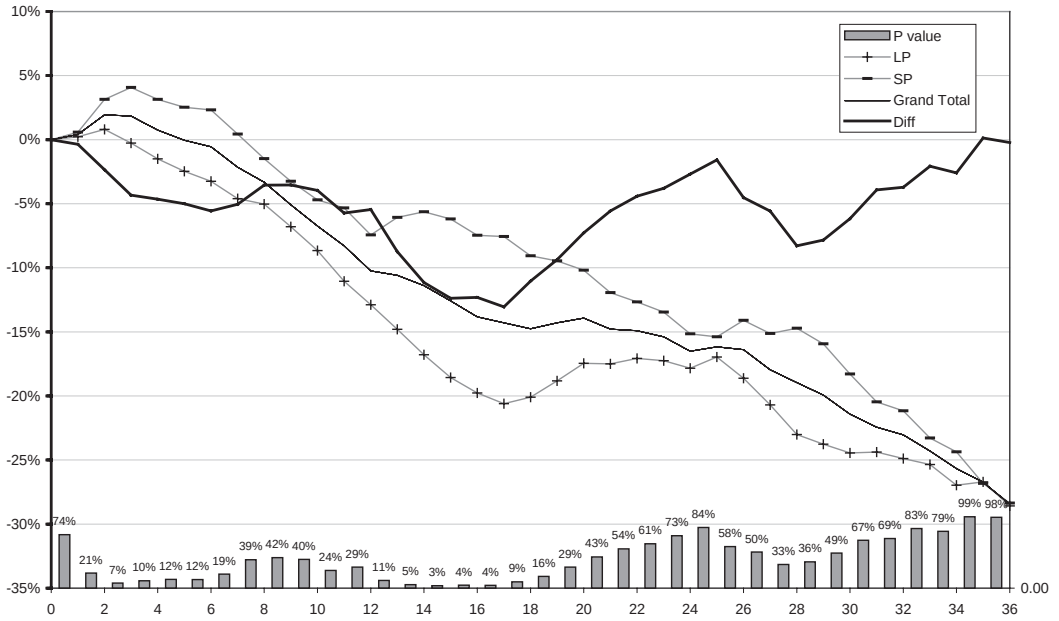

Figure 12. Long photoperiod (LP) versus short photoperiod (SP), excess returns difference and average, using matching firms as benchmark, initial returns excluded. Diff = difference.

tion, we employ CAR measurement that include and exclude the IPOs' initial excess returns, denoted by CAR_t^w and $CAR_t^{w/o}$, respectively.

First, we analyzed the IPOs partitioned by increasing, as opposed to decreasing, photophase duration of the calendar offering date (the IP and DP mood proxy indicators).

Figure 9 depicts the CARs, including their respective initial excess returns (i.e., CAR_t^w), of the whole data set (dashed), of the two cohorts of DP and IP (marked with − and +, respectively), as well as their difference (i.e., the CARs of the IP subsample over those of the DP, in bold). Additionally, using a secondary vertical axis, the CAR-difference *p* values are presented.[11] The short-run underpricing is reflected in the emanating points of the CAR graphs in the figure, and the long-run underperformance by the downward trend of the graphs over the inspected period.

With respect to the long-run hypothesis, the data indicate that the cum-initial-return stock performance is approaching similar levels within a quarter of a year, implying that the short-run initial excess return of the stocks issued in the cheerful periods is fully absorbed by that time in the IPOs' subsequent performance. In other words, the initial tendency related to the photophase duration seems to be reversed over the months after the offering. Inspecting the CARs beyond 3 months reveals at first a similar decline by both IPO subgroups, which turns into a slightly steeper, though nonsignificant ($p = 18\%$, two-tailed) CAR of the DP subgroup when approaching a year and a half after the offering. Inspecting the subgroups' relative CAR excluding the initial excess return ($CAR^{w/o}$; Figure 10) reveals that the IP subgroup significantly underperformed its counterpart, up to a maximal difference occurring by a year and a half after the offering, amounting to about 14% ($p = 2\%$, two-tailed). The underperformance of the IP subgroup remains until the end of the sampling period (36 months), though

[11] The *p* values for the respective CAR *t* statistics are $CAR_t^w \times \sqrt{n_t}/csd_t^w$ and $CAR_t^{w/o} \times \sqrt{n_t}/csd_t^w$, where n_t is the number of firms trading at month *t*; $csd_t^w = [t \times var + 2 \times (t-1) \times cov]^{1/2}$; $csd_t^w = [(t-1) \times var + var^* + 2 \times (t-1) \times cov]^{1/2}$; *var* is the average cross-sectional variance over the 36 months after going public; *cov* is the first-order autocovariance of the monthly abnormal returns implied by their autocorrelation; and *var** is the first-month cum-initial-return cross-sectional variance.

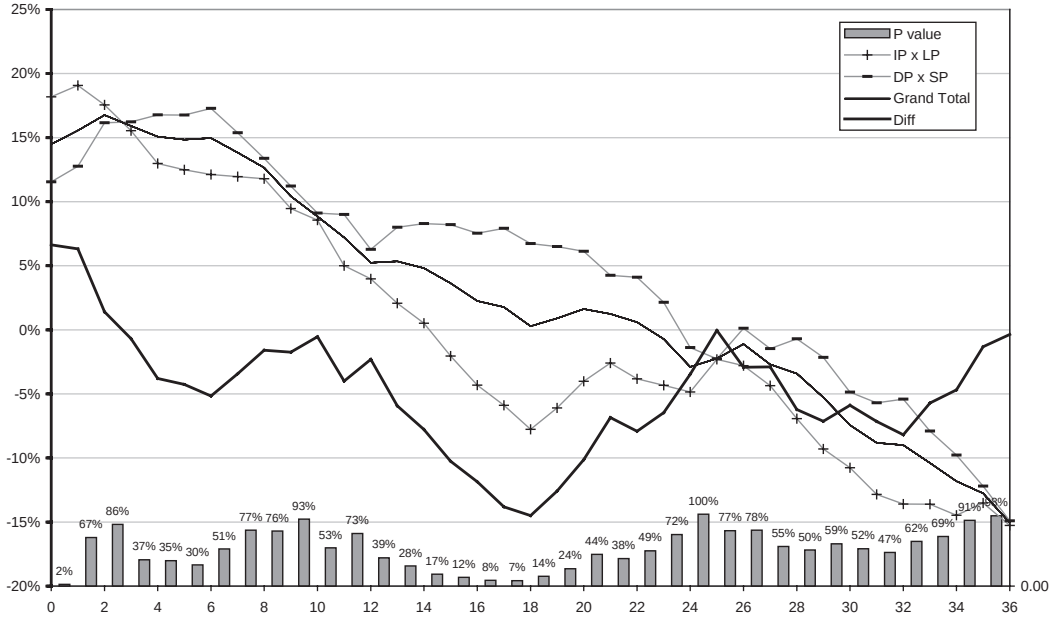

Figure 13. IP (increasing photoperiod) × LP (long photoperiod) versus DP (decreasing photoperiod) × SP (short photoperiod), excess returns difference and average, using matching firms as benchmark, initial returns included. Diff = difference.

by a lower magnitude and significance level, possibly reflecting the increased length of the measurement window.

Next, we analyzed the two IPO cohorts according to the photophase duration level of the calendar offering date.

Figure 11 depicts the cum-initial-return CARs (CAR_t^w), in a fashion similar to Figure 9, but for the partition according to SP versus LP. The CARs excluding the initial excess returns ($CAR_t^{w/o}$; Figure 12) reveal equality of the cum-initial-return stock performance within 2 month, that is, the short-run initial excess returns of the LP subsample were fully annulled faster than those of the IP (first indicator) subsample with high significance (p range: 2−4%, two-tailed). To wit, the high initial excess returns of the long- photophase subsample were overturned subsequent to the offering, resulting in CAR differences of 13% and almost 15%, respectively, between the subgroups. The underperformance of the LP subgroup with respect to SP then offsets by the end of sampling period (36 months). Specifically, both subsamples' $CAR^{w/o}$ approach the whole data set cumulative average abnormal excess return.

Finally, we performed a comparative analysis of the extreme observations of short-and-decreasing, versus long-and-increasing, daylight duration (Figures 13 and 14).

All of the aforementioned trends were even more pronounced and achieved higher significance when the extreme observations of short-and-decreasing and long-and-increasing photophase duration periods were compared.

Conclusion

We examined the effect of investors' mood, as captured by the daylight duration and its gradient, on IPO pricing. Our results show that the calendar date of the offering and its corresponding seasonal mood exerts substantial influence on short- and long-run IPO performance. Specifically, examining IPO first trading day prices indicated that, in the short run, stocks issued on days associated with depressing photophase conditions (most prominently, shortening days) earned lower excess returns than stocks issued in cheerful periods (lengthening days); in the long run, up to a season (about a quarter of a year), the stocks' cum-initial-

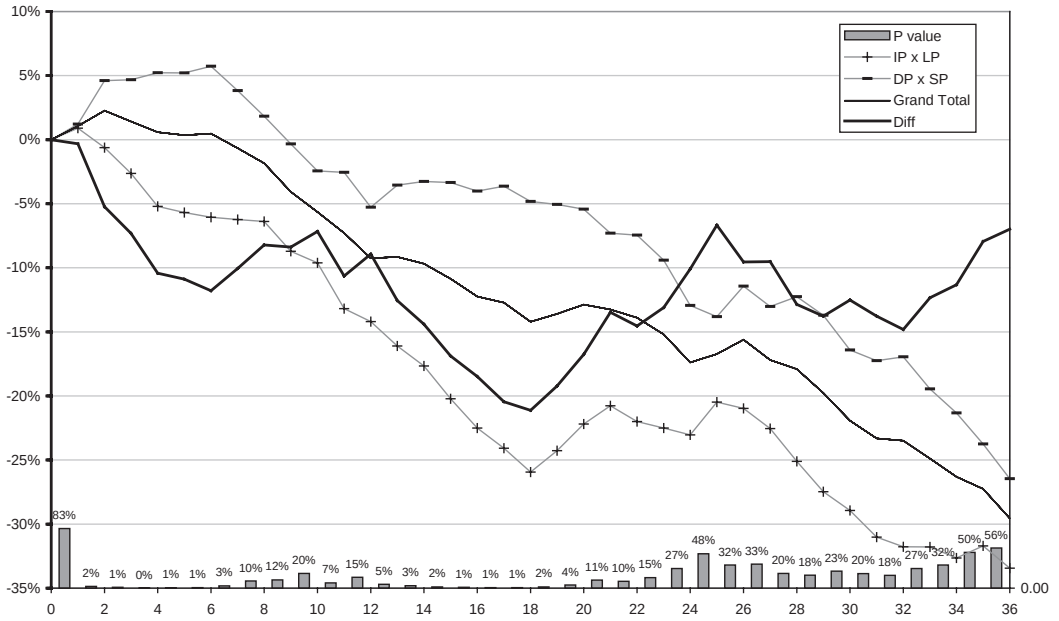

Figure 14. IP (increasing photoperiod) × LP (long photoperiod) versus DP (decreasing photoperiod) × SP (short photoperiod), excess returns difference and average, using matching firms as benchmark, initial returns excluded. Diff = difference.

returns were equated, implying that the short-run initial excess returns of the stocks issued in the cheerful periods were fully absorbed by subsequent performance; and after about one season, the stocks issued in the cheerful periods continued to underperform (until about a year and a half) and subsequently (up to 3 years) possibly reverted to the grand average of IPO underperformance. We attribute the seasonal mood-related effects on IPO underpricing to the lack of trading history, which normally serves as an anchor in the valuation process. We find average excess return differential between the IPOs issued in depressing and cheerful days to be in the order of 5−10% of the offering, approaching 15−25% for the relatively less publicly exposed firms, as assessed using a database of 1,526 IPOs with average gross proceeds of $15 million. Our findings corroborate the presumption that investors' mood affects their decision-making process even in real-life, market situations.

References

Berson, D. M., Dunn, F. A., & Takao, M. (2002). Phototransduction by retinal ganglion cells that set the circadian clock. *Science, 295,* 1070–1073. doi: 10.1126/science.1067262

Dam, H., Jakobsen, K., & Mellerap, E. (1998). Prevalence of winter depression in Denmark. *Acta Psychiatrica Scandinavica, 97,* 1–4. doi:10.1111/j.1600-0447.1998.tb09954.x

Dolvin, S. D., & Pyles, M. K. (2007). Seasonal affective disorder and the pricing of IPOs. *Review of Accounting and Finance, 6,* 214–228. doi: 10.1108/14757700710750865

Garrett, I., Kamstra, M. J., & Kramer, L. A. (2005). Winter blues and time variation in the price of risk. *Journal of Empirical Finance, 12,* 291–316. doi: 10.1016/j.jempfin.2004.01.002

Haim, A., Shanas, U., Zubidat, A. S., & Scantelbury, M. (2005). Seasonality and seasons out of time – The thermoregulatory effects of light interference. *Chronobiology International, 22,* 59–66. doi: 10.1081/CBI-200038144

Hirshleifer, D. (2001). Investor psychology and asset pricing. *Journal of Finance, 56,* 1533–1597. doi: 10.1111/0022-1082.00379

Ibbotson, R. G. (1975). Price performance of common stock new issues. *Journal of Financial Economics, 2,* 235–272. doi:10.1016/0304-405X(75)90015-X

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47,* 263–291. doi:10.2307/1914185

Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2000). Losing sleep at the market: The daylight-saving anomaly. *American Economic Review, 90,* 1005–1011. doi:10.1257/aer.90.4.1005

Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2003). Winter blues: A sad stock market cycle. *American Economic Review, 93,* 324–343. doi:10.1257/000282803321455322

Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2012). A careful re-examination of seasonality in international stock markets: Comment on sentiment and stock returns. *Journal of Banking and Finance, 36,* 934–956. doi:10.1016/j.jbankfin.2011.10.010

Kamstra, M. J., Kramer, L. A., Levi, M. D., & Wermers, R. (2011). *Seasonal asset allocation: Evidence from mutual fund flows.* Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1907904

Kaplanski, G., & Levy, H. (2008). *Mispricing of options: Perceived market risk and seasonal affective disorder (SAD).* Working Paper.

Keller, M. C., Fredrickson, B. L., Ybarra, O., Cote, S., Johnson, K., Mikels, J., . . . Wager, T. (2005). A warm heart and a clear head. *Psychological Science, 16,* 724–731. doi:10.1111/j.1467-9280.2005.01602.x

Kliger, D., & Levy, O. (2003). Mood-induced variation in risk preferences. *Journal of Economic Behavior & Organization, 52,* 573–584. doi:10.1016/S0167-2681(03)00069-6

Kliger, D., & Levy, O. (2008). Mood impacts on probability weighting functions: Large-gamble evidence. *The Journal of SocioEconomics, 37,* 1397–1411. doi:10.1016/j.socec.2007.08.010

Lam, R. W. (1998). Seasonal affective disorder and beyond: diagnosis and management. *Primary Care Psychiatry, 4,* 63–74.

Ljungqvist, A. (2007). IPO underpricing. In B. E. Eckbo (Ed.), *Handbook in corporate finance: Empirical corporate finance* (pp. 123−160). Amsterdam, Netherlands: Elsevier/North Holland.

Loughran, T., & Ritter, J. R. (2002). Why don't issuers get upset about leaving money on the table in IPOs? *Review of Financial Studies, 15,* 413–444. doi:10.1093/rfs/15.2.413

Ma, T., & Shen, Y. (2003, October). *Prospect theory and the long-run performance of the IPO stocks.* Presented at the 14th Annual Conference on Financial Economics and Accounting. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=488146

Nelson, R. J. (2005). *An introduction to behavioral endocrinology* (3rd ed.). Sunderland, MA: Sinauer Associates.

Oren, D. A., & Rosenthal, N. E. (1992). Seasonal affective disorders. In E. S. Paykel (Ed.), *Handbook of affective disorders* (2nd ed., pp. 551–567). London, England: Churchill Livingstone.

Reilly, F. K. (1973). Further evidence on short-run results for new issues investors. *Journal of Financial and Quantitative Analysis, 8,* 83–90. doi:10.2307/2329750

Reimann, M., & Bechara, A. (2010). The somatic marker framework as a neurological theory of decision-making: Review, conceptual comparisons, and future neuroeconomics research. *Journal of Economic Psychology, 31,* 767–776. doi:10.1016/j.joep.2010.03.002

Reiter, R. J. (1991). Pineal melatonin: Cell biology of its synthesis and of its physiological interactions. *Endocrine Reviews, 12,* 151–180. doi:10.1210/edrv-12-2-151

Reiter, R. J. (1993). The melatonin rhythm: Both a clock and a calendar. *Experientia, 49,* 654−664. doi:10.1007/BF01923947

Ritter, J. R. (1991). The long-run performance of initial public offerings. *Journal of Finance, 46*(1), 3–27.

Ritter, J. R., & Welch, I. (2002). A review of IPO activity, pricing, and allocations. *Journal of Finance, 57,* 1795–1828. doi:10.1111/1540-6261.00478

Roenneberg, T., & Aschoff, J. (1990). Annual rhythm of human reproduction: II. Environmental correlations. *Journal of Biological Rhythms, 5,* 217–239. doi:10.1177/074873049000500304

Rosen, L. N., Targum, S. D., Terman, M., Bryant, M. T., Hoffman, H., Kasper, S. F., . . . Rosenthal, N. E. (1990). Prevalence of seasonal affective disorder at four latitudes. *Psychiatry Research, 31,* 131–144. doi:10.1016/0165-1781(90)90116-M

Rosenthal, N. E., Sack, D. A., Gillin, J. C., Lewy, A. J., Goodwin, F. K., Davenport, Y., . . . Wehr, T. A. (1984). Seasonal affective disorder: A description of the syndrome and preliminary findings with light therapy. *Archives of General Psychiatry, 41,* 72−80. doi:10.1001/archpsyc.1984.01790120076010

Saeed, S. A., & Bruce, T. J. (1998). Seasonal affective disorders. *American Family Physician, 57*(6), 1340−1346.

Stoll, H. R., & Curley, A. J. (1970). Small business and the new issues market for equities. *Journal of Financial and Quantitative Analysis, 5,* 309–322. doi:10.2307/2329998

Von Neumann, J., & Morgenstern, O. (1944). *Theory of games and economic behavior.* Princeton, NJ: Princeton University Press.

White, H. (1980). A heteroscedasticity-consistent covariance matrix and a direct test for heteroscedasticity. *Econometrica, 48,* 817–838. doi:10.2307/1912934

Received February 12, 2012
Revision received June 11, 2012
Accepted June 13, 2012 ■