Article

Gamesmanship and Seasonality in U.S. Stock Returns

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Abstract: We re-examined the seasonal pattern in the excess returns of highly visible American firms. In contrast to the seasonality for risky, less visible firms, we found that highly visible stocks display return seasonality that shows the opposite trend. Fund managers are prone to gamesmanship, putting downward pressure on prices for highly visible firms at the beginning of the year, which is reversed later with buying pressure. Due to the bonus culture, fund managers start the year by buying small, risky stocks in order to beat benchmarks. Once targets are met, they adjust toward visible, less risky stocks to lock in returns, providing them with a seasonal returns pattern opposite to that of small firms. A re-examination is warranted because the world has become increasingly globalized, and some argue that managers' incentives are aligned with investors due to increased scrutiny. We used analyst following as a proxy for visibility and examined the seasonal pattern for 1997–2018. Though the anomaly was first reported twenty years ago, it persists in recent data. Rational investors may be limited in their ability to arbitrage mispricing because institutional investors who drive the market are self-interested. Future research may examine the seasonal pattern in countries with more stringent regulation of financial professionals or with high-frequency data.

Keywords: financial analysts; gamesmanship; window dressing; agency considerations; institutional investors

JEL: G11; G12

In the light of the scanty evidence presented here, it can readily be seen that forecasts predicated upon seasonal movements alone, completely ignoring the customary cycle and trend analysis, have an extremely high probability of success. Certainly, the seasonal curve is well worth watching when formulating actual investment policy.

(Wachtel 1942)

1. Introduction

Economist and investment banker Sidney Wachtel recognized that the "December to January seasonal rise" in stock prices presents a trading opportunity for investors. Wachtel further notes that selling for tax purposes at the year end could be a driving force behind return seasonality. However, as Ackert and Athanassakos (2000) argue, tax-loss selling cannot explain why we observe different seasonal patterns in the returns for small, little known stocks and those of large, highly visible firms. To understand this seasonal difference, we need to consider the behavior of professional mutual fund managers and the structure of their incentives.

Institutional investors are clearly important participants in securities markets. As remuneration is typically tied to the performance of the managed portfolio, a mutual fund manager's goal is to end the year with strong performance. To look strong at the end of the year, the manager adds risky, potentially high-return securities at the start of the year and then moves toward lower risk, well-known, and visible securities toward the year end. By following this strategy, the manager earns the year-end performance bonus that is hoped for and investors see solid returns and portfolio holdings in visible, highly regarded, and lower risk assets at the end of the year.

In the following section, we review the evidence of a number of persistent return patterns that are driven by mispricing (Heston and Sadka 2008; Keloharju et al. 2016, 2021). As is well documented, the stocks of small, more risky firms earn high returns, on average, in January when demand for these stocks is high (e.g., (Banz 1981; Blume and Stambaugh 1983; Keim 1983)). As the year progresses, prices for small, risky stocks are bid up, and returns fall. In contrast to the seasonality reported for small firms, stocks of highly visible firms display return seasonality that shows the opposite trend, as documented by Ackert and Athanassakos (2000). In this paper, we re-examine the seasonal pattern in excess returns for highly visible stocks. As the behavior was first reported over twenty years ago, surely the observed seasonal patterns will have evaporated if markets are efficient and the incentives of fund managers are aligned with investors. Today, markets are quite globalized. Furthermore, re-visiting seasonality is important as recent commentary suggests that strategic portfolio rebalancing among fund managers for self-interested purposes has "pretty much disappeared completely ever since state regulators and the SEC cracked down on the practice in 2001 and 2008" (Institute of Business & Finance 2021) Here, we ask whether, as this quote suggests, managers have evolved so that conflicts of interest no longer impact the portfolio management behavior of professional fund managers.

The remainder of this paper is organized as follows. Section 2 provides a review of the related literature. Section 3 describes the sample construction and provides summary information. Sections 4 and 5 report the primary and supplemental results. Section 6 contains a discussion of the results and concluding remarks.

2. Literature Review

The January effect, a seasonal pattern in the returns for small stocks, has been documented by a number of studies including Banz (1981); Blume and Stambaugh (1983); Keim (1983); Haug and Hirschey (2006); and Keloharju et al. (2016). Finance academics believe that asset markets are efficient, so that prices reflect all available information. In such case, no trading strategy using public information could consistently generate abnormal returns. Yet, seasonal return patterns uncovered by researchers in recent years, including the Monday effect (Fishe et al. 1993; Athanassakos and Robinson 1994; Chiah and Zhong 2019), day-of-the-month effect (Booth et al. 2001; Kunkel et al. 2003; Singh et al. 2021), Holiday effect (Cao et al. 2009; Brockman and Michayluk 2010; Robbins and Smith 2019), and Halloween effect (Bouman and Jacobsen 2002; Jacobsen and Marquering 2008; Zhang and Jacobsen 2021), have called this belief into question. Some researchers report that not all anomalies are robust (Linnainmaa and Roberts 2018; Harvey and Liu 2019), though other evidence suggests that these return patterns are driven by mispricing and are quite persistent (Heston and Sadka 2008; Keloharju et al. 2016, 2021).

For small, more risky firms, high returns are observed in January as demand for such stocks is high due to bonus-chasing portfolio rebalancing and gamesmanship by professional portfolio managers. This behavior causes prices to be bid up at the start of the year. Over the year, as professional portfolio managers lock in the desired performance, they adjust away from small, risky stocks, and these stocks' returns fall over the year. In contrast to the seasonality reported for small firms, stocks of highly visible firms display return seasonality that shows the opposite trend (Ackert and Athanassakos 2000). Due to gamesmanship and window dressing, the stocks of large, visible firms experience selling

pressure at the beginning of the year and buying pressure toward the end. In fact, Ma et al. (2019) report that the majority of their sample mutual funds compensate managers using a bonus scheme rather than a fixed salary. Furthermore, 79% of the funds explicitly tie the manager's bonus to the fund's investment performance. In addition to aiming to clinch a bonus, a manager may engage in window dressing to provide a positive image to investors by systematically rebalancing portfolio holdings over the year after locking in desired returns (Haugen and Lakonishok 1988; Lakonishok et al. 1991; Ortiz et al. 2015). Gamesmanship and window dressing are tactics fund managers use to gain a psychological advantage and provide a winning strategy that assures a performance-based bonus. To this end, the manager adds risky, potentially high-return securities at the start of the year and then gravitates toward lower risk, well-known, and visible securities toward the year end to lock in a Christmas bonus. With this strategy, the manager earns the desired bonus, and investors see solid returns and portfolio holdings in visible, highly regarded, and lower risk assets at the end of the year.

This paper re-examines reported seasonality in excess returns for highly visible stocks. As Ackert and Athanassakos (2000) argue, the incentives of fund managers can explain the seasonal patterns in small, little known stocks as well as those that are large and highly visible. At the beginning of the year, institutional investors add small, less visible stocks to their portfolios, and these stocks experience abnormally high returns due to buying pressure. As the year progresses, fund managers rebalance away from small stocks leading to selling pressure and lower returns. In contrast, at the beginning of the year, highly visible stocks have low returns that adjust up as institutional investors adjust toward these stocks after achieving targeted returns. A large body of research provides evidence consistent with the seasonal impact of fund manager behavior on both stock and bond returns (e.g., (Ng and Wang 2004; Morey and O'Neal 2006; Ortiz et al. 2012). It has been twenty years since Ackert and Athanassakos (2000) first reported the seasonal pattern in returns for visible stocks. If investors are rational, surely smart traders will have taken advantage of this opportunity, eliminating systematic excess returns.

If an anomaly is due to mispricing, it should not persist. McLean and Pontiff (2016) argue that after the academic publication of a predictable pattern in returns, investors should learn about the anomaly. On average, they find that return predictability falls by 58% after publication in an academic outlet. More recently, Jacobs and Müller (2020) report that the United States is the only nation with a reliable decline in predictability after publication, with high arbitrage costs limiting the ability to eliminate mispricing in other countries. As compensation schemes tied to fund performance are still widely used, self-interested behavior among managers may remain undeterred by smart investors. Gamesmanship and window dressing are fund manager behaviors that may persist.

3. Data Description

We obtained the number of analysts following a firm, forecasted earnings, actual earnings, and the standard deviation of earnings estimates from the Institutional Brokers Estimate System (IBES) for each month from January 1980 through December 2018. Here, we report results for the later time period, January 1997 through December 2018, because our goal is to re-examine the results of Ackert and Athanassakos (2000) whose data end in 1996. We repeated all analyses reported subsequently with data from January 1980 through December 2018, and inferences were unchanged. These results are available upon request. Though our sample ends in 2018, we believe our results reflect the long-term American experience. However, we recognize that the economic upheaval of 2019–2020, with the black swan effect of COVID-19, led to a sharp reduction in inflation and interest rates, which may have impacted the seasonal patterns. The final sample for 1997–2018 (1980–2018) includes 24,280 (30,831) monthly observations for 549 (692) unique companies representing 63 industries classified by the two-digit Standard Industrial Classification (SIC) code. The two-digit code is the last non-zero Standard Industrial Classification (SIC) code found in a specific security's name structure in CRSP's database. We obtained data

on prices, returns, and market values from the CRSP NYSE/AMEX database. The data included in the final sample passed through several filters, described below.

(1) The IBES database includes analysts' consensus forecasts for at least twelve consecutive months starting in January of the forecast year and ending in December.

(2) At least three individual forecasts determine the consensus forecast of earnings per share per month.

(3) The company's fiscal year ends in December. We excluded firms with non-December year ends to ensure appropriate intertemporal comparisons over our cross-section (Givoly 1985).

(4) The CRSP NYSE/AMEX database includes price, raw, and beta excess returns, and shares outstanding information.

We compounded daily returns for each firm using holding period and excess returns to compute monthly returns. The CRSP daily excess return is the excess of the daily return above the return on a portfolio of stocks with similar risk. Benchmark portfolios are defined using portfolio rankings determined by beta values (beta excess return) for the entire population of firms included in the CRSP database.

Table 1 presents summary information for the overall sample. Panel A reports sample statistics for quartiles based on the standard deviation of analysts' forecasts scaled by price (σ(FEPS)), and Panel B reports information for quartiles based on market value (MV). Ackert and Athanassakos (1997) report that analysts' earnings forecasts are too optimistic for firms in highly uncertain information environments, where uncertainty is measured using the standard deviation of earnings forecasts. However, when uncertainty is low, analysts' forecasts are more accurate. As these authors show that strategies based on uncertainty can generate abnormal returns, we examined whether differences arise across the level of uncertainty. In addition, because the January seasonal is reported to be related to firm size, in Panel B of Table 1, we report summary information by market value quartile (Keim 1983).

Table 1. Summary statistics: The table reports summary information for our sample which includes data from January 1997 through December 2018. In addition to full sample information, Panel A provides sample statistics for quartiles based on the standard deviation of analysts' forecasts scaled by price (σ(FEPS)), and Panel B reports information for quartiles based on market value (MV). First, the table reports the number of analysts following sample firms as reported in the IBES database. Next, the table reports on forecasted and actual earnings, σ(FEPS), stock price, and market value (in millions of dollars).

Panel A: Means for the Full Sample as Well as Quartiles Determined by the Standard Deviation of Analysts' Earnings Forecasts Scaled by Price (σ(FEPS)).					
	Overall	**Q1 (Low)**	**Q2**	**Q3**	**Q4 (High)**
Number of analysts	30.59	31.09	31.26	30.00	30.00
Forecasted earnings	USD 2.77	USD 2.71	USD 3.12	USD 2.60	USD 2.65
Actual earnings	USD 2.69	USD 2.69	USD 3.04	USD 2.57	USD 2.47
σ(FEPS)	0.0250	0.0048	0.0111	0.0193	0.0663
Price	USD 40.32	USD 49.19	USD 45.09	USD 39.15	USD 27.37
Market value	USD 25,445	USD 46,918	USD 27,524	USD 16,817	USD 9749
Panel B: Means for Quartiles Determined by Market Value.					
		Q1 (Low)	**Q2**	**Q3**	**Q4 (High)**
Number of analysts		24.34	USD 31.81	USD 34.06	USD 32.31
Forecasted earnings		USD 0.98	USD 2.49	USD 3.13	USD 4.55
Actual earnings		USD 0.84	USD 2.47	USD 3.00	USD 4.54
σ(FEPS)		0.0197	0.0185	0.0189	0.0110
Price		USD 22.02	USD 36.69	USD 44.06	USD 59.25
Market value		USD 2029	USD 6112	USD 14,630	USD 80,684

The statistics reported in Table 1 indicate that the average following is substantial for the overall sample and each uncertainty (σ(FEPS)) and MV quartile. Overall, our sample firms are followed by almost 31 professional financial analysts, on average. Forecasted earnings exceed actual earnings in all cases, consistent with the large body of research that reports analyst optimism about the earnings for firms they follow (e.g., (Ali et al. 1992)). For the low-uncertainty quartile, analyst optimism is 2 cents, on average, whereas for the high-uncertainty quartile, average optimism is 18 cents. Interestingly, analyst optimism has declined significantly over time. In comparison, Ackert and Athanassakos (2000) report an average optimism of 86 cents for their high uncertainty quartile. In Panel B, we also observed, not surprisingly, that larger firms as measured by MV are associated with higher analyst following, lower σ(FEPS), and higher stock prices, on average.

From Table 1, we can see that, consistent with expectations, our sample includes many large firms. This is expected, given that firms that are widely followed by analysts tend to have larger market capitalization. Importantly, however, a significant number of our highly visible sample firms are of small to moderate size. Of course, there is no single definition of small and medium capitalization, and the definitions change from year to year. For a reference point, we look to the Standard and Poor's classifications. Prior to 20 February 2019, the S&P SmallCap600 (MidCap400) indices included firms with market capitalizations of USD 450 million to 2.1 billion (USD 1.6 billion to 6.8 billion). For the capitalization eligibility criteria before and after 20 February 2019 (S&P Global 2021). In fact, approximately one-half of our sample of highly visible firms fall into the small to mid-sized range.

4. Results

We estimated the following pooled cross-sectional, time series model to examine the seasonal pattern in returns for highly visible firms:

$$R_{i,t} = \alpha_0 + \sum_{j=2}^{12} \alpha_j D_{j,t} + e_{i,t} \tag{1}$$

where α_0 is the sample average January return, $R_{i,t}$ is the time t return for firm i, and $D_{j,t}$ is a dummy variable taking the value of one for month j, and zero otherwise. The estimate of the coefficient of each dummy variable, α_j, measures the difference is return for month j from the return in January.

Table 2 reports OLS regressions for raw returns for our sample of highly followed firms over the January 1997 through December 2018 time period. We used Pooled OLS because it obtains unbiased estimates when attributes are constant through time. Other approaches, such as Generalized Methods of Moments, might be used in future research if concern about unbiasedness arises (Ferson and Harvey 1992). Table 2 reports estimates of the seasonal dummy variables as represented by Equation (1) for the full sample as well as for quartiles based on the standard deviation of analysts' forecasts scaled by price (σ(FEPS)). In the table, we report t-statistics below each coefficient estimate and the final two rows report F-tests and χ^2-tests of the null hypothesis of no difference in medians across months. Asterisks of *, **, and ** indicate significance at the 10%, 5%, and 1% level, respectively. Both the F-statistics and χ^2-statistics indicate strong seasonality in returns. However, unlike Ackert and Athanassakos (2000), for the raw returns, we did not observe the typical seasonal pattern in returns, with high returns in January and adjustment down over time. Instead, Table 2 indicates a lower return in January as compared to other months, though the coefficient for the January dummy is only significant for the highest uncertainty quartile and not for the overall sample. There is some significant adjustment upward, particularly in the first four months of the year across all uncertainty quartiles and the overall sample. This pattern was also observed in the seasonal pattern for raw returns across market value quartiles (not tabulated, but available upon request). As these

are raw returns, though, we do not know whether the abnormal pricing leads to predictable trading opportunities. Thus, we turn to excess returns.

Table 2. Tests for monthly seasonal effects in raw returns with uncertainty quartiles. The table reports of OLS regressions for our sample of raw returns, which includes data from January 1997 through December 2018. The table reports estimates of seasonal dummy variables for the full sample as well as for quartiles based on the standard deviation of analysts' forecasts scaled by price (σ(FEPS)). *t*-statistics appear below each coefficient estimate with asterisks indicating statistical significance. The final two rows report F-tests and χ^2-tests of the null hypothesis of no difference across months. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Month	Overall	Q1 (Low)	Q2	Q3	Q4 (High)
January	−0.0036	0.0086	0.0077	−0.0054	−0.0259
	(−1.04)	(1.58)	(1.18)	(−0.79)	(−3.07) **
February	0.0163	0.0117	0.0011	0.0167	0.0360
	(3.36) ***	(1.52)	(0.12)	(1.73)	(3.01) **
March	0.0407	0.0122	0.0245	0.0482	0.0795
	(8.40) ***	(1.59)	(2.67) **	(5.00) ***	(6.64) ***
April	0.0477	0.0247	0.0331	0.0505	0.0837
	(9.84) ***	(3.22) **	(3.60) ***	(5.25) ***	(7.00) ***
May	0.0084	−0.0036	−0.0004	0.0115	0.0266
	(1.73)	(−0.46)	(−0.05)	(1.20)	(2.22) *
June	−0.0021	−0.0147	−0.0102	−0.0031	0.0205
	(−0.43)	(−1.92)	(−1.11)	(−0.32)	(1.72)
July	−0.0029	−0.0137	−0.0058	−0.0048	0.0132
	(−0.61)	(−1.78)	(−0.63)	(−0.50)	(1.10)
August	−0.0032	−0.0249	−0.0151	−0.0027	0.0314
	(−0.65)	(−3.24) **	(−1.65)	(−0.28)	(2.62) **
September	0.0154	−0.0015	0.0077	0.0154	0.0410
	(3.18) **	(−0.19)	(0.84)	(1.60)	(3.43) ***
October	0.0074	0.0056	−0.0065	0.0031	0.0278
	(1.53)	(0.73)	(−0.71)	(0.33)	(2.32) *
November	0.0049	0.0037	−0.0124	−0.0012	0.0300
	(1.01)	(0.48)	(−1.34)	(−0.13)	(2.50) *
December	0.0079	0.0063	0.00001	0.0034	0.0223
	(1.63)	(0.82)	(0.01)	(0.35)	(1.86)
F-statistic	23.3777 ***	6.2017 ***	4.9402 ***	7.8823 ***	8.3862 ***
χ^2-statistic	1611.00 ***	412.42 ***	400.64 ***	410.27 ***	393.16 ***

Table 3 reports OLS regressions for excess returns for our sample of highly followed firms with estimates of the seasonal dummy variables for the full sample and quartiles based on the standard deviation of analysts' forecasts scaled by price (σ(FEPS)). Excess returns are computed using portfolio rankings indicated by beta, as explained in Section 2 of the paper. As Ackert and Athanassakos (1997) argue that strategies based on uncertainty have the potential to generate abnormal returns, we examined whether seasonal differences arise across the level of uncertainty. Asterisks of *, **, and ** indicate significance at the 10%, 5%, and 1% level, respectively. As with raw returns, the F-statistics and χ^2-statistics indicate strong seasonality in excess returns. Here, as in Ackert and Athanassakos (2000), we observed that the typical seasonal pattern of high returns in January that adjust down over time is reversed. The estimates reported in Table 3 indicate a significantly lower return in January as compared to other months for the full sample, as well as the third and fourth uncertainty quartiles, with adjustment upward over most of the year. The pattern is consistent across uncertainty quartiles, though not always statistically

significant. We repeated all analyses for market value quartiles, and inferences were unchanged. These results are not tabulated but are available upon request.

Table 3. Tests for monthly seasonal effects in excess returns with uncertainty quartiles. The table reports of OLS regressions for our sample of excess returns, which includes data from January 1997 through December 2018. The table reports estimates of seasonal dummy variables for the full sample as well as for quartiles based on the standard deviation of analysts' forecasts scaled by price (σ(FEPS)). Excess returns are computed using portfolio rankings indicated by beta. *t*-statistics appear below each coefficient estimate with asterisks indicating statistical significance. The final two rows report F-tests and χ^2-tests of the null hypothesis of no difference across months. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Month	Overall	Q1 (Low)	Q2	Q3	Q4 (High)
January	−0.0131	−0.0022	−0.0031	−0.0130	−0.0350
	(−4.44) ***	(−0.45)	(−0.55)	(−2.24) *	(−4.85) ***
February	0.0181	0.0111	0.0046	0.0178	0.0394
	(4.33) ***	(1.64)	(0.57)	(2.18) *	(3.85) ***
March	0.0206	−0.0028	0.0054	0.0265	0.0544
	(4.91) ***	(−0.42)	(0.66)	(3.23) **	(5.32) ***
April	0.0187	0.0037	0.0064	0.0176	0.0482
	(4.47) ***	(0.54)	(0.79)	(2.15) *	(4.71) ***
May	0.0109	−0.0024	0.0023	0.0116	0.0329
	(2.60) **	(−0.36)	(0.28)	(1.42)	(3.22) **
June	0.0070	−0.0054	0.0016	0.0050	0.0275
	(1.67)	(−0.80)	(0.20)	(0.61)	(2.69) **
July	−0.0030	−0.0143	−0.0056	−0.0063	0.0150
	(−0.71)	(−2.11) *	(−0.69)	(−0.76)	(1.46)
August	0.0157	−0.0036	0.0056	0.0136	0.0486
	(3.76) ***	(−0.54)	(0.70)	(1.66)	(4.75) ***
September	0.0221	0.0055	0.0155	0.0217	0.0467
	(5.29) ***	(0.82)	(1.92)	(2.65) **	(4.56) ***
October	0.0118	0.0093	−0.0022	0.0060	0.0346
	(2.81) **	(1.37)	(−0.27)	(0.73)	(3.37) ***
November	0.0006	0.0022	−0.0186	−0.0055	0.0247
	(0.14)	(0.32)	(−2.31) *	(−0.67)	(2.41) *
December	−0.0020	−0.0040	−0.0101	−0.0051	0.0116
	(−0.47)	(−0.59)	(−1.25)	(−0.62)	(1.13)
F-statistic	9.8043 ***	2.1204 *	2.3791 **	3.7718 ***	5.4037 ***
χ^2-statistic	1622.29 ***	415.45 ***	401.28 ***	412.22 ***	394.88 ***

We again documented seasonality in returns for highly visible firms that shows the opposite trend to the seasonality reported for small firms or those with low stock prices. Uncertainty in a firm's information environment as measured by the standard deviation of earnings forecasts appears to have some importance in this seasonal pattern as it is stronger for firms with greater uncertainty. Ackert and Athanassakos (1997) provide evidence that analysts are more prone to act on their inclinations when greater uncertainty surrounds a firm, a behavior that might also describe fund manager behavior. If fund managers are prone to gamesmanship and window dressing, there is downward pressure on the stock price at the start of the year for highly visible firms, and this pressure reverses as the year progresses.

A role for gamesmanship in understanding monthly seasonality seems to rely on annual contracting. Often, it is assumed in the literature that portfolio managers are evaluated on an annual basis. However, Ma et al. (2019) note that 3 years is the most commonly

observed evaluation window, though many of their sample managers are evaluated annually. Though a longer evaluation window might seem to weaken our ability to detect an annual seasonal pattern, annual performance is quite important to managers who seek significant end-of-year performance bonuses. In any case, we provide evidence of a very strong seasonal pattern that is consistent with annual seasonality caused by the forces of gamesmanship and window dressing impinging on the behavior of fund managers.

5. Additional Analysis

As we noted earlier in this paper, arbitrage costs may be an impediment to efficient pricing in markets (Jacobs and Müller 2020). Rational traders exploit profit opportunities, but if they are constrained by high costs of trading, stocks may remain mispriced. Correlated opinions based on misinformation can move markets (e.g., (Shleifer and Summers 1990)). Stambaugh et al. (2012) examine the role of investor sentiment in explaining stock return anomalies. Their evidence suggests that anomalies are stronger when sentiment is high. In contrast, Hulbert (2019) suggests that when it comes to mutual fund managers and return seasonality, the anomaly could be weaker in good years. In a bull market, driven by positive investor sentiment, fund managers have less pressure to adjust portfolios at the year end. Ortiz et al. (2013) provide evidence that window dressing is more prevalent among Spanish fund managers in bear markets. Whether the seasonal pattern varies across bull and bear markets is a question Ackert and Athanassakos (2000) did not address.

To shed light on sentiment and seasonality in returns, we designated 1987, 1990, 2000, 2002, 2008, and 2011 as bear market years, with all other years in the 1986 through 2018 period characterized as bull markets. The timing of bull and bear markets is from the (Dow Theory 2021). For this analysis, we used the sample period from 1980 through 2018 because there are few bear years in recent years. Table 4 provides summary information for bull (Panel A) and bear (Panel B) years. For bull market years, we observed higher actual earnings, stock prices, and market values, on average. Interestingly, average analyst optimism is considerably higher in bear market years (USD 0.26), as compared to bulls (USD 0.09). Consistent with Ackert and Athanassakos (1997), we observed that analysts' earnings forecasts are more optimistic for firms in highly uncertain information environments (Q4), particularly in bear market years.

Table 4. Summary statistics for bull and bear years. The table reports summary information for our sample, which includes data from January 1980 through December 2018. In addition to full sample information, Panel A provides sample statistics for bull-market years and quartiles based on the standard deviation of analysts' forecasts scaled by price (σ(FEPS)), and Panel B reports information for bear-market years and quartiles based on market value (MV). First, the table reports the number of analysts following sample firms as reported in the IBES database. Next, the table reports on forecasted and actual earnings, σ(FEPS), stock price, and market value (in millions of dollars).

Panel A: Means for the Bull-Market Years and Quartiles Determined by the Standard Deviation of Analysts' Earnings Forecasts Scaled by Price (σ(FEPS)).					
	Overall	**Q1 (Low)**	**Q2**	**Q3**	**Q4 (High)**
Number of analysts	25.75	26.02	26.59	25.34	25.05
Forecasted earnings	USD 2.22	USD 2.24	USD 2.42	USD 2.03	USD 2.20
Actual earnings	USD 2.13	USD 2.21	USD 2.31	USD 1.92	USD 2.07
σ(FEPS)	0.0213	0.0038	0.0088	0.0157	0.0579
Price	USD 31.80	USD 38.42	USD 35.29	USD 30.31	USD 22.85
Market value	USD 16,912	USD 30,476	USD 18,296	USD 11,434	USD 6960
Panel B: Means for the Bear-Market Years and Quartiles Determined by the Standard Deviation of Analysts' Earnings Forecasts Scaled by Price (σ(FEPS)).					
	Overall	**Q1 (Low)**	**Q2**	**Q3**	**Q4 (High)**
Number of analysts	23.89	22.83	23.94	23.99	24.87
Forecasted earnings	USD 2.35	USD 1.83	USD 2.46	USD 2.60	USD 2.52

Actual earnings	USD 2.09	USD 1.74	USD 2.28	USD 2.47	USD 1.85
σ(FEPS)	0.0238	0.0048	0.0124	0.0222	0.0570
Price	USD 28.53	USD 30.31	USD 29.97	USD 31.06	USD 22.56
Market value	USD 14,679	USD 24,071	USD 16,757	USD 11,040	USD 6434

We estimated the seasonal returns patterns represented by Equation (1) for bull and bear market years and our sample of highly visible firms. While the estimated seasonal dummies are somewhat stronger for the bull market years, the seasonal pattern in excess returns reported earlier in Table 3 continues to hold for both bull and bear samples. These results are available upon request. We observed negative excess returns in January, with upward adjustment over the year for our sample of visible firms. Managers who are prone to gamesmanship and window dressing may exhibit similar behavior in bull and bear years if their goal is to consistently beat the market. Thus, incentives to adjust portfolio holdings over the year may not change from frothy to pessimistic environments.

6. Discussion and Concluding Remarks

This paper reports the results of a re-examination of the seasonal pattern in the returns of highly visible stocks. Ackert and Athanassakos (2000) provide evidence that highly visible stocks have low returns in January that adjust up over the year. At the beginning of the year, fund managers add small, less visible stocks to their portfolios, causing these stocks to experience buying pressure and abnormally high returns. As the year progresses, fund managers adjust toward highly visible firms after achieving targeted returns.

Gamesmanship and window dressing are consistent with the observed pattern in excess returns. Institutional investors may hold small, risky stocks at the start of the year to meet performance-based incentives. Later, when the target is met, a manager prone to gamesmanship will adjust toward more visible firms. Most funds explicitly tie the manager's bonus to the fund's investment performance. Fund managers also engage in window dressing by adding back the visible firms they removed at the start of the year to the managed portfolio toward the year end in order to provide a positive image to investors at the end of the year.

Of course, rational traders will recognize and take advantage of this opportunity, eliminating systematic excess returns. As this anomaly has persisted, it may not be the result of a systematic behavioral bias. Instead, limits to arbitrage may impede smart traders' ability to push the market toward rational pricing. As arbitrage is more limited in markets characterized by positive sentiment, we examined the patterns of excess returns in bull and bear years. The pattern was unchanged. A caveat to this analysis is that the stock market may rationally have increasing prices in a strong economy.

Therefore, why does the seasonal pattern persist? Keloharju et al. (2016) provide compelling evidence to suggest that return seasonalities are strongly persistent and caused by different sources. Thus, a "one size fits all" explanation for seasonal returns patterns will be ineffective. Here, we provide evidence that is consistent with the view that professional fund managers drive seasonalities in American equity returns. It is estimated that institutional investors account for 70% of the volume of trade in stocks, and further institutional investors manage 70% of the stock market. See (Smart Asset 2021; and Learning Markets 2021).

Thus, it is highly possible that a seasonal pattern persists because institutional investors drive the market. Incentives impact their behavior which, in turn, shapes market outcomes. Is it surprising that the market is impacted by behavior when the incentives in place pressurize fund managers who drive the majority of trade? While finance theory posits that mispricing will be eliminated by arbitrageurs, the motivations of the vast majority of traders in the market are quite different. Professional fund managers do not focus on identifying and taking advantage of arbitrage opportunities. These managers seek to

lock in year-end performance bonuses and end the year with portfolio holdings in visible, highly regarded, and lower risk assets. The evidence presented in this paper suggests that the seasonal pattern will persist for as long as fund managers incentives are unchanged. Conflicts of interest will continue due to the annual remuneration cycle and fund managers' desire to please investors by revealing a portfolio of visible stocks at the year end.

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