Seasonality in the Cross-Section of Stock Returns[†]

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Abstract

This paper presents a new pattern in the cross-section of expected stock returns. Stocks with relatively high (low) returns tend to have high (low) returns every year in the same calendar month. We recognize the annual return pattern documented in Jegadeesh (1990) at lags of 12, 24, and 36 months as part of a general pattern that lasts up to 20 annual lags, superimposed on the general momentum/reversal patterns. This pattern explains an economically and statistically significant magnitude of the cross-sectional variation in average stock returns. Volume and volatility exhibit similar seasonal patterns but they do not explain the seasonality in returns. The pattern is independent of size, industry, earnings announcements, dividends, and fiscal year. The results are consistent with the existence of a persistent seasonal effect in stock returns.

Introduction

This paper investigates seasonal patterns in the cross-section of expected returns on common stocks. There is an extensive literature on seasonality in stock market index returns (i.e., the January effect documented by Rozeff and Kinney (1976) and recent papers by Bouman and Jacobsen (2002) and Kamstra, Kramer, and Levi (2003)). A seasonal approach to asset-pricing models has also been used by Ogden (2003). Yet there are only a few papers that investigate seasonality in cross-sectional *differences* of stock returns. Keim (1983) and Reinganum (1983) find that small stocks outperform large stocks in January, and Tinic and West (1984) find that high-beta stocks outperform low-beta stocks in January. However, the empirical literature has not fully explored general seasonal variation across individual stocks, which is the focus of our study.

The relative performance of stocks based on their historical returns has long been a fertile area of finance research. Different strands of literature characterize the performance of return-based portfolio strategies over short, intermediate, and long-term horizons. Lehmann (1990) shows evidence of short-term "reversals" that generate abnormal returns to contrarian strategies which select stocks based on their performance in the previous week or month. In contrast, Jegadeesh (1990) and Jegadeesh and Titman (1993, 2001) demonstrate robust profits to "momentum" strategies that buy stocks based on their success in the previous 3 to 12 months. Finally, DeBondt and Thaler (1985, 1987) show contrarian strategies are profitable over longer-term horizons of 3 to 5 years.

In contrast to previous results of monotonic "reversal" or "continuation", this paper presents a new periodic oscillating pattern in stock returns. Specifically, winners outperform losers at annual intervals for up to 20 years, while underperforming in between. This extends the DeBondt and Thaler (1985, 1987) results out to 20 years while uncovering an opposite interspersed anomaly. This pattern is consistent with Conrad and Kaul's (1998) explanation if there is large cross-sectional variation in average returns that depends on the calendar month. We therefore recognize that the annual return pattern shown in Jegadeesh (1990) for lags of 12, 24 and 36 months as part of a general pattern that lasts up to for 20 annual lags, superimposed on the general momentum/reversal patterns. Importantly, we interpret this pattern as a persistent seasonal effect in stock returns. We show this seasonality is economically important and overturns previous empirical findings. Allowing seasonality in the framework of Conrad and Kaul (1998) and Jegadeesh and Titman (2002) shows an economically and statistically significant magnitude of the cross-sectional variation in expected stock returns. Seasonality is therefore important to our understanding of stock returns and asset pricing.

A simple approach to illustrate and exploit the seasonality of stock returns is to form winner-loser decile spreads based on seasonal returns in previous years. For example, we would buy and hold stocks in April of a particular year if their average returns were in the upper 10% of all stocks' returns over previous Aprils. This resembles the strategies of Conrad and Kaul (1998) and Jegadeesh and Titman (2002), but it is based on historical returns in periodic months rather than cumulative returns over a contiguous historical interval. We find these strategies produce significantly positive returns for up to 20 years, averaging over 50 basis points per month. This finding is consistent with individual stocks that earn high returns during specific calendar months. The strategies are unaffected by demeaning stock returns across all months, but their profits vanish when returns are demeaned seasonally. This is consistent with seasonal variation in expected returns.

There are a number of seasonal variables potentially related to stock returns. Kramer, Kamstra, and DeGennaro (2005) have documented seasonality in overall market liquidity. Eleswarapu and Reinganum (1993), Hasbrouck (2005), and Hong and Yu (2005) find average stock liquidity varies seasonally. Additionally, Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), and Easley, Hvidkjaer, and O'Hara (2002) show stocks that are illiquid in a particular period subsequently have high average returns. Therefore we investigate whether liquidity variables are related to the seasonal pattern in returns. Indeed, we find seasonal patterns in the cross-section of liquidity, as measured by volume and volatility. However the seasonality in returns is largely independent of past volume and volatility. Additional analysis indicates that the profitability of seasonal strategies is not associated with size, industry, earnings announcements, dividends, calendar effects, nor fiscal year. While the returns are large on an annualized basis, they last for only one month and may not justify 100% portfolio turnover. This explains why short-lived seasonal variations in stock returns may have persisted over the years.

Section 1 illustrates the periodic pattern of winner-loser strategies in event time and presents a seasonal explanation. Section 2 describes simple portfolio strategies to exploit this pattern. Section 3 applies the Conrad and Kaul (1998) approach to measure a large seasonal component in the cross-section of stock returns. Section 4 shows stock volume and volatility have similar periodic patterns to stock returns, but they do not explain the return effect. Section 5 shows the return pattern is robust to size, industry, earnings, dividends, calendar effects and fiscal year. A final section concludes.

1. A Periodic Pattern in Stock Returns

We begin our study by relating the cross-section of stock returns over a given month to historical cross-sections of stock returns. The initial goal is to reconcile the conflicting results of DeBondt and Thaler (1985, 1987) with those of Jegadeesh (1990) and Jegadeesh and Titman (1993, 2001). These studies use similar methodologies to study portfolio strategies that buy and sell stocks based on their historical returns. These winner-loser strategies buy "winner" stocks that earned high returns in some historical formation period and sell "loser" stocks that earned low returns over the formation period. Jegadeesh and Titman find winners subsequently earn higher returns than losers at horizons of up to one year. Yet, DeBondt and Thaler find winners underperform losers between three and five years later. Our monthly analysis is consistent with previous results, but it also uncovers a periodic pattern that motivates our subsequent trading strategies.

This paper calculates returns on portfolio strategies over the years 1965-2002. Our sample includes NYSE/AMEX-listed firms whose data is available on the CRSP monthly returns file. Some of our portfolio strategies depend on up to 20 years of lagged returns, therefore we use stock returns back to January 1945. Given such long lags there is a concern about whether we have an adequate sample of firms with a long return history. Figure 1 shows the number of available firms does indeed fall dramatically when we require them to have long return histories. While nearly 100% of firms have returns in the previous month, less than 30% of firms have CRSP returns for the past 20 years. This problem is less important than it appears since CRSP includes thousands of firms. Over 500 firms had 20 years of return history over all years of our relevant sample, and over 1,000 firms had at least 10 years of history by 1999. By comparison the entire CRSP database includes less than 2,000 firms at the beginning of our return sample in January 1965. Therefore we have an adequate data to perform statistical analysis with lags up to 20 years. The critical issue is avoiding survivorship bias by using only firms available strictly before each date.

We would like to clarify the temporal pattern in the cross-section of stock returns and identify the "crossover" point when winners stop outperforming losers and begin to underperform. Previous studies generally classify winner and loser stocks based on their historical returns over a multi-month formation period. Then they measure subsequent returns over multi-month formation periods. For example, the popular 6-month/6-month strategy used by Jegadeesh and Titman (1993, 2001) and Moskowitz and Grinblatt (1999) classify winners and losers based on their January – June returns and then hold them from July – December. This is not precise enough for our purpose because it confounds the one-month effect of June returns on July returns with the eleven-month effect of January returns on December returns. Therefore we choose a methodology based on returns over a single month.

We apply the cross-sectional regression methodology (Fama and MacBeth (1973), Fama and French (1992)) to monthly returns

$$r_{it} = \alpha_{kt} + \gamma_{kt} r_{i,t-k} + e_{it} \tag{1}$$

where r_{it} is the return on stock i in month t. We call these coefficient estimates "return responses" because they show the cross-sectional response of returns at one date to returns at a previous date. For a given lag k we then compute average return responses or "return effects" over all available dates t. Then we compute these averages for different lags k ranging from 1 month to 240 months. The resulting return responses are highly correlated with results from other methodologies, including decile spreads (Jegadeesh and Titman (1993)) and weighted relative strength portfolios (Lehmann (1990) and Lo and MacKinlay (1990)).

These return responses have an interpretation as portfolio returns. In particular the estimated regression coefficient is simply a weighted long-short portfolio

$$\gamma_{kt} = \sum_{i=1}^{N} w_i(t,k) r_{it}, \tag{2}$$

where

$$\sum_{i=1}^{N} w_i(t,k) = 0,$$

$$\sum_{i=1}^{N} w_i(t,k) r_{it-k} = 1.$$

In words, the portfolio has zero net investment and historical return of 100% at date t-k. We construct these cross-sectional regression portfolios from a sample that includes all stocks with available return data in the formation month t-k preceding the event month t. This avoids any sample selection or "look-ahead" bias in our strategies. Therefore we may interpret the results as feasible portfolio strategies.

Figure 2 shows the average return responses as a function of event time (Panel A). It also shows a smoothed version of this graph (Panel B). The smoothed graph is consistent with previous literature. It shows a positive effect for the first year, and then a negative effect from 2–7 years. But the unsmoothed graph reveals a distinct periodic pattern. There are positive "pulses" at annual intervals from 12 to 240 months. Jegadeesh (1990) originally revealed the annual effects at 24 months and 36 months with his analysis of momentum effects at shorter intervals of 1-12 months. Our results are noteworthy because the positive annual returns persist through DeBondt and Thaler's otherwise negative horizon of 3-5 years. The remainder of our paper explores this unexpected pattern.

To ensure the robustness of our methodology and measure the incremental effect of historical returns we also apply the cross-sectional multiple regression of Jegadeesh (1990). This specification is similar to Equation (1) with return responses estimated jointly for multiple lags

$$r_{it} = \alpha_{kt} + \sum_{k=1}^{12} \gamma_{kt} r_{it-k} + \gamma_{24t} r_{i,t-24} + \gamma_{36t} r_{i,t-36} + \ldots + e_{it} \tag{3}$$

Jegadeesh includes lags 24 and 36 in the context of a short-term “momentum” effect. We recognize it as a potentially permanent periodic effect out to 240 months. Table 1 presents the average return responses and standard errors computed using the Newey-West (1987) correction for autocorrelation up to 12 lags. Using the univariate regressions (1) or the multiple regressions (3), all the annual return effects are statistically positive at the 95% level for the first 10 years of lags. For lags beyond 10 years the univariate methodology generally finds more statistical significance. For example, the univariate return effect with a lag of 20 years has a t-statistic of 2.99, but the corresponding multivariate return effect has a t-statistic of only 1.47. Nevertheless, the multivariate methodology still finds t-statistics greater than 2 for lags of 14, 15, and 16 years. Therefore, the multivariate methodology produces evidence of significant incremental profits from portfolio strategies formed on the basis of distant historical returns.

To understand the nature of the periodic profits to winner-loser strategies we consider a simplified seasonal version of the model used by Jegadeesh and Titman (1993) and Conrad and Kaul (1998). Our model describes the monthly returns on a stock, r_{it}, in excess of the equally weighted market index return $\overline{r}_t$

$$r_{it} - \overline{r}_t = \mu_{it} + e_{it}, \tag{4}$$

$$E[e_{it}] = 0,$$

where μ_{it} is the unconditional expected return on stock i in month t in excess of the market index and e_{it} is the innovation in return. We use a monthly time interval instead of a longer interval to allow expected returns to vary within the year. In contrast to previous papers, we allow the expected stock returns to depend on time. We specifically allow them to differ across calendar months but assume they are constant across the same calendar month in different years

$$\mu_{it} = \mu_{it+12}. \tag{5}$$

This means particular stocks may have distinctly high or low expected returns every 12 months. For example, small stocks might have high expected returns every January. This model has distinct implications for the performance of portfolio strategies based on historical returns.

To explain these implications, it is easiest to analyze the profits from Lo and MacKinlay's (1990) and Lehmann's (1990) weighted relative-strength strategies. Unreported diagnostics show these strategies are highly correlated with our return responses, and produce a similar pattern of returns. Our empirical analysis uses cross-sectional regressions and equally weighted decile portfolios because they are easier to interpret and compare with previous literature. The following elaboration of Jegadeesh and Titman's (1993) analysis shows how weighted relative-strength strategies provide a tractable framework to explain the periodic pattern in return effects.

The Lo and MacKinlay strategies buy stocks with weights proportional to their return in excess of the index in a historical formation month. If the portfolio is formed based on performance in month t and held in month t+k then the expected profit from stock i in excess of the index is $E[(r_{it} - \overline{r}_t)(r_{it+k} - \overline{r}_{t+k})]$. Under our seasonal model (5) this decomposes into two components

$$E[(r_{it} - \overline{r}_t)(r_{it+k} - \overline{r}_{t+k})] = \mu_{it}\mu_{it+k} + \mathrm{Cov}(e_{it}, e_{t+k}). \quad (6)$$

The first component arises from expected returns, the second from serial covariance in returns. The return on Lo and MacKinlay's strategy would be the average of these effects across stocks.

The first term involves cross-sectional variation in expected returns at time t and time t+k. Intuitively, stocks with relatively high realized returns in the historical formation period t tend to have high expected returns in that period. According to our seasonal model they will also tend to have high returns in subsequent months when the holding month matches the formation calendar month, i.e., the event time k is a multiple of 12. In this case the first term is μ_{it}^2 and must be nonnegative. When the event time is not a multiple of 12 then there may be no particular relation between μ_{it} and μ_{it+k}. But we can make some mild observations. On the one hand, if the average return on a stock is equal to the market return throughout the calendar year then positive μ_{it} in one month must be offset by negative values in other months. In this case the product $\mu_{it}\mu_{it+k}$ would typically be negative. On the other hand, if a stock had consistently above average or below average returns then this component may be positive. Yet, in any case, $\mu_{it}\mu_{it+k}$ cannot exceed the average of μ_{it}^2 and μ_{it+k}^2. Therefore, the contribution of expected returns will produce a positive "pulse" every 12 months in terms of event time.

The second component of the excess return (6) is due to autocorrelation in returns. To the extent markets underreact to news about stocks, there may be some positive autocorrelations. Moreover, if this news has a seasonal component then it may also produce periodic annual components. For example, earnings announcements are released quarterly with strong annual components. In order for returns to have finite variance, the autocorrelation should die out at long lags.[1] In this case the positive annual return effects would also decay at long lags and ultimately be determined only by permanent seasonal variation in means. If the autocorrelation were extremely persistent then it might last for our entire sample. In this case it would be indistinguishable from a permanent seasonal effect. The subsequent section of the paper examines returns at long lags to distinguish the permanent seasonal explanation (5) from a temporary autocorrelation explanation.

[1] Unreported diagnostics indicated no significant autocorrelation in the return responses. However, these tests would have low power if the returns were extremely persistent.

2. Annual Winner-Loser Strategies

The unexpected periodic pattern in Figure 2 motivates us to try new portfolio strategies based on historical return. We wish to form winner-loser strategies to exploit the effect of lagged returns at distinct annual and non-annual intervals. In order to distinguish results over the Jegadeesh and Titman horizon of 1 year from the DeBondt and Thaler horizon of 2–5 years, we consider these intervals separately. We further consider portfolio formation intervals for years 6–10, years 11–15, and years 16–20. These long-horizon intervals increase the power to measure permanent seasonal effects and distinguish them from temporary seasonal autocorrelation. We form decile portfolios based on the average monthly return of stocks over all months in each lagged interval and measure the returns over the next month. For example, the 2–5 year winner portfolio held in January 2003 would be an equally weighted combination of stocks that had the highest average return from January 1998 to December 2001.

Table 2 shows the results for portfolios based on "all" months in a given interval reproduce the findings of previous literature. The year 1 returns are uniformly increasing through the deciles, with the decile 10 winners outperforming the decile 1 losers by 146 basis points per month. Yet, the year 2–5 winners underperform the losers by 107 basis points per month. Interestingly, the winners also underperform the losers with formation lags of 6–10, 11–15, and 16–20 years.

We also divide the historical formation months into annual lags 12, 24, …, 240 and non-annual lags. Then we form decile spreads based on average performance in only those lags. The essential difference is instead of sorting stocks based on their returns in all contiguous months in a given historical interval, we sort on noncontiguous months.

In addition to using all months in a lagged formation interval, Table 2 shows the returns to winner-loser strategies formed only on the basis of only the annual or non-annual months in the lagged time interval. In the year 1 interval there is only one annual lag – the 12-month lagged return. Given the decile spreads based on “all” months in the 1-year interval are positive, it is not surprise to see the decile spread is still positive when sorting only on the 12-month lagged return. But the magnitude of 115 basis points is impressive compared to the 146 basis points for all months. It appears most of the performance from winners and losers over the past year can be captured based on stocks that were winners or losers exactly 12 months ago. In fact, the t-statistic for this 12-month winner-loser strategy exceeds the t-statistic for the full-year strategy, indicating it produces a higher Sharpe ratio. The simple strategy of buying winners and selling losers based on the 12-month lagged returns produces a higher return for risk than the full-year strategy.

The surprising results come for the longer horizon strategies. Recall winner-loser deciles based on “all” months in years 2–5 lost 107 basis points per month. But when sorting only on annual lags 24, 36, 48, and 60 the decile 1 winners outperformed decile 10 losers by 67 basis points. We get a positive effect in the middle of DeBondt and Thaler’s negative effect. This positive effect appears for all the annual strategies—68 basis points based on years 6–10, 66 basis points based on years 11–15, and 52 basis points based on years 16–20. All these returns are statistically significant at conventional levels. Since the positive return effect extends to at least 20 years it is either permanent or extremely persistent, lasting for most of our 38-year return measurement period.

Table 2 shows the average winner-loser returns based on non-annual months are negative for all formation intervals and usually statistically significant. It is striking that winner-loser strategies can produce significant returns up to 20 years later, and that these returns are positive in some months and negative in adjacent months.

3. Magnitude of Seasonal Cross-Sectional Variation in Expected Returns

This section measures the economic significance of seasonality in expected returns. It uses the stationary model of stock returns from Equation (4). This model extends to allow seasonality in expected returns in Equation (5). The seasonal version specifically allows expected returns to vary separately across different calendar months instead of being constant throughout the whole year. Applying the same methodology to separate calendar months instead of combined months produces dramatically different conclusions.

Equation (4) presents the essential model used by Jegadeesh and Titman (1993) and Conrad and Kaul (1998). We apply the methodology of Jegadeesh and Titman (2002) to measure the variation in monthly expected returns, holding the expected return constant across all months. This methodology is based on average cross-sectional relation between returns at one date and returns at another. Intuitively, stocks with high means tend to have high returns at both dates, and stocks with low means tend to have low returns at both dates. The Appendix explains the estimator of cross-sectional variance of expected returns, σ^2_μ, presented in Table 3. The null hypothesis is that σ^2_μ is zero, i.e., there is no cross-sectional variation in expected stock returns. This hypothesis is rejected if the estimate is significantly positive. The estimate is actually slightly negative, small, and statistically insignificant at -0.0009% per month. This agrees with the statistically insignificant results found by Jegadeesh and Titman (2002) using 6-month cumulative returns. Theoretically, buying historical winners and selling historical losers should result in investing in stocks with high average returns. But Table 3 shows it is not profitable to buy winners and sell losers based on a random, typically distant, historical date.

While there may be no evidence for year-round variation in expected returns across stocks, the previous evidence indicates the existence of seasonal variation in expected returns. We therefore allow the individual means to be seasonal dependent as suggested in model (5). This implies particular stocks may have distinctly high or low expected returns every 12 months. For example, Keim (1983) finds small stocks have high returns in January. This model has distinct implications for the performance of weighted relative-strength strategies at annual lags. It predicts the component of cross-sectional variance σ^2_μ will be positive when means are restricted to be equal at lags that are multiple of 12. In other words, it predicts a positive return to buying winners and selling losers based on their historical performance in the same calendar month of any previous year.

Table 3 reports positive results when estimating Equation (5) based on annual lags k = 12, 24, … 468. This is surprising because Table 3 reports an average over all annual lags in our sample of 40 years. In other words it is not an estimate based on short-term annual autocorrelation, but based on the cross-section of returns in relation to all other cross-sections in the same calendar month within the past 40 years. The point estimate of σ^2_μ is 1.33 basis points, which seems fairly small. But it implies large variation in stock returns; the implied cross-sectional standard deviation of expected stock returns is $\sqrt{0.000133}$ = 1.15% per month. Since this is a seasonal effect, it changes every month and cannot be used in a longer-term buy and hold strategy. But for comparison, the equivalent annualized standard deviation of expected stock returns is $12\sqrt{0.000133}$ = 13.8%. It is instructive to compare this with conventional assessments of the cross-sectional variance of expected stock returns. Jegadeesh and Titman (2002) consider Fama and French (1992) estimates of the Capital Asset Pricing Model (CAPM) as a benchmark. The cross-sectional standard deviation of the CAPM-beta is 0.31. With a 6% market risk premium this corresponds to a 1.86% standard deviation of annual stock returns. Our estimate is over seven times as large. This implies the seasonal effect on expected returns is economically important.

If this seasonal explanation is correct then the positive returns to annual winner-loser strategies in Table 2 are a result of buying stocks with high average returns and selling stocks with low average returns. This effect should be eliminated subtracting the average returns from each stock. Following Jegadeesh and Titman (2002) we consider three different types of estimates of mean return for each stock. The first type of estimate is the average monthly return on a stock prior to the formation month t-k. We call this the "preranking estimate".

$$\hat{\mu}_i(1) = \frac{1}{t-k-1} \sum_{j=1}^{t-k-1} r_{ij}. \qquad (7)$$

The second type of estimate uses all months after the formation month t-k except for the holding month t.

$$\hat{\mu}_i(2) = \frac{1}{T-t+k-1} \sum_{j>t-k, j\neq t}^{T} r_{ij}. \tag{8}$$

We call this the "postranking estimate". Finally, we also compute average returns over all months excluding the formation month t-k and the holding month t.

$$\hat{\mu}_i(3) = \frac{1}{T-2} \sum_{j\neq t-k, j\neq t} r_{ij}. \tag{9}$$

If expected returns are different in different calendar months then we should estimate them separately across months. Therefore, we also estimate the average returns for each stock using only those preranking or postranking months that match the calendar month of the holding period t. For example, if the holding period is March 2000 then we would compute the seasonal preranking estimate using average return for each stock based on all March returns prior to the year 2000. Similarly, we form seasonal postranking and seasonal combined estimates of average return for each stock in specific calendar months.

Table 4 presents the seasonal profits of Table 2 adjusted by the different estimates of expected return. It shows the adjustment to mean returns using "all" months does not substantially alter the profitability of annual strategies. Moreover, it does not appear to matter whether the adjustment uses preranking or postranking months. Yet adjusting the means using seasonal estimates sharply reduces the magnitude of the one-year annual effect and eliminates the statistical significance of profits beyond one year. It therefore appears that the profitability of these strategies is entirely explained by seasonal variation in individual stock returns.

4. Volume, Volatility, and Expected Stock Returns

One potential source of seasonality in stock returns is seasonality in liquidity and trading activity. If trading for a particular stock concentrates in particular calendar months then the stock might display a liquidity premium around those months. In the theoretical models of Kyle (1985) and Admati and Pfleiderer (1988), abnormally high volume arises with informed trading. Alternatively, in the behavioral model of Baker and Stein (2004) it represents the entry of "noise traders" into the market. Empirical research shows a relation between liquidity and stock returns (e.g., Amihud and Mendelson (1986)). This motivates us to explore volume and volatility to see whether they can explain the periodic pattern in winner-loser returns.

The existing literature often focuses on *cross-sectional* differences in liquidity across stocks (see, e.g., Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), and Easley, Hvidkjaer, and O'Hara (2002)). In contrast, we are interested in whether *changes* in firm-specific liquidity are predictable in the cross-section. In other words, we use time-series predictability to focus on *longitudinal* changes in trading volume across the cross-section of stocks. This helps control for stock-specific characteristics that might be correlated with levels of volume in the cross-section. We choose abnormal volume as our primary measure (scaled by number of shares outstanding). Abnormal volume is calculated as the logarithm of the ratio of current volume and its past-six-month average (henceforth simply referred to as volume). This definition of volume alleviates the problem of the non-stationarity of trading volume over the sample period. Also, it is likely to capture months of informational events because such events are usually associated with increased trading volume. Since the microstructure literature has mix interpretations of volume as a measure of liquidity, we do not take a position on this issue. Instead we use volume as an easily observable proxy for trading activity.[2] We proceed to investigate the extent to which volume can explain the seasonal pattern of return.

Following the analysis of returns, we apply the cross-sectional regression methodology by regressing monthly volume on its k-month lags

$$v_{it} = \alpha_{kt} + \gamma_{kt} v_{i,t-k} + e_{it} \tag{10}$$

where v_{it} is the abnormal volume on stock i at time t. For a fixed lag k and time t, regression (10) is run for the cross-section of firms. This captures predictability in the *cross-sectional* distribution of volume. We expect the coefficients γ_{kt} to be positive, indicating that stocks with above-average volume in one month tend to have above average volume after "k" subsequent months. We call the coefficients γ_{kt} "volume responses" because they represent the cross-sectional average relationship of volume at one date to trading volume at a previous date. The "volume effect" is computed as the time-series average of the coefficients γ_{kt}. This procedure is repeated for every lag k to form a term structure of volume effects. We interpret the time-series averages of γ_k for different lags k as the term structure of volume in response to previous volume. It shows the temporal pattern of predictable liquidity in the cross-section of stocks.

[2] Unreported results show that proportional bid-ask spread and the illiquidity measure of Amihud (2002) also display oscillating predictability analogous to the results with volume shown in this section.

We obtain volume data on NYSE/AMEX-listed firms whose data are available on the CRSP monthly returns file. The monthly volume data are available from July 1962 to December 2002. This time period is comparable to the time period used for related research and allows us to later consider Compustat data without substantially changing the sample period.[3] Given the relatively short data history, we measure average volume effects for up to 60 months of lags, starting in July 1967.

Figure 3 Panel A shows the average volume effects for different time lags “k”. For comparison this graph is superimposed on the graph of return effects (from Figure 2). The pattern of volume literally parallels the pattern in returns. The volume response function is generally positive indicating high volume in one month (relative to the cross-section) tends to be followed by high volume in future months. Similar to the return effects there are large spikes in volume effects at annual intervals of exactly 12, 24, 36, 48, and 60 months. It appears that some stocks have predictably high volume at annual intervals. If every stock has distinct trading activity at a different month of the year then the spikes in the volume response function capture this seasonality during the same calendar month of subsequent years. There are also smaller intermediate quarterly spikes. This pattern confirms our premise of predictable variation in the cross-section of stock volume. The interesting issue is whether the pattern of volume can explain the effect in returns.

To analyze whether past volume can explain the predictability of returns we run cross-sectional multiple regressions of returns on lagged returns and volume

[3] For comparison, Conrad and Kaul (1998) use NYSE/AMEX-listed firms for the period 1926-1989, while Jegadeesh and Titman (2002) use NYSE/AMEX-listed firms for the period 1965-1997.

$$r_{it} = \alpha_{kt} + \gamma_{kt} r_{i,t-k} + \delta_{kt} v_{i,t-k} + e_{it} \quad (11)$$

where r_{it} is the return on stock i in month t and $v_{i,t-k}$ is volume lagged by k months. The time-series averages of γ_{kt} and δ_{kt} across different lags show the cross-sectional relationship between historical return, historical volume, and future stock returns.[4] We also report t-statistics corrected for autocorrelation using the Newey-West correction with 12 monthly lags.

Figure 3 Panel B shows the average return responses from these cross-sectional multiple regressions. The returns continue to be positively related to the cross-section of historical returns at annual intervals. Figure 3 Panel B shows that the seasonal pattern of multiple regression responses of returns to historical returns resembles the pattern of univariate regression responses in Panel A. In other words, controlling for past volume does not substantially change the effect of past returns on the cross-section of future returns. Volume displays similar annual periodicity to returns, but the periodicity in volume does not explain the pattern of returns on winner-loser strategies.

Volatility is an alternative measure of trading activity and informational events that may be related to returns. Therefore, in each month we calculated the sample standard deviation of daily stock returns. We define the abnormal volatility for each stock as the logarithm of the ratio of current standard deviation and its past-six-month average (henceforth simply referred to as volatility). Following the volume analysis, we

[4] We also run this multiple regression with multiple lags of return and volume, using up to 12 lags. Incorporating multiple lags produced qualitatively similar results in this case. We therefore report average responses from the single lag specification (11).

calculate volatility for each stock from July 1962 to December 2002. Then we replace volume in the cross-sectional regression (10) and multiple regression (11) with volatility.

Figure 4 Panel A shows the resulting volatility response function from the univariate cross-sectional regression (10), again superimposed on the graph of return effects. The pattern of the univariate volatility response function matches the return response function. The positive spikes again occur at annual intervals of exactly 12, 24, 36, 48, and 60 months. Just as with return and volume, high volatility in one month predicts high volatility in same calendar month of subsequent years. The cross-section of abnormal volatility has the same predictable periodic pattern as return and volume.

Given similar patterns, we address whether volatility can explain the pattern of winner-loser returns. Figure 4 Panel B shows the response of returns to past returns controlling for past volatility, estimated using the cross-sectional multiple regression (11). The multivariate response of returns to past returns resembles the univariate response function. Similar to our results with volume, volatility displays annual periodicity but does not explain the pattern of returns on winner-loser strategies.

5. Robustness and Further Discussion

This section searches for other variables that may be linked to the periodic pattern of expected returns. This ensures that the phenomenon is robust across different times of the year and different universes of stocks. For example, earnings announcements and the turn-of-year are seasonal events that may simultaneously affect trading activity and stock returns. Motivated by various candidate explanations associated with risk and information release, this section shows the seasonal pattern of returns persists across size, industry, calendar month, earnings announcements, dividends, and fiscal year.

5.1. Size and Industry

It is not clear why stocks would earn substantially different expected returns in one month than another. One explanation is that seasonal variation in returns is associated with stock exposure to systematic seasonal risks. These risks might be correlated with factors such as size or industry. This section considers the performance of annual winner-loser strategies within size and industry categories. We implement the strategies within three size-based subsamples (small, medium, and large) and decompose the profits into inter-industry and intra-industry components. Measuring the profitability of winner-loser strategies within size subsamples shows whether the performance of our strategies is limited to small or large firms. Size and industry membership also provide diagnostic information about the source of the winner-loser profits. Size may proxy for stock market liquidity. Size and industry may be considered as characteristics that are related to risk (Daniel and Titman (1997)). In this case the cross-sectional dispersion of expected returns should be less within size subsamples or industries than within the full sample. Therefore, the winner-loser profits may be reduced by controlling for size and industry.

Table 5 shows the winner-loser profits for different strategies within size subsamples. Interestingly, the years 2-5 and years 6-10 annual strategies are more profitable among large firms than among small or medium firms. This finding also suggests that the profitability pattern is not an artifact of the well-known January effect, which predominantly affects small firms.[5] In contrast, the years 2-5 and years 6-10 non-annual strategies are most profitable among small firms. The year 11-15 annual winner-loser profits remain statistically significantly positive in all size categories, and the year 16-20 annual winner loser profits remain significant within medium and large firms. The profitability and pattern of winner-loser profits is not limited to a particular size subsample.

Previous research by Moskowitz and Grinblatt (1999) and Lewellen (2002) has shown a role for industry in 1-year winner-loser strategies. We address this by classifying stocks into the 20 industry groups of Moskowitz and Grinblatt and then decomposing returns into industry and intra-industry components. The industry component of a stock return is simply the return of its equally weighted industry group, and the intra-industry of a stock is its return in excess of industry. Thus, our winner-loser strategies have industry and intra-industry components that sum to the entire return by definition.

Figure 5 shows the average monthly winner-loser decile spreads broken into intra-industry and inter-industry components. The inter-industry graph in Panel A has the same annual pattern in event time as the whole return in Figure 2. Panel B shows the industry component is positive for event times less than 12 months, consistent with the findings of Moskowitz and Grinblatt (1999) and Grinblatt and Moskowitz (2003). But the industry component is small, with no periodic pattern in event time. The "industry momentum" effect appears to be a distinct and qualitatively different phenomenon.

[5] We thank Ken French for noting this point.

Table 6 decomposes decile spreads of annual and non-annual winner-loser strategies into inter-industry and intra-industry components. The magnitudes and statistical significance of intra-industry components are similar to the raw returns in Table 2. While the industry component is occasionally statistically significant, it is always comparatively small in magnitude. For example, the industry component of the years 6-10 annual strategy is 12 basis points per month, but the inter-industry component is 58 basis points per month. Neither industry nor size explains the bulk of the winner-loser returns. It appears the seasonal variation in expected returns is not subsumed by size nor industry categories.

5.2. Seasonal Patterns and Turn-of-Year

This section tests for seasonal effects in annual winner-loser strategies. Previous research by Jegadeesh and Titman (1993, 2001) has shown 1-year winner-loser strategies are unprofitable in January but profitable in other months. Our annual winner-loser strategies measure historical returns over formation months that match the calendar holding period month. For example our year 2–5 annual strategy would hold stocks in April that were winners in previous Aprils. The average return might vary across calendar months.

Table 7 shows the average returns of winner-loser portfolios in different calendar months. The year-1 decile spreads show results similar to those of Jegadeesh (1990) and Jegadeesh and Titman (1993, 2001). Winner-loser strategies based on the previous year calendar month are profitable in every season, and earn an especially large 333 basis points in January. In contrast, winner-loser strategies based on the past 11 months (i.e., non-annual) are profitable in every month except January, and lose an average of almost 7% in January.

In contrast to the year 1 non-annual strategy, the longer horizon strategies do not change sign in January. The annual winner-loser strategies tend to be profitable in almost every month and are particularly high in January. The years 2–5 and years 6–10 annual strategies average over 3% in January, and the years 11–15 and years 16–20 strategies exceed 2% in January. The annual strategies show positive decile spreads in almost all other calendar months too. Due to the reduced number of observations, the numbers are not always statistically significant. Nevertheless, the years 2–5 strategy is significantly positive at conventional levels in November, December, and January, and the years 6–10 annual strategy is significant in October, November, December, and January.

The non-annual winner-loser strategies tend to lose money in almost every calendar month. Consistent with results of DeBondt and Thaler (1985, 1987), average return spreads are particularly low in January, averaging -960 basis points for the years 2–5 non-annual strategy. The average January return spreads are significantly negative (at conventional significance levels) for all the non-annual winner-loser strategies, but tend to be insignificant in other individual months. However, the combined February-December results are significantly negative at the 95% level for the years 2–5, years 6–10, and years 16–20 non-annual strategies. In sum, annual winner-loser return spreads are positive while non-annual winner-loser return spreads are negative. These effects are larger in January, but also occur in other months.

Given the history of the January effect and related anomalies, the turn-of-year is a natural candidate for producing seasonal patterns in expected returns. Indeed, Table 7 shows that the annual strategies are particularly profitable in January. However, it also shows they earn positive returns in nearly every other calendar month too. Other potential explanations suggest months other than January may play a critical role due to turn-of-quarter, end of tax year, etc. We wish to address these concerns and show the results are not sensitive to a particular calendar holding period. We therefore compute monthly returns from the 15^{th} day of each month to the 15^{th} day of each subsequent month. We then perform cross-sectional regressions (1) of "mid-month" returns on various lags of these "mid-month" returns and measure their average responses. Figure 6 shows the return response function estimate using these alternative returns. To avoid the turn-of-year effect, we excluded the December 15^{th} – January 15^{th} returns. Figure 6 shows the resulting pattern is identical to the original results in Figure 2. The seasonal pattern remains in mid-month returns and does not depend on the turn-of-year.

5.3. Earnings, Dividends, and Fiscal Year

Jegadeesh and Titman (1993) show short-term winner-loser profits are associated with earnings releases. Earnings announcements are seasonal and contain firm-specific information. If markets have biased expectations about firm-specific information then our seasonal return strategies may be exploiting predictable returns associated with dissemination of earnings. Other firm-specific season events include dividends and fiscal year-end. This section examines the returns of past winner and losers over these periods.

Consider, for example, the possibility that markets underreact to persistent seasonal earnings information. In this case, stocks with favorable earnings news in one year will tend to have favorable news in subsequent years. Moreover, incomplete market reaction in the first year will result in positive returns around under-anticipated earnings announcements in subsequent years (see Bernard and Thomas (1990)). To the extent that firms consistently announce earnings in the same calendar month, this may explain the success of annual winner-loser strategies.

To investigate the relation of our results to earnings announcements, we limit the data to firms covered by the Compustat earnings database. This results in 6,631 firms over the period January 1965 to December 2002. Roughly one-third of the observations have an earnings announcement and two-thirds do not have an earnings announcement in any given month.

Table 8 Panel A separates the monthly holding periods for winner-loser strategies into earnings-announcement months and non-announcement months. The formation of winner and loser deciles is identical to the whole sample in Table 2, but is limited those firms covered by Compustat. In any given month roughly one third of the firms have earnings announcements. We construct decile portfolios using only those firms with earnings announcements in that month, and using only firms without announcements. The year 1 non-annual results confirm Jegadeesh and Titman's (1993) finding that positive returns are concentrated around earnings announcements. The average winner-loser decile spread of 191 basis points is more than twice the 91 basis point return in non-announcement months. This is consistent with markets underreacting to previous persistent earnings news and then completing the reaction when new earnings are released in the holding month.

The results for longer horizons are not substantially different across announcement months and non-announcement months. The years 2-5 annual winners outperform years 2-5 annual losers by 78 basis points in earnings announcement months, and 67 basis points in non-announcement months. The years 2-5 non-annual winners continue to underperform corresponding losers by over 100 basis points in both announcement and non-announcement months. The results for longer horizons are qualitatively similar to results for years 2-5 strategies. Annual winners outperform losers in announcement months and non-announcement months, while non-annual winners underperform losers.

Overall our earnings results are consistent with those of previous research, yet they also demonstrate some distinctive new features of stock returns. We confirm Jegadeesh and Titman's (1993) finding that positive returns to year 1 winner-loser strategies are concentrated around earnings announcements. But the longer horizon strategies show little difference in announcement months. The positive returns to annual winner-loser strategies also contrast with findings of Bernard and Thomas (1990). Bernard and Thomas find returns around earnings announcements to be negatively related to earnings surprise four quarters earlier. This would suggest winners underperform losers at subsequent annual intervals, which is the opposite of our results. We conclude that the positive returns to annual winner-loser strategies are not associated with earnings and represent a distinct anomaly from previous literature.

Dividends are another quarterly event for most firms. We consider both the dividend-announcement month and the ex-dividend month. The dividend-announcement month may be associated with informational release that affects expectations or trading activity. The ex-dividend month is not an informational event, but it might be associated with tax-motivated trading. It would be interesting if either event were associated with winner-loser profits.

Following our analysis of earnings, Table 8 Panel B shows the performance of winner-loser strategies separated according to dividend-announcement months. The results are not particularly different in those months. For example, the years 2-5 annual winner-loser decile strategy earns 63 basis points in dividend-announcement months and 75 basis points in other months. This annual strategy is positive and statistically significant at conventional levels in both samples, while the non-annual 2-5 year winner-loser strategy is negative and statistically significant. The results are not particularly different between the two subsamples.

Similarly, we separate the sample into ex-dividend months and other months. Table 8 Panel C reports these results. Again, the results are similar across the two subsamples. For example, the years 2-5 annual strategy earns 53 basis points in ex-dividend months and 78 basis points in other months. If anything the effect is actually smaller in ex-dividend months. It does not appear to be associated with the ex-dividend events.

Finally, we investigate the effect of fiscal year. If the fiscal year has an informational role then it may affect trading either at the end of the fiscal year or the beginning of the subsequent year. We therefore create a subsample of months for firms covered by Compustat that included both the month of fiscal year-end along with the subsequent month. The results are reported in Table 8 Panel D. While the subsample of fiscal turn-of-year is smaller and more variable, the point estimates of winner-loser returns are close to the whole sample. For example, the years 2-5 annual strategy earns 82 basis points in the fiscal year subsample and 84 basis points in the other months. The long-horizon annual strategies remain positive and statistically significant in the sample that excludes fiscal turn-of-year.

Overall this section has sorted the sample of firms and months based on a number of periodic dividend and accounting events. The results are broadly similar across these subsamples. The periodic profitability of winner-loser strategies is not concentrated around these particular events.

5.4. Fama-French Risk-Adjusted Returns

To the extent that market efficiency does not eliminate seasonal differences in expected returns, there may be some offsetting seasonal features of these stocks. We attempt to use size and industry as proxies for risk in Section 5.1 and find little change in results. Unreported diagnostics show little sensitivity of seasonal strategies to the market portfolio return or to the Fama and French (1993) three factors. The decile-spread strategies all have approximately zero loadings with respect to these risk factors. Therefore, the risk-adjusted returns are very close to their average returns. This is similar to results for the momentum anomaly (see Fama and French (1996) and Grundy and

Martin (2001)). Therefore, we do not find that conventional measures of systematic risk are successful in explaining seasonal variation in expected returns.

5.5. Transaction Costs

The estimates of our paper have simple interpretations in terms of portfolio returns. This suggests they might be captured through an investment strategy. For example, the magnitude of the annual decile spread strategies in Table 2 exceeds 60 basis points per month, which is comparable to many other "anomalies" in the empirical finance literature. However, there is an important distinction between seasonal strategies and simple "momentum" or "contrarian" strategies of Jegadeesh and Titman (1993) or DeBondt and Thaler (1985, 1987). Momentum and contrarian strategies require rebalancing only a part of the portfolio every few months, while seasonal strategies require rebalancing the entire portfolio every month. In this respect, it may not be generally profitable to incur round-trip transaction costs for a 60-70 basis point monthly gain. While returns are particularly high in January, Sadka (2001) shows evidence that transaction costs may also be higher in January (see also Korajczyk and Sadka (2004)). In any case, the existence of short-lived fluctuations in monthly expected return may not form an effective foundation for a long-term investment strategy. Nevertheless, the results are strong enough to merit investment consideration for an active portfolio. It is relatively simple to postpone the sale or purchase of a particular stock if it has a large positive or negative expected return over the next month. This suggests large transaction costs and illiquidity must play an important role in determining seasonal variation in expected stock returns.

5.6. Behavioral Explanations

It is tempting to conjecture other variables that may cause annual patterns in expected returns. There is a substantial body of behavioral research that explains return variation in terms of underreaction and overreaction to news (DeBondt and Thaler (1985), Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, Subrahmanyam (1998), and Hong and Stein (1999)). While these theories are typically framed in terms of temporal reaction, they may apply to our current findings if underreaction and overreaction occur in response to regular seasonal news. In order to explain the data, this reaction must be both seasonal and abruptly discontinuous. For example, Table 2 shows the average decile spread to buying stocks based on their 12-month historical return is 115 points per month. In contrast, the decile spread to buying stocks based on their 13-month historical return is less than -30 basis points per month, and the average return to buying stocks based on their 14-month historical return is -50 basis points per month. Any theory that successfully explains the annual pattern of expected returns must explain both the seasonality and the sharp difference between returns in one month and returns in adjacent months.

6. Conclusions

This paper investigates a new periodic pattern in the cross-section of average stock returns. Stocks with above-average returns in a given month tend to above-average returns at annual intervals for up to 20 years. We attribute this to seasonal variation in stock returns. The seasonal effect is strong enough to measure using return data alone. We apply the Conrad and Kaul (1998) and Jegadeesh and Titman (2002) methodology to measure the seasonal effect on the cross-section of stock returns. Following previous findings there is no effect when measuring returns across all months. But there is an economically significant effect when measuring the cross-section of expected stock returns across seasonal months.

The results of our paper are robust. We form a variety of seasonal strategies and find the decile-spread performance exceeds 50 basis points per month and continues for up to 20 years. In other words, it appears to be a large and long-lasting seasonal effect. This performance is eliminated when demeaning stock returns by their seasonal averages. This result is consistent with individual stocks that persistently earn different returns over different calendar months within our sample.

In addition to the returns, trading volume and intra-month volatility also exhibit seasonality. However, volume and volatility do not subsume the seasonal effect of historical returns. Additional diagnostics show the seasonal effect occurs within industry and size categories. In this respect, it does not appear to be a byproduct of stock characteristics or simple proxies for risk. It is also not associated with natural candidates for annual seasonal news such as earnings releases, dividends, or fiscal year-end. Seasonal stock strategies are profitable in virtually every month of the year. However, capturing these returns requires nearly 100% turnover per month during periods of presumed illiquidity. If round-trip transaction costs exceed 70 basis points then it would not be profitable to implement seasonal strategies and the results could persist in equilibrium. This can explain how the costs of trading play an important role in limiting seasonal variation in the cross-section of expected stock returns.

Appendix: Estimator of Cross-Sectional Variance

Jegadeesh and Titman (1993) and Conrad and Kaul (1998) develop estimators of the cross-sectional variance of expected stock returns. These estimators are based on weighted relative-strength strategies. A weighted relative-strength strategy with lag k is a portfolio that buys or sells stocks at time t using weights $w_{it}(k)$ based on the lag-k historical return relative to the market

$$w_{it}(k) = \frac{1}{N}(r_{it-k} - \bar{r}_{t-k}). \tag{A1}$$

where N is the number of stocks available at time t.[6] This forms a long-short portfolio strategy with zero net investment. Importantly, this strategy involves no hindsight bias because it is based only on information available at the end of month t-k, strictly before month t. The realized return on this strategy at time t is

$$\pi_t(k) = \frac{1}{N}\sum_{i=1}^{N} w_{it}(k) r_{it} = \frac{1}{N}\sum_{i=1}^{N}(r_{it-k} - \bar{r}_{t-k}) r_{it}. \tag{A2}$$

Substituting the simple model of Equation (4) into Equation (A2) decomposes the average returns into two components

$$E[\pi_t(k)] = \sigma^2_\mu + \overline{Cov}(e_{it}, e_{it-k}), \tag{A3}$$

where σ^2_μ denotes the cross-sectional variance of expected returns and $\overline{Cov}(e_{it}, e_{it-k})$ denotes the average lag-k autocovariance of idiosyncratic returns. In other words, returns

[6] We assign zero weight to stocks at time t that lack historical returns at time t-k and suppress the notational dependence of N on t and k.

to weighted relative-strength strategies may stem from cross-sectional variation in returns or from autocorrelation in stock returns.

We do not know whether autocorrelation in stocks returns is zero at short horizons. But in order to have a finite variance stationary process the autocorrelation should vanish at long lags

$$\lim\,(k \rightarrow \infty)\ \overline{\mathrm{Cov}}(e_{it}, e_{it-k}) = 0. \tag{A4}$$

In particular, the "average" autocorrelation effect should be zero at long lags. A simple consistent estimator of the cross-sectional variance of expected returns is obtained by averaging the weighted relative strength returns $\pi_t(k)$ at all lags. Our estimator of σ^2_μ is

$$\hat{\sigma}^2_\mu = \frac{1}{T(T-1)/2} \sum_{t=2}^{T} \sum_{k=1}^{T-1} \pi_t(k) = \frac{1}{NT(T-1)/2} \sum_{t=2}^{T} \sum_{k=1}^{T-1} \sum_{i=1}^{N} (r_{it-k} - \bar{r}_{t-k})(r_{it} - \bar{r}_t). \tag{A5}$$

The expectation of the estimator $\hat{\sigma}^2_\mu$ equals the true cross sectional variance plus terms due to autocorrelation.

$$E[\hat{\sigma}^2_\mu] = \sigma^2_\mu + \frac{1}{T(T-1)/2} \sum_{t=2}^{T} \sum_{k=1}^{T-1} \overline{\mathrm{Cov}}(e_{it}, e_{it-k}) \tag{A6}$$

This autocorrelation effect should be small since we average over all lags up to 40 years. In fact, Conrad and Kaul (1998) and Jegadeesh and Titman (2002) use very similar bootstrap estimators based on randomly sampling the dates t and lags k for individual stock returns in Equation (A6).[7] The essential difference is that our estimator takes an equally weighted average over *all* stock pairs of dates and lags, whereas Conrad and Kaul (1998) and Jegadeesh and Titman (2002) use an equally weighted average over 500 *randomly selected* combinations of date and lag. To facilitate comparison of our results with those previous bootstrap results we calculate standard errors by dividing the population standard deviation of $\pi_t(k)$ by the square-root of 500.

[7] Jegadeesh and Titman (2002) make the crucial distinction of bootstrap sampling returns without replacement to avoid forming a portfolio using the same return as the holding period month. Our estimator also avoids this because it corresponds to a lag of k=0.

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Table 1

Univariate and Multivariate Cross-Sectional Regressions of Returns

Monthly univariate cross-sectional regressions of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + u_{i,t}$ are calculated for each month t and lag k, and where $r_{i,t}$ is the return of stock i in month t. The lagged variable $r_{i,t-k}$ is return of stock i in month t–k. The regression is calculated for every month t from January 1965 through December 2002 (456 months), and for lag k values 1 through 12, and each twelfth lag thereafter through 240. The time-series averages of $\gamma_{k,t}$ are reported in Panel A. Panel B calculates multivariate cross-sectional regressions, including all past lags in the same regression. Three regression specifications are considered: including lags 1 through 12, 24, and 36; then adding each twelfth lag through 120; and finally adding each twelfth lag through 240. Regression estimates are reported in percent. The reported Fama and MacBeth (1973) t-statistics are corrected for heteroskedasticity and autocorrelation (using Newey and West (1987) correction with 12 lags). The analysis uses NYSE/AMEX-listed stocks.

	Panel A. Univariate regressions		Panel B. Multivariate regressions					
Lag	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
1	-5.03	-9.03	-6.80	-12.75	-7.10	-13.48	-7.30	-13.96
2	-0.07	-0.16	-1.23	-2.53	-1.31	-2.76	-1.35	-2.89
3	1.36	3.96	0.83	1.91	0.84	1.98	0.83	1.98
4	0.58	1.42	0.49	1.08	0.45	1.01	0.42	0.97
5	0.96	2.42	1.03	2.31	1.09	2.52	1.14	2.70
6	0.98	2.48	1.34	3.28	1.47	3.69	1.49	3.88
7	1.06	3.18	1.08	2.64	1.17	2.96	1.15	3.00
8	0.58	1.30	-0.05	-0.12	0.03	0.07	-0.03	-0.06
9	1.31	3.10	1.24	2.77	1.28	2.97	1.27	3.01
10	0.85	2.35	1.07	2.79	1.00	2.72	0.95	2.62
11	1.39	3.66	1.19	3.14	1.11	3.01	1.10	3.04
12	2.61	7.40	2.57	6.24	2.42	6.03	2.32	5.90
24	1.30	3.47	1.94	5.13	1.88	5.13	1.80	5.02
36	1.27	3.33	1.47	4.33	1.39	4.19	1.19	3.68
48	1.29	3.20			1.11	3.42	1.10	3.46
60	0.62	1.44			1.17	3.52	1.10	3.36
72	1.08	2.98			1.24	3.74	1.14	3.58
84	1.03	3.09			1.26	3.92	1.17	3.76
96	0.93	2.19			0.75	2.23	0.67	2.08
108	1.41	3.78			0.80	2.37	0.55	1.62
120	1.34	4.11			0.93	2.76	0.77	2.35
132	1.68	5.26					1.36	4.74
144	1.19	3.55					0.72	1.79
156	0.70	1.83					0.31	0.94
168	0.78	1.91					0.81	2.45
180	1.29	3.96					0.77	2.55
192	1.43	3.07					0.70	2.18
204	1.21	3.07					0.47	1.49
216	1.14	2.62					0.34	1.11
228	0.00	0.00					-0.19	-0.63
240	1.14	2.99					0.42	1.47

Table 2
Returns of Strategies Based on Past Performance

Every month stocks are grouped into ten portfolios (with equal number of stocks in each portfolio) according to various categories based on past performance. For example, the trading strategy that is formed based on past annual returns during years 2 through 5 ranks stocks according to their average returns during the historical lags 24, 36, 48, and 60. The stocks in each portfolio are assigned equal weight, and the portfolios are rebalanced monthly. The average monthly returns of the various trading strategies for the period January 1965 through December 2002 (456 months) are reported below, as well as the corresponding *t*-statistics (two digit numbers). The analysis uses NYSE/AMEX-listed stocks.

Strategy		1 (losers)	2	3	4	5	6	7	8	9	10 (winners)	10-1
Year 1	All	0.0064	0.0090	0.0101	0.0108	0.0117	0.0125	0.0136	0.0152	0.0173	0.0210	0.0146
		1.65	3.12	3.97	4.54	5.11	5.50	5.77	6.05	6.31	6.39	5.58
	Annual	0.0082	0.0097	0.0106	0.0111	0.0121	0.0127	0.0138	0.0148	0.0160	0.0197	0.0115
		2.53	3.66	4.36	4.77	5.20	5.56	5.78	5.82	5.77	5.80	7.60
	Non-Annual	0.0080	0.0105	0.0111	0.0109	0.0119	0.0120	0.0128	0.0144	0.0165	0.0197	0.0117
		1.99	3.59	4.23	4.53	5.23	5.26	5.48	5.88	6.08	6.13	4.20
Years 2-5	All	0.0191	0.0145	0.0135	0.0127	0.0129	0.0126	0.0128	0.0116	0.0112	0.0084	-0.0107
		5.28	5.25	5.50	5.59	5.68	5.39	5.25	4.50	3.99	2.57	-5.02
	Annual	0.0110	0.0103	0.0105	0.0109	0.0126	0.0124	0.0137	0.0149	0.0157	0.0177	0.0067
		3.48	3.85	4.37	4.74	5.44	5.27	5.74	5.83	5.71	5.44	5.35
	Non-Annual	0.0199	0.0159	0.0141	0.0130	0.0129	0.0126	0.0120	0.0114	0.0101	0.0074	-0.0125
		5.42	5.67	5.78	5.74	5.71	5.36	4.99	4.44	3.59	2.28	-5.60
Years 6-10	All	0.0156	0.0147	0.0138	0.0131	0.0121	0.0121	0.0111	0.0111	0.0118	0.0117	-0.0039
		5.17	5.76	5.97	5.82	5.40	5.27	4.71	4.46	4.31	3.68	-3.32
	Annual	0.0104	0.0093	0.0101	0.0112	0.0117	0.0114	0.0135	0.0144	0.0155	0.0172	0.0068
		3.44	3.68	4.27	4.90	5.24	5.10	5.90	6.02	5.92	5.60	6.15
	Non-Annual	0.0167	0.0156	0.0146	0.0135	0.0126	0.0114	0.0110	0.0102	0.0105	0.0112	-0.0055
		5.47	6.14	6.23	5.96	5.61	5.02	4.64	4.09	3.91	3.51	-4.62
Years 11-15	All	0.0135	0.0116	0.0110	0.0120	0.0120	0.0122	0.0123	0.0126	0.0127	0.0133	-0.0002
		4.67	4.76	4.87	5.46	5.60	5.51	5.54	5.33	5.01	4.69	-0.17
	Annual	0.0101	0.0104	0.0102	0.0111	0.0112	0.0129	0.0130	0.0134	0.0145	0.0166	0.0066
		3.61	4.25	4.52	5.13	5.24	5.87	5.83	5.77	5.81	5.97	6.43
	Non-Annual	0.0144	0.0122	0.0122	0.0120	0.0122	0.0115	0.0124	0.0121	0.0119	0.0125	-0.0019
		4.98	5.02	5.28	5.37	5.61	5.37	5.56	5.07	4.71	4.45	-1.77
Years 16-20	All	0.0150	0.0117	0.0116	0.0110	0.0113	0.0120	0.0117	0.0113	0.0123	0.0119	-0.0031
		5.48	4.89	5.21	5.11	5.29	5.54	5.43	5.01	5.14	4.65	-2.82
	Annual	0.0100	0.0100	0.0103	0.0111	0.0112	0.0115	0.0122	0.0131	0.0137	0.0153	0.0052
		3.78	4.24	4.61	5.02	5.14	5.36	5.64	5.95	5.86	5.84	4.58
	Non-Annual	0.0154	0.0128	0.0115	0.0122	0.0115	0.0111	0.0108	0.0120	0.0109	0.0115	-0.0039
		5.57	5.38	5.16	5.60	5.37	5.17	4.95	5.37	4.61	4.49	-3.35

Table 3

Weighted Relative-Strength Strategy (WRSS) Profits and Cross-Sectional Dispersion in Mean Returns

For every pair of month t and its lag month k we calculate the return of each stock in each month excess of the equally weighed market return that month (using the cross-section of stocks with available returns in both months j and k). For each stock, the product of is excess returns during months t and k is calculated. The sum of these products across firms is denoted $\pi_k(t)$ and it represents a return of a zero cost portfolio strategy. Three groups of returns are then defined: "All" includes all $\pi_k(t)$ such that $k \neq 0$; "Non-Annual" include all $\pi_k(t)$ such that $k \neq 12i$, for any integer i; and "Annual" includes all $\pi_k(t)$ such that $k = 12i$, for any non-zero integer i. The table reports the mean return of each group. Standard errors are calculated by dividing the population standard deviation of each group by the square root of 500. The analysis employs NYSE/AMEX-listed firms for the period January 1963 through December 2002.

	All	Non-Annual	Annual
Mean (%)	-0.0006	-0.0019	0.0133
T-statistic	-0.26	-0.65	3.57

Table 4

Mean-Adjusted Returns of Strategies Based on Past Performance

Every month stocks are grouped into ten portfolios (with equal number of stocks in each portfolio) according to past performance during various ranking periods. For example, the trading strategy that is formed based on past annual returns during years 2 through 5 ranks stocks according to their average returns during the historical lags 24, 36, 48, and 60. The stocks in each portfolio are assigned equal weight, and the portfolios are rebalanced monthly. For each stock each month, the monthly return is adjusted by subtracting off the stock's mean return. Three different periods are separately used to calculate this mean return: pre-ranking, post-ranking, and all. The pre-ranking period corresponds to the period starting at the beginning of the sample period until one month prior to the beginning of the ranking period. The post-ranking period includes all months one month after the end of the ranking period until the end of the sample period (excluding the return month itself). "All" includes all month during the pre- and post-ranking periods. The standard mean return corresponds to the regular monthly return average over the period, while to only returns during the same calendar month as the return month are used to calculate the seasonal mean return over the period. The table reports the average monthly adjusted returns of the long-short strategy (10 minus 1), as well as the corresponding *t*-statistics (two digit numbers). The analysis uses NYSE/AMEX-listed stocks for the period January 1965 through December 2002.

	No Adjustments	Standard Mean Adjustments			Seasonal Mean Adjustments		
Strategy		Pre-Ranking	Post-Ranking	All	Pre-Ranking	Post-Ranking	All
1 year	0.0115	0.0112	0.0119	0.0121	0.0063	0.0040	0.0070
	7.60	7.06	7.56	7.88	4.14	2.75	4.89
2-5 years	0.0067	0.0111	0.0082	0.0083	0.0038	-0.0014	0.0004
	5.36	6.62	6.54	6.58	2.28	-1.09	0.35
6-10 years	0.0069	0.0108	0.0081	0.0082	0.0018	0.0004	0.0010
	6.22	6.78	7.36	7.42	1.10	0.39	0.92
11-15 years	0.0065	0.0107	0.0075	0.0076	0.0008	0.0010	0.0010
	6.37	6.49	7.36	7.39	0.47	0.94	0.95
16-20 years	0.0051	0.0091	0.0058	0.0058	-0.0013	-0.0002	-0.0005
	4.43	5.59	5.06	5.09	-0.74	-0.21	-0.43

Table 5

Relative Strength Portfolio Returns for Different Size Groups

Every month stocks are grouped into ten portfolios (with equal number of stocks in each portfolio) according to various categories based on past performance. For example, the trading strategy that is formed based on past annual returns during years 2 through 5 ranks stocks according to their average returns during the historical lags 24, 36, 48, and 60. The stocks in each portfolio are assigned equal weight, and the portfolios are rebalanced monthly. The average monthly return difference between the highest past-performing decile and the lowest past-performing decile is then calculated for the period January 1965 through December 2002 (456 months). The table below reports the results of this procedure, performed separately for three different size groups (measured by market capitalization). Small firms are defined as the bottom 30 percent, large firms are the top 30 percent, and the remaining 40 percent are medium size firms. The size categorization is re-evaluated in the beginning of every month. The corresponding *t*-statistics are also reported (two digit numbers). The analysis uses NYSE/AMEX-listed stocks.

Strategy		Small	Medium	Large
Year 1	All	0.0129	0.0186	0.0102
		4.04	7.53	3.97
	Annual	0.0090	0.0095	0.0069
		4.27	6.68	4.19
	Non-Annual	0.0105	0.0173	0.0090
		3.07	6.86	3.49
Years 2-5	All	-0.0128	-0.0061	-0.0056
		-5.31	-3.78	-2.90
	Annual	0.0041	0.0042	0.0069
		2.32	3.54	5.01
	Non-Annual	-0.0161	-0.0071	-0.0079
		-6.34	-4.28	-4.11
Years 6-10	All	-0.0048	-0.0025	-0.0015
		-2.44	-1.85	-1.16
	Annual	0.0037	0.0045	0.0067
		1.82	3.57	5.90
	Non-Annual	-0.0059	-0.0035	-0.0032
		-2.84	-2.69	-2.47
Years 11-15	All	-0.0004	0.0005	0.0010
		-0.17	0.39	0.92
	Annual	0.0081	0.0034	0.0035
		3.17	2.67	3.34
	Non-Annual	-0.0012	-0.0006	-0.0007
		-0.47	-0.49	-0.61
Years 16-20	All	-0.0053	-0.0006	-0.0020
		-1.75	-0.39	-1.68
	Annual	0.0002	0.0035	0.0024
		0.06	2.34	2.17
	Non-Annual	-0.0037	-0.0013	-0.0024
		-1.14	-0.88	-2.05

Table 6
Controlling for Industry Effects

Every month stocks are grouped into ten portfolios (with equal number of stocks in each portfolio) according to various categories based on past performance. For example, the trading strategy that is formed based on past annual returns during years 2 through 5 ranks stocks according to their average returns during the historical lags 24, 36, 48, and 60. The stocks in each portfolio are assigned equal weight, and the portfolios are rebalanced monthly. The monthly return of every stock is then decomposed into intra- and inter-industry components. The intra-industry component is the monthly return of the stock excess of its industry group return, and the inter-industry component is the monthly return of the industry group itself. The industry groups (twenty groups) are formed according to the classification in Moskowitz and Grinblatt (1999). The average monthly returns of the various trading strategies (for both intra- and inter-industry components) for the period January 1965 through December 2002 (456 months) are reported below, as well as the corresponding *t*-statistics (two digit numbers). The analysis uses NYSE/AMEX-listed stocks.

Strategy		Intra-Industry	Inter-Industry
Year 1	All	0.0124	0.0022
		5.50	3.97
	Annual	0.0103	0.0012
		8.20	2.98
	Non-Annual	0.0097	0.0020
		3.96	3.71
Years 2-5	All	-0.0096	-0.0011
		-4.98	-2.54
	Annual	0.0063	0.0004
		5.79	1.16
	Non-Annual	-0.0113	-0.0012
		-5.58	-2.85
Years 6-10	All	-0.0037	-0.0003
		-3.75	-0.58
	Annual	0.0056	0.0012
		5.77	3.70
	Non-Annual	-0.0049	-0.0006
		-4.83	-1.51
Years 11-15	All	-0.0005	0.0003
		-0.57	0.86
	Annual	0.0056	0.0010
		6.19	2.99
	Non-Annual	-0.0020	0.0001
		-2.13	0.25
Years 16-20	All	-0.0030	0.0000
		-3.25	-0.08
	Annual	0.0046	0.0006
		4.68	1.76
	Non-Annual	-0.0035	-0.0003
		-3.57	-0.79

Table 7

Seasonal Returns of Zero-Investment Strategies Based on Past Performance

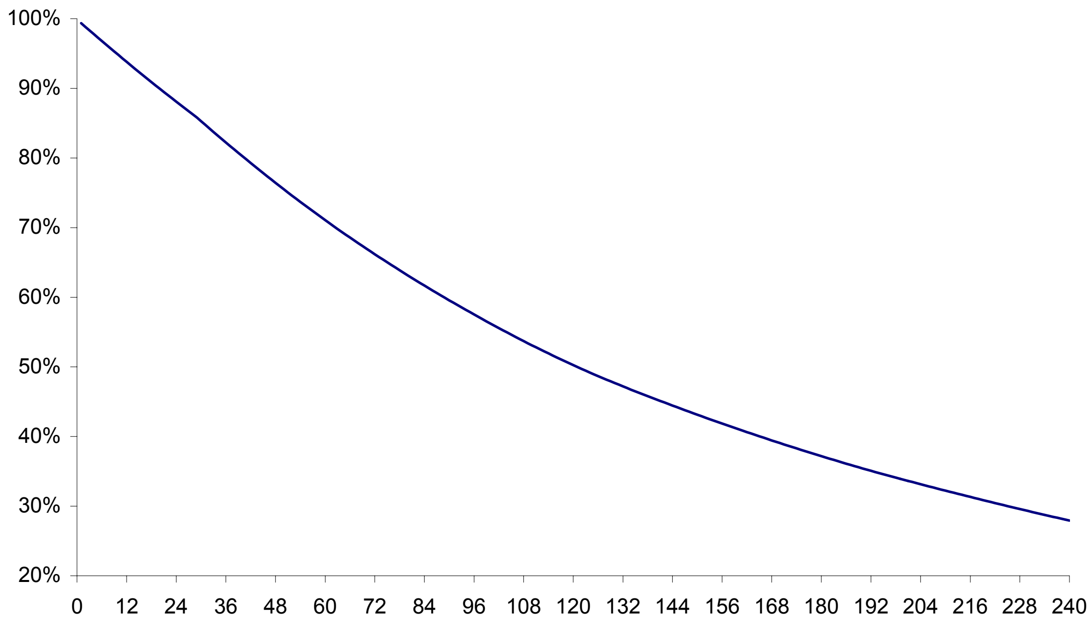
Every month stocks are grouped into ten portfolios (with equal number of stocks in each portfolio) according to various categories based on past performance. For example, the trading strategy that is formed based on past annual returns during years 2 through 5 ranks stocks according to their average returns during the historical lags 24, 36, 48, and 60. The stocks in each portfolio are assigned equal weight, and the portfolios are rebalanced monthly. The average monthly returns of the various trading strategies are reported separately for every calendar month during the period January 1965 through December 2002. The corresponding *t*-statistics are also reported below (two digit numbers). In a separate column, returns are computed using all non-January months. The analysis uses NYSE/AMEX-listed stocks.

Strategy		January	February	March	April	May	June	July	August	September	October	November	December	Feb-Dec
Year 1	All	-0.0449	0.0101	0.0134	0.0217	0.0082	0.0307	0.0127	0.0126	0.0241	0.0189	0.0256	0.0419	0.0200
		-2.92	1.06	2.15	3.57	1.19	4.97	1.92	2.10	3.34	1.99	2.60	5.07	8.62
	Annual	0.0333	0.0019	0.0093	0.0099	0.0049	0.0110	0.0006	0.0083	0.0130	0.0097	0.0153	0.0209	0.0095
		3.52	0.32	2.17	3.17	1.41	3.16	0.14	2.22	3.27	1.80	2.70	3.84	6.93
	Non-Annual	-0.0683	0.0090	0.0091	0.0244	0.0075	0.0295	0.0138	0.0133	0.0224	0.0189	0.0214	0.0397	0.0190
		-3.98	0.96	1.53	4.08	1.09	4.84	1.98	2.10	2.99	1.95	2.23	4.86	8.18
	Difference	0.1016	-0.0072	0.0002	-0.0145	-0.0026	-0.0186	-0.0132	-0.0050	-0.0093	-0.0092	-0.0061	-0.0188	-0.0095
		4.77	-0.62	0.03	-2.04	-0.39	-3.45	-1.78	-0.73	-1.23	-0.88	-0.59	-2.40	-3.84
Years 2-5	All	-0.0807	-0.0237	-0.0189	-0.0059	-0.0085	-0.0083	-0.0107	0.0045	-0.0004	0.0091	0.0045	0.0107	-0.0043
		-6.19	-3.22	-3.60	-1.11	-1.42	-1.87	-2.05	0.90	-0.11	1.72	1.04	1.65	-2.56
	Annual	0.0389	-0.0032	0.0030	0.0043	0.0020	0.0013	0.0025	0.0006	0.0040	0.0028	0.0104	0.0137	0.0038
		6.16	-0.83	0.87	1.11	0.67	0.44	0.76	0.16	1.13	0.60	2.23	3.39	3.31
	Non-Annual	-0.0960	-0.0234	-0.0182	-0.0071	-0.0084	-0.0093	-0.0108	0.0057	-0.0034	0.0098	0.0046	0.0069	-0.0049
		-7.30	-3.19	-3.40	-1.44	-1.41	-2.08	-2.06	1.07	-0.90	1.65	1.11	1.11	-2.89
	Difference	0.1350	0.0203	0.0212	0.0113	0.0104	0.0106	0.0133	-0.0051	0.0075	-0.0070	0.0058	0.0068	0.0087
		9.33	2.82	3.68	2.38	1.68	2.21	2.31	-0.85	1.68	-0.81	1.07	1.24	4.74
Years 6-10	All	-0.0143	-0.0045	-0.0016	-0.0042	-0.0055	-0.0022	-0.0092	-0.0039	-0.0067	0.0017	0.0073	-0.0034	-0.0029
		-2.52	-0.99	-0.44	-1.09	-1.56	-0.73	-1.83	-1.21	-2.13	0.46	1.70	-0.96	-2.54
	Annual	0.0323	0.0008	0.0043	0.0025	0.0008	0.0064	-0.0003	0.0005	0.0024	0.0106	0.0118	0.0091	0.0044
		4.98	0.23	1.17	1.10	0.26	2.20	-0.11	0.18	0.89	2.72	2.77	2.92	4.57
	Non-Annual	-0.0235	-0.0060	-0.0047	-0.0033	-0.0054	-0.0009	-0.0091	-0.0051	-0.0072	0.0002	0.0051	-0.0062	-0.0039
		-3.88	-1.28	-1.33	-0.83	-1.49	-0.32	-1.73	-1.62	-2.20	0.07	1.39	-1.73	-3.37
	Difference	0.0559	0.0068	0.0090	0.0057	0.0061	0.0074	0.0088	0.0056	0.0096	0.0104	0.0068	0.0154	0.0083
		6.54	1.15	1.90	1.38	1.39	1.87	1.55	1.31	2.14	2.05	1.71	3.69	5.96
Years 11-15	All	-0.0090	-0.0019	0.0029	-0.0011	-0.0005	0.0022	-0.0013	0.0008	-0.0012	0.0044	0.0092	-0.0065	0.0006
		-1.72	-0.46	0.81	-0.40	-0.15	0.76	-0.42	0.25	-0.44	0.99	3.23	-2.01	0.62
	Annual	0.0269	0.0025	0.0043	0.0005	0.0076	0.0025	-0.0003	0.0023	0.0089	0.0093	0.0054	0.0091	0.0047
		5.63	0.79	1.24	0.18	2.63	0.86	-0.11	0.77	3.23	2.18	1.34	2.61	4.82
	Non-Annual	-0.0220	-0.0054	0.0022	-0.0001	-0.0014	0.0020	-0.0015	0.0027	-0.0033	0.0016	0.0090	-0.0067	-0.0001
		-4.24	-1.35	0.66	-0.03	-0.44	0.70	-0.47	0.90	-1.26	0.31	2.89	-2.08	-0.08
	Difference	0.0489	0.0079	0.0021	0.0006	0.0089	0.0006	0.0013	-0.0004	0.0121	0.0077	-0.0035	0.0158	0.0048
		5.89	1.67	0.47	0.17	2.59	0.13	0.33	-0.09	2.87	1.08	-0.69	4.16	3.52
Years 16-20	All	-0.0148	-0.0116	-0.0038	-0.0058	0.0012	0.0006	-0.0060	-0.0042	0.0009	0.0001	0.0067	-0.0006	-0.0020
		-3.81	-3.14	-1.17	-1.75	0.34	0.18	-1.79	-1.13	0.26	0.03	1.58	-0.13	-1.79
	Annual	0.0297	-0.0036	0.0022	0.0044	0.0033	0.0064	0.0023	0.0023	0.0038	0.0084	0.0026	0.0009	0.0030
		4.23	-1.18	0.63	1.53	0.97	1.91	0.81	0.57	1.29	1.99	0.76	0.35	2.99
	Non-Annual	-0.0209	-0.0117	-0.0040	-0.0080	0.0028	-0.0014	-0.0046	-0.0044	0.0022	-0.0023	0.0059	0.0003	-0.0023
		-3.62	-3.05	-1.22	-2.20	0.83	-0.40	-1.40	-1.37	0.73	-0.52	1.50	0.08	-2.07
	Difference	0.0506	0.0081	0.0063	0.0124	0.0005	0.0078	0.0069	0.0068	0.0016	0.0108	-0.0034	0.0006	0.0053
		4.37	2.32	1.40	2.75	0.13	1.94	1.63	1.27	0.40	1.87	-0.75	0.15	3.93

Table 8
Controlling for Earnings, Dividends, and Fiscal-Year End

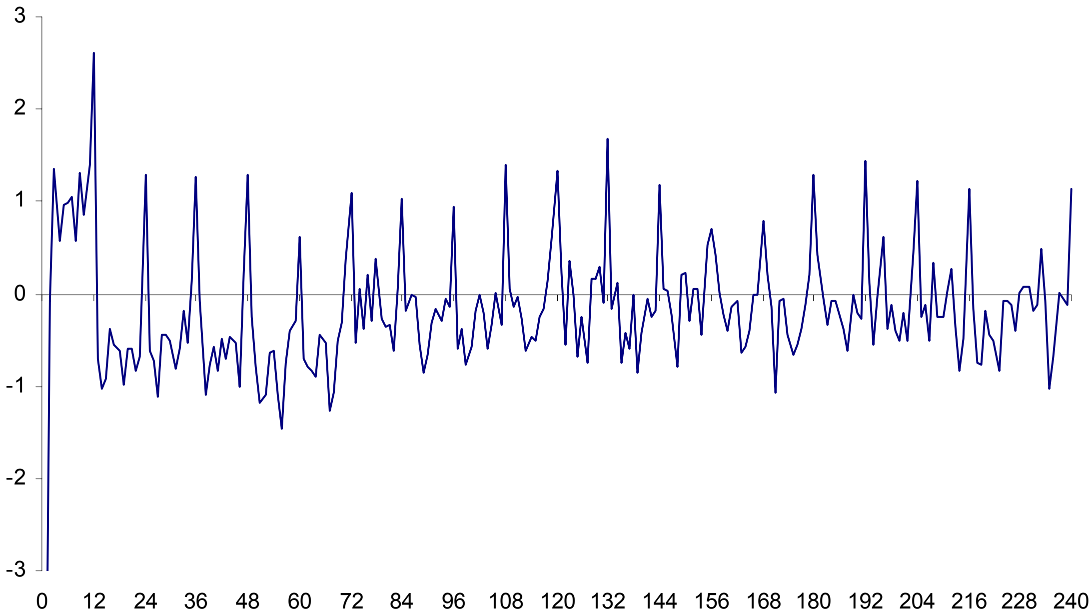
Every month stocks are grouped into ten portfolios (with equal number of stocks in each portfolio) according to various categories based on past performance. For example, the trading strategy that is formed based on past annual returns during years 2 through 5 ranks stocks according to their average returns during the historical lags 24, 36, 48, and 60. The stocks in each portfolio are assigned equal weight, and the portfolios are rebalanced monthly. The sample in each panel includes only NYSE/AMEX-listed firms whose respective events are recorded on COMPUSTAT. The table reports the portfolio returns using (a) only returns during event months, and (b) only returns during non-event months. The average monthly returns of the various trading strategies for the period January 1965 through December 2002 (456 months) are reported below, as well as the corresponding *t*-statistics (two digit numbers).

Strategy		Panel A. Earnings announcements		Panel B. Dividend announcements		Panel C. Ex-dividend months		Panel D. Fiscal-year-end months	
		Event months	Non-event months	Event months	Non-event months	Event months	Non-event months	Event months	Non-event months
Year 1	All	0.0219	0.0122	0.0125	0.0137	0.0083	0.0152	0.0093	0.0143
		6.15	4.20	4.91	4.62	3.25	5.14	2.20	4.61
	Annual	0.0106	0.0127	0.0094	0.0122	0.0083	0.0125	0.0073	0.0145
		4.25	7.13	6.02	7.17	4.93	7.22	2.24	7.49
	Non-Annual	0.0191	0.0091	0.0107	0.0107	0.0064	0.0124	0.0080	0.0110
		5.34	2.91	4.23	3.37	2.48	4.00	1.79	3.37
Years 2-5	All	-0.0124	-0.0097	-0.0078	-0.0085	-0.0083	-0.0081	-0.0021	-0.0133
		-4.27	-3.84	-4.08	-3.26	-4.43	-3.15	-0.56	-4.57
	Annual	0.0078	0.0067	0.0063	0.0075	0.0053	0.0078	0.0082	0.0084
		3.30	4.67	4.11	5.20	3.66	5.35	2.79	5.50
	Non-Annual	-0.0138	-0.0120	-0.0092	-0.0113	-0.0108	-0.0109	-0.0065	-0.0157
		-4.83	-4.53	-4.79	-4.14	-5.58	-4.00	-1.67	-5.13
Years 6-10	All	-0.0043	-0.0042	-0.0039	-0.0048	-0.0049	-0.0041	-0.0044	-0.0044
		-1.91	-2.84	-2.45	-3.53	-3.14	-3.05	-1.29	-2.77
	Annual	0.0074	0.0062	0.0066	0.0062	0.0057	0.0065	-0.0013	0.0079
		3.20	4.56	4.39	4.59	3.99	4.69	-0.39	5.53
	Non-Annual	-0.0057	-0.0055	-0.0059	-0.0065	-0.0057	-0.0065	-0.0042	-0.0071
		-2.55	-3.59	-3.73	-4.74	-3.64	-4.81	-1.26	-4.18
Years 11-15	All	-0.0013	0.0005	-0.0019	-0.0013	-0.0018	-0.0016	0.0040	-0.0007
		-0.57	0.40	-1.29	-0.98	-1.26	-1.28	1.01	-0.49
	Annual	0.0085	0.0054	0.0037	0.0051	0.0015	0.0057	0.0024	0.0073
		3.92	3.95	2.38	3.92	0.99	4.37	0.63	4.12
	Non-Annual	-0.0026	-0.0018	-0.0026	-0.0026	-0.0029	-0.0030	0.0040	-0.0018
		-1.18	-1.34	-1.79	-1.87	-1.86	-2.29	1.01	-1.27
Years 16-20	All	0.0031	-0.0028	0.0005	-0.0014	0.0006	-0.0019	-0.0104	-0.0019
		1.22	-2.03	0.30	-1.01	0.39	-1.36	-2.65	-1.08
	Annual	0.0058	0.0045	0.0036	0.0045	0.0059	0.0046	0.0083	0.0042
		2.08	3.09	2.16	3.29	3.55	3.31	1.86	2.87
	Non-Annual	-0.0005	-0.0037	-0.0015	-0.0028	-0.0015	-0.0022	-0.0092	-0.0030
		-0.18	-2.58	-0.92	-2.05	-0.94	-1.65	-2.25	-1.90

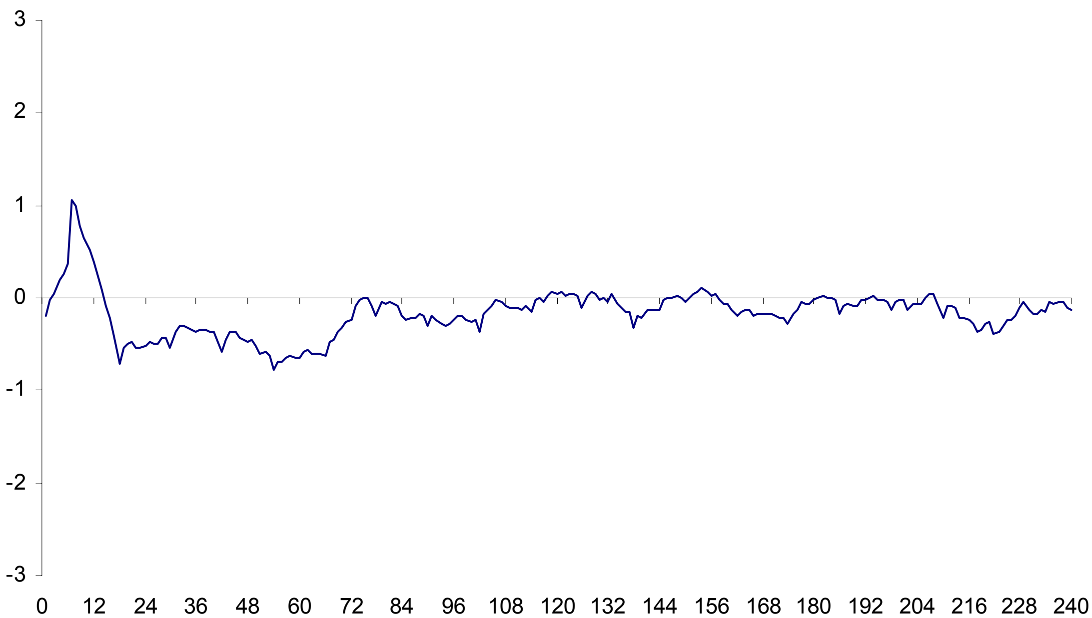


Average fraction of firms that exist at time t–k out of total number of firms at time t, as a function of lag k

Figure 1. Diagnostics of sample size. The figures describe the sample available for regression analysis, which includes NYSE/AMEX-listed stocks for the period January 1945 through December 2002.



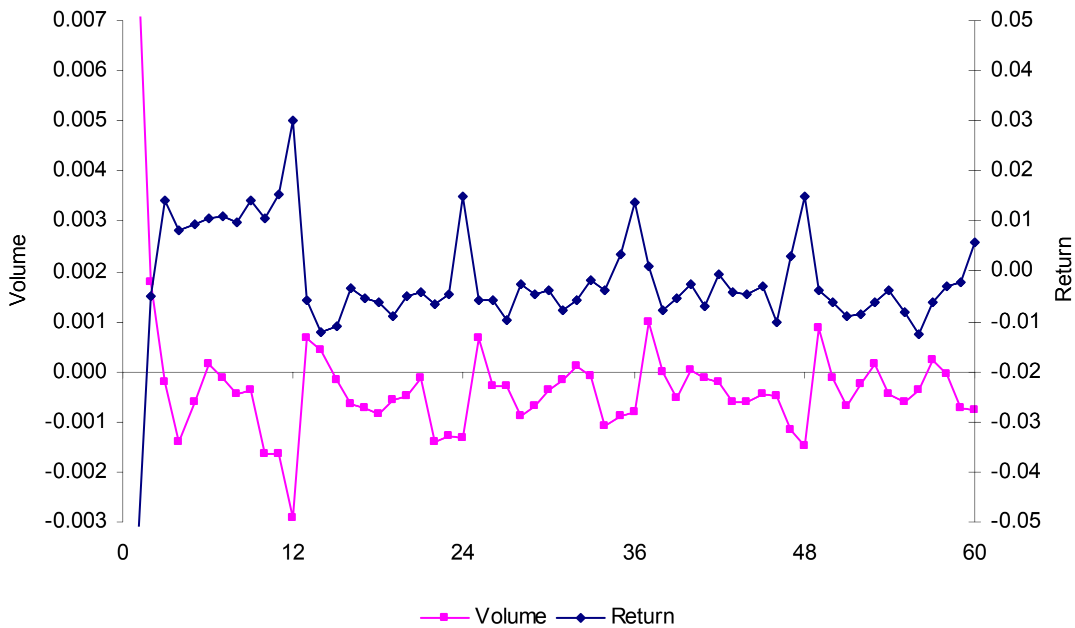
Panel A: Average univariate regression estimates as a function of historical lag



Panel B: Smoothed graph

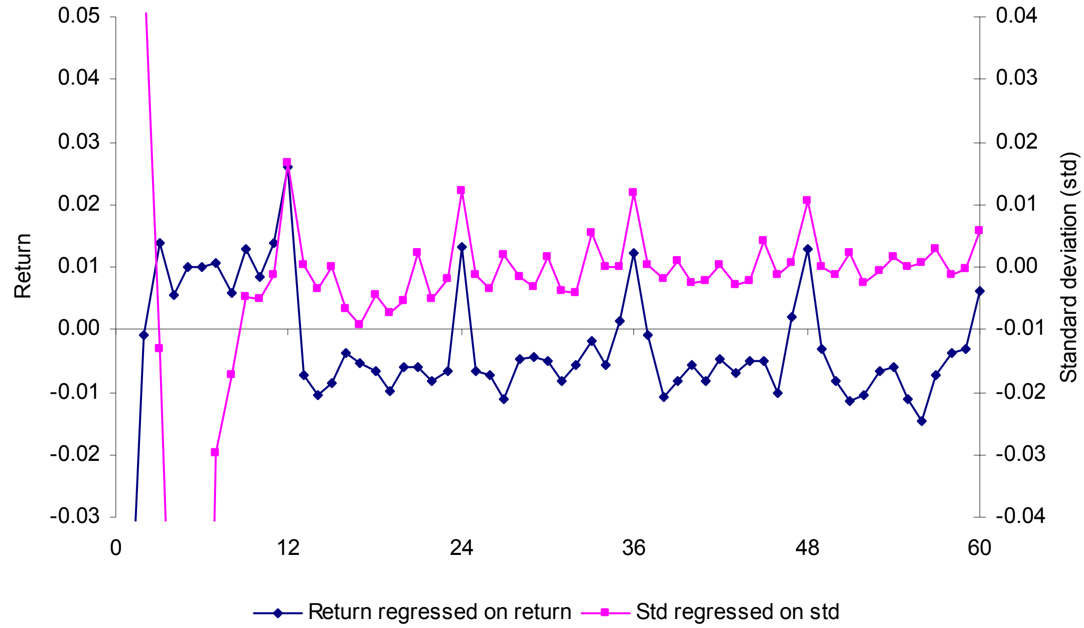
Figure 2. Cross-sectional regressions of return. Monthly cross-sectional univariate regressions of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t}r_{i,t\text{-}k} + u_{i,t}$ are calculated for each month t and lag k, and where $r_{i,t}$ is return of stock i in month t. The lagged variable $r_{i,t\text{-}k}$ is return of stock i in month t–k. The regression is calculated for every month t from January 1965 through December 2002 (456 months), and for lag k values 1 through 240. Panel A plots the time-series averages of $\gamma_{k,t}$. Panel B presents a smoothed version of Panel A by replacing each observation in Panel A with the average return using a moving window of [–5,+5]. All regression estimates are reported in percent. The analysis uses NYSE/AMEX-listed stocks.

Panel A: Univariate cross-sectional regressions

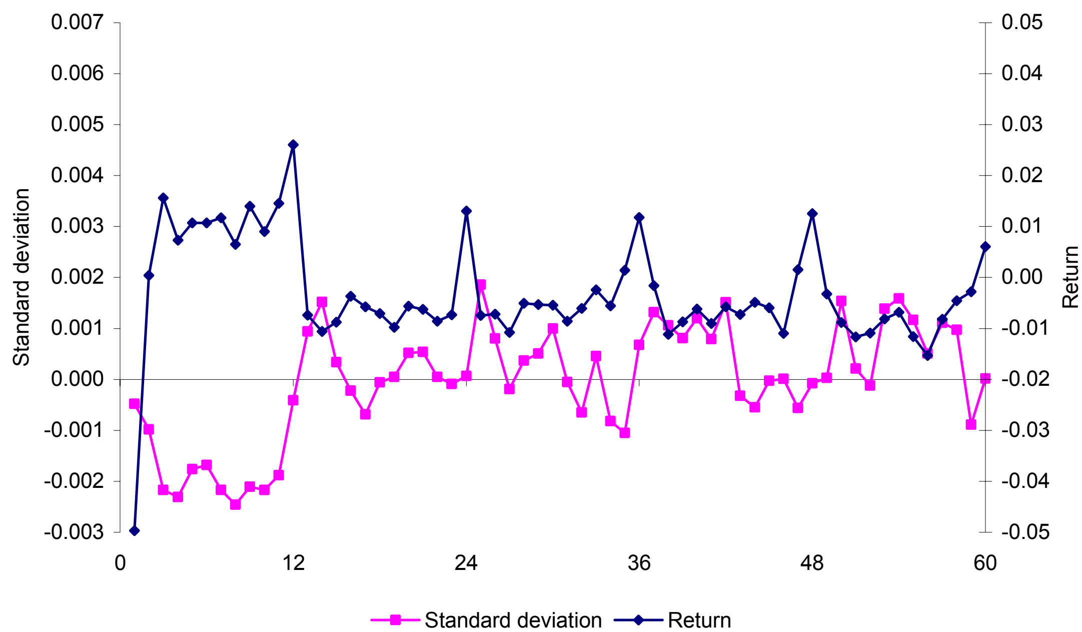


Panel B: Multivariate cross-sectional regressions of return on return and volume

Figure 3. Cross-sectional regressions of volume and return. Monthly cross-sectional univariate regressions of the form $x_{i,t} = \alpha_{k,t} + \gamma_{k,t} x_{i,t-k} + u_{i,t}$ are calculated for each month *t* and lag *k*. The regressions are run separately for two definitions of $x_{i,t}$ (stock *i* in month *t*): volume and return. Volume is defined as the number of shares traded scaled by the number of shares outstanding. For the analysis, volume is the logarithm of the ratio of volume and its prior six-month average. The lagged variable $x_{i,t-k}$ is either volume or return of stock *i* in month *t–k*. The regression is calculated for separately for volume and return, for every month *t* from July 1967 through December 2002 (426 months), and for lag *k* values 1 through 60. The time-series averages of $\gamma_{k,t}$ are plotted in Panel A. Similarly, Panel B plots the time-series averages of the coefficients $\gamma_{k,t}$ and $\delta_{k,t}$ from the cross-sectional multivariate regressions $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + \delta_{k,t} v_{i,t-k} + u_{i,t}$, which are also calculated for every month *t* from July 1967 through December 2002 (426 months), and for lag *k* values 1 through 60. The analysis uses NYSE/AMEX-listed stocks.

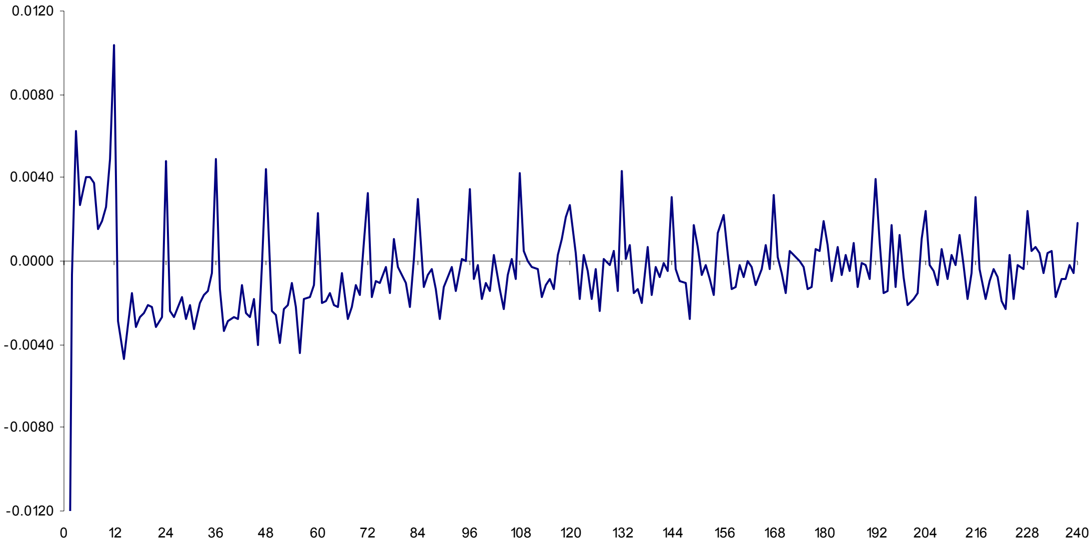


Panel A: Univariate cross-sectional regressions

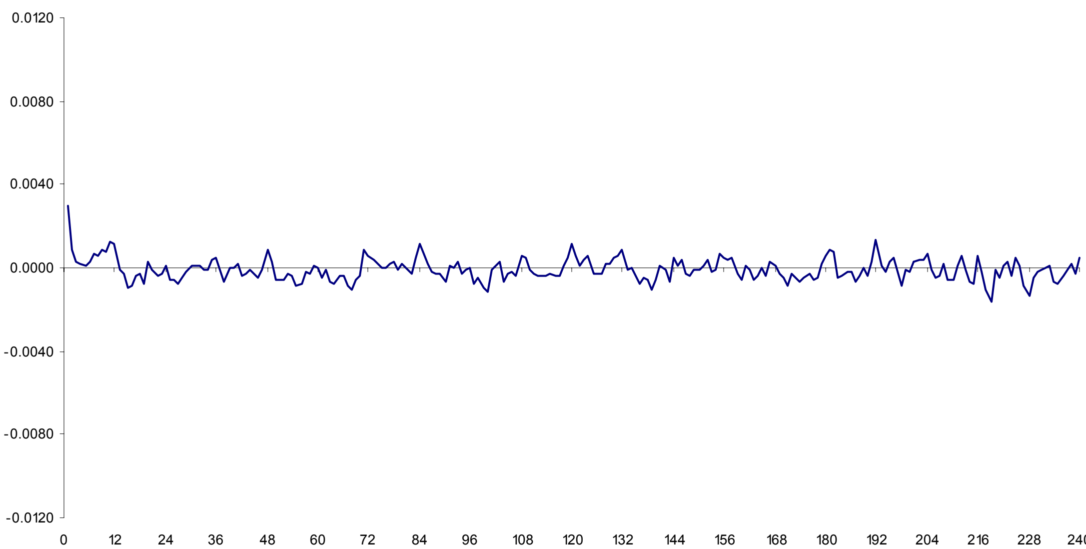


Panel B: Multivariate cross-sectional regressions of return on return and volume

Figure 4. Cross-sectional regressions of standard deviaion and return. Monthly cross-sectional univariate regressions of the form $x_{i,t} = \alpha_{k,t} + \gamma_{k,t}x_{i,t-k} + u_{i,t}$ are calculated for each month t and lag k. The regressions are run separately for two definitions of $x_{i,t}$ (stock i in month t): standard deviation and return. Standard deviation is calculated using the daily returns in any given month. For the analysis, standard deviation is the logarithm of the ratio of standard deviation and its prior six-month average. The lagged variable $x_{i,t-k}$ is either standard deviation or return of stock i in month t–k. The regression is calculated for separately for standard deviation and return, for every month t from July 1967 through December 2002 (426 months), and for lag k values 1 through 60. The time-series averages of $\gamma_{k,t}$ are plotted in Panel A. Similarly, Panel B plots the time-series averages of the coefficients $\gamma_{k,t}$ and $\delta_{k,t}$ from the cross-sectional multivariate regressions $r_{i,t} = \alpha_{k,t} + \gamma_{k,t}r_{i,t-k} + \delta_{k,t}std_{i,t-k} + u_{i,t}$, which are also calculated for every month t from July 1967 through December 2002, and for lag k values 1 through 60. The analysis uses NYSE/AMEX-listed stocks.



Panel A: Intra-Industry



Panel B: Inter-Industry

Figure 5. Industry-Adjusted Returns of Winners-minus-Losers Strategies. Every month stocks are grouped into ten portfolios (with equal number of stocks in each portfolio) according to the performance during one month in the past. The stocks in each portfolio are assigned equal weight, and the portfolios are rebalanced monthly. The monthly return of every stock is then decomposed into intra- and inter-industry components. The intra-industry component is the monthly return of the stock excess of its industry group return, and the inter-industry component is the monthly return of the industry group itself. The industry groups (twenty groups) are formed according to the classification in Moskowitz and Grinblatt (1999). The average monthly return difference (for both intra- and inter-industry components) between the highest pastperforming decile and the lowest past-performing decile is then calculated for the period January 1965 through December 2002 (456 months). The figure plots the average monthly returns for 240 different trading strategies, each corresponding to one historical month out of the past 20 years. The analysis uses NYSE/AMEX-listed stocks.

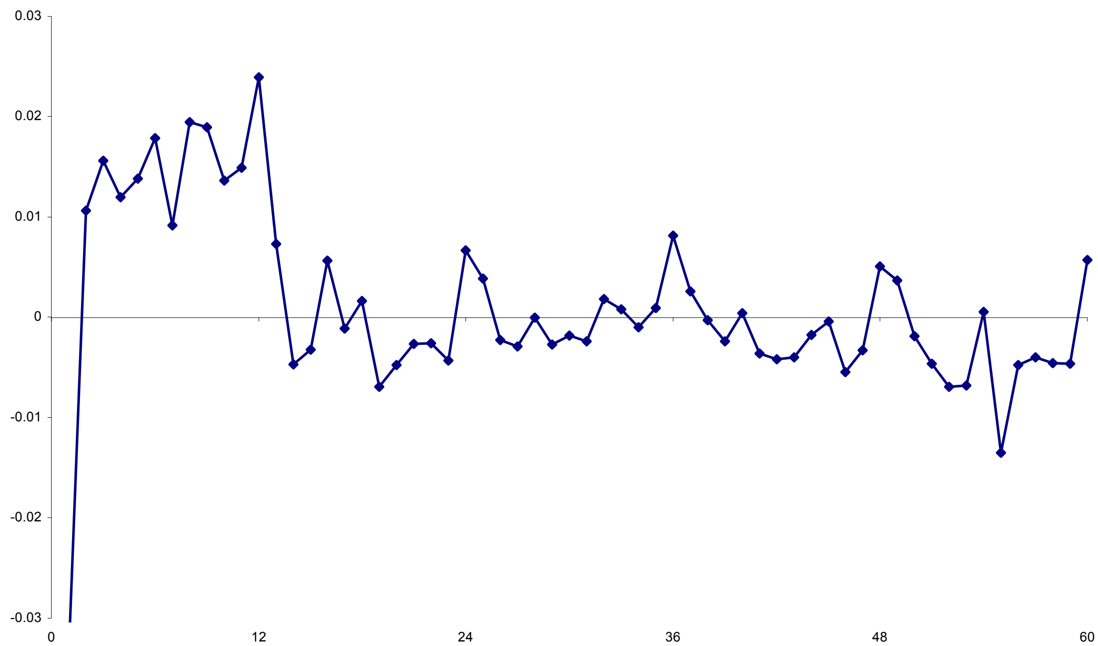


Figure 6. Response function of mid-month returns (without the turn of year). Cross-sectional regressions of monthly returns on lagged monthly returns $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + u_{i,t}$ are calculated for each month t and lag k; $r_{i,t}$ is the return of stock i in month t. Monthly returns are calculated for the periods between mid calendar months. The regression is calculated for every month t from January 15th, 1968, through December 15th, 2002, excluding the periods between December 15th and January 15th (385 months), and for every lag k from 1 to 60. The time-series averages of $\gamma_{k,t}$ are plotted above. The analysis uses NYSE/AMEX-listed stocks.