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The Vanishing January Effect

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Abstract

Seasonality in U.S. stock prices is investigated using monthly average data on the Dow Jones Industrial Average over the period 1970-2005. By estimating a dummy variable model using OLS and rolling regressions, the results reveal the presence of a significant January effect except in the most recent period, 1990-2005, when a strong negative July effect surfaced. This finding is confirmed by using a more sophisticated structural time series model with an autoregressive structure. Some explanations are suggested for the disappearance of the January effect and the surfacing of the July effect.

Introduction

A significant amount of research has been carried out to examine stock market seasonality.[1] This research has led to the acceptance (as a stylized fact) of the so-called January effect, which is the tendency of stock prices to rise in January relative to December. Wachtel (1942) was the first economist to examine and document seasonality in the Dow Jones Industrial Average from 1927 to 1942. He observed frequent bullish tendencies from December to January in eleven of the fifteen years he studied. Over three decades later, Rozeff and Kinney (1976) conducted serious empirical research to examine seasonality in the U.S. stock market and found statistically significant differences in mean returns among months. Subsequent empirical research revealed strong January seasonality in stock returns and money market returns in the U.S. and other markets.[2] In a recent paper, however, Lindley et al (2004) demonstrated that many years during the period 1962-2000 did not have a significant January effect and that some years had a negative January effect.

The finding of Lindley et al (2004) that support for the January effect is not as strong as it was once thought makes it desirable to re-examine the hypothesis of the January effect by using data from a recent period. It could be the case that things have changed in such a way as to remove the sources of the January effect. The objective of this study, therefore, is to investigate the January effect in U.S. stock prices using data on the Dow Jones Industrial Average over the period 1970-2005.

The January Effect Hypothesis

There is no consensus view on the causes of the January effect. Of the potential explanations, the most compelling is tax-induced selling: during December, the final month in a tax year, investors sell stocks that have already declined during the year to book capital losses, thereby tax-sheltering realized gains

[1] Excellent surveys of the literature can be found in Van Den Bergh and Wessles (1985), Keim (1986) and Clark and Ziemba (1987).
[2] Jones and Wilson (1989) tested the January effect using seven assets from 1871 to 1986. Also, Musto (1997) tested the January effect in the commercial papers market.

on other stocks and further depressing the prices of losing stocks. Beyond the year's end, this downward price pressure is not just relieved but reversed as the proceeds of sales are reinvested.

Although the tax-loss selling hypothesis has received widespread recognition as an explanation of the January effect, it has been challenged and critically examined by many economists.[3] Reinganum (1983) stated that "while tax-loss selling may account for the unusually large returns at the beginning of January, several questions still remain unanswered". He also wondered why firms exhibit a January seasonal effect even after purging the data of potential tax-loss selling effect, and why this seasonal pattern still seems to be related to market capitalization. Brown, Keim, Kleidon and Marsh (1983) concluded that the relation between the U.S. tax year and the January seasonal is correlation rather than causation. Constantinides (1984) argues that tax-loss selling only in December is not an optimal investment strategy. Jones et al (1987) provide some empirical evidence indicating that the January effect existed before the imposition of income taxes.

Another explanation is that the January effect is caused by portfolio managers engaging in window dressing at year-end: selling losing and risky stocks and holding instead cash and blue-chip stocks to make their year-end portfolios appear more conservative. The other motive of portfolio managers is locking in their bonuses, which are typically based on the rate of return achieved during the year. At the beginning of the year, portfolio managers put the funds allocated to them to work. If, during the year, their portfolios produce satisfactory return, many managers will be inclined to lock it in to secure their annual bonuses by reducing the risk profile of their portfolios. As a new financial year begins in January, the cycle starts all over again as managers move funds back into stocks.

Some explanatory hypotheses are based on measurement problems, particularly studies that focus on the relation between market capitalization and seasonality in the stock market. The argument here is simply that excess return on the stocks of small firms is postulated to be either deception caused by poor measurement of the returns on these stocks or compensation for the extra risk that investors bear by holding these stocks.[4] Furthermore, there are hypotheses pertaining to the seasonality or the timing of information release. Because of the coincidental clustering of the calendar year-end and the tax year-end in the U.S., Rozeff and Kinney (1976) suggested that January sees the release of an unusual amount of accounting information, thus speculating that seasonality is perhaps associated with accounting news. The seasonal difference in the information about the underlying stocks has been examined by some researchers and considered as an alternative explanation for the January effect.[5]

An Informal Examination of the Data

The statistical analysis presented in this paper is based on monthly average observations (calculated from the daily closing prices) of the DJIA over the period January 1970 to July 2005. The use of monthly averages, as opposed to end of month observations, can be justified on the grounds that seasonal variation occurs throughout the month rather than being concentrated at the end of the month. Figure 1 displays the DJIA over the sample period. Most striking in the behaviour of the market index are the boom of the 1990s and the crash of the early 21st Century. Obviously, it is not possible to observe any seasonality here because of the dominant effect of the trend. This effect is removed by calculating the monthly percentage change in the DJIA, which we call the monthly return.

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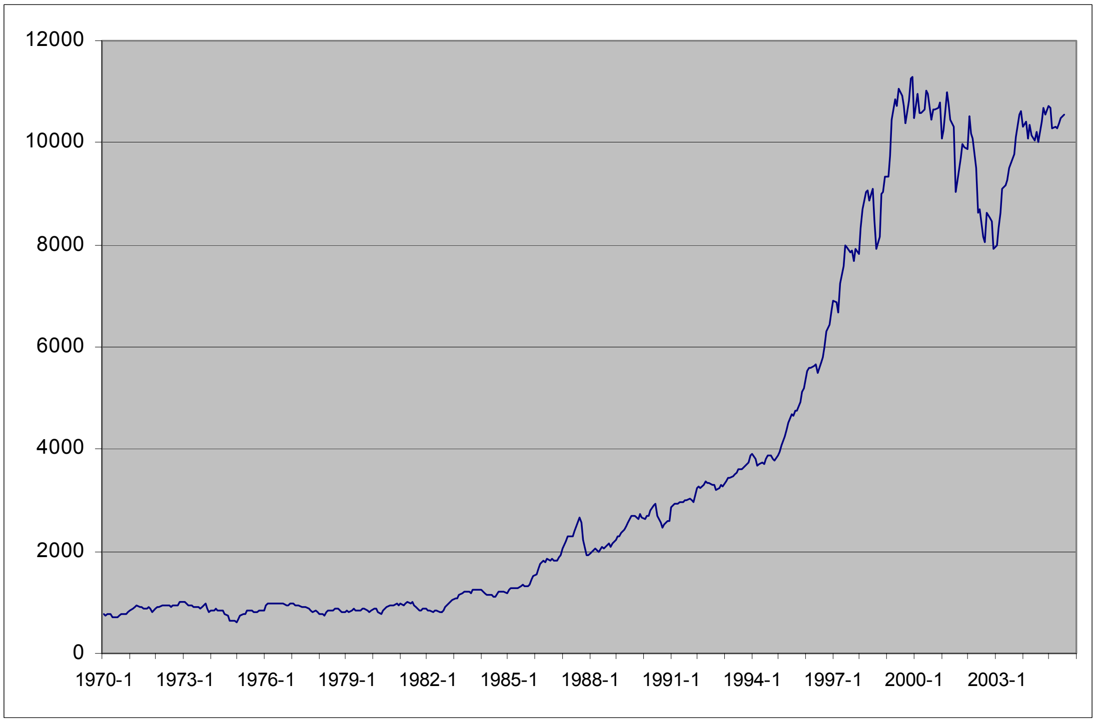
[3] See, for example, Brown, Keim, Kleidon and Marsh (1983), Schwert (1983), Constantinides (1984), Van Den Bergh and Wessels (1985), Chan(1986), Jones, Pearce, and Wilson (1987), Ritter and Chopra (1989), and Hillier and Marshall (2002).

[4] See Banz (1981), Brown, Kleidon and Marsh (1983), Reinganum (1983) and Roll (1983).

[5] See, for example, Brauer and Chang (1990).

Figure 1: Dow Jones Industrial Average (Monthly Average, 1970:1-2005:7)



The behaviour of the monthly return is shown in Figure 2. Table 1 exhibits the mean DJIA return in January and July during the periods 1970-2005, 1980-2005 and 1990-2005, together with their respective t statistics. While the January return is significant during the periods 1970-2005 and 1980-2005, it is not so in the most recent period, 1990-2005. Conversely, a significantly negative July effect appears in the most recent period, 1990-2005. Figures 3(a), 3(b) and 3(c) show the mean return of the DJIA over the periods 1970-2005, 1980-2005 and 1990-2005, respectively, telling us exactly the same story.

Figure 2: DJIA Monthly Returns

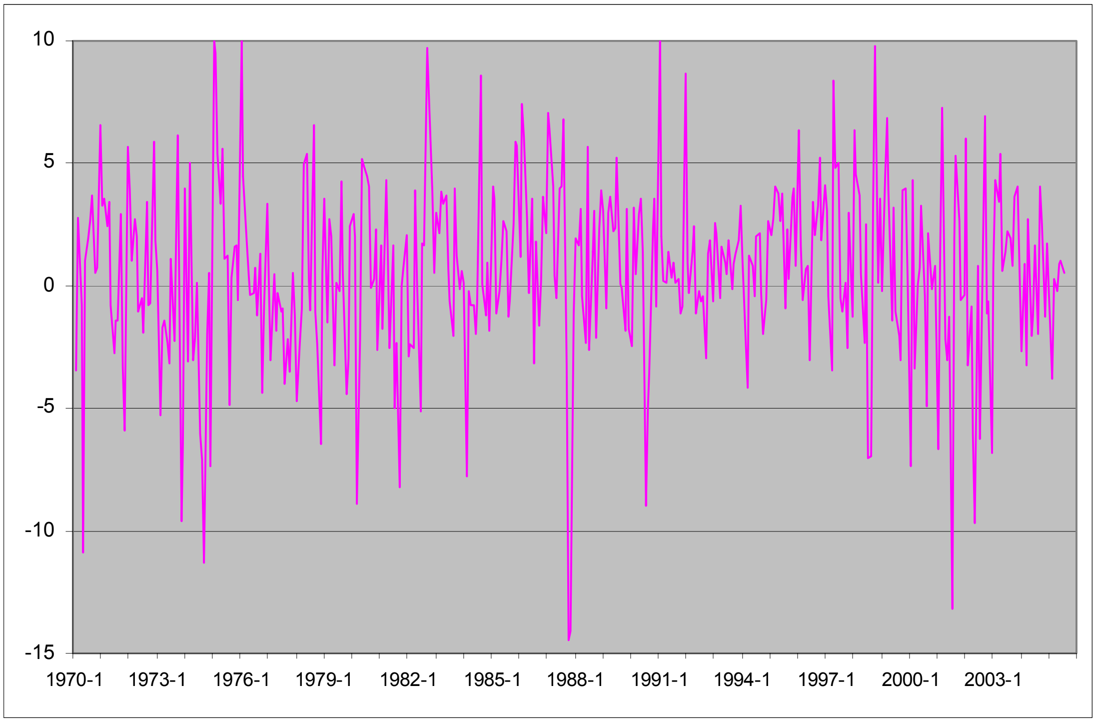


Figure 3(a): Mean Monthly DJIA Returns (1971-2005)

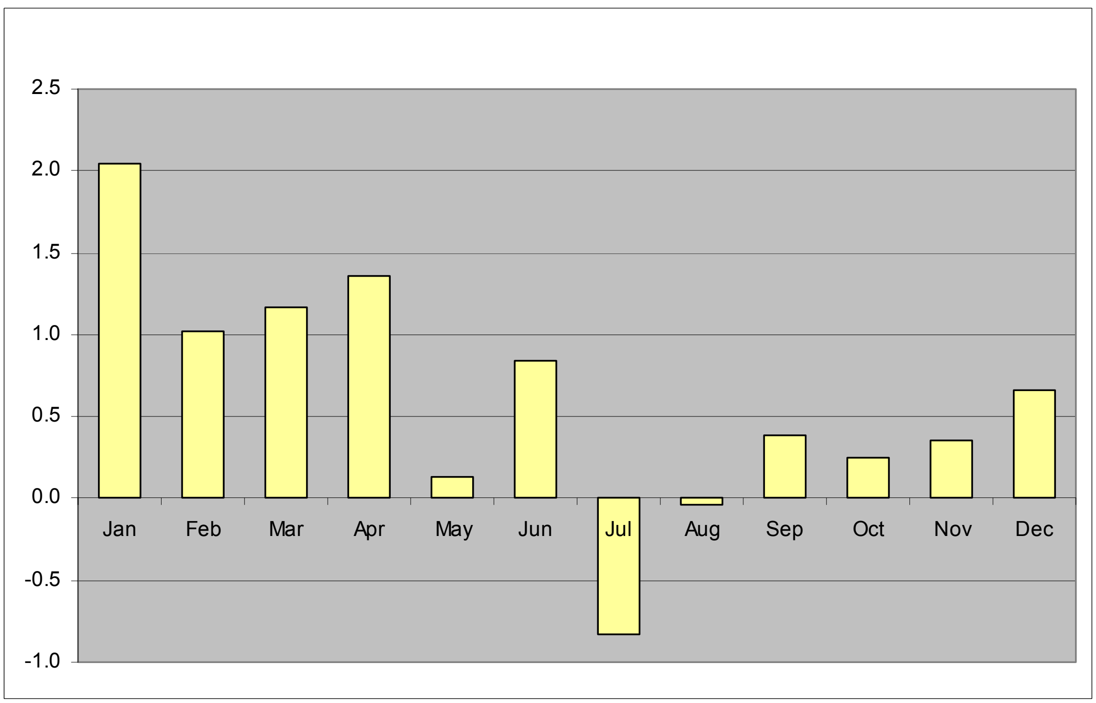


Figure 3(b): Mean Monthly DJIA Returns (1980-2005)

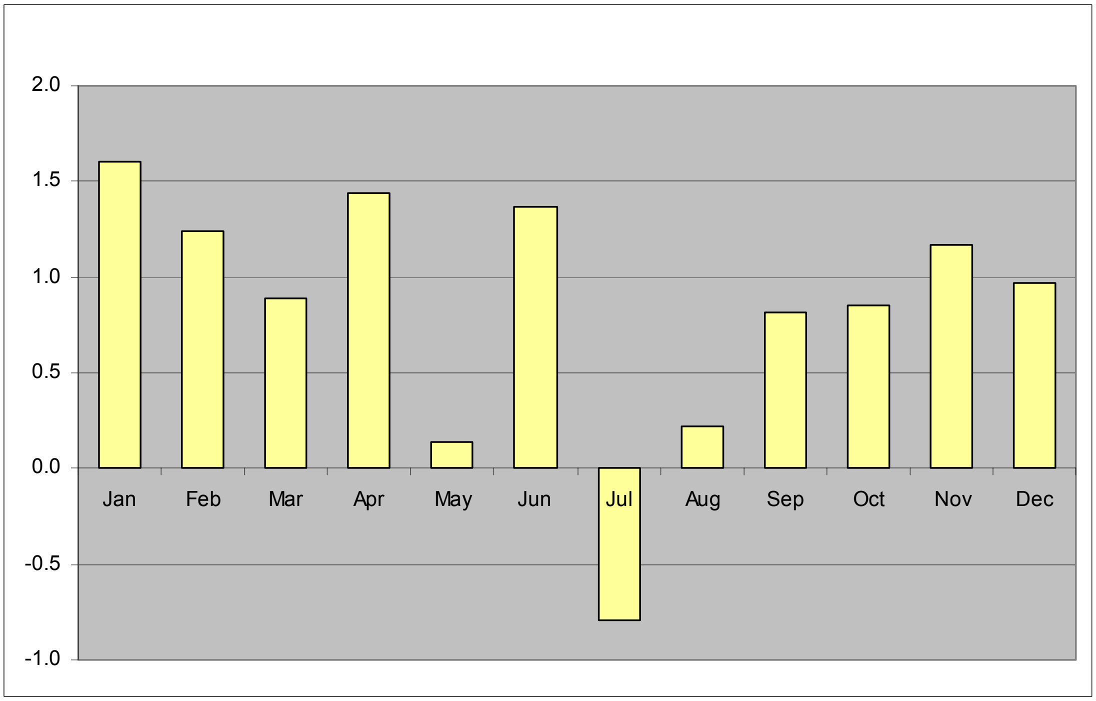


Figure 3(c): Mean Monthly DJIA Returns (1990-2005)

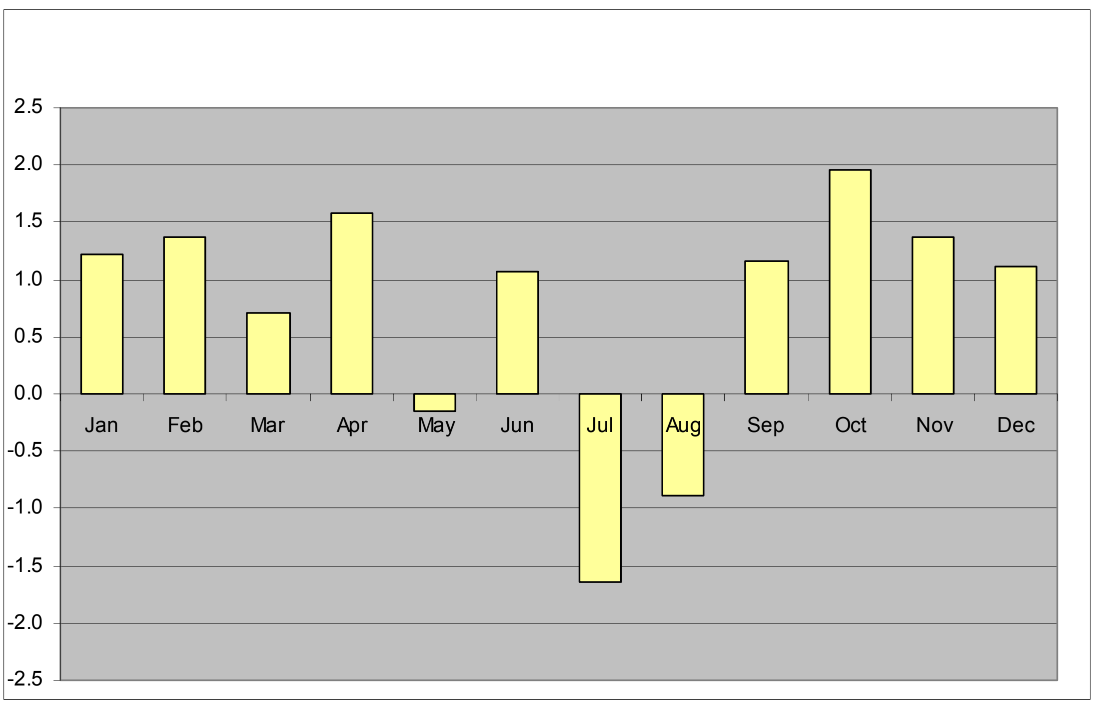


Table 1: Mean DJIA Monthly Return*

Period	January		July	
	Mean	t Stat	Mean	t Stat
1971-2005	2.05*	2.90	-0.83	-1.26
1980-2005	1.60*	2.39	-0.80	-1.09
1990-2005	1.22	1.58	-1.65*	-2.15

* Significant at the 5% level.

Conventional Analysis of Seasonality

Seasonality in stock prices (returns) is typically based on the ARDL model

$$r_t = \sum_{i=1}^{m} \alpha_i r_{t-i} + \sum_{i=1}^{12} \lambda_i D_t^i + \xi_t \quad (1)$$

where $r_t \equiv \Delta \log P_t$ is the rate of return (measured as the first log difference of the general market index, P_t), D^i is a seasonal dummy assuming the value 1 in month *i* and zero otherwise, and *m* is the order of the autoregressive process, which is determined according to the Schwartz Bayesian criterion. A significant λ_i indicates a significant seasonal factor in month *i*.

Table 2 reports the OLS estimated coefficients (seasonal factors), clearly confirming the disappearance of the January effect and the emergence of a July effect in the period 1990-2005. Over the whole period, 1970-2005, and the sub-period 1980-2005, the January effect is significant, whereas the July effect is insignificant, as indicated by the t statistics of the estimated coefficients. This conclusion, however, is reversed when the latest period is considered on its own.

Table 2: Seasonal Factors (%) Estimated by OLS

Month	1970:1-2005:7		1980:1-2005:7		1990:1-2005:7	
	λ_i	t Stat	λ_i	t Stat	λ_i	t Stat
January	1.945*	3.25	1.434*	2.09	1.207	1.46
February	0.598	0.93	0.902	1.31	1.243	1.47
March	1.054	1.78	0.658	0.92	0.601	0.71
April	1.081	1.79	1.327	1.90	1.661	1.91
May	-0.479	-0.73	-0.221	-0.30	-0.382	-0.44
June	0.905	1.51	1.383	1.98	1.110	1.28
July	-0.918	-1.52	-1.038	-1.50	-1.669*	-2.02
August	0.275	0.46	0.452	0.64	-0.634	-0.72
September	0.526	0.88	0.821	1.18	1.315	1.52
October	0.215	0.36	0.740	1.06	1.872	2.15
November	0.370	0.61	1.014	1.45	1.149	1.31
December	0.791	1.32	0.727	1.04	0.997	1.14

* Statistically significant at the 5% significance level.

While Table 1 shows that the average percentage return in January for the DJIA was 2.05 per cent, Table 2 shows that the seasonal contribution was 1.95 per cent. In other words, the high January value was predominantly due to seasonal variation, hence justifying the label “the January effect”. However, there is no significant January contribution, and therefore no January effect, during the period 1990-2005. By comparison, the July figures in the latest period show smaller monthly returns in absolute terms than the seasonal factor associated with July, suggesting that other influences were positive, thus dampening the negative seasonal effect.

Further evidence can be obtained by estimating equation (1) using rolling regressions, and for this purpose, a window size of 120 observations is used. Table 3 presents the estimated seasonal factors, confirming the earlier finding that the January effect has, indeed, faded and that a July effect is now present.

Table 3: Seasonal Factors from Rolling Regressions

Ten Years Ending in	January		July	
	λ_i	t Stat	λ_i	t Stat
1980	3.218*	2.80	-0.518	-0.49
1985	2.474*	2.19	-0.009	-0.001
1990	1.565	1.20	-0.059	-0.04
2000	0.677	0.69	-0.050	-0.36
2005	0.567	0.54	-2.267*	-1.99

- Statistically significant at the 5% significance level.

Structural Time Series Analysis of Seasonality

A version of Harvey's (1989, 1997) structural time series model that encompasses an autoregressive structure instead of cycles may be written as

$$r_t = \mu_t + \alpha_t r_{t-1} + \gamma_t + \varepsilon_t \tag{2}$$

where μ_t is the trend component, γ_t is the seasonal component and ε_t is the random component, which is assumed to be white noise. The main emphasis here is on the seasonal component, which will be extracted and examined to judge the presence and nature of seasonality. The trend component, which represents the long-term movement in a series, is represented by

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \tag{3}$$

$$\beta_t = \beta_{t-1} + \zeta_t \tag{4}$$

where $\eta_t \sim NID(0,\sigma_\eta^2)$, and $\zeta_t \sim NID(0,\sigma_\zeta^2)$. μ_t is a random walk with a drift factor, β_t , which follows a first order autoregressive process as represented by equation (4). This is a general representation of the trend, which encompasses all other possibilities.

There are a number of different specifications for the seasonal component (see Harvey, 1989, chapter 2). Harvey and Scott (1994) use a trigonometric specification that allows a smoother change in the seasonals. The problem with this specification, however, is that it does not lend itself to a straightforward interpretation.[6] For this reason, stochastic dummies are preferred, in which case the stochastic component is specified as

$$\gamma_t = -\sum_{j=1}^{s-1} \gamma_{t-j} + \kappa_t \tag{5}$$

where s is the number of seasons in one year (12 for monthly data) and $\kappa_t \sim NID(0,\sigma_\kappa^2)$. The interpretation is straightforward: γ_t is the seasonal factor corresponding to time (month) *t*, which is generated by the seasonals corresponding to times *t*-1, *t*-2, …., *t*-10, and as well as the random term κ_t.

Once it has been written in state space form, the model can be estimated by maximum likelihood, using the Kalman filter to update the state vector (whose elements are the time series components), as new observations become available. Related smoothing algorithms can be used to obtain the best estimate of the state vector at any point in time within the sample period. For details of the estimation method, see Harvey (1989, chapters 4 and 7) and Koopman et al. (1995, chapter 14).

The structural time series model represented by equation (2) is applied to monthly return data covering the period 1990:1-2005:7. The estimation results, which are reported in Table 4, pertain to the final state vector, when the information embodied in the full sample has been utilised. Perhaps a word on the meaning of the elements of the final state vector would be useful. μ_t is the level of the series, which is equivalent to the constant term in a conventional regression. β_t is the slope of the trend, which is equivalent to the coefficient on a (deterministic) time trend in a conventional regression model. γ_{1t} is the seasonal factor corresponding to the last month in the sample (July 2005), whereas

[6] On the difficulty of interpreting trigonometric seasonals, see Koopman et al. (1995, p 226).

γ_{2t} is the seasonal factor corresponding to June, and so on. Table 4 also reports the goodness of fit and diagnostics. The goodness of fit measures include the coefficient of determination (R^2), a modified coefficient of determination (R_s^2), the standard error of the estimates ($\tilde{\sigma}$) and Akaike's information criterion (*AIC*). Diagnostic test statistics for serial correlation, normality and heteroscedasticity are reported, including: the Durbin-Watson statistic (*DW*), the Ljung-Box (1978) test for serial correlation (*Q*), the Bowman-Shenton (1975) test for normality of the residuals (*N*), and a test for heteroscedasticity (*H*).[7]

Table 4: The Final State Vector

Component	Estimated Value	t Statistic
μ_t	0.991	2.17
β_t	0.001	0.91
α_t	0.663	0.83
γ_{1t}	-2.134*	-2.35
γ_{2t}	0.353	0.34
γ_{3t}	-1.408	-1.68
γ_{4t}	0.867	0.90
γ_{5t}	-0.038	-0.03
γ_{6t}	0.863	0.67
γ_{7t}	0.467	0.54
γ_{8t}	0.429	0.46
γ_{9t}	0.368	0.39
γ_{10t}	1.048	1.14
γ_{11t}	0.889	0.98
R^2	0.08	
R_s^2	0.37	
$\tilde{\sigma}$	3.52	
AIC	2.60	
DW	1.98	
Q*	19.23	
$H^{\#}$	0.91	

* Distributed as $\chi^2(15)$. # Distributed as F(62,62).

The results show that the model is reasonably determined in terms of the goodness of fit measures and diagnostics. The significance of γ_{1t} implies the presence of a negative July effect, whereas no evidence is present for the January effect, since γ_{7t} (representing the January seasonal factor) is insignificant. The extracted seasonal component is presented in Figure 4, showing only a slight change in the seasonal pattern.

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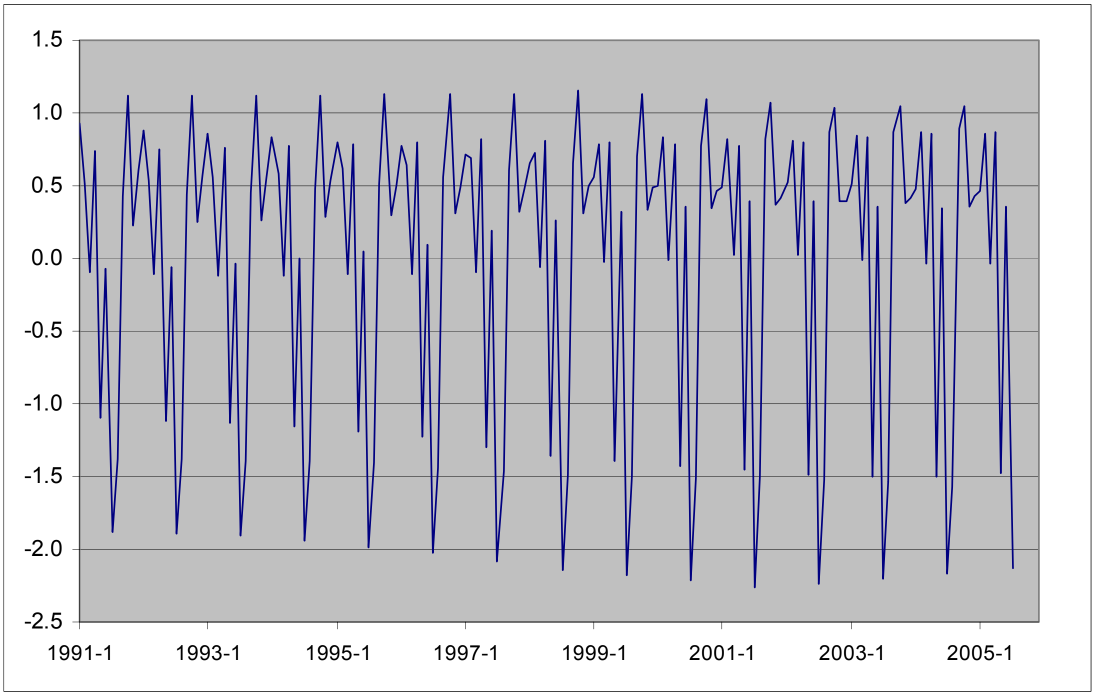
[7] R_s^2 is the coefficient of determination calculated on the basis of the seasonal mean which is more appropriate for seasonal data than the conventional R^2. $\tilde{\sigma}$ is the standard error of the estimate calculated as the square root of the one-step ahead prediction error variance which is also used to calculate Akaike's *AIC* by adjusting for the number of estimated parameters. The *Q* statistic is distributed as $\chi^2(n+1-k)$ where *n* is the number of autocorrelation coefficients and *k* is the number of estimated parameters. The *N* test measures the departure of the third and fourth moments from their expected values under normality. H(*h*) is calculated as the ratio of the squares of the last *h* residuals to the squares of the first *h* residuals, where *h* is the closest integer to one third of the sample size. It is distributed as *F*(*h*,*h*).

Figure 4: The Seasonal Component of Monthly DJIA Returns



The seasonal factors corresponding to each month at the end of the sample period are shown in Figure 5. Figure 6 displays the evolution of the seasonal factors corresponding to July and January in the most recent period that ends in July 2005. It shows conspicuously the decline of the January effect and the emergence of the July effect. The results of structural time series analysis, therefore, confirm the findings of the conventional econometric methods used earlier: the positive January effect has been replaced with a negative July effect.

Figure 5: Monthly Seasonal Factors at the End of the Sample Period

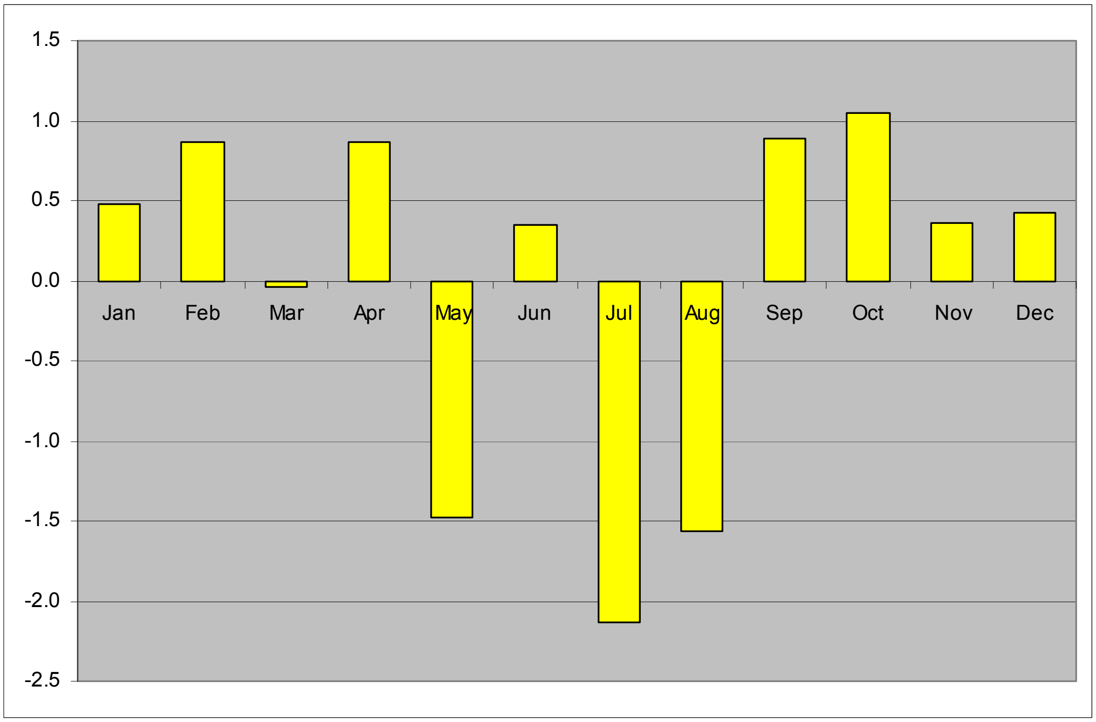
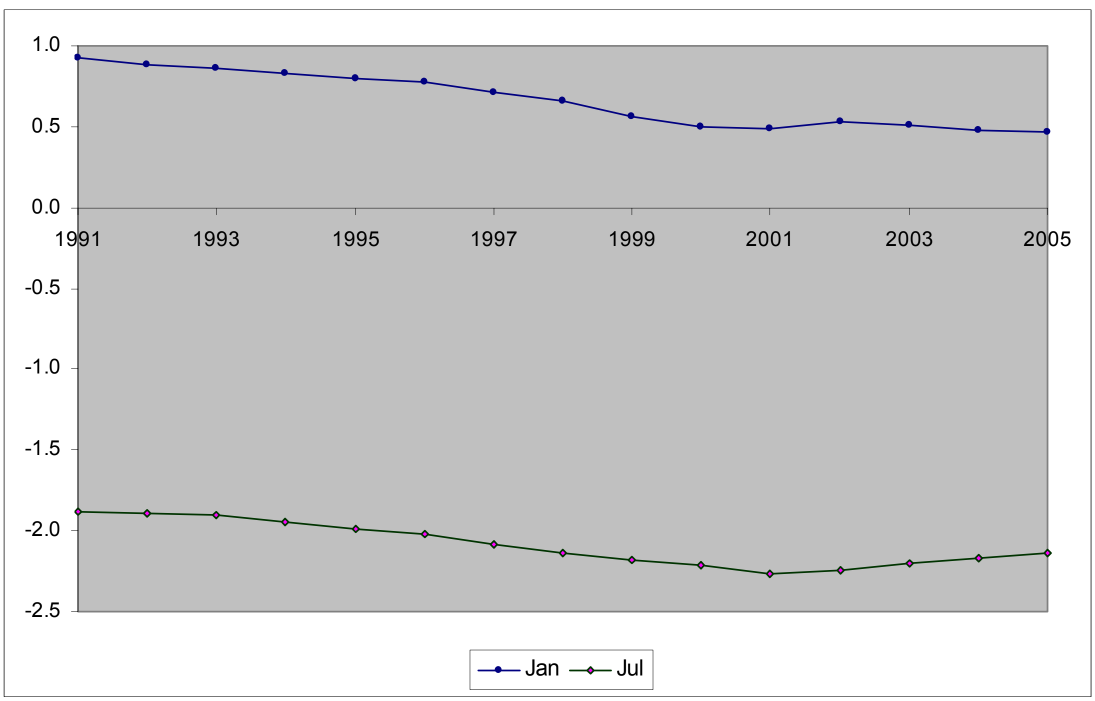


Figure 6: January and July Seasonal Factors



Conclusion

The preceding analysis presented robust evidence showing that the positive January effect has paled into insignificance while the negative July effect has become prominent. Price anomalies like these hint at market inefficiencies. On the other hand, economic reasoning suggests that financially significant anomalies would tend to disappear once traders become aware of them and begin to exploit them. Apart from this, the vanishing January effect can be attributed to: (i) changes in accounting standards that do not make as great a distinction as in the past between realized and unrealized capital gains and losses; (ii) changes in the tax treatment of realized and unrealized gains/losses; and (iii) lower marginal tax rates, which dampens the incentive to engage in tax motivated trading. Given the scope of this paper, we were more interested in the existence or otherwise of seasonal phenomena than in their causes, therefore making no attempt to investigate the reasons for the disappearance of the January effect.

Finally, one possible explanation for the July effect is that it might be caused by the selling pressure associated with the summer holiday season in the northern hemisphere. Individual investors sell stocks to raise cash to finance their holidays, whereas fund mangers cautiously reduce their market risk while they are not closely watching their portfolios during their vacations.

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