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Seasonality in U.S. Stock Prices

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Introduction

It is natural for stock traders, aiming to achieve above average return for a given market risk, to strive to identify repetitive patterns in stock prices in the hope of capitalizing on them. Such patterns might be seasonal with stock prices rising in certain month(s) and/or falling in others. Theoretically, if such a pattern were fairly regular and its financial implication significant, then short-term speculators would adopt a strategy of buying when stocks are seasonally low and selling them when the transitory discount disappears, or indeed changes to a premium. Alternatively, long-term investors could concentrate more of their buying programs in the seasonally low months in a form of "seasonal" dollar cost averaging strategy.

One of the most publicized seasonal patterns is the so-called "January effect": the tendency for stock prices to rise in January relative to December. The first to detect a significant tendency for the Dow Jones Industrial Average (DJIA) to rise in January was a study covering the period 1927-1942.[1] A subsequent study covering the period 1904-1974 reaffirmed this January effect.[2] Several studies conducted during the 1980s also came to a similar conclusion. However, a recent study covering the period 1962-2000 concluded that "many years do not have a significant (January) effect and some (January) effects are negative".[3] This raised a question in our minds whether the January effect has in fact disappeared, prompting us to revisit it.

In carrying out the analysis, we decided to focus on the period January 1970-July 2005 to see if there has been any recent change in seasonal patterns, in response to a multitude of factors not the least of which relate to the technology of analyzing data. We also opted to use DJIA, for two reasons. First, it is composed of stocks with the largest market capitalization and, consequently, intensely watched by market

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[1] Sidney Watchel, Certain Observations on Seasonal Movements in Stock Prices, Journal of Business, vol 15 (1942), pp 184-193.

[2] Michael Rozeff and William Kinney, Capital Market Seasonality: The Case of Stock Returns, Journal of Financial Economics, vol 3 (1976) pp 379-402.

[3] James Lindley, Kartono Liano and Sean Slater, The Strength of the Tax Effect at the Turn of the Year, Department of Economics and Finance, Mississippi State University, Working Papers, No 6-2004, 20.

participants and, theoretically, enjoys the greatest market efficiency and therefore least likely to have a predictable, repetitive pattern. Second, it has the longest price history of any market index with analytical studies stretching back to over a century, making identification of changes in patterns, if any, all the more interesting and informative. On the other hand, to reduce the randomness of the price data, we decided to use monthly averages of the daily closing prices instead of month-end closing prices.

Why a January Effect?

There is no consensus on the causes of the January effect, but, keeping in mind traders' pursuit of self-interest, explanations include tax-induced trading, performance hedging, window dressing and portfolio rebalancing.

Of these potential explanations, the most compelling is the tax-induced trading: during December, the final month in a tax year, investors make above average sales of stocks that have already declined during the year to book capital losses, thereby tax-sheltering realized gains on other stocks and in the process further depressing stock prices which have already drifted lower. Beyond the year's end, this price pressure is reversed as the proceeds of sales are reinvested and stock prices recover.

Another intriguing explanation is related to performance hedging: portfolio managers that achieve a relatively high rate of return during the year try to lock it for that year, and with it their bonuses, by selling stocks that have achieved above average returns. Thus, they begin the following year with relatively liquid portfolios which must be put to work, making them net buyers in January. A third explanation is that portfolio managers engage in window dressing at year-end: selling losing and risky stocks and replacing them with cash and blue-chip stocks to make their year-end portfolios appear more conservative. This sets the scene for them to be net buyers in January, pushing prices higher.

Statistical Analysis of Monthly Returns

Figure 1 is a chart of DJIA monthly average over the period January 1970 to July 2005. Most worrisome in this chart is the boom of the 1990s and the subsequent crash at the start of the 21st Century: those major events seem to dwarf seasonality and with that any hope of isolating it.

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

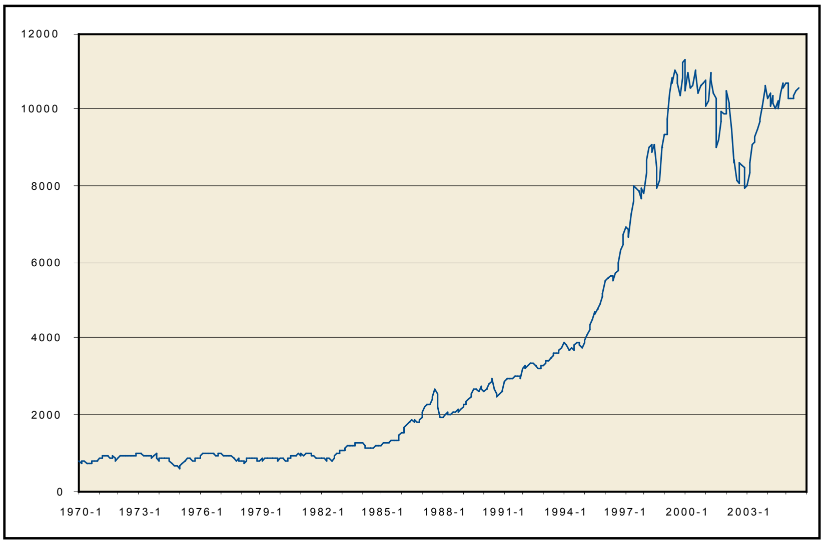


Figure 2 presents the corresponding monthly percentage return on DJIA.

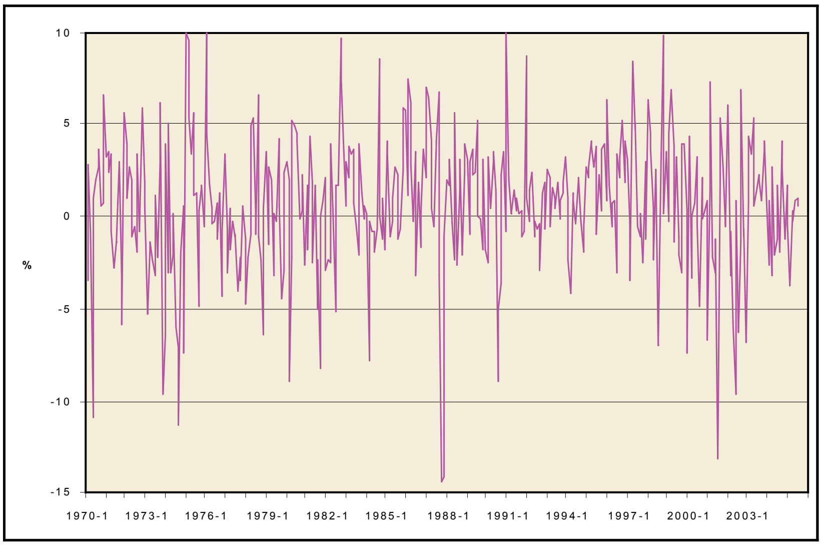


Figure 2: DJIA Monthly Returns

Figure 3 presents the average monthly return on DJIA (the percentage change in) for three periods all ending in 2005. The periods 1971 to 2005 and 1980 to 2005 are shown in Figures 3 (a) and 3 (b) show that the mean return in January was higher than that of any other month. This however conceals a reversal in pattern in the most recent sub-period, 1990-2005 shown in Figure 3(c); the fading of the January effect is noticeable and so is the emergence of a negative return in July.

Table 1 presents the mean DJIA returns and their respective t statistics for January and July during the three periods covered in Figure 3. A more detailed table at the end of this paper, with monthly returns for the whole period, appears to confirm the fading of the January effect and the emergence of a July effect.

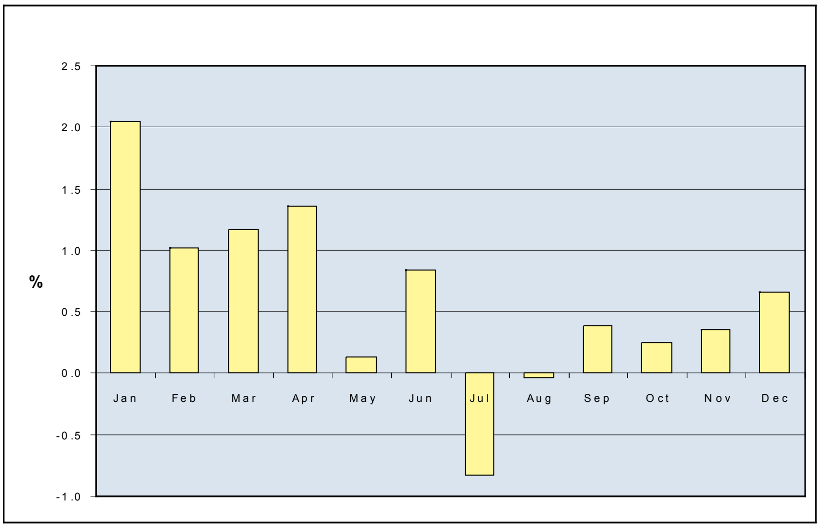


Figure 3(a): Mean Monthly DJIA Returns (1971-2005)

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

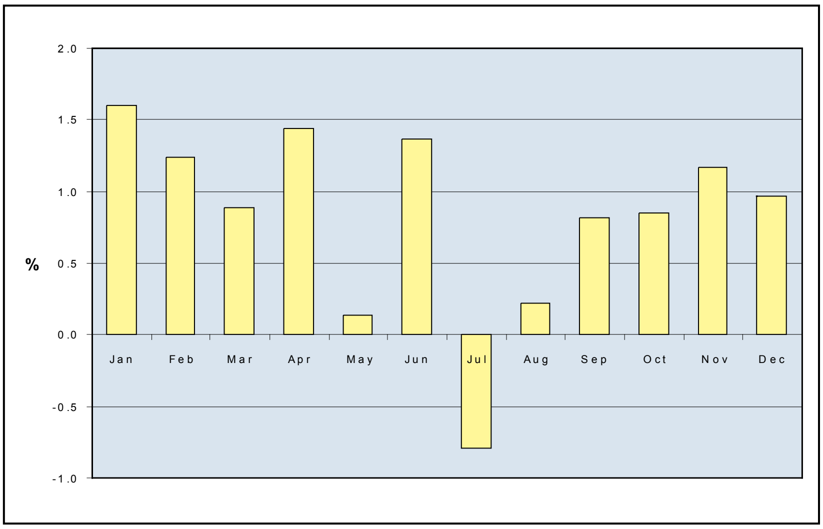


Figure 3(c): Mean Monthly DJIA Returns (1990-2005)

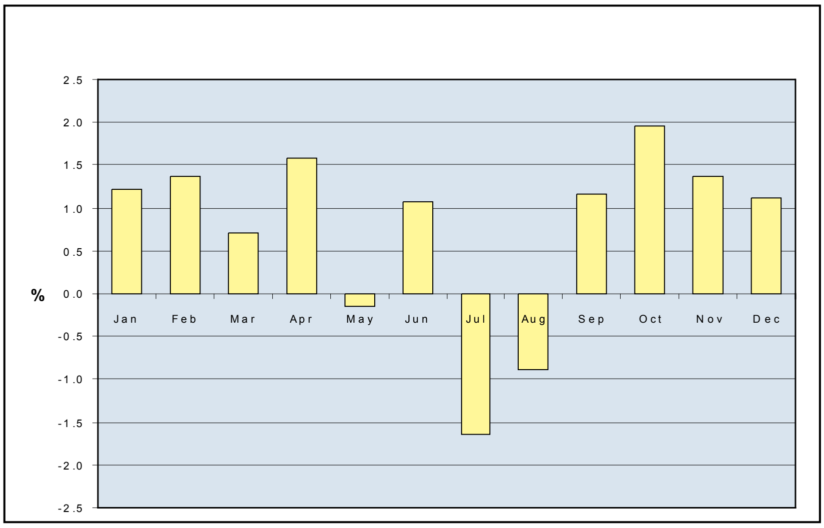


Table 1: Mean DJIA Monthly Returns

Period	January		July	
	Return (%)	t Stat	Return (%)	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

Note: t statistics values of more than 1.96 indicates statistical significance in that there is only 5 per cent probability that the return is zero.

Statistical Analysis of the Seasonal Factors

In this section, we focus on the part of return attributable to seasonal variation, the seasonal component. We commenced our investigation by employing a dummy variable regression model to estimate the average seasonal factors. Table 2 presents the findings. Over the whole period 1970-2005, and the sub period 1980-2005, the January effect was significant, while July had no significant seasonality as indicated by the t statistics. However, in the sub-period 1990-2005, the January effect seemed to disappear and to be replaced by a July effect.

Table 2: Seasonal Factors (%) Estimated from a Regression Model

Month	1970:1-2005:7		1980:1-2005:7		1990:1-2005:7	
	Factor	t Stat	Factor	t Stat	Factor	t Stat
January	1.473*	2.51	0.798*	1.98	0.532	0.66
February	0.289	0.49	0.412	0.62	0.611	0.76
March	0.599	1.03	0.073	0.11	-0.021	-0.02
April	0.659	1.14	0.601	0.90	0.838	1.05
May	-0.802	-1.38	-0.711	-1.06	-0.892	-1.16
June	0.195	0.34	0.513	0.78	0.289	0.36
July	-1.361	-1.34	-1.597	-1.39	-2.331*	-2.91
August	-0.571	-0.97	-0.612	-0.91	-1.642	-1.79
September	-0.129	-0.22	-0.006	-0.01	0.412	0.50
October	-0.338	-0.57	0.058	0.09	1.225	1.48
November	-0.230	-0.39	0.348	0.51	0.604	0.73
December	-0.015	-0.02	0.478	0.52	0.978	0.88

** Statistically significant as indicated by the t statistic.*

Table 1 shows that during the period 1970-2005, the total monthly return in January attributable to all factors namely, trend, cyclicality, seasonality and random was 2.05 per cent. On the other hand, Table 2 shows that during the same period, the seasonal contribution of January was 1.47 per cent. In other words, the high January value was predominantly due to seasonal variation, thereby justifying the label "the January effect". However, during the sub-period 1990-2005, the January contribution dwindled to 0.53 percent. By comparison, the July figures as per table 1 in the latest period show smaller monthly returns in absolute terms than the seasonal contribution of July as per Table 2, suggesting that other influences were positive, dampening the negative seasonal effect.

Further evidence was obtained using rolling regressions. We estimated a model with seasonal dummies over a constant rolling period of 10 years (120 months), starting with the first observation in 1970 and ending with the last observation in July 2005. Table 3 presents the estimated seasonal factors; it confirms our earlier finding that the January effect has in fact faded and that a July effect has emerged.

Table 3: Seasonal Factors (%) from Rolling Regressions

Ten Years Ending in	January		July	
	Factor	t Stat	Factor	t Stat
1980	3.284*	2.86	-0.770	-0.67
1985	1.938	1.98	-0.647	-0.58
1990	0.827	0.732	-0.391	-0.33
1995	1.917	1.82	-0.874	-0.87
2000	0.986	1.09	-2.201*	-2.34
2005	-0.094	-0.09	-2.705*	-2.62

** Statistically significant as indicated by the t statistics.*

Finally, we employed structural time series analysis, using the Kalman filter iterative process, to extract the seasonal components from a time series. The underlying model decomposes monthly DJIA returns into trend, cyclical, seasonal and random components. The model was estimated over the period 1991-2005 and the seasonal component extracted, as presented in Figure 4. The seasonal factors and their t statistics for the final 12 months are shown in Table 4. The only significant seasonal factor was for July with a negative value of 2.13 percent.

Figure 4: Seasonal Component of Monthly DJIA Returns

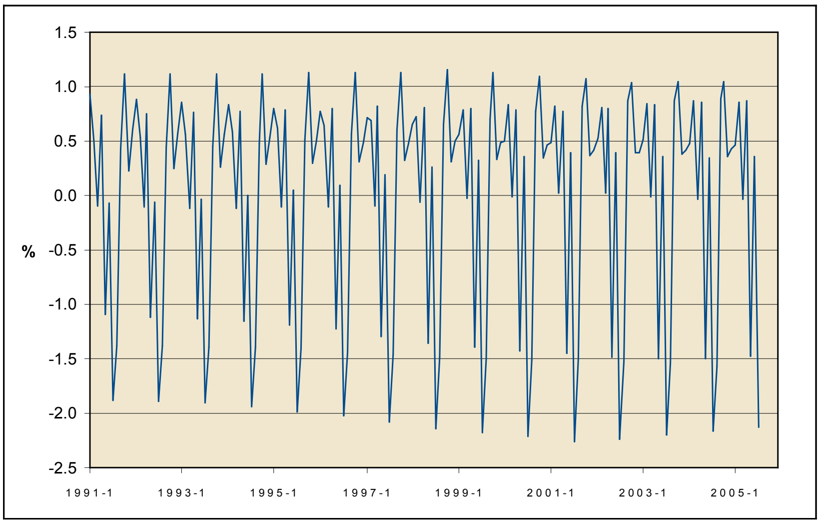


Table 4: Seasonal Factors (%) for the Final 12 Months Derived from STM

Month	Seasonal Factor	t Statistic
January	0.467	0.54
February	0.863	0.67
March	-0.038	-0.03
April	0.867	0.90
May	-1.480	-1.68
June	0.353	0.34
July	**-2.134***	**-2.35**
August	-1.569	-1.69
September	0.889	0.98
October	1.048	1.14
November	0.363	0.39
December	0.429	0.46

** Statistically significant as indicated by the t statistic.*

Figure 5 is a graphical presentation of the seasonal factors in Table 4 above.

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

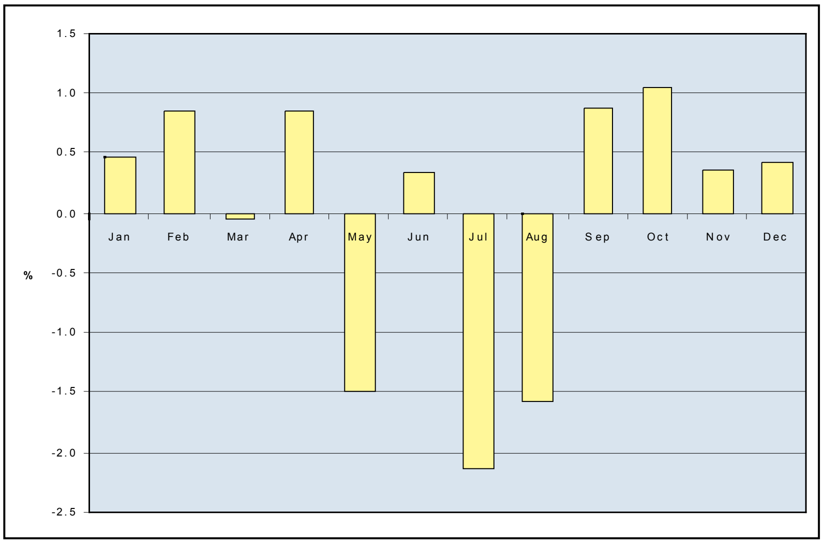
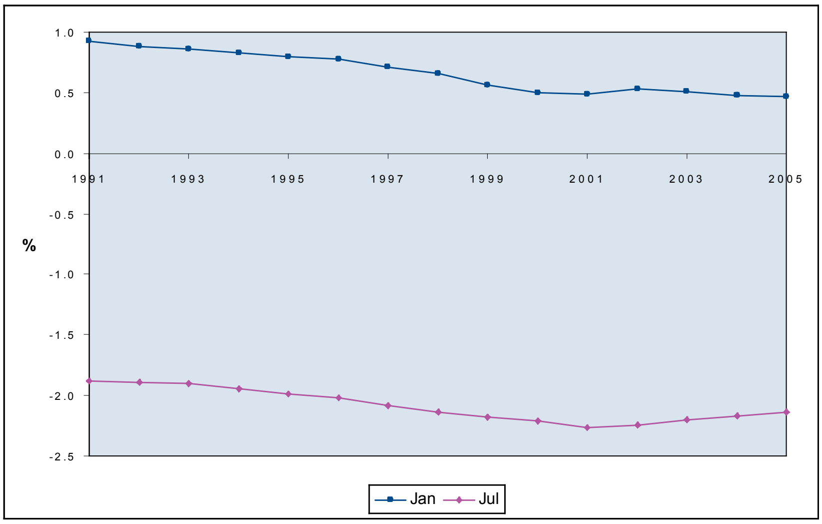


Figure 6 plots the evolution of the seasonal factors corresponding to January and July for the sub-period 1991-2005. It is interesting for its portrayal of the gradual decline of the January effect and the persistence of the July effect. These results confirm the findings of the conventional statistical methods sighted earlier.

Figure 6: January and July Seasonal Factors (%) Since 1991



Conclusion

The preceding analysis presented robust evidence that the positive January effect has faded into insignificance and a negative July effect has emerged. Such seasonal price patterns hint at market inefficiency. However, economic reasoning suggests that financially significant anomalies would tend to disappear once traders become aware of them and begin exploiting them. There are several plausible explanations why the January effect has vanished: the actions of arbitrageurs exploiting market inefficiencies, changes in accounting standards that do not make as great a distinction as in the past between realized and unrealized capital gains and losses, changes in the tax treatment of realized and unrealized gains/losses, the reduction in the marginal tax rate reducing the incentive to engage in tax motivated trading, etc. Given the scope of this paper, we were more interested in the existence or otherwise of seasonal phenomena rather than the causes and therefore made no attempt to investigate the reasons for the vanishing of the January effect.

On the other hand, one possible explanation of the emergence of a July effect is that it might be caused by selling pressure associated with the summer holidays in the northern hemisphere: individual investors selling stocks to raise cash to finance their holidays and fund manger cautiously reducing their market risk while they are not closely watching their portfolios during their vacations.

Statistical Appendix: Monthly DJIA Returns

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1971	3.30	3.55	2.43	3.41	-0.76	-2.75	-1.41	-1.41	2.91	-3.28	-5.91	5.65
1972	3.92	1.07	2.68	2.00	-1.04	-0.51	-1.87	3.44	-0.81	-0.68	5.87	1.89
1973	0.64	-5.28	-1.73	-1.39	-2.32	-3.14	1.08	-2.22	2.93	6.14	-9.61	-6.45
1974	3.95	-3.07	5.00	-3.04	-2.09	0.14	-6.00	-7.10	-11.32	-1.96	0.54	-7.37
1975	9.98	9.52	5.39	3.33	5.61	1.09	1.24	-4.88	0.34	1.57	1.70	-0.56
1976	10.01	4.46	1.72	0.40	-0.37	-0.33	0.77	-1.17	1.29	-4.36	-0.78	3.36
1977	-0.64	-3.02	0.46	-1.81	-0.30	-1.06	-0.92	-4.04	-2.19	-3.51	0.55	-1.18
1978	-4.72	-2.27	-0.95	4.94	5.38	0.20	-1.02	6.54	-1.05	-2.41	-6.43	0.45
1979	3.58	-1.47	2.71	2.00	-3.24	0.15	-0.20	4.28	0.56	-4.42	-2.99	2.46
1980	2.90	2.01	-8.88	-2.17	5.19	4.91	4.49	4.04	-0.07	0.26	2.28	-2.62
1981	1.70	-1.74	4.31	1.78	-2.55	1.70	-4.97	-2.31	-8.19	-0.02	0.84	2.05
1982	-2.87	-2.40	-2.53	3.93	0.21	-5.13	1.73	1.66	9.74	7.50	3.87	0.52
1983	2.98	2.15	3.80	3.38	3.73	0.71	-0.62	-2.06	3.94	1.22	-0.18	0.61
1984	0.10	-7.80	-0.21	-0.80	-0.81	-1.97	-0.70	8.56	0.06	-1.18	1.00	-1.86
1985	4.05	3.58	-1.13	-0.20	1.02	2.67	2.20	-1.27	-0.62	2.52	5.84	5.71
1986	1.17	7.40	6.14	2.79	-0.29	3.59	-3.14	1.84	-1.64	0.20	3.60	2.12
1987	7.07	6.43	4.02	0.44	-0.50	3.98	4.02	6.75	-3.22	-14.46	-14.11	-1.13
1988	1.93	1.70	3.16	-0.40	-2.35	5.67	-2.58	1.39	3.04	-2.13	2.33	3.93
1989	3.07	-0.92	3.02	3.60	2.24	2.34	5.23	0.08	-0.05	-1.86	3.12	-1.73
1990	-2.46	3.24	0.45	2.96	3.55	1.35	-8.99	-5.02	-3.60	2.33	3.56	-0.85
1991	10.12	1.98	0.18	0.10	1.36	0.32	0.93	0.16	0.30	-1.16	-0.88	8.68
1992	0.93	-0.30	1.43	2.42	-1.11	-0.25	-0.66	-0.41	-2.93	1.33	1.88	-0.64
1993	2.57	2.16	-0.50	1.63	0.97	0.44	1.90	-0.13	0.93	1.34	1.87	3.26
1994	0.96	-2.30	-4.16	1.26	0.79	-0.42	2.01	2.17	-0.32	-1.98	-0.59	2.67
1995	2.08	2.72	4.05	3.73	2.68	3.74	-0.93	2.29	0.29	3.62	3.98	0.84
1996	6.35	1.68	-0.58	0.66	0.82	-2.99	3.39	2.06	3.26	5.23	1.84	4.13
1997	3.09	-0.40	-3.43	8.42	4.82	5.02	-0.53	-1.03	0.12	-2.55	2.98	-1.29
1998	6.39	4.53	3.70	0.47	-2.31	2.50	-7.04	-6.94	3.17	9.81	0.14	3.56
1999	-0.25	4.52	6.83	3.85	-1.39	3.20	-1.06	-2.05	-3.00	3.89	3.96	0.31
2000	-7.34	4.30	-3.38	0.03	0.75	3.24	-0.42	-4.92	2.13	-0.13	0.28	0.86
2001	-6.65	1.51	7.26	-2.18	-3.04	-1.25	-13.16	1.95	5.29	2.62	-0.56	-0.33
2002	5.98	-3.25	-0.84	-6.01	-9.68	0.80	-6.23	-1.39	6.93	-1.16	-0.61	-6.82
2003	0.77	4.35	3.44	5.36	0.62	1.41	2.21	1.98	0.82	3.65	4.02	0.58
2004	-2.66	0.91	-3.26	2.75	-2.07	-1.18	1.70	-2.01	4.02	2.48	-1.26	1.73
2005	-0.39	-3.81	0.26	-0.26	0.92	1.06	0.56					
Mean												
1971-2005	2.05	1.02	1.17	1.35	0.13	0.84	-0.83	-0.03	0.38	0.25	0.36	0.66
1980-2005	1.60	1.24	0.89	1.44	0.14	1.36	-0.80	0.22	0.82	0.86	1.17	0.97
1990-2005	1.22	1.36	0.72	1.57	-0.15	1.06	-1.65	-0.89	1.16	1.96	1.37	1.11
Std Dev												
1971-2005	4.48	3.73	3.53	2.76	3.00	2.49	3.87	3.72	3.89	4.24	4.19	3.42
1980-2005	3.83	3.42	3.84	2.82	2.99	2.58	4.34	3.44	3.73	4.40	3.72	3.07
1990-2005	4.69	2.73	3.54	3.23	3.31	2.10	4.69	2.92	3.04	3.19	1.98	3.37
t Statistics												
1971-2005	2.96	1.82	1.94	2.93	0.26	1.91	-1.27	-0.02	0.57	0.34	0.50	1.13
1980-2005	2.49	2.53	1.36	3.09	0.21	3.04	-1.12	0.37	1.28	1.13	1.83	1.85
1990-2005	1.62	4.10	1.19	2.99	-0.37	2.88	-2.17	-1.77	2.22	3.56	4.05	1.93

Technical Appendix: Methodology

The estimated seasonal factors reported in Table 2 were obtained by estimating a regression equation of the form

$$r_t = \alpha + \sum_{i=1}^{11} \beta_i (D_{i,t} - D_{12,t}) + \varepsilon_t$$

where r_t is the monthly return and D_i is a dummy variable that takes the value of 1 in month i and zero otherwise. We also have

$$\beta_{12} = -\sum_{i=1}^{11} \beta_i$$

The results reported in Table 2 were obtained by estimating this equation over the respective time periods.

The results reported in Table 3 were obtained by estimating the same equation over successive time periods of 10 years (120 observations), starting with the first observation and ending with the last observation of the whole sample. For example, the first estimate of the seasonal factor (3.316) was obtained by estimating the equation over the ten year period ending in January 1980, and so on.

The structural time series model is based on the specification

$$r_t = \mu_t + \phi_t + \gamma_t + \varepsilon_t$$

where μ_t is the trend, ϕ_t is the cyclical component, γ_t is the seasonal component and ε_t is the random component. The analysis is based on the extracted seasonal component, γ_t, which is shown in Figure 4. Table 4 and Figure 5 show the values of the seasonal component corresponding to each month in 1994 (the last full year of the sample period). Figure 6 displays the values of the seasonal component corresponding to January and July in the period since 1991.