Weekends Can Be Rough:

Revisiting the Weekend Effect

in Stock Prices

By

Peter Fortune
Federal Reserve Bank of Boston
600 Atlantic Avenue
Boston, MA 02106
Peter.Fortune@Bos.Frb.Org

The performance of stock prices during breaks in trading has received considerable attention in recent years. While some studies focus on performance surrounding periods of unscheduled trading breaks (trading halts in individual stocks, circuit breakers for exchanges), other studies look at performance around periods of scheduled trading breaks (holidays, weekends).

This paper fits into the second group. We revisit the “weekend effect” in common stock returns. Our focus is on two characteristics of differential returns over intraweek trading days and over weekends: the mean return, or “drift,” and the standard deviation of returns, or “volatility.”

We find that in the last 18 years the volatility over weekends has been stable, at about 10-20 percent greater for the three days from Friday’s close to Monday’s close than for a single intraweek trading day. However, while there was a large and statistically significant negative return over weekends prior to 1987, the post-1987 results indicate no weekend drift. In short, the negative weekend drift appears to have disappeared although weekends continue to have low volatility.

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This paper fits into the second group. We revisit the "weekend effect" in common stock returns. Our focus is on two characteristics of differential returns over intraweek trading days and over weekends: the "drift" and the "volatility." Although our underlying model is much richer, these characteristics can be understood by reference to the simple diffusion model:

$$(1) \qquad \ln(S_{t+T}/S_t) = \alpha T + \varepsilon\sqrt{T} \qquad \varepsilon \sim N(0, \sigma^2)$$

where σ is the instantaneous volatility, α is the instantaneous drift in the stock price, T is the discrete time interval over which price changes are recorded, and ε is a normally distributed random variable. The drift parameter over a single discrete unit of time, say, a day, is $\alpha = (\mu - \frac{1}{2}\sigma^2)$, where μ is the mean instantaneous return; this reflects the reduction in mean returns associated with high volatility.[1]

We consider the "weekend effect" as having two parts. The first, the "weekend drift effect," is that stock prices tend to decline over weekends but rise during the trading week. Cross (1973) found that stock prices tend to decline over weekends in the three-day interval from Friday's close to Monday's close. At first this was attributed to a "Monday effect," but Rogalski (1984) found that the entire decline occurred between Friday's close and Monday's open and that the open-to-close returns on Mondays were non-negative. Harris (1986) further refined this, showing that prices tended to decline during the first 45 minutes of Monday trading, but to recoup the loss over the remainder of Monday. Dyl (1988), using S&P 500 futures prices, found that significant price changes are more likely to occur over weekends than during the trading week, and that price declines were more likely over weekends than intraweek.

The second part of the weekend effect, the "weekend volatility effect," is that the volatility of returns over weekends is less *per day* than the volatility over contiguous trading days. Though the notion of price evolution over a period without trading seems oxymoronic, investors do receive and process information during periods when markets are closed. If the information arriving per day over weekends is of the same quantity and consequence as intraweek news, the implicit price movements over weekends should be the same as the explicit movements during the week. Thus, if σ is the volatility over a day from close to close during a week, then the volatility from close to

[1] The mean return over a discrete time interval is less than the instantaneous mean return by an amount proportional to the variance of asset returns; this is a result of nonlinearity in asset prices.

close over a weekend should be $\sigma\sqrt{3}$.[2]

French and Roll (1986) examined the descriptive statistics for returns on all common stock traded on the NYSE and AMEX. They found that the volatility over entire weekends was only about 10 percent greater than the intraweek volatility. This translated to a *per day* volatility over weekends well below the intraweek daily volatility. Thus, even though information might be arriving during Saturday and Sunday, either the frequency of its arrival or the volatility of returns that resulted was so low that prices behaved *as if* investors ignored any weekend information, treating Monday as if it were a trading day contiguous to Friday.[3]

Explanations for the Weekend Effect

The weekend drift effect has received the most attention in the literature. Miller (1988) attributes the negative returns over weekends to a shift in *the broker-investor balance* in decisions to buy and sell. During the week, Miller argues, investors, too busy to do their own research, tend to follow the recommendations of their brokers, recommendations that are skewed to the buy side. However, on weekends investors, free from their own work as well as from brokers, do their own research and tend to reach decisions to sell. The result is a net excess supply at Monday's opening. Miller's hypothesis is supported by evidence showing that brokers do tend to make buy

[2] The log return over T periods is $\ln(S_{t+T}/S_t) = \Sigma(1+r_i)$ where r_i is the ith period's return. If each period's return is independently and identically distributed with variance σ^2, the T-period log return will have variance $T\sigma^2$.

[3] French and Roll concluded that trading induces volatility and that when markets are particularly volatile a trading halt might reduce volatility.

recommendations,[4] by evidence that odd-lot transactions tend to be net sales, and by data showing that odd-lot volume is particularly high and institutional volume is particularly low on Mondays. Thus, individual investors tend to sell on Mondays when the lack of institutional trading reduces liquidity. Ziemba (1993) provides evidence that the same phenomenon exists in Japanese stock prices.

Another explanation for the negative weekend effect is that stock prices close "too high" on Fridays or "too low" on Mondays. One variant attributes unusually high Friday closing prices to *settlement delays*. The delay between the trade date and the settlement date creates an interest-free loan until settlement.[5] Friday buyers get two extra days of free credit, creating an incentive to buy on Fridays and pushing Friday prices up. The decline over the weekend reflects the elimination of this incentive. This hypothesis is supported by the intraweek behavior of volume and returns: Friday is the day with the greatest volume and with the most positive stock returns.

A second variant, the *dividend exclusion* hypothesis, argues that Monday's prices are "too low" if ex-dividend dates for common stocks tend to cluster on Mondays. Virtually all studies of the weekend effect (including the present study) ignore dividend payments when calculating daily returns. This creates a bias toward stock price decline over weekends if ex-dividend dates do cluster around Mondays. Any ex-dividend effects would be realized very early on Monday, after which positive returns would occur on the rest of Monday. The evidence cited above suggests some support for this

[4] Groth, Lewellen, Schlarbaum and Lease (1979) found that about 87 percent of 6,000 broker recommendations were to buy, leaving only 13 percent on the sell side.

pattern.

According to yet another hypothesis, the *information release* hypothesis, information released during the week tends to be positive and information released over weekends tends to be negative. A firm with good news will release it quickly so investors can bid the stock price up, but bad news is an orphan, hopefully hidden from investor scrutiny by release after the Friday close.

Abraham and Ikenberry (1994) find support for a *serial correlation* hypothesis. Monday's price performance is conditioned on Friday's performance: a strong Friday tends to be followed by positive weekend returns; a weak Friday is followed by negative weekend returns. While only one third of the Friday's in their sample show price decreases, these dominate the Monday results, suggesting that bad Fridays are given heavy weight in Monday trades. This observation is consistent with small investors who initiate Monday morning trades being particularly sensitive to poor performance on Fridays.

We should not ignore a final hypothesis, that there is no economics rationale to justify the persistence of a negative weekend drift. Rather, it might be an anomaly that was hidden from the eyes of investors but brought to light by the data mining of academics. If this is the case, the weekend effect should have disappeared after its discovery and diffusion.

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[5] Settlement delays for U.S. common stocks, now three days, were five days in the 1980s.

The Jump Diffusion Model

Previous studies have focused on descriptive statistics derived from raw data on daily prices of a large number of individual stocks. We approach our two hypotheses by estimating the parameters of a jump diffusion model of returns on a stock index, the S&P 500. The advantage of estimating the parameters of a jump diffusion model is that it can tell us not only what differences occur, but also what are the proximate sources of those differences.

Proposed by Press (1967) and popularized by Merton (1976) and by Cox and Ross (1976) in the context of option pricing, the jump diffusion model incorporates some of the known characteristics of stock prices that are not consistent with the simple diffusion model, such as skewness and fat tails in the returns distribution. In recent years, papers have emerged that involve direct estimation of the parameters of this stochastic process. For example, Johnson and Schneeweis (1994) estimated a jump diffusion model to examine the impact of macroeconomic news on foreign exchange rates. Kim, Oh, and Brooks (1994) estimated the parameters of a jump diffusion model for individual stocks in the Major Market Index.

The jump diffusion model builds on the simple diffusion model, in which log returns on an asset are normally distributed with a constant mean (the drift) and a constant standard deviation (the volatility). In addition, stock prices are also affected by a discrete number of “shocks,” which create discontinuous jumps (positive or negative) in returns. The effect of each shock on returns is a normally distributed random variable with a constant mean (denoted by θ) and a constant standard deviation (denoted by δ). The number of shocks in a unit of time (denoted below by x) is a random variable drawn from a Poisson distribution with the parameter λ . Thus, on the average day λ shocks will occur, and the mean and variance of the effect of these shocks on returns will be $\lambda\theta$ and $\lambda\delta^2$, respectively. The number of shocks in an interval (x) will have mean λ and variance λ.

The model for returns with x shocks, each of size s_i, is

$$(2) \qquad \ln(S_{t+T}/S_t) = \alpha' T + \varepsilon\sqrt{T} + \sum_{i=1}^{x} s_i \qquad \varepsilon \sim N(0, \sigma^2) \quad s_i \sim N(\theta, \delta^2) \quad x \sim PO(\lambda)$$

The analogue of the simple diffusion process's expected instantaneous return, or drift, over one period is α'. However, because the expected effect of the shocks is $\lambda\theta$, the jump diffusion model's drift is $\alpha' + \lambda\theta$. The total variance of returns is the simple-diffusion model variance plus the variance attributable to jumps, $[\sigma^2 + \lambda(\theta^2 + \delta^2)]$. For an interval of T periods, the same model applies but with drift $(\alpha' + \lambda\theta)T$ and total variance $[\sigma^2 + \lambda(\theta^2 + \delta^2)]T$. While a simple diffusion model allows only two parameters for returns, the drift and normal volatility, a jump process allows both skewness in returns (negative if $\theta < 0$, positive if $\theta > 0$), and kurtosis or "fat tails" (if $\delta > 0$).

The first estimation of a jump diffusion model, Press (1967), relied on the "method of cumulants," a method used more recently by Beckers (1981). This method involves calculating the first six moments of the sample distribution of stock returns.

From these six moments, the parameters of the jump diffusion model can be estimated. While this method can be useful in developing initial estimates to be used in an iterative estimation process, it suffers from two shortcomings. First, the method allows several possible parameter vectors to be associated with the same distribution; therefore it is under-identified. Second, no statistical tests are available for this method.

A more direct approach is the method of maximum likelihood. For an interval length of T periods with N observations on R, the T-period logarithmic return, the jump diffusion process's likelihood function is:

(3) $$lnL(\alpha^*, {}^*\sigma, \lambda^*, \theta, \delta) =$$

$$\sum_{n=1}^{N} \{ln \sum_{x=0}^{\infty} \{[\mathbf{e}(-\lambda^*)(\lambda^*)^x/x!][2\pi({}^*\sigma^2 + x\delta^2)]^{-1/2}\mathbf{e}\{-1/2\{[R - [\alpha^* + x\theta]]^2/({}^*\sigma^2 + x\delta^2)\}\}$$

$$\text{where } \alpha^* = \alpha' T,\ \lambda^* = \lambda T \geq 0,\ {}^*\sigma = \sigma\sqrt{T} > 0,\ \delta > 0$$

The five parameters of interest (α^*, $^*\sigma$, λ^*, θ, and δ) can be directly estimated by finding the vector that maximizes the likelihood of occurrence of the sample distribution. The per day values of α, σ, and λ over weekends can be computed as $\alpha^*/3$, $^*\sigma/\sqrt{3}$, and $\lambda^*/3$, respectively.[6]

[6] The maximum likelihood method requires a summation over all possible values for the number of jumps at each iteration. Since there are an infinite number of possible jumps, exact estimation using the method of maximum likelihood is not possible. Honore (1998) suggests a modified approach to deal with this, but we have simply summed over a large number of jumps, so that very little of the upper tail of the Poisson distribution is discarded.

Results

The focus of this paper is on differences in stock market returns within the week and over weekends. Our data are the daily closing values of the S&P 500 Stock Price Index. Thus, we use close-to-close prices for a market capitalization-weighted index of returns rather than close-to-close or open-to-close prices for individual stocks. The jump diffusion model is estimated using intraweek returns (with one day between closings) and weekend returns with three days (one trading and two nontrading) between closings. Mid-week holidays and long weekends are excluded.

Table 1 reports the descriptive statistics for our data. For the full sample, average weekend returns are very slightly negative (but not statistically significant) while intraweek returns average 13.46 percent per year. Weekend returns are both left-skewed (an unusual proportion on the downside) and leptokurtic (showing fat tails), while intraweek returns show no skewness and only mild kurtosis. Thus, weekend returns tend to be more negative with a higher frequency of large movements.

However, several of these properties disappear when the October 1987 crash--which included a really bad Monday--is excluded. When the fourth quarter of 1987 is eliminated from our sample, the mean annual return over weekends is a positive 1.72 percent, though much lower than the annual 13.08 percent during the week. Some negative skewness remains but it, and the degree of kurtosis, are both close to the intraweek numbers. In short, when the 1987 crash is excluded, the distribution of stock returns is about the same both intraweek and over weekends, with the major difference being a much lower but still positive, mean return over weekends.

Table 2 reports the maximum likelihood estimates of the jump diffusion model for the full sample and for two subsamples: trading days prior to September 30, 1987 and trading days after January 1, 1988. The top panel reports the estimated parameters. The bottom panel reports values constructed from those estimates. In each case the drift (α), the normal volatility (σ), and the jump frequency (λ) will depend on the number of days. For intraweek trading, these will be based on one day between closes. For weekends *per day* values are calculated by dividing the three raw parameter estimates by 3, $\sqrt{3}$ and 3, respectively. The first number reported for each parameter in the top panel is the estimated value *per day*, the second number (in parentheses) is the t-statistic, and the third number (reported in bold face) is the three-day value of the parameter for weekend data. Because the underlying data are in percentage points, the coefficients are also in percentage point units; thus, except for λ, which has the units of a frequency, a value of 0.10 is equivalent to 10 basis points.

The full sample strongly supports the existence of weekend drift and volatility effects. The simple diffusion daily drift is 5 basis points intraweek and 4 basis points over weekends. While the simple drift over weekends is positive, the negative jumps on weekends result in a total daily drift on weekends of about zero. Thus, for the full sample, the weekend daily drift is far below the intraweek daily drift, though there is no decline over weekends.

The simple daily volatility is 35 basis points per day over weekends, translating to 60 basis points over a three-day weekend. The jump frequency over an entire weekend is much less than over a weekday (about 0.3 as opposed to 0.5 for weekdays) but the volatility of a jump's effect is greater over weekends (1.51 vs. 0.94). As a result, the total volatility over entire weekends is about 20 percent greater than over a weekday (1.02 vs. 0.86). It is as if investors do recognize very little information arriving on Saturday and Sunday.

The main difference between intraweek trading days and weekends in the full sample is the mean size of a jump: Slightly positive but insignificant during the week, the weekend mean jump size is –40. With 0.3 jumps per weekend, the mean return due to jumps over a weekend is –12 basis points, translating to about –5.4 percent per year. Although weekend returns are flat, this still indicates a significant weekend effect with weekend drift well below intraweek drift. Note that the jump process is a very important part of S&P 500 returns. About 80 percent of total volatility is attributed to the jump process; this applies both intraweek and over weekends.

In short, the jump diffusion parameters for the full sample strongly support the earlier studies. While less information arrives per day on a weekend, the bang-per-bit of that information is greater than during the week, creating a slightly greater total volatility over weekends. Even so, the extra 20 percent volatility over a full weekend is much less than the extra 73 percent volatility that is theoretically expected if weekend days are equivalent to weekdays: Weekends do tend to have smaller daily volatility. The weekend drift effect is also strongly supported by the full sample—weekends typically have negative jumps and flat drift.

These results carry over to the pre-October 1987 sample with small exceptions. The number of jumps is now greater over a three-day weekend (though still less on *a per day* basis than the intraweek number), and the intraweek mean jump size is now more positive and statistically significant. The mean jump size over weekends is smaller than in the full sample, but the higher jump frequency means that prices decline by 15 basis points over a weekend, comparable to the full sample result of –12 basis points. The weekend volatility prior to 1988 is about 13 percent greater than intraweek volatility, and there is a negative total drift over weekends, confirming the earlier studies using data from that period.

However, the weekend drift effect disappears after 1987, even though the weekend volatility effect continues. While the normal and total volatilities are still roughly the same over three-day weekends as over an intraweek day (the total volatility over weekends is about 10 percent greater than over a weekday), the mean jump size after 1987 for both weekends and intraweek is only slightly negative and is not statistically significant. After 1987 the total daily drift over weekends is about 3.7 basis points, very close to the 4.7 basis points intraweek. Any evidence of a weekend effect disappeared after 1987!

These results suggest that the drift portion of a weekend effect may have been an anomaly with no basis in economics. Rather, it was an artifact of investor ignorance that was eliminated when investors became aware of the anomaly. The weekend volatility story is persistent, suggesting stability in the intraweek/weekend differences in information arrival and information effects.

<u>Summary</u>

During the 1980s a flood of academic research on stock market anomalies washed over the efficient markets hypothesis. At the time, the question was whether these anomalies had an economic foundation, so they could be expected to be persistent and did not reveal opportunities for economic profit, or whether they were real anomalies arising from investor ignorance that would be eliminated as investors became aware of the anomalies.

This paper revisits the weekend effect, interpreting it as having two parts. First, the per day volatility of stock returns is lower over weekends than during intraweek trading, so much lower that the three-day volatility for an entire weekend is only slightly greater than the one-day intraweek volatility. Second, stock returns are negative over weekends. These propositions are tested using daily close-to-close data for the S&P 500 from January 1980 through June 1998. Unlike previous studies that were based on descriptive statistics from a large number of individual stocks, this paper is based on the explicit estimation of the parameters of the distribution of returns on a stock index.

Our results are derived from maximum likelihood estimation of the five parameters of a jump diffusion model of stock returns. The five parameters are the normal drift and volatility of a simple diffusion process (α and σ, respectively) and the three parameters of the jump process: the mean frequency of a shock (λ), the mean size of a shock's effect on returns (θ) and the standard deviation, or volatility, of a shock's effect on returns (δ). The jump process is strongly confirmed with about 0.5 shocks per intraweek day and 0.1 per weekend day, but the lower weekend jump frequency is offset by a weekend jump volatility about 50 percent greater than for an intraweek day. As a result while per day volatility is less over weekends, total volatility over a three-day weekend is about 20 percent greater than intraweek. Furthermore, for the full sample and for both subsamples, about 80 percent of total volatility is attributed to jumps; this holds both intraweek and for weekends.

The results for the full sample and for a pre-October 1987 subsample confirm the negative weekend returns found in earlier studies. For the full sample, the mean jump size is –40 basis points over weekends; it is –20 basis points for the pre-October 1987 subsample. The intraweek values of θ are positive in the full sample and the earlier subsample (but not statistically significant in the full sample). However, after 1987 there is no evidence of a negative weekend return: The estimated value of θ for weekends is only –5 basis points, as opposed to an intraweek value of –4 basis points, and neither is statistically significant.

Thus, our paper supports the volatility portion of the weekend effect found in earlier studies: Investors behave as if information arriving on Saturday and Sunday is not meaningful, as evidenced by the nearly equal volatility of returns over a three-day weekend as over a single intraweek day. However, we find no support for the continuation of negative returns over weekends. We find that the mean return over weekends is fully described by a simple diffusion model and is not affected by the jump process. In short, the drift portion of the weekend effect has disappeared.

This suggests that the 1980s efforts to provide an economic rationale for negative returns over weekends in terms of economics might have ignored the possibility that investors are typically ignorant of subtleties about stock returns. Once made aware of anomalies through the data mining of financial economists, investors behave in ways that eliminate the newfound anomaly.

Table 1

Descriptive Statistics for Changes in Log S&P 500[a]
January 1, 1980 - June 30, 1998

	Full Sample	Excluding Oct-Dec, 1987
Contiguous Trading Days		
Number, total	3,655	3,605
per year	198	198
Mean Return, per day	0.0638%	0.0621%
per year	13.46%	13.08%
StandDev, per day	0.8756%	0.8333%
per year	12.32%	11.73%
Skewness	0.04	-0.24
Kurtosis	6.77	4.08
Three-Day Breaks (for example, Friday close to Monday close)		
Number , total	856	844
per year	46	46
Mean Return, per day	- 0.0002%	0.0124%
per weekend	- 0.0005%	0.0371%
per year	-0.0230%	1.7209%
Stand Dev, per day	0.7377%	0.4811%
per weekend	1.2778%	0.8333%
per year	8.6665%	6.4107%
Skewness	- 7.41	-0.79
Kurtosis	123.42	4.96

[a] The daily changes in log S&P500 are (approximately) the daily rate of change in the S&P500. The mean annual return and standard deviation are computed as $(1+m)^n - 1$ and $s\sqrt{n}$ where m and s are the daily or per weekend mean and standard deviation and n is the number of contiguous trading days or weekends in a year.

Table 2
Estimated Jump Diffusion Parameters
Daily Changes in Log S&P 500[a]

Estimated Values		1/1/80-6/30/98 IntraWeek	1/1/80-6/30/98 WeekEnd	1/1/80-9/30/87 IntraWeek	1/1/80-9/30/87 WeekEnd	1/1/88-6/30/98 IntraWeek	1/1/88-6/30/98 WeekEnd
Simple Drift, Daily	(α')	0.0516	0.0407	0.0230	0.0326	0.0699	0.0435
		(+4.68)	(+5.37)	(+1.45)	(+2.68)	(+6.85)	(+5.86)
Weekend[b]			**[0.1221]**		**[0.0979]**		**[0.1306]**
Simple Volatility, Daily	(σ)	0.5347	0.3500	0.6008	0.3742	0.4982	0.2939
		(+12.4)	(+11.4)	(+10.6)	(+8.00)	(+19.8)	(+6.39)
Weekend[b]			**[0.6062]**		**[0.6482]**		**[0.5091]**
Jump Frequency, Daily	(λ)	0.5206	0.1002	0.5826	0.2526	0.5234	0.1134
		(+13.1)	(+10.2)	(+10.2)	(+8.97)	(+10.2)	(+7.74)
Weekend			**[0.3006]**		**[0.7577]**		**[0.3401]**
Mean Jump Size	(θ)	0.0245	-0.3954	0.1127	-0.2109	-0.0430	-0.0582
		(+1.28)	(-10.6)	(+2.75)	(-4.45)	(-1.55)	(-1.10)
Jump Standard Deviation	(δ)	0.9414	1.5084	0.8330	0.8602	0.8509	1.2046
		(+39.7)	(+35.0)	(21.7)	(+7.81)	(+10.4)	(+14.6)
Constructed Values							
Total Drift, Daily[c]		0.0644	0.0011	0.0887	-0.0207	0.0474	0.0369
Weekend[b]			[**0.0033]**		**[-0.0621]**		**[0.1107]**
Total Volatility, Daily[c]		0.8644	0.5920	0.8748	0.5718	0.7919	0.5010
Weekend[b]			**[1.0254]**		**[0.9904]**		**[0.8678]**
Proportion Due to Jumps[c]		78.6%	80.7%	72.7%	75.6%	77.7%	81.0%
Number of Observations		3,654	856	1,533	360	2,071	484

[a] The return on the S&P500 is the daily log difference, measured in percent. Thus, a value of 0.01 for any parameter except λ is equivalent to 1 basis point. Intraweek observations have one day between closings; weekend observations have three days between closings. The values of α, σ and λ are reported as *per day* values, so the *per weekend* values are the per day values multiplied by 3, $\sqrt{3}$, and 3, respectively. The *per weekend* values are reported in the bold numbers in brackets. For example, in the full sample the weekend data indicate $\sigma = 0.3500$ per day and 0.6062 per weekend.

[b] The weekend drift and volatility are daily values multiplied by 3 and $\sqrt{3}$, respectively

[c] The daily total drift and daily total volatility are $\alpha' + \lambda\theta$ and $\sqrt{(\sigma^2 + \lambda\delta^2)}$, respectively. The proportion of total volatility due to jumps is $\sqrt{(\lambda\delta^2)}/\sqrt{(\sigma^2 + \lambda\delta^2)}$.

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