Intraday Patterns in the Returns, Bid-ask Spreads, and Trading Volume of Stocks Traded on the New York Stock Exchange

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Abstract

Much research has demonstrated the existence of patterns in high-frequency equity returns, return volatility, bid-ask spreads and trading volume. In this paper, we employ a new test for detecting periodicities based on a signal coherence function. The technique is applied to the returns, bid-ask spreads, and trading volume of thirty stocks traded on the NYSE. We are able to confirm previous findings of an inverse J-shaped pattern in spreads and volume through the day. We also demonstrate that such intraday effects dominate day of the week seasonalities in spreads and volumes, while there are virtually no significant periodicities in the returns data. Our approach can also leads to a natural method for forecasting the time series, and we find that, particularly in the case of the volume series, the predictions are considerably more accurate than those from naïve methods.

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1. Introduction

One of the virtually indisputable stylised features of financial time series is that they exhibit periodicities, or systematically recurring seasonal patterns. Such patterns have been observed in returns, return volatility, bid-ask spreads and trading volume, and significant effects appear to be present at various frequencies. Early research employed daily or weekly data and was focused on examining the returns themselves, including French (1980), Gibbons and Hess (1981), and Keim and Stambaugh (1984). All three studies found that the average market close-to-close return on the New York Stock Exchange (NYSE) is significantly negative on Monday and significantly positive on Friday. Moreover, Rogalski (1984), and Smirlock and Starks (1986) observed that this negative return between the Friday close and Monday close for the Dow Jones Industrial Average (DJIA) occurs on Monday itself during the 1960's but moves backward to the period between the Friday close and Monday open in the late 1970's. By contrast, Jaffe and Westerfield (1985) found that the lowest mean returns for the Japanese and Australian stock markets occur on Tuesdays. Harris (1986) also examined weekly and intraday patterns in stock returns and found that most of the observed day-of-the-week effects occur immediately after the open of the market, with a price drop on Mondays on average at this time and rises on all other weekdays; see also Wood, McInish and Ord (1985).

Research has additionally employed intradaily data in order to determine whether there are periodically recurring patterns at higher frequencies. Wood *et al*. (1985), for example, examine minute-by-minute returns data for a large sample of NYSE stocks. They find that significantly positive returns are on average earned during the first 30 minutes of trading and at the market close, a result echoed by Ding and Lau (2001) using a sample of 200 stocks from the Stock Exchange of Singapore. An extensive survey of the literature on intraday and intraweek seasonalities in stock market indices and futures market contracts up to 1989 is given in Yadav and Pope (1992).

More recent studies have also observed periodicities in bid-ask spreads and trading volume. Chan, Chung and Johnson (1995), for example, investigate bid-ask spreads for CBOE stock options and for their underlying assets traded on the NYSE. They obtain the familiar U-shape spread pattern for the stock spreads, as McInish and Wood (1992) and Brock and Kleidon (1992) had argued previously, but the option spreads are wide at the open and then fall rapidly, remaining flat through the day. A large spread at the open that falls and then remains constant for the remainder of the day was also found by Chan, Christie and Schultz (1995) in their examination of stocks traded on the NASDAQ. The differences in results between the NYSE and the NASDAQ / CBOE has been attributed to their differing market structure, the NYSE having specialists while the NASDAQ is a dealer market. Finally, Jain and Joh (1988) employ hourly aggregated volume for all NYSE stocks and observe that a U-shaped pattern is also present in trading volume. This result is corroborated by Foster and Viswanathan (1993) using volume data on individual NYSE stocks.

Many theoretical models of investor and market behaviour have also been proposed to explain these stylised features of financial time series, including those that account for the strategic behaviour of liquidity traders and informed traders (see, for example, Admati and Pfleiderer, 1988). An alternative method for reconciling a finding of recurring seasonal patterns in financial markets with the notion of efficient markets is the possible existence of time-varying risk-premia, implying that expected returns need not be constant over time, and could vary in part systematically without implying market inefficiency.

Traditionally, studies concerned with the detection of periodicities in financial time series would either use a regression model with seasonal dummy variables (e.g., Chan, Chung and Johnson, 1995) or would apply spectral analysis to the sample of data (e.g. Bertoneche, 1979; Upson, 1972). Spectral analysis may be defined as a process whereby a series is decomposed into a set of mutually orthogonal cyclical components of different frequencies. The spectrum, a plot of the signal amplitude against the frequency, will be flat for a white noise process, and statistically significant amplitudes at any given frequency are taken to indicate evidence of periodic behaviour. In this paper, we propose and employ a new test for detecting periodicities in financial markets based on a signal coherence function. Our approach can be applied to any fairly large, evenly spaced sample of time series data that is thought to contain periodicities. A periodic signal can be predicted infinitely far into the future since it repeats exactly in every period. In fact, in economics and finance as in nature, there are no truly deterministic signals and hence there is always some variation in the waveform over time. The notion of partial signal coherence, developed in this paper into a statistical model, is a measure of how much the waveform varies over time. The coherence measures calculated are then employed to hone in on the frequency components of the Fourier transforms of the signal that are the most stable over time. By retaining only those frequency components displaying the least variation over time, we are able to detect the most important seasonalities in the data.

The remainder of this paper is organised as follows. Section 2 describes the data, while Section 3 introduces some notation, defines the test statistics employed to detect the periodicities and describes the forecasting procedure. Section 4 presents and analyses the results while Section 5 concludes and offers suggestions for extensions and further research.

2. Data

The data employed in this paper comprise the returns, the bid-ask spread, and the natural logarithm of trading volume for a sample of thirty stocks traded on the NYSE[2]. The TAQ database of all stocks was split into quintiles by market capitalisation as at 4 January 1999, and ten stocks for analysis were selected randomly from the top, middle and bottom quintiles. Selecting stocks in this manner allows us to examine whether our findings are influenced by firm size. The data are sampled every 10-minutes from 9:40am until 4pm EST, making a total of 39 observations per day. The sample covers the period 4 January 1999 – 24 December 2000, a total of 504 trading days, and thus there are 19,656 observations in total on each series. We employ continuously compounded mid-point quote returns based on the last recorded quotation in each 10-minute period. Table 1 presents the names of the companies selected, their ticker symbol mnemonics, and their market capitalisations.

The 2-year sample period is split into 504 non-overlapping frames, each of length one day, with each day comprising 39 ten-minutely observations. This implies that a total of 19 periodicities are examined: 39, 39/2, 39/3, …, 39/19. The autocoherence measures are thus calculated for each periodicity across the 504 frames.

3. Methodology

3.1 Development of a Test for Signal Autocoherence

This paper develops below a model for a signal with randomly modulated periodicity, and a measure known as a signal coherence function, which embodies the amount of random variation in each Fourier component of the signal. Any periodic function of period T can be

[2] Issues involved with the analysis of such sampled trade-by-trade data are discussed in Hinich and Patterson (1985, 1989).

written as a sum of weighted sine and cosine functions whose frequencies are integer multiples of the fundamental frequency *1/T*. These frequencies are called Fourier frequencies. The weights, called amplitudes, are fixed constants for a deterministic periodic function. The sum is called a Fourier transform of the periodic function. But a perfectly periodic function is an idealisation of a real periodic process. Each amplitude of the Fourier transform of a real periodic process is a constant plus a zero mean random time series that may or may not be stationary. The random time variations makes the amplitudes "wobble" over time causing the signal to have period-to-period random variation. Hinich (2000) introduces a measure of the wobble of the Fourier amplitudes as a function of frequency. This new form of spectrum is called a signal coherence spectrum and is very different from the ordinary power spectrum. Most fundamentally, it is a normalised statistic that is independent of the height of the power spectrum at each frequency.

Introducing some notation to outline the approach, let $\{x(t), t = 0, 1, 2, \ldots\}$ be the time series of interest, sampled at regular intervals. The series would be said to exhibit randomly modulated periodicity with period T if it is of the form

$$x(t) = a_0 + \frac{1}{T}\sum_{k=1}^{K}(a_{1k} + u_{1k}(t))\cos(2\pi f_k t) + \frac{1}{T}\sum_{k=1}^{K}(a_{2k} + u_{2k}(t))\sin(2\pi f_k t) \qquad (1)$$

where $f_k = k/T$ and u_{ik} (i=1,2) are jointly dependent zero mean random processes that are periodic block stationary and satisfy finite dependence. Note that we do not require u_{ik} to be Gaussian. It is apparent from (1) that the random variation occurs in the modulation rather than being additive noise; in statistical parlance, the specification in (1) would be termed a random effects model. The signal $x(t)$ can be expressed as the sum of a deterministic (periodic) component, $a(t)$, and a stochastic error term, $u(t)$, so that (1) can be written

$$x(t) = a_0 + \frac{1}{K}\sum_{k=1}^{K} a_k \exp(i2\pi f_k t) + \frac{1}{K}\sum_{k=0}^{K} u_k(t)\exp(i2\pi f_k t) \qquad (2)$$

where $a_k = a_{1k} + ia_{2k}$ and $u_k = u_{1k} + iu_{2k}$. The task at hand then becomes one of quantifying the relative magnitude of the modulation, a_k.

A common approach to processing signals with a periodic structure is to portion the observations into M frames, each of length T, so that there is exactly one waveform in each sampling frame. There could alternatively be an integer multiple of T observations in each frame. The periodic component of $a(t)$ is the mean component of $x(t)$. In order to determine how stable the signal is at each frequency across the frames, the notion of signal coherence is employed. Signal coherence is loosely analogous to the standard R^2 measure used in regression analysis, and quantifies the degree of association between two components for each given frequency. It is worth noting that the methodology that we propose here is based on the coherence of the signal across the frames for a single time series (which may also be termed autocoherence). This is quite different from the tests for signal coherence across markets used, for example, by Hilliard (1979) and Smith (1999)[3].

The discrete Fourier transform of the m^{th} frame, beginning at observation $\beta_m=((m\text{-}1)T)+1$ and ending at observation mT, for frequency $f_k = k/T$ is given by

$$x_m(t) = \sum_{t=0}^{T-1} x_m(\beta_m + t)\exp(-i2\pi f_k t) = a_k + U_m(k) \tag{3}$$

where $U_m(k) = \sum_{t=0}^{T-1} u_m(t)\exp(-i2\pi f_k t)$. The variance of $U_m(k)$ is given by

$$\sigma_u^2(k) = \sum_{\tau=0}^{T-1} \exp(-i2\pi f_k \tau) \sum_{t=0}^{T-\tau-1} c_u(t, t+\tau) \tag{4}$$

where $c_u(t_1, t_2) = E[u_m^*(t_1)u_m(t_2)]$, and the variance is of order $O(T)$. Provided that $u_m(t)$ is weakly stationary, (4) can be written

$$\sigma_u^2(k) = T\left[S_u(f_k) + O(1/T)\right] \tag{5}$$

where $S_u(f)$ is the spectrum of $u(t)$.

The signal coherence function, $\gamma_x(k)$, measures the variability of the signal across the frames, and is defined as follows for each frequency f_k

$$\gamma_x(k) = \sqrt{\frac{|a_k|^2}{|a_k|^2 + \sigma_u^2(k)}} \tag{6}$$

It is fairly obvious from the construction of $\gamma_x(k)$ in (6) that it is bounded to lie on the (0,1) interval. The endpoint case $\gamma_x(k) = 1$ will occur if $a_k \neq 0$ and $\sigma_u^2(k)=0$, which is the case where the signal component at frequency f_k has a constant amplitude and phase over time, so that there is no random variation across the frames at that frequency (perfect coherence). The

[3] Both of these papers employ the frequency domain approach in order to examine the extent to which stock markets co-move across countries. Our technique is also distinct from that proposed by Durlauf (1991) and used by Fong and Ouliaris (1995) to detect departures from a random walk in five weekly US dollar exchange rate series.

other endpoint, $\gamma_x(k) = 0$, will occur if a_k=0 and $\sigma_u^2(k)\neq 0$, when the mean value of the component at frequency f_k is zero, so that all of the variation across the frames at that frequency is pure noise (no coherence).

The signal coherence function is estimated from the actual data by taking the Fourier transform of the mean frame and for each of the M frames. The mean frame will be given by

$$\bar{x}(t) = \frac{1}{M}\sum_{m=1}^{M} x(\beta_m + t) \qquad , \qquad t = 0, 1, \ldots, T\text{-}1 \tag{7}$$

Letting $\hat{a}(t)$ denote the mean frame estimate, with its Fourier transform being $\hat{A}(k)$, and letting $X_m(k)$ denote the Fourier transform for the m^{th} frame, then $D_m(k) = X_m(k) - \hat{A}(k)$ is a measure of the difference between the Fourier transforms of the m^{th} frame and the mean frame for each frequency. The signal coherence function can then be estimated by

$$\hat{\gamma}_x(k) = \sqrt{\frac{\left|\hat{A}_k\right|^2}{\left|\hat{A}_k\right|^2 + \frac{1}{M}\left|D_m(k)\right|^2}} \tag{8}$$

and 0 ≤ $\hat{\gamma}_x(k) \geq$ 1. It can be shown (see Hinich, 2000) that the null hypothesis of zero coherence at frequency f_k can be tested using the statistic $M\frac{\hat{\gamma}_x(k)^2}{1-\hat{\gamma}_x(k)^2}$, which is asymptotically distributed under the null as a non-central chi-squared with two degrees of freedom and non-centrality parameter given by $\lambda_k = \frac{Ma_k^2}{TS_u(f_k)}$, where $S_u(f_k)$ is the spectrum of $\{u(t)\}$ at the frequency f_k. We also employ a joint test of the null hypothesis that there is zero coherence across the M frames for all $K/2$ frequencies examined. This test statistic will asymptotically follow a non-central Chi-squared distribution with K degrees of freedom.

3.2 Forecast Production

One of the primary advantages of the method that we propose is that a method for out-of-sample forecasting of seasonal time series arises naturally from it. This method is explained in detail in Li and Hinich (2002), who demonstrate that seasonal ARMA models can produce inaccurate long-term forecasts of time-series that are subject to random fluctuations in their periodicities. Thus we focus on those periodic components that are the most stable over the sample, whereas seasonal ARMA models focus upon the most recent seasonal patterns, which are not necessarily stable over time.

Explaining the approach intuitively, suppose that the mean frame is computed from the non-overlapping frames and is subtracted from each frame. The Fourier transform of the mean frame is computed along with the Fourier transforms of each residual frame. The signal coherence spectrum is computed from these Fourier transform amplitudes. The coherent part of the mean frame (COPAM) is the inverse Fourier transform of the Fourier transform of the mean frame where those amplitudes whose coherence values are less than a threshold are set to zero. Thus the COPAM is a “clean” version of the mean frame purged of the noisy amplitudes. Only frequencies that are statistically significant at the 1% level or lower are retained for use in forecast production. Once the COPAM is computed, the amplitudes of the non-zeroed components of the Fourier transforms of the residual frames are forecasted using a VAR with a lag selected by the user. The dimension of the VAR is twice the number of non-zero amplitudes in used to computer the COPAM. The one step ahead forecast from the VAR of the residual frames is added to the COPAM to produce a forecast of the next frame to be observed if the data segment can be extended. Further details of the approach can be found in Li and Hinich (2002).

The prediction framework that is employed in this paper is organised as follows. The coherent part of the mean frame is constructed from the first 403 frames (days), amounting to 15,717 observations and then forecasts are produced for one whole frame (one day) ahead. The out-of-sample forecasting period begins on 7 August 2000. That day’s observations are then added to the in-sample estimation period and an updated estimate of the coherent part of the mean frame is calculated. A further day of forecasts is produced and so on until the sample is exhausted. A total of 101 frames (trading days) are forecast, and the root mean squared error (RMSE) and mean absolute error (MAE) are computed in the usual way. The forecast accuracies are compared with naïve forecasts constructed on the basis of the unconditional mean of the series over the in-sample estimation window. A more complete forecasting exercise encompassing a wider range of potential models is left for future research. Since forecasts are produced for whole frames in advance (in our case, a day of 10-minutely observations), the procedure would be of particular use to those requiring multi-step ahead forecasts, and over such a long horizon, the majority of stationary forecasting models would have produce predictions that converged on the long-term mean of the series. Therefore, we conjecture that the long-term mean is likely to represent a reasonable comparator model in this case[4].

4. Results

4.1 Testing for the Presence of Periodicities in Returns, Spreads and Volumes

Table 2 gives the *p*-values for tests of the joint null hypothesis that there is zero coherence at all 19 frequencies examined, together with the number of frequencies with significant coherence, for each of the returns, spread and volume series. The returns show some limited evidence of coherence at one or more frequencies with most firms' returns having no significantly coherent periodicities at all. A non-rejection from the joint test does not in practice imply that there is actually no coherence at any frequency, however, since the effect of significance at one or two frequencies could be diluted by many insignificant frequencies. A case in point is the Firstenergy (FE) returns series, where there is one frequency with statistically significant coherence, but where the joint test is very far from a rejection.

The results for the returns are in stark contrast to those for the bid-ask spreads and volume series, all of which have *p*-values for the joint test that are zero to four significant figures. It is wholly consistent with both existing empirical evidence and theoretical intuition that these quantities would show a greater degree of seasonality than the returns. There is little consistent evidence of either increasing or decreasing numbers of coherent periodicities as firm size increases for any of the returns, spreads or volume.

However, the number of significant periodicities gives no real guide as to how strong each of the individual seasonal components are, and which of them dominate in the joint test. Hence Table 3 presents the periodicities and the coefficients of autocoherence for which the individual autocoherence estimates are statistically significant. Since there are so many significant periodicities, we employ the considerably stricter statistical significance criterion of 0.01% (i.e. a *p*-value of 0.0001 or less) for inclusion in this table. This has the effect of highlighting only the very strongest periodic signals, and requires an autocoherence

[4] Brooks (1997) also observed that the long-term mean of financial series was usually the best predictor among several models tested across a range of forecast horizons.

coefficient (which, like a correlation coefficient, is scaled to lie within –1, +1) of at least 0.134 before it would be included in the table.

Several features of Table 3 are worthy of comment. First, there is again little evidence of periodicity in the returns – only the Birmingham Steel Corp (BIR) and EOG Resources (EOG) firms have significant autocoherence at a periodicity of 39 ten-minutely units (BIR) and 19.5 ten-minutely units (BIR and EOG). These periodicities correspond to 6 and a half hours (one trading day) and 3 and a quarter hours (half a trading day) respectively, which correspond to 1 cycle and 2 cycles per day. Whilst there is no single periodicity where all 30 series of spreads or volumes show significant coherence simultaneously (except the periodicity of 39, corresponding to a daily frequency), there are several common features across the firms. First, the daily and half-daily periodicities dominate in terms of their coherence across the 2 years of daily windows for both the spreads and the volume series. Second, examining relationship between the extent of coherence and firm size, there appear to be slightly stronger coherent seasonal patterns for the small cap stocks than the large cap stocks, although there is an overwhelming degree of idiosyncratic firm behaviour. As for the returns, it seems to be the 39 and 19.5 period seasonalities that are the most common, although the majority firms also have 13 unit periodicities in their bid-ask spreads and volume, corresponding to 3 cycles per day. The coefficients of autocoherence (which are standardised to fall on the 0,1 interval) are in many cases very high for both the spreads and the volume series – typically of the order of 0.2 to 0.45 for the daily and half-daily cycles. This demonstrates a remarkable degree of stability of these relatively low frequency signal components so that there is surprisingly little variation in the waveform over the frames for the most coherent parts of the signal.

Tables 2 and 3 show the frequencies of the most stable periodic signals for each of the series, but they do not show the amplitudes of these stable signals. An idea of the spectral amplitude can be gleaned by plotting the coherent part of the mean frame for each of the series, giving the average sizes of the periodic movements in terms of the heights of the peaks and troughs of the coherent periodicities. Whilst autocoherence quantifies how stable these periodicities are, the amplitude measures the size of the cyclical fluctuations. Figures 1 to 6 plot the coherent part of the mean frame for frames of length one week for a sample of 2 firms from each size quintile, with returns and the bid-ask spread being plotted on the left-hand scale and the natural logarithm of volume on the right-hand scale[5]. Note that the mean frame has been purged of all frequencies with higher amounts of random variation, and the numbers have been standardised to have zero mean across the week. One might expect the graphs to look very different from one another since different frequencies have been retained for different stocks, and even when the same frequencies are included, differences in their relative amplitudes would alter the shape of the plot. In all cases, however, the cyclical patterns quite similar, across firms and both for the spread and for the log of volume. In Figure 1, which shows the coherent part of the mean frame for Shandong Huaneng Power Development (SH), the bid-ask spread is slightly higher in the first 10 minutes of the trading day and then is largely flat through the rest of the day. Volume is also highest from 9:30-9:40am, and above its daily average until 11:00, before falling rapidly and then rising again to reach a peak at the end of the trading day. No interesting and stable patterns are present in the returns over the day for SH, although this contrasts with the returns line in Figure 2 for Osmonics Inc (OSM). In this latter case, a simple cycle with small amplitude has been identified, with returns peaking at around 10am and 1:40pm. A very similar daily returns pattern is observed in Figure 3 (Toll Brothers) and Figure 6 (Firstenergy). In this latter case, the inverted hockey stick pattern in the spread and the u-shape in volume become more apparent.

Only one coherent frequency was significant for Western Gas Resources (WGR) returns, plotted in Figure 4, and this leads to the single trough in returns mid-way through the day with symmetrical highest levels at the open and the close. No less than seven coherent frequencies were retained in the case of International Paper (IP), however, which leads the plot of the mean frame over the day to be very jagged as a number of cycles overlay one another. Finally, we can observe that for all six series, the volume cycles are much more volatile through the day than those of the spread or returns, in part reflecting the larger number of coherent frequencies of the former.

4.2 Forecast Production using Periodicities

Tables 4 to 6 give the root mean squared error and mean absolute error for the forecasts of the returns, spreads and log volume respectively for the signal coherence approach described above and for forecasts produced using the long-term mean of the series. The results

[5] Only a small sample of firms is examined and the three quantities for each firm are plotted in the same figure in the interests of maintaining a manageable number of plots; the intraday patterns for other firms are

described above for the in-sample coherence statistics suggested that there is relatively little periodicity in the returns themselves to be used for forecasting, and therefore one would expect only minor improvements on the naïve model in such cases. This is exactly what we find - indeed, for many of the series such as Coles Myer (CM) and Timberland (TBL), no significant frequencies at all were observed and therefore, none would remain after the noisy amplitudes are purged. In these instances, the forecasts (and therefore the forecast error measures) will be exactly identical to those of the unconditional mean. The signal coherence-based approach is still able to lead to modest improvements in forecast accuracy over a simple average rule for 4 of the series.

The picture is rather different for the bid-ask spreads and in particular for the volume series. In the case of the spreads, small reductions in both the RMSE and MAE occur for 8 of the series, including Coles Myer and Staten Island Bancorp (SIB). The method is able to improve upon the naïve approach in 28 of the 30 instances for the volume series, and these improvements are typically quite large – for example, the RMSE and MAE in the case of EOG Resources are 2.00 and 1.43 for the signal coherence approach, while they are 2.23 and 1.73 for the simple mean forecasts. These represent reductions of the order of 11% and 17% respectively.

5. Conclusions

This paper has proposed and employed a new method for evaluating and quantifying the autocoherence of financial time series, which was then tested on a set of ten-minutely returns, bid-ask spreads, and volume for a sample of 30 NYSE stocks. Significant coherence for at least one frequency across frames was revealed for firms for the spread and volume series, although there is far less seasonality in the returns. Overall we find the signal coherence to be maximal at the daily frequency, with spreads mostly following an inverse J-shape through the day and volume being high at the open and at the close and lowest in the middle of the day. These results for the spreads are consistent with the arguments put forward in the theoretical literature (Brock and Kleidon, 1992, for example) that the market power of specialists near the open and close combined with inelastic demand for shares at these times. The similar patterns observed over the day for trading volume are also consistent with theories of strategic behaviour of liquidity traders and informed traders, such as that of Admati and

qualitatively identical to those shown.

Pfleiderer (1988), as well as features of the market such as settlement timing that is affected by the date of trades but not their timing within the day. Such models suggest no role for seasonalities in returns, which is to a large extent what we find, since the theories imply that prices should follow a martingale. We find no differences in the presence or strength of seasonal patterns according to market capitalisation. An investigation using longer frame lengths of one week[6] suggested that intradaily effects completely swamp any lower frequency seasonalities such as day of the week effects. Such a statement could not have been made categorically on the basis of existing tools for time series analysis.

Finally, the approach to measuring the extent of periodicities in data proposed here can also be employed as a method for forecasting the series. A comparison of the forecasts from this model was made with those from a simple long-term mean rule. In the case of the spread series, reasonable improvements in forecast accuracy were made in some cases, while considerable improvements were possible for the volume data. This improvement did not, however, also apply to the returns or spread series. We conjecture that the approach employed in this paper could be a useful tool for researchers to detect and to quantify the various periodic components in other time series data.

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Table 1: List of Stocks Employed and their Market Capitalisations

Company Name	Mnemonic	Market Capitalisation
Panel A: Small Stocks		
Sinopec Shanghai Petroleum	SHI	34269
Getty Petroleum Marketing	GPM	54985
Coles Myer	CM	61832
Brimingham Steel Corp	BIR	76829
Osmonics Inc	OSM	108560
Dover Downs Entertainment	DVD	145145
Dan River Inc	DRF	145933
Shandong Huaneng Power Development	SH	146906
Starrett L S	SCX	148299
Doncasters	DCS	159599
Panel B: Mid-Cap Stocks		
Imation	IMN	628772
Western Gas Resources	WGR	637058
Oakley	OO	804035
Staten Island Bancorp	SIB	837379
Philippine Long Distance Tele	PHI	971035
Toll Brothers	TOL	1158727
Cooper Tire and Rubber	CTB	1160123
Orthodontic Centres of America	OCA	1225163
Heller Financial	HF	1259811
Timberland	TBL	1279885
Panel C: Large Stocks		
EOG Resources	EOG	4531390
Union Planters	UPC	5501656
Firstenergy	FE	7455382
El Paso Energy	EPG	10471071
FPL Group	FPL	11919726
International Paper	IP	16707546
National City	NCC	20735387
Walgreen	WAG	35715995
Philp Morris	MO	114045117
Exxon Mobil	XOM	239997400

Note: Market capitalisation is measured in US dollars as at 24 December 2000.

Table 2: *P*-values for Joint Test of Null Hypothesis that there is no signal coherence for all 19 Frequencies and Number of Frequencies with Significant Coherence at the 1% Level

Company Mnemonic	**Returns**		**Bid-Ask Spread**		**Volume**	
	p-value	No. Sig. Freqs.	*p*-value	No. Sig. Freqs.	*p*-value	No. Sig. Freqs.
			Panel A: Small Stocks			
SHI	0.1569	0	0.0000	15	0.0000	17
GPM	0.0033	0	0.0000	6	0.0000	19
CM	0.4599	0	0.0000	19	0.0000	4
BIR	0.0000	5	0.0000	16	0.0000	14
OSM	0.0892	1	0.0000	7	0.0000	18
DVD	0.0000	4	0.0000	9	0.0000	17
DRF	0.0000	3	0.0000	19	0.0000	17
SH	0.0000	5	0.0000	18	0.0000	19
SCX	0.0452	0	0.0005	3	0.0000	9
DCS	0.4877	0	0.0000	8	0.0000	9
			Panel B: Mid-Cap Stocks			
IMN	0.2960	0	0.0000	7	0.0000	8
WGR	0.0000	1	0.0000	9	0.0000	13
OO	0.5156	0	0.0000	11	0.0000	12
SIB	0.0000	10	0.0000	18	0.0000	11
PHI	0.0000	8	0.0000	19	0.0000	11
TOL	0.0000	2	0.0000	19	0.0000	6
CTB	0.0009	0	0.0000	14	0.0000	8
OCA	0.0000	5	0.0000	15	0.0000	5
HF	0.0000	1	0.0000	14	0.0000	7
TBL	0.0327	0	0.0000	7	0.0000	8
			Panel C: Large Stocks			
EOG	0.0000	7	0.0000	17	0.0000	4
UPC	0.3737	0	0.0000	19	0.0000	3
FE	0.3405	1	0.0000	16	0.0000	4
EPG	0.0214	0	0.0000	11	0.0000	3
FPL	0.0197	0	0.0000	19	0.0000	5
IP	0.0000	7	0.0000	9	0.0000	5
NCC	0.3613	0	0.0000	4	0.0000	10
WAG	0.9999	0	0.0000	5	0.0000	14
MO	0.0000	3	0.0000	2	0.0000	19
XOM	0.7111	0	0.0000	5	0.0000	19

Table 3: Periodicities with Coherence Statistics that are Significant at the 0.01% Level

Company Mnemonic	Returns		Bid-Ask Spread		Volume	
	Period	Autocoherence	Period	Autocoherence	Period	Autocoherence
			Panel A: Small Stocks			
SHI	-	-	39	0.191	39	0.528
			19.5	0.168	19.5	0.351
			9.75	0.140	13	0.329
			7.8	0.144	9.75	0.283
			6.5	0.137	7.8	0.239
			4.875	0.168	6.5	0.244
			4.333	0.145	5.571	0.207
			2.785	0.138	4.875	0.230
			2.437	0.141	4.333	0.195
					3.9	0.169
					3.545	0.184
					3.25	0.146
					3	0.217
					2.6	0.140
					2.29	0.149
GPM	-	-	39	0.181	39	0.293
			13	0.174	19.5	0.173
					13	0.208
					9.75	0.167
					7.8	0.188
					6.5	0.190
					5.57	0.173
					4.875	0.141
					3.9	0.140
					3.545	0.180
					3.25	0.153
					3	0.177
					2.438	0.194
					2.053	0.145
CM	-	-	39	0.352	39	0.211
			19.5	0.354	19.5	0.141
			13	0.365		
			9.75	0.343		
			7.8	0.290		
			6.5	0.282		
			5.57	0.293		
			4.875	0.285		
			4.333	0.339		
			3.9	0.308		
			3.545	0.277		
			3.25	0.262		
			3	0.273		
			2.786	0.305		
			2.6	0.283		
			2.438	0.291		
			2.294	0.276		
			2.167	0.307		
			2.053	0.282		
BIR	39	0.180	39	0.271	39	0.523
	19.5	0.167	19.5	0.229	19.5	0.322
	4.875	0.157	13	0.185	13	0.183
	4.333	0.150	6.5	0.148	5.571	0.188
			5.57	0.140	4.875	0.253
			3.9	0.157	4.333	0.184
			3.545	0.150	3.9	0.290

Company Mnemonic	Returns		Bid-Ask Spread		Volume	
	Period	Autocoherence	Period	Autocoherence	Period	Autocoherence
			3	0.175	3.545	0.158
					3.25	0.147
					3	0.171
					2.6	0.184
OSM	-	-	39	0.188	39	0.370
					19.5	0.213
					13	0.211
					9.75	0.274
					7.8	0.219
					6.5	0.154
					4.875	0.188
					4.333	0.173
					3.9	0.234
					3.545	0.213
					3.25	0.167
					3	0.145
					2.786	0.154
					2.6	0.152
					2.438	0.186
					2.294	0.190
					2.167	0.166
					2.053	0.180
DVD	39	0.141	39	0.210	39	0.445
			13	0.151	19.5	0.179
			7.8	0.153	13	0.240
					9.75	0.182
					5.57	0.154
					4.875	0.137
					4.333	0.167
					3.9	0.150
					3.25	0.134
					2.29	0.134
					2.167	0.158
					2.053	0.135
DRF	-	-	39	0.234	39	0.397
			19.5	0.218	19.5	0.205
			9.75	0.185	13	0.250
			7.8	0.146	9.75	0.180
			3.9	0.166	7.8	0.260
			3.545	0.136	6.5	0.198
			3	0.144	5.571	0.174
			2.6	0.146	4.875	0.173
			2.438	0.173	4.333	0.135
			2.294	0.148	3.9	0.157
			2.167	0.152	3	0.150
					2.6	0.143
SH	-	-	39	0.210	39	0.377
			19.5	0.208	19.5	0.237
			13	0.171	13	0.289
			9.75	0.137	9.75	0.191
			5.571	0.157	7.8	0.187
			4.875	0.167	6.5	0.204
			3.9	0.183	5.57	0.172
			3.545	0.146	4.875	0.230
			3.25	0.154	4.333	0.159
			3	0.174	3.9	0.203
			2.6	0.180	3.545	0.165

Company Mnemonic	Returns		Bid-Ask Spread		Volume	
	Period	Autocoherence	Period	Autocoherence	Period	Autocoherence
			2.437	0.148	3.25	0.169
			2.167	0.165	3	0.137
			2.053	0.153	2.6	0.218
					2.294	0.203
					2.167	0.195
					2.053	0.165
SCX	-	-	-	-	39	0.236
					13	0.152
					7.8	0.155
					5.571	0.163
					4.333	0.149
					3.9	0.156
DCS	-	-	9.75	0.139	39	0.230
			3	0.135	13	0.137
					4.875	0.153
					2.438	0.145
Panel B: Mid-Cap Stocks						
IMN	-	-	19.5	0.138	39	0.506
			7.8	0.158	19.5	0.221
					4.875	0.151
WGR	-	-	39	0.203	39	0.504
			19.5	0.141	19.5	0.304
			13	0.157	13	0.199
			3.9	0.149	9.75	0.158
					7.8	0.150
					6.5	0.159
					5.571	0.142
					4.875	0.164
					4.333	0.180
					3.9	0.167
					3.25	0.164
					2.6	0.149
OO	-	-	39	0.146	39	0.411
			19.5	0.177	19.5	0.261
			13	0.123	13	0.235
			9.75	0.165	9.75	0.147
			6.5	0.149	7.8	0.188
			5.571	0.136	6.5	0.173
					4.875	0.148
					3.545	0.151
SIB	13	0.210	39	0.221	39	0.476
	9.75	0.157	19.5	0.181	19.5	0.224
			13	0.168	13	0.209
			9.75	0.215	9.75	0.162
			7.8	0.163	5.571	0.153
			4.875	0.191		
			4.333	0.159		
			3.9	0.165		
			3.25	0.138		
			2.785	0.137		
			2.294	0.146		
			2.167	0.151		
PHI	6.5	0.148	39	0.250	39	0.505
			19.5	0.260	19.5	0.273
			13	0.220	13	0.271
			9.75	0.238	9.75	0.152
			7.8	0.197	3	0.196

Company Mnemonic	Returns		Bid-Ask Spread		Volume	
	Period	Autocoherence	Period	Autocoherence	Period	Autocoherence
			6.5	0.214		
			5.571	0.176		
			4.875	0.161		
			4.333	0.223		
			3.9	0.225		
			3.545	0.141		
			3	0.166		
			2.6	0.164		
			2.438	0.167		
			2.294	0.149		
			2.053	0.158		
TOL	-	-	39	0.227	39	0.494
			19.5	0.235	19.5	0.188
			13	0.207	13	0.189
			9.75	0.176	9.75	0.151
			6.5	0.160		
			3.545	0.157		
			2.786	0.145		
			2.6	0.138		
CTB	-	-	39	0.155	39	0.508
			9.75	0.176	19.5	0.199
			6.5	0.139	9.75	0.173
			3.9	0.142		
			2.786	0.167		
			2.438	0.167		
OCA	-	-	39	0.197	39	0.492
			19.5	0.163	19.5	0.170
			13	0.229	13	0.136
			7.8	0.144		
			6.5	0.134		
			5.571	0.134		
			4.875	0.136		
HF	19.5	0.150	39	0.155	39	0.454
			13	0.138	19.5	0.184
					6.5	0.137
TBL	-	-	13	0.162	39	0.455
Panel C: Large Stocks						
EOG	39	0.163	39	0.236	39	0.444
	19.5	0.169	19.5	0.182	19.5	0.146
			13	0.204		
			9.75	0.201		
			7.8	0.150		
			5.571	0.164		
UPC	-	-	39	0.304	39	0.486
			13	0.193		
			9.75	0.162		
			7.8	0.170		
			6.5	0.155		
			4.875	0.151		
			4.333	0.160		
			3.9	0.142		
			3.545	0.153		
			3.25	0.161		
			2.785	0.151		
			2.6	0.169		
			2.438	0.169		
			2.294	0.196		

Company Mnemonic	Returns		Bid-Ask Spread		Volume	
	Period	Autocoherence	Period	Autocoherence	Period	Autocoherence
			2.167	0.177		
			2.053	0.134		
FE	-	-	39	0.335	39	0.489
			19.5	0.206		
			13	0.161		
			5.571	0.149		
			3.545	0.164		
			2.786	0.169		
			2.6	0.171		
			2.438	0.156		
			2.294	0.175		
			2.053	0.172		
EPG	-	-	39	0.219	39	0.363
			13	0.189		
			4.333	0.164		
FPL	-	-	39	0.293	39	0.456
			7.8	0.166	3.545	0.134
			6.5	0.175		
			4.875	0.135		
			4.333	0.141		
			3.9	0.150		
			3.25	0.160		
			2.786	0.163		
			2.6	0.178		
			2.053	0.184		
IP	4.875	0.158	39	0.298	39	0.428
			19.5	0.177	19.5	0.279
			13	0.195		
NCC	-	-	3.25	0.140	39	0.471
					19.5	0.241
					13	0.165
					6.5	0.160
					4.333	0.140
					3.9	0.145
WAG	-	-	39	0.292	39	0.381
			6.5	0.123	19.5	0.285
					13	0.157
					9.75	0.182
					4.875	0.175
					4.333	0.180
					3.9	0.143
					3.545	0.141
MO	-	-	39	0.193	39	0.412
					19.5	0.382
					13	0.272
					9.75	0.232
					7.8	0.149
					6.5	0.238
					5.57	0.219
					4.875	0.228
					4.333	0.244
					3.9	0.239
					3.545	0.222
					3.25	0.199
					3	0.232
					2.786	0.215
					2.6	0.181

Company Mnemonic	Returns		Bid-Ask Spread		Volume	
	Period	Autocoherence	Period	Autocoherence	Period	Autocoherence
					2.438	0.210
					2.294	0.221
					2.167	0.234
					2.053	0.212
XOM	-	-	39	0.406	39	0.419
			19.5	0.168	19.5	0.326
					13	0.204
					9.75	0.183
					7.8	0.141
					6.5	0.189
					5.57	0.187
					4.875	0.225
					4.333	0.219
					3.9	0.194
					3.545	0.160
					3.25	0.155
					3	0.229
					2.786	0.147
					2.6	0.151
					2.438	0.166
					2.294	0.167
					2.167	0.162

Note: We employ a considerably stricter statistical significance criterion for inclusion in this table compared with the previous one in order to keep it at a manageable size.

Table 4: Forecasts of Returns using Signal Coherence Approach and Simple Average

	Signal Coherence Approach		Simple Average Approach	
	RMSE	**MAE**	**RMSE**	**MAE**
		Panel A: Small Stocks		
SHI	0.480	0.141	0.477	0.127
GPM	0.974	0.245	0.972	0.221
CM	0.327	0.050	0.327	0.050
BIR	2.204	0.940	2.212	0.890
OSM	0.307	0.088	0.307	0.071
DVD	0.481	0.217	0.481	0.195
DRF	0.998	0.338	0.998	0.305
SH	0.140	0.069	0.125	0.029
SCX	0.344	0.089	0.343	0.078
DCS	0.510	0.159	0.510	0.159
		Panel B: Mid-Cap Stocks		
IMN	0.540	0.248	0.540	0.248
WGR	0.421	0.237	0.420	0.224
OO	0.603	0.349	0.603	0.349
SIB	0.272	0.142	0.273	0.127
PHI	0.408	0.157	0.410	0.143
TOL	0.456	0.266	0.457	0.262
CTB	0.547	0.342	0.546	0.331
OCA	0.660	0.381	0.659	0.371
HF	0.405	0.232	0.404	0.219
TBL	0.566	0.335	0.566	0.335
		Panel C: Large Stocks		
EOG	0.454	0.285	0.456	0.278
UPC	0.309	0.195	0.309	0.195
FE	0.329	0.219	0.329	0.217
EPG	0.372	0.248	0.372	0.248
FPL	0.316	0.206	0.316	0.204
IP	0.477	0.318	0.477	0.313
NCC	0.384	0.256	0.384	0.251
WAG	0.387	0.253	0.387	0.253
MO	0.417	0.269	0.414	0.261
XOM	0.256	0.172	0.256	0.172

Table 5: Forecasts of Bid-Ask Spreads using Signal Coherence Approach and Simple Average

	Signal Coherence Approach		Simple Average Approach	
	RMSE	**MAE**	**RMSE**	**MAE**
	Panel A: Small Stocks			
SHI	0.091	0.072	0.091	0.073
GPM	0.045	0.033	0.043	0.030
CM	0.094	0.074	0.096	0.078
BIR	0.051	0.043	0.051	0.043
OSM	0.047	0.041	0.046	0.040
DVD	0.073	0.060	0.070	0.058
DRF	0.066	0.057	0.066	0.058
SH	0.062	0.057	0.061	0.057
SCX	0.410	0.248	0.112	0.088
DCS	0.149	0.122	0.097	0.079
	Panel B: Mid-Cap Stocks			
IMN	0.052	0.040	0.048	0.037
WGR	0.076	0.065	0.074	0.063
OO	0.060	0.047	0.062	0.049
SIB	0.062	0.051	0.063	0.051
PHI	0.054	0.041	0.054	0.042
TOL	0.104	0.082	0.105	0.083
CTB	0.049	0.042	0.044	0.039
OCA	0.091	0.071	0.092	0.072
HF	0.078	0.067	0.072	0.063
TBL	0.091	0.074	0.104	0.086
	Panel C: Large Stocks			
EOG	0.075	0.055	0.076	0.054
UPC	0.053	0.045	0.053	0.045
FE	0.044	0.039	0.044	0.039
EPG	0.063	0.049	0.062	0.045
FPL	0.061	0.047	0.062	0.047
IP	0.056	0.045	0.050	0.040
NCC	0.057	0.048	0.039	0.037
WAG	0.051	0.041	0.050	0.041
MO	0.039	0.035	0.035	0.031
XOM	0.051	0.038	0.049	0.038

Table 6: Forecasts of Volume using Signal Coherence Approach and Simple Average

	Signal Coherence Approach		Simple Average Approach	
	RMSE	**MAE**	**RMSE**	**MAE**
	Panel A: Small Stocks			
SHI	4.179	3.665	4.288	3.904
GPM	4.783	3.043	4.839	3.115
CM	2.314	1.346	2.297	1.202
BIR	5.989	5.737	6.186	6.097
OSM	4.112	2.933	4.181	3.043
DVD	5.390	5.210	5.488	5.392
DRF	4.829	4.066	4.923	4.214
SH	5.321	4.782	5.464	5.003
SCX	3.798	2.883	3.771	2.789
DCS	5.308	4.015	5.376	3.931
	Panel B: Mid-Cap Stocks			
IMN	4.888	3.402	4.964	3.645
WGR	5.594	5.340	5.748	5.594
OO	5.133	4.697	5.281	4.943
SIB	5.729	5.306	5.764	5.470
PHI	6.015	5.712	6.176	6.018
TOL	4.611	4.090	4.847	4.426
CTB	3.442	2.018	3.523	2.174
OCA	3.619	2.536	3.786	2.842
HF	4.880	4.019	5.041	4.367
TBL	3.963	3.359	4.160	3.646
	Panel C: Large Stocks			
EOG	2.004	1.431	2.231	1.734
UPC	2.168	1.136	2.221	1.254
FE	1.969	1.102	2.047	1.231
EPG	1.490	1.003	1.969	1.611
FPL	1.589	0.947	1.690	1.097
IP	1.347	0.741	1.415	0.839
NCC	1.477	0.885	1.545	0.975
WAG	1.338	0.733	1.373	0.796
MO	1.299	0.658	1.365	0.738
XOM	1.225	0.546	1.275	0.620

Figure 1 : Coherent Part of the Mean Frame for a Day – Shangdong Huaneng Power Development

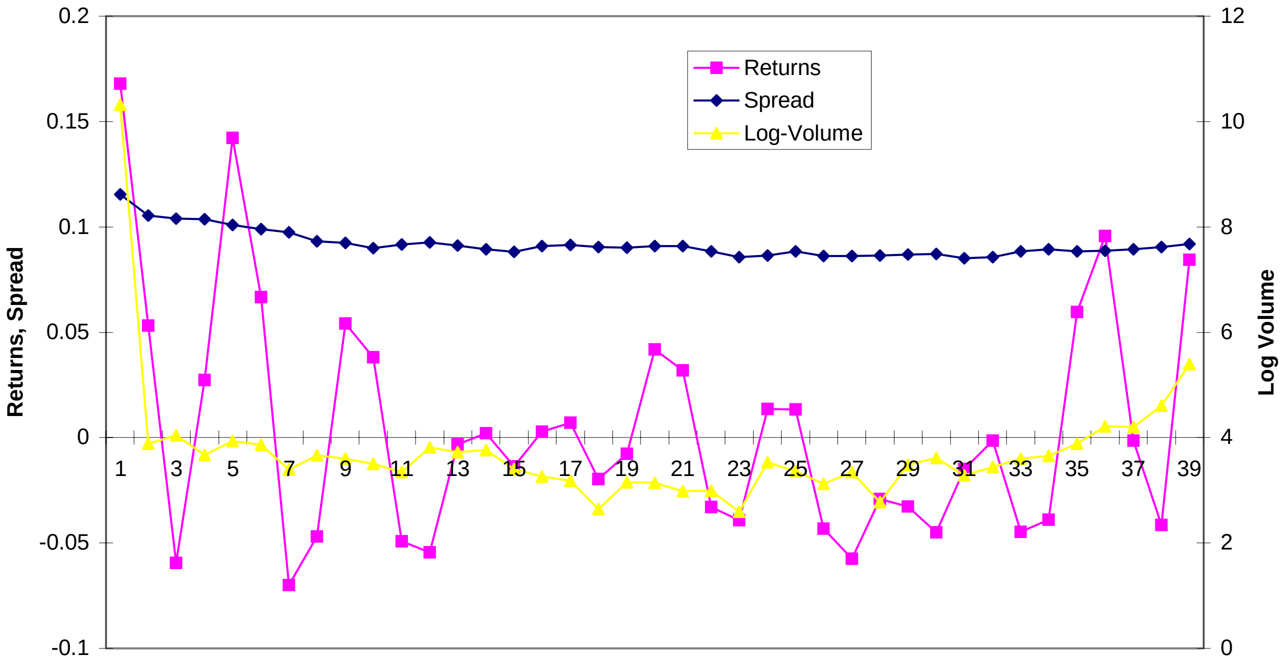

Figure 2: Coherent Part of the Mean Frame for a Day – Osmonics Inc

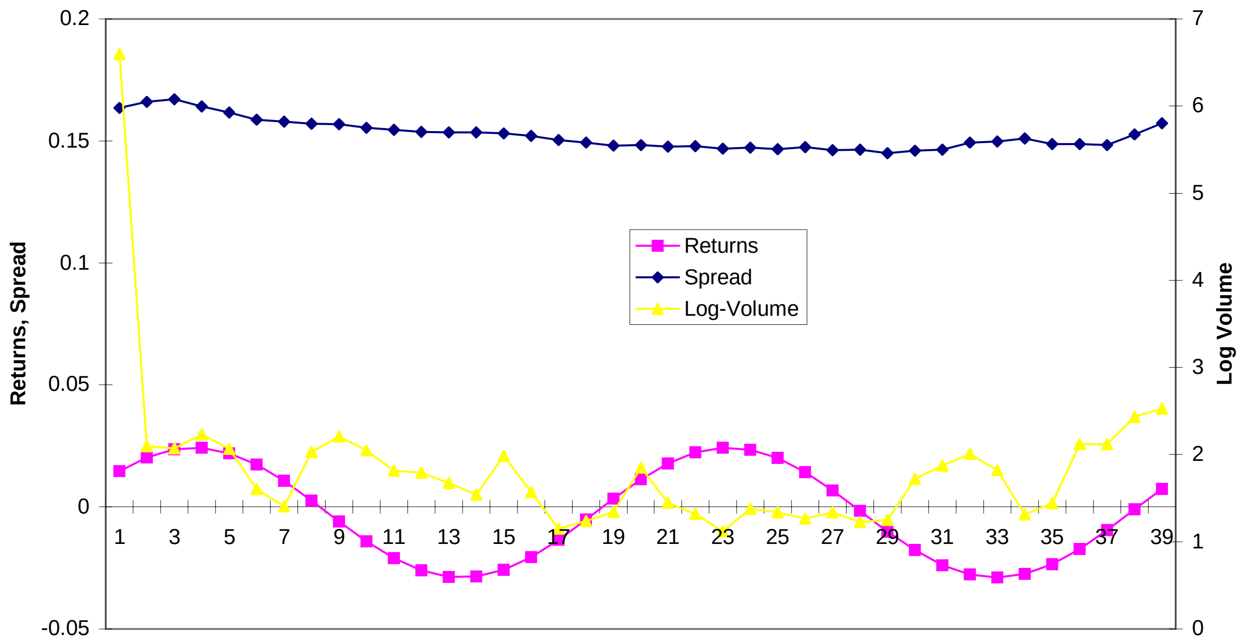

Figure 3: Coherent Part of the Mean Frame for a Day – Toll Brothers

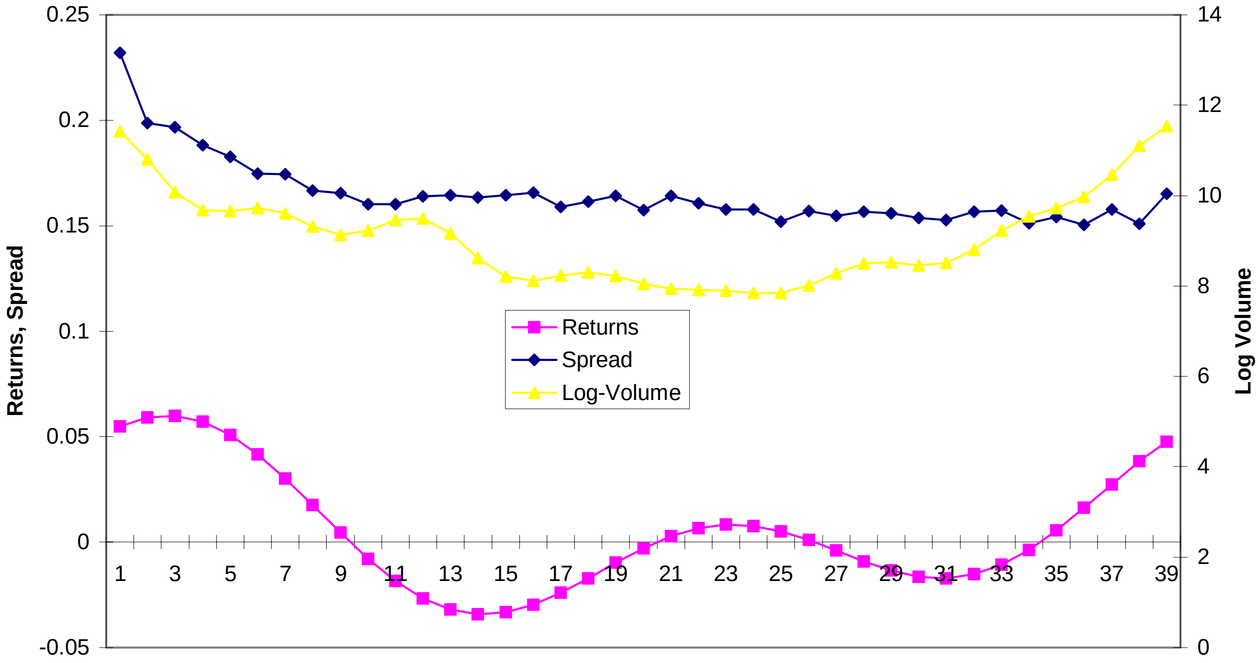

Figure 4: Coherent Part of the Mean Frame for a Day – Western Gas Resources

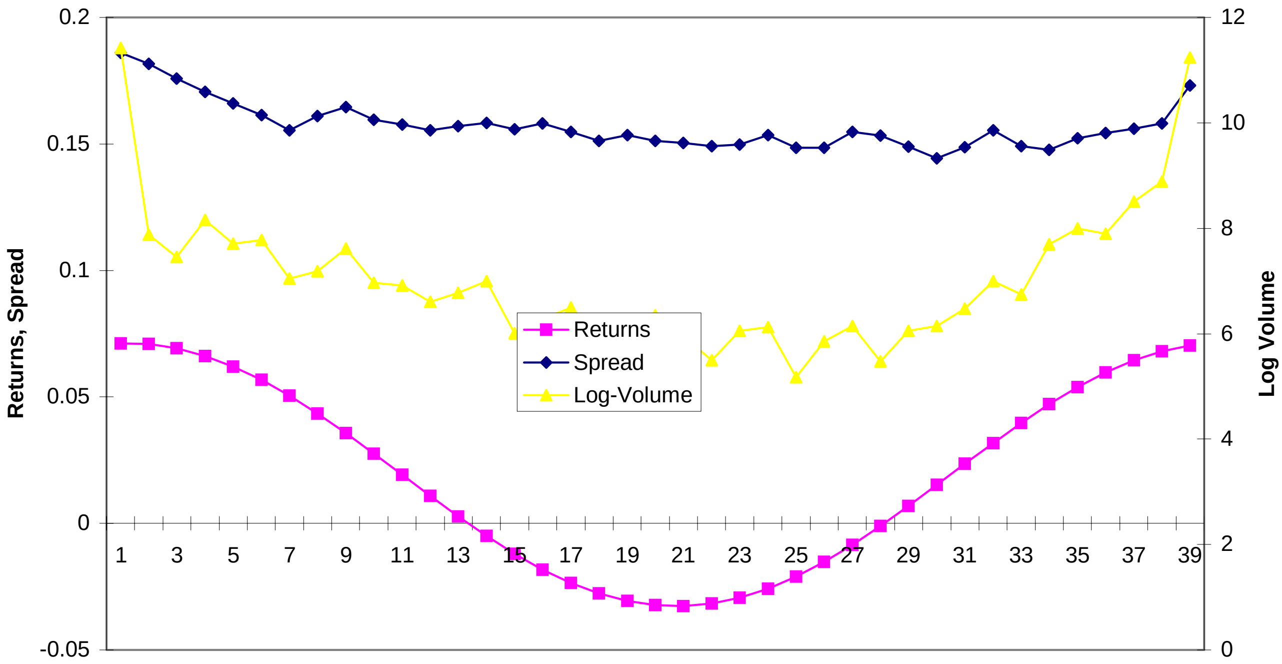

Figure 5: Coherent Part of the Mean Frame for a Day – International Paper

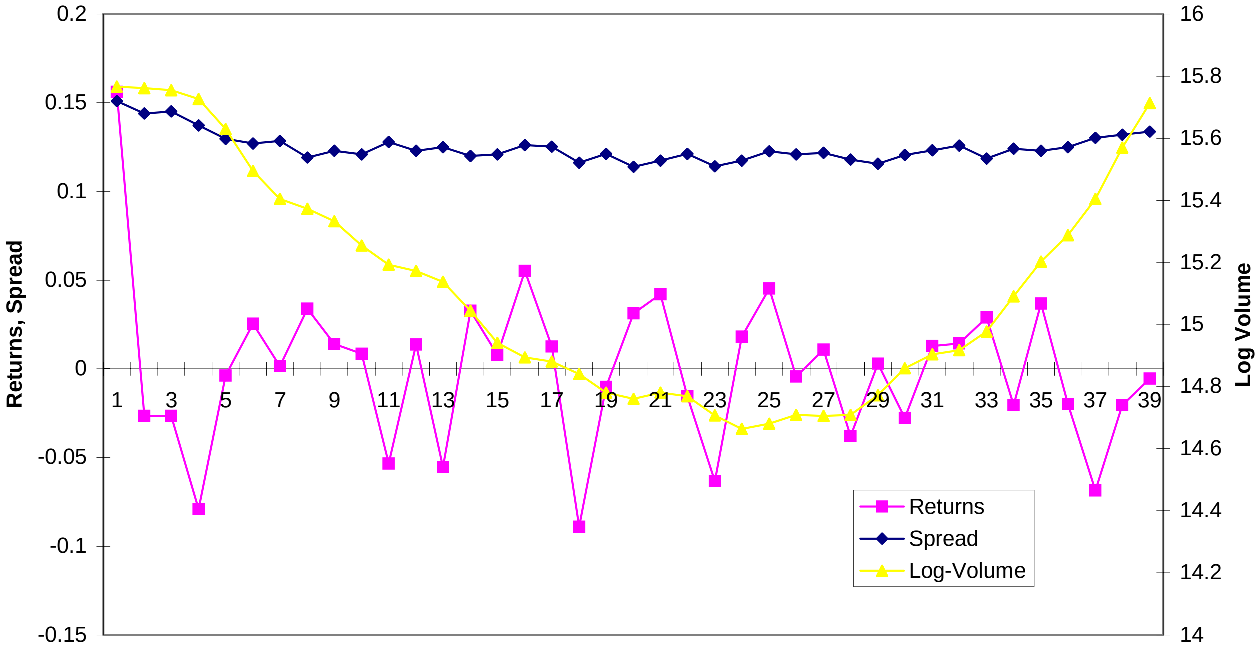

Figure 6: Coherent Part of the Mean Frame for a Day - Firstenergy