Announcement Effects and Seasonality in the Intra-day Foreign Exchange Market

By

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Abstract

This paper examines two aspects of spot FX volatility. Using intra-daily quotation data on the DeutscheMark/Dollar we simultaneously estimate the deterministic intra-daily seasonal pattern inherent in volatility and the effects of U.S. macroeconomic announcements. The empirical specification and estimation technique is based on the Stochastic Volatility methodology contained in Harvey, Ruiz, and Shephard (1994). Results conform with previous work, in that 'news' effects are strong and persistent, being felt for over one hour after the initial release time. Inclusion of an explicit seasonal is shown to be essential for the accurate estimation of other volatility components. Further estimations allow us to examine which particular pieces of U.S. data move the markets. These results show that the most important statistics are those associated with the Employment and Mercantile Trade reports.

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1 Introduction

In recent times it has become a well established fact that intra-day volatility in financial markets is subject to pronounced deterministic seasonality. Volatility effects around market closures, over weekends and within lunch hours have all been shown to be subject their own specific patterns. Works in this area include French and Roll (1986) for the NYSE, Barclay, Litzenberger, and Warner (1990) for the Tokyo Stock Exchange and the series of papers emanating from Olsen and Associates (Zurich) which concentrate on the FX market.

Perhaps the most striking examination of seasonality comes from Andersen and Bollerslev (1994). They examine two series of intra-daily financial market returns, the first from the foreign exchange market and the second from the Standard and Poors 500. As the figures at the end of their paper indicate, both markets display pronounced seasonality in volatility; the familiar U-shaped pattern is apparent for the Standard and Poor data, whilst a much less regular seasonal is estimated for the FX data. The authors go on to pre-filter the data for deterministic seasonality, using a Flexible Fourier Form, before estimating GARCH specifications for both series over varying observation frequencies. Results demonstrate that removing the seasonal component gives estimated GARCH parameters which conform much more closely with the predictions of theory as data are aggregated over time.

Over the same period of time, a second strand of literature has begun to examine the effects of scheduled news announcements on financial market volatility. The work of Goodhart, Hall, Henry, and Pesaran (1993) concentrates on the FX market, taking two specific announcements and investigating their effects on both the level and variance of exchange rates. Ederington and Lee (1993) and Ederington and Lee (1995) examine the impact of regular, scheduled US announcements on the volatility of T-bond, Eurodollar and Deutsche Mark futures prices. Both conclude that there is a significant impact from these announcements, both at the announcement instant and for an extended length of time afterwards.

The focus of this paper is to combine the above. We too seek to examine and estimate intra-day seasonality in volatility, but do so in conjunction with the estimation of announcement effects for certain US macroeconomic news. Our empirical model is an extension of the Stochastic Volatility models presented in, for example, Harvey, Ruiz, and Shephard (1994) and Taylor (1994). The model incorporates an unobserved AR(1) component, (designed to pick up volatility clustering effects,) deterministic seasonal effects and deterministic news dummies. The data employed are quotations for the DeutscheMark/Dollar exchange rate, recorded continuously over the period from October 1992 to September 1993.[1]

The main objective of the work is to provide an accurate assessment of the importance of each of these three volatility components. Firstly, we aim to confirm the conjecture contained in Ederington and Lee (1993), that the response of spot FX rates to news should be similar to the behaviour they demonstrate for the DM futures contract. However, as the work of Andersen and Bollerslev (1994) shows, modelling the seasonal component is essential for an accurate analysis of intraday volatility. The covariation of the seasonal with short-run volatility elements, such as news effects, is likely to imply that ignoring the seasonal will bias estimated news effects. Therefore we estimate a model containing both seasonality and announcement effects. This further allows us to confirm the findings of Anderson and Bollerslev, also providing a simple alternative method of intra-daily seasonal estimation. We compare the estimated parameters of various models combining various different volatility components, demonstrating how the omission of one component or another may lead to mis-estimation of those components which remain in the specification.

In a final set of empirical estimations we examine the impact which individual announcements have on volatility. Using both announcement specific dummies and the median forecast errors associated with particular releases we construct a ranking of the U.S. macroeconomic data based on their estimated effect on quote variation.

The remainder of the paper is set out as follows. Section 2 provides background information and a review of existing studies on both seasonality and announcement effects. Our empirical model is set out in Section 3 and the results presented and discussed in Section 4. Section 5 concludes.

[1]The data were provided by Olsen and Associates (Zurich), to whom the author is most grateful.

2 Background: News and Seasonality

In this section we review the established facts regarding the components of, and the changes in, intra-daily volatility, focussing on market activity and scheduled announcements. With regard to the impact of news, we seek to define clearly the relationship of the announcement data to news and go on to present a discussion of the possible impacts before, at and after announcement

2.1 News and Announcements

In this sub-section we describe the composition of our announcement data and our hypotheses regarding the behaviour of volatility around announcement times. Before doing so, we present a summary of some of the previous work regarding news and volatility, and go on to attempt to clarify the relationship between announcements and news.

One of the pioneering studies on the impact of news on FX volatility was performed by Goodhart, Hall, Henry, and Pesaran (1993). In this work the authors employ a tick-by-tick data set of Dollar/Pound quotations, spanning a calendar time interval of eight weeks, and examine how two specific events affect volatility.[2] Employing a GARCH-M framework, they find that a system without news effects indicates that the level of the exchange rate has a unit root and also that the conditional variance is very nearly integrated. This latter conclusion alters dramatically when news effects are incorporated; the persistence of the conditional variance equation drops dramatically, and large and highly significant announcement effects are indicated. The authors model the announcement effects via dummy variables in the conditional variance equation, an approach we broadly follow in our empirical specifications. A further point to note regarding this study is that their usage of tick-by-tick data renders their results incomparable to those we present in the following sections.

Another work which examines this issue is Ederington and Lee (1993). They, however, do not examine the spot FX market, rather the reaction of the prices of three nearby futures contracts, the Deutsche Mark/Dollar exchange rate, T-bond and Eurodollar. Using a news data set of scheduled US macroeconomic (and survey) releases, they investigate how both volatility and price-adjustment behave. As our focus is on the spot FX market, we discuss only their results on the volatility of the nearby Deutsche Mark contract. The authors construct a set of five-minute transaction price returns from their tick-by-tick data and take the standard deviation of returns

[2]These events are the unexpectedly good US Trade figures announced on 17/5/89 and a 1% rise in UK base rates revealed on 24/5/89.

for each interval across all the days in their sample. This clearly demonstrates that that the interval from 8:30 to 8:35 EST, the interval which is immediately after most of the announcements, is by far the most volatile of the day. The authors further show that this spike in volatility is only apparent for days on which announcements occur. As regards the persistence of this abnormal volatility, they show that the immediate impact of announcements is to increase volatility by five times, this drops to twice normal volatility over the next ten minutes and finally decays over the next few hours. Significantly higher volatility is felt up to 40 minutes after the initial impact. The authors also analyse which announcements are most influential for the DM future. Results suggest that those which matter are the Employment report, Mercantile Trade, Retail Sales, GNP, PPI and Durable Goods orders, in declining order of significance.

Along the same lines, Harvey and Huang (1991) analyse the volatility patterns of currency futures traded on IMM and LIFFE. They show that the first hour of Thursday and Friday mornings are exceptionally volatile, a consequence which they assert is due to the release of US macroeconomic data of the type Ederington and Lee study, rather than any private information concentration at the market open.

A more recent study, and one which employs the same data period as this, is DeGennaro and Shrieves (1995). This work utilises hourly quotation returns on the Yen/Dollar exchange rate, investigating how three types of news impact the market. These categories are scheduled macroeconomic announcements, unscheduled policy news and unscheduled interest rate reports. Results for the scheduled macroeconomic reports suggest that volatility is significantly higher in the hour prior to release, is insignificantly greater in the hour of release, before rising once more and then decaying gently over time.

A relevant issue, for all the above studies, is the relationship between announcements and news. Until now we have used these terms interchangeably, although their interpretations are quite different. All of the 'news' data used in the following empirical analysis, and mostly used in those papers above, are US macroeconomic and survey statistics whose precise release date and time are known in advance. This allows market participants to form expectations over their content. Clearly then, there is not an identity between announcements and news, announcements only being newsworthy to the extent that they are unexpected. Further, each announcement is likely to differ in the amount of information it carries, some having been largely predictable whilst others contain entirely unexpected results. Best practice in this situation is to create a news measure from the announcements by employing the consensus expectation of the market. This approach has been employed in the investigation of news effects on the level of exchange rates by, for example, Hakkio and Pearce (1985). A further consideration is touched on in Ederington and Lee (1993). It is most likely that certain announcements are more important for certain assets e.g. the Trade figures being vitally important for FX rates but, apparently, for little else. Ederington and Lee's demonstration of the influential items shows that if one were to construct the type of news metric mentioned above, not only would the size of the unexpected element be important, but also the type of announcement itself. We address both these points in our final set of estimations. There we examine the effect of individual announcement series on volatility, utilising both a dummy variable specification and a more precise 'news' measure derived from the difference between actual announced figures and the consensus expectations of the market. Finally, changing market sentiment will be important here also. Over time, the market's belief as to which series are important alters. At a certain point markets may believe unemployment figures are the key indicator of economic performance, although a year further down the road their focus may have shifted to the Producer Price Index. Hence it must be recognised that the impact of an individual announcement series is likely to be time-varying, as market sentiments shift.

Nevertheless, all the papers mentioned above show that a prominent role is played by announcement effects in short run volatility determination. Here we hope to demonstrate the same kind of impact which Ederington and Lee show, but for the spot FX rate. We depart from previous work on the spot market by employing a very fine, calendar time sampling frequency and explicitly modelling the seasonal component of volatility, which is discussed in the sub-section below. A relative disadvantage of focussing on the spot market is that transaction prices, over a time period long enough to examine the issues addressed, are unavailable. In what follows we employ quotation returns as a proxy for transaction returns.

Our hypotheses about the effects of 'news' on volatility in the pre- and post- announcement periods are as follows. We believe in the periods immediately preceding announcements there are two possible effects. Firstly there is the possibility that volatility is abnormally high. This in turn could have at least two sources. The first, a channel stressed by DeGennaro and Shrieves, is that the details of the announcement are uncovered by some market participants. This creates an informational asymmetry between agents, the informed proceeding by trading on their information and gradually disseminating it to the rest of the market. This will engender high, pre-release volatility. The second possibility is based more on an inventory control idea. Dealers, knowing that an information event will occur at a precise point in the future may desire to trade out of exposed positions towards an equilibrium inventory. This generates a spate of inventory rebalancing trades just prior to the announcement, again causing higher than normal volatility.

It is also possible that in the periods immediately before announcements, volatility will be abnormally low. Again this is based on the fact that the dealers know a news release is occuring shortly and effectively cease all activities whilst they wait to see what the information content of the release is. Hence, pre-announcement volatility could possibly be lower or higher than normal. Which effect predominates is clearly an empirical issue. Note that the interval containing the actual announcement should strictly be treated as a pre-announcement period. This is due to the fact that all the news data examined are released on the hour, the quarter-hour or the half-hour, hence each announcement occurs precisely at the end of an interval.

In the post-announcement period we would expect to observe a surge in volatility as the information contained in the release is incorporated into quotations and dealers trade towards their new desired positions. What is interesting in the post-announcement period is the length of time over which this process takes place. How quickly do markets react to information? Again this is an empirical issue. Ederington and Lee (1993) stress that persistent increased volatility after announcement can come from two sources: firstly the price formation process can be inherently slow, quotations taking time to reach their equilibrium level, or secondly the information contained in announcements is only disseminated slowly, such that the market is reacting to a flow of information which is instantaneously incorporated into quotes. Which of these effects dominates will dictate whether 'news' opens the possibility of profitable trading opportunities, although from a volatility perspective they are indistinguishable.

High post-release volatility could also be propagated through an inventory control channel. After an announcement it is likely that some traders will update their beliefs over the fundamental value of the asset, engendering a change in desired inventory holdings. If the transactions which restore each trader's inventory to equilibrium are not worked through immediately then one will again notice persistently high, post-release volatility. One way to distinguish between the effects of information revelation in the FX market and impacts from inventory trading to give persistently high volatility after a release is to examine simultaneously the impact of 'news' both on the level and volatility of exchange rates. In this work, this question is left unaddressed although we hope to examine it in the near future.

The above discussion defines our empirical hypotheses. In the pre-announcement period, the effect of news on volatility is, a priori, indeterminant, whereas in the post-release period one should expect an increase in volatility as long as there is an information content to the announcement. As indicated above, the focus in the post-release period is the persistence of the volatility surge.

Before moving on to an examination of seasonality in volatility we present the announcement data actually employed in estimations. All are monthly, US, macroeconomic or survey statistics, the list being: the Unemployment rate, Merchandise Trade Deficit, Producer Price Index, Consumer Price Index, Retail Sales, Consumer Confidence Index, Leading Indicators, Durable Goods Orders, Industrial Production and Capacity Utilisation[3] and finally the NAPM survey. All but four of these announcements are made at 8.30 EST. The Industrial Production and Capacity Utilisation (IP/CU) figures are announced together at 9.15 EST whilst the NAPM survey and Consumer Confidence figures are released at 10.00 EST. Market participants know both the time of announcement and the date on which the release will occur in advance.

2.2 Seasonality

The major movements of intra-daily return volatility can be attributed to the passage of market activity around the globe and it is this which underlies the seasonals we observe. One can regard the global FX market as being composed of three major regional centres, the Far East, Europe and North America, all of which have their own activity pattern. To begin to interpret the seasonal one needs a feel for the openings and closures of the three components. Roughly one can say that the Far East is open from 21:00 GMT to 7:00 GMT, Europe trades between 6:00 GMT and 16:00 GMT, whilst trading occurs in North America from 14:00 GMT to 21:00 GMT. The accumulation of activity in open markets gives the level of the seasonal at any point over the day, hence interpretation of the seasonal pattern is performed by appealing to the conditions in these open markets.

First we give a brief presentation of the data. As indicated in the Introduction the data employed are observations on the DM/Dollar exchange rate over the period 1/10/92 to 30/9/93. The data are essentially a filtered transcription of the activity on Reuters FXFX pages; the original form of the data is tick-by-tick quotation inputs from the banks which participate on the system. We convert these data into a calendar time-series by imposing a five-minute observation grid, an observation being taken at the end of each interval.[4] A modification to this structure is the omission of weekends (defined as 21:00 GMT on Friday to 21:00 GMT on Sunday,) as these are periods of little or no activity. The five minute observation window implies that a day spans 288 observations and the omission of weekends leaves us with 261 trading days.

[3]These two announcements are paired here as they are always annnounced simultaneously.

[4]This sampling interval was chosen on the following basis. First, as earlier work shows, there are prominent intra-hourly effects from macroeconomic releases, necessitating a short observation window. Second, the computational tractability of the problem decreases very quickly with the sampling interval. Our five minute window was chosen to balance these two effects.

This leads to a time-series of 75168 observations.[5]. The basic statistical features of both the quotation and returns series are given in Table 1 and analysed in Section 4

We show in Figure 1 the pattern of our volatility measure, the logarithm of squared returns[6], averaged over the 261 trading days in our sample, for the 288 five minute intervals of the day. The seasonal pattern which emerges for this measure is more-or-less identical to that demonstrated for average absolute returns in Andersen and Bollerslev (1994) and that shown in Dacorogna, Müller, Nagler, Olsen, and Pictet (1993). Further evidence of the daily seasonal structure shows up in the autocorrelation function of our volatility proxy. In Figure 2 we show the autocorrelation function for $\log(r^2)$ over a span of 288 lags i.e. over one full trading day. What is notable is the peak in the representation at precisely the daily frequency, demonstrating that the memory of volatility is most closely attuned with what occurred precisely one day ago rather than at any point between now and then.

We also present the average pattern and autocorrelation of our volatility proxy over [redacted] the pattern evident over different days. A point which the weekly autocorrelation function demonstrates is that there seems to be some seasonal structure at the weekly frequency. This can be seen through the local maximum at a lag of precisely 5 trading days (lag 1440) dominating those maxima attributable to lags of two, three and four trading days. However, in what follows we ignore this weekly structure, concentrating solely on the daily pattern.

Using the discussion of market openings and closures presented at the beginning of this subsection we can break down the volatility seasonal as follows.

The first interval of the day corresponds to the five minutes between 0:00 and 0:05 GMT, a time when the Far Eastern market has already been trading for around 3 hours and market activity is high. From this point till about 3:20 GMT (interval 40) volatility and activity levels remain high. At this point we come across the most prominent feature of the series, lunchtime in Tokyo. Volatility drops sharply, flooring at near zero levels and only regaining its former value at about 5:00 GMT. The next market to open is Europe, generally beginning to contribute to activity at around 6:30 GMT as the Far Eastern market begins to wane. This gives a small peak in volatility between intervals 80 and 120, before activity and volatility both experience a slight

[5] At various points in the series, no quote is entered in a 5 minute interval. These data holes were filled by linear interpolation between the nearest preceding and succeeding quote.

[6] Our choice of $\log(r^2)$ as a volatility proxy is motivated by the empirical model in Section (3). The pattern demonstrated in Figure 1 is robust to the use of alternative volatility measures such as absolute returns and squared returns.

lull during European lunch hours. The most active period of the day is clearly the interval when both the European and North American markets are open (intervals 160-180), after which volatility starts to decline as first the European, and then the US markets, wind down. Finally at around 21:00, the Pacific market begins to trade again and the daily cycle is repeated after midnight.

Daylight Saving Time also has an effect on the seasonal pattern. In summer months, both North America and Europe lose one hour relative to GMT. This implies that, as the Far Eastern local time remains unchanged, the seasonal pattern alters in composition (rather than simply shifting laterally relative to the GMT hour of the day.) In estimation this phenomenon is handled by the introduction of two seasonal regimes, one relating to the winter months and the second for summer, parameterised using a simple dummy variable formulation.[7] A comparison of the average daily $\log(r^2)$ pattern in summer and winter, showing precisely the effect which DST has on the seasonal, is presented graphically in Figure 5.

Hence the seasonal pattern which emerges seems fully explicable. What is less obvious, however, is the way in which the omission of this component in estimation might impinge upon examination of other volatility components. As long as these components are not fully orthogonal it is likely that mis-specifying the model, by omitting the intra-daily seasonal for example, will lead to biased estimation of the parameters in other components.

The works mentioned in the previous subsection dealt with the seasonal as follows. Ederington and Lee (1993) base their results on a comparison of announcement and non-announcement days, implicitly filtering the seasonal by examining the announcement to non-announcement volatility ratio. Further, volatility in the futures markets they treat may be far less seasonal than that in the spot FX market. DeGennaro and Shrieves (1995) treat the seasonal explicitly. In certain of their specifications they add opening and closure dummies to account for weekend effects and employ a quotation frequency variable as a proxy for the seasonal pattern. This proxy is, in general, very good. However, one might expect quotation frequency to rise deterministically around 'news' announcements also. If this is the case, then their seasonal proxy will absorb part of the news effects which they are attempting to estimate, biasing the 'news' coefficients downwards. Finally, Goodhart, Hall, Henry, and Pesaran (1993) include no seasonal effects whatsoever, although, as they use tick-by-tick data, the effects of this omission are likely to be less severe.

Some other studies which examine the seasonal patterns in the intra-day FX market

[7] In the strictest sense there are actually four regimes here, as North America and Europe alter their times about one week apart, but we ignore these short periods, subsuming them into one of the major regimes.

are as follows. Baillie and Bollerslev (1991) presented one of the pioneering examinations of this phenomenon in their analysis of four spot FX rates. Employing hourly returns on the Dollar/Sterling, DM/Dollar, Swiss Franc/Dollar and Yen/Dollar they estimate seasonal GARCH models of volatility, the seasonality captured with a dummy variable specification. Results demonstrate very similar seasonals across currencies and, clearly, the dummy specification for seasonality works well in this context. For the data set we employ, however, a dummy variable formulation would require the estimation of 287 parameters, an obvious drawback.

Andersen and Bollerslev (1994), as already mentioned, use a flexible Fourier form to pre-filter the data for seasonality. The implication of this technique is that seasonality is treated as a nuisance component in the data which simply obscures the behaviour of underlying volatility. If, however, one also wishes to examine announcement effects, which are periodic too, then pre-filtering volatility will necessarily pre-filter a portion of the 'news' impact. Also neither this study nor Baillie and Bollerslev (1991) address the effect of DST in their estimations, implying that their estimated seasonal is 'blurred' i.e. a linear combination of the seasonals apparent in two distinct regimes.

Lastly, a fairly large literature has arisen which concentrates on the concept of time-deformation in order to explain and estimate the seasonality patterns apparent. The motivation behind these models can be found in Stock (1988) and it is, essentially, that markets work on a time scale which differs from simple clock time. Relevant variables evolve in market time and their behaviour in clock time is derived by applying a non-linear transformation between the two time scales. An application of this approach can be found in Ghysels, Gouriéroux, and Jasiak (1995) who estimate a time-deformed SV model. In related work, Dacorogna, Müller, Nagler, Olsen, and Pictet (1993) model intra-daily seasonality by introducing a market activity variable, the integral of which defines a market time-scale. Examination of a regularly spaced price change series in this market time-scale demonstrates the removal of the seasonal in volatility.

3 The Empirical Methodology

3.1 The Basic SV Model

The starting point for our empirical model can be found in Harvey, Ruiz, and Shephard (1994). The basis of their model is a representation of asset returns as shown in equations (1) and (2) below,

$$r_t = \sigma \epsilon_t e^{h_t/2}, \quad \epsilon_t \sim N(0,1) \tag{1}$$

$$h_t = \phi h_{t-1} + \nu_t, \quad \nu_t \sim N(0, \sigma_\nu^2) \tag{2}$$

Here, r_t is the return on the asset in question, σ is a volatility scale parameter, ϵ_t is a white noise term and h_t is a time varying volatility component. As equation (2) demonstrates, h_t is assumed to follow a first order autoregressive process, a specification chosen to parallel the volatility clustering motivation behind the GARCH literature. The disturbance term in this equation is also assumed white noise, with given variance, σ_ν^2, and independent of ϵ_t.

The return process is clearly stationary if the process generating h_t is stationary, a situation which occurs when $\phi < 1$. Using this approach, h_t is treated as an unobserved component which is retrieved via the estimation and smoothing associated with the Kalman Filter. In order to apply the filter to the above specification, the measurement equation, equation (1), must be linearized in the state (h_t). This is achieved by transforming the return equation into that shown below.

$$\log(r_t^2) = \log(\sigma^2) + h_t + \log(\epsilon_t^2) \tag{3}$$

Given the standard normal distribution posited for ϵ_t, the transformed error term is known to have a mean of -1.27 (and a variance of $\pi^2/2$,) such that creating a term, $\xi_t = \log(\epsilon_t^2) + 1.27$, gives the following specification,

$$\log(r_t^2) = -1.27 + \log(\sigma^2) + h_t + \xi_t \tag{4}$$

in which the new disturbance term has zero mean. Combining equations (2) and (4) gives a time-invariant state-space form whose parameters can be estimated via the Kalman Filter. If estimation demonstrates that ϕ is approximately unity, a situation which parallels the IGARCH specification, then a unit root can be imposed upon the transition equation. In order to pre-test for the presence of a unit root in $\log(r_t^2)$ one can employ an ADF test, although, as mentioned in Harvey, Ruiz, and Shephard (1994), the power of this test in this situation may be questionable due to the possible near non-invertibility of the volatility representation.

3.2 Modifications

We generalise the above model as follows. The first modification is the addition of a set of deterministic trigonometric components used to model the seasonality inherent in volatility. These terms are constructed as shown below,

$$\psi_t = \sum_{j=1}^{s/2} (\gamma_j \cos \lambda_j t + \gamma_j^* \sin \lambda_j t), \quad \lambda_j = 2\pi j/s \tag{5}$$

with $s = 288$, as described in Section 2. If each of the seasonal frequencies were to be included this would lead to the estimation of 287 parameters for the seasonal, the same number of parameters that one would expend on a dummy variable seasonal specification. However, as the seasonal is likely to change fairly smoothly, subject to the qualification below, some of the high frequency components may be omitted without sacrificing a great deal of accuracy in estimation.

In order to gauge which of the components are most important, in Section 4 we examine the seasonal periodogram for the returns series. The periodogram simply plots the amplitude of each Fourier component against it's frequency, with each amplitude constructed as shown below,

$$P_j = \frac{2}{T}\left[(\sum_{t=1}^{T} r_t \cos \lambda_j t)^2 + (\sum_{t=1}^{T} r_t \sin \lambda_j t)^2 \right] \tag{6}$$

Examination of the periodogram then indicates which of the frequencies are dominant, allowing one to trim the number of harmonics used in estimation.

An addition to the seasonal specification is made to cope with the sharp drop in volatility around lunch in the Far East. The smooth seasonal generated from the dominant Fourier terms is unlikely to cope well with this discontinuity, in all likelihood the drop will be largely underestimated. We therefore employ a set of dummy variables to cope with this phenomenon. Also, as mentioned earlier, daylight saving time in North America and Europe will engender an alteration in the form of the seasonal. Hence we estimate two seasonal regimes (indexed by m) over which the parameters of the trigonometric terms are allowed to alter. Note that, as there is no Daylight Saving Time in the Far East, we can leave the lunch dummy unchanged across the two regimes. This gives the final form for the seasonal which is presented below,

$$\psi_{mt} = \sum_{j=1}^{s/2}(\gamma_{mj}\cos\lambda_j t + \gamma^*_{mj}\sin\lambda_j t) + \sum_{i=0}^{k}\mu_i l_{t-i}, \quad \lambda_j = 2\pi j/s, \quad m = 1,2 \qquad (7)$$

where k is the number of intervals which lunch encompasses and l_t is a variable defined to be unity only in the first interval of the Japanese lunch hour. By adding lagged values of l_t to the specification we allow the dummy coefficients in each interval of lunch to differ. In the most general case the coefficients on the dummies are unconstrained, although a fixed lunchtime effect can be imposed by setting $\mu_i = \mu$ for all i.

If desired, the seasonal can also be made stochastic, allowing the parameters γ_{mj} and γ^*_{mj} to evolve over time (see Harvey (1989),) but this route is not followed in the current work as it seems that the pattern observed is quite stable. An alternative to the trigonometric formulation presented above would be to model the seasonal using a periodic spline formulation, à la Harvey and Koopman (1993) and Harvey, Koopman, and Riani (1995), a formulation which can also be deterministic or stochastic.

The second extension of the basic model is centered around the addition of a further dummy variable, d_t. This indicator is unity for only those five minute intervals which contain one of the news announcements in our data set. In practice, as all the included announcements occur either on the hour, the quarter-hour or the half-hour, this implies that the instant of release is precisely at the end of a period. We allow for the possibility of news effects prior to, at the time of, and post-announcement by including leads of, the contemporaneous value of and lags of the news dummy in our specification. Appropriate trimming of the lead and lag specifications gives us the approximate impact intervals before and after announcement. Hence the final specification for volatility is as below,

$$\log(r_t^2) = -1.27 + \log(\sigma^2) + h_t + \psi_{mt} + \sum_{i=-p}^{q} a_i d_{t-i} + \xi_t, \quad p,q \geq 0, \quad m = 1,2 \qquad (8)$$

where ξ_t is as specified as above, ψ_{mt} is as in equation (7) and d_{t-i} is the indicator of an announcement at lag i.[8]

[8]The effect of news on volatility before announcement is represented by i taking the requisite negative value.

Combining equations (2) and (8) gives our final specification. As noted earlier, it involves elements which allow for volatility clustering, a smooth, deterministic seasonal pattern and an extended impact of announcements on volatility.

3.3 Individual Announcements

A last set of empirical exercises examines whether the volatility responses differ across announcement types. This is done by splitting our announcement data into 10 distinct variables, one for each announcement type. We then estimate a restricted version of the final model for each announcement type. The restrictions embodied in estimation are as follows. First, we impose a geometric decay on the post-release volatility response. In terms of the parameters of equation (8) we allow a_1 and a_2 to vary freely but restrict all subsequent impacts to decay at rate ρ, i.e. $a_i = a_{i-1}(1-\rho)$, for $i \geq 3$.

Secondly, these estimations are run with the seasonal pre-filtered. We subtract the seasonal estimated from the final specification (i.e. equations (8) and (2),) from our $\log r^2$ series in order to form the dependent variable in the measurement equation. This procedure should minimize any systematic bias in the estimation of the impacts for each announcement as the seasonal employed was originally estimated in the presence of a full complement of 'news' dummies.

We run these estimations using both a simple dummy specification for announcements (i.e. a variable taking the value unity at the point when a specific announcement occurs only) and using the forecast errors associated with announcements. The forecast errors are created as the difference between the actual announced figure and a median survey expectation.[9] By using both the above measures, we can get the general impact of a certain announcement from the first estimation and a more precise economic impact, e.g. the impact of an unexpected 1% rise in unemployment on FX volatility, from the latter.

Hence, from these results, we can examine which announcements really move the market. Are all pieces of macroeconomic data equally important for the determination of the DM/Dollar rate, or do some announcements dominate? Note, however, that for each announcement we only have 12 observations within our one year span of data. Moreover, given the possibility of markets altering their opinion on the most important indicator of economic performance, these results may not generalise to other time periods.

[9]The survey medians employed were obtained from MMS International, who survey around 40 major market watchers for their forecasts on the Friday previous to the release of each piece of information.

3.4 Estimation

As previously mentioned, the basis for estimation of the class of models examined above is the Kalman Filter. The final specification for $\log(r_t^2)$ in equation (8) serves as the measurement equation, whilst equation (2) provides the transition equation. The unobserved component in our model is h_t, a measure which one might refer to as 'underlying' market volatility. This method is by no means the only way in which to estimate SV models. Scott (1987), Chesney and Scott (1989) and Melino and Turnbull (1990) use GMM type estimations whilst others advocate Bayesian estimation methods, e.g. Jacquier, Polson, and Rossi (1994), pointing to the increased efficiency these methods bring. In our case however, with such a large data set, efficiency losses are likely to be minimised and, further, these alternative estimation techniques become computationally intractable.

The problem in using the Kalman Filter in this case is the non-normality of ξ_t. This implies that the filter delivers only MMSLE's, such that the approach must be treated as a QMLE estimation, i.e. working as if ξ_t was distributed normally, with mean zero and variance $\pi^2/2$. The filter is initialised using the unconditional distribution of h_t, except in the case where h_t is constrained to be a random walk, when the initial observation is used. From then on, the quasi-likelihood function is built observation by observation. The quasi-likelihood is maximised over the parameter space using the optimisation algorithm of Broyden, Fletcher, Goldfarb and Shanno. Standard errors for the hyperparameters, ϕ and σ_ν^2, are calculated using the results presented in Ruiz (1994).

Once the parameters have been estimated, the smoothing algorithm of Koopman (1993) is employed in order to retrieve the within-sample values of the state, h_t. This allows one to examine, after accounting for the seasonal and announcement impacts, the time-series volatility of the FX market, from where a clarified picture of the volatility profile, and perhaps its determinants, can be drawn.

4 Results

Before presenting the empirical estimations of the models outlined in the previous section we briefly introduce the variables used in estimation, examining their basic statistical behaviour. Summary statistics for these variables are presented in Table 1.

Examining first the behaviour of the return series, two facts are immediately apparent. First of all the series displays pronounced excess kurtosis, confirming the findings of many previous studies which demonstrate that the distribution of financial market returns tend to have very thick tails. A second point is that the Box-Ljung statistic demonstrates that there is serial dependence in the returns series. This motivates our examination of the second series, a set of residual returns constructed after the removal of a first order moving average from the original return series. One can note that the dependence in this series is substantially lower than that of the raw returns (although still statistically significant) and again excess kurtosis is apparent. The real series of interest, however, is our volatility proxy. This is constructed as the logarithm of squared residual returns. It is clearly apparent from a comparison of BL statistics that it is in volatility that the real temporal dependence lies. The BL statistic for $\log(r^2)$ is over 250 times that of raw returns and it is this phenomenon which we seek to address and explain in the estimations below.

4.1 Non-seasonal SV models

Our first empirical application consists of fitting the basic SV model [10], demonstrated in equations (2) and (4). As described in Section 3.4 the model is estimated by Quasi-ML via the Kalman Filter, the procedure containing the restrictions that ϕ be between zero and one and σ_ν^2 be positive. Results of this specification are shown in Table 2.

The estimate of ϕ conforms with the results of many other volatility studies (mainly of GARCH form,) which demonstrate that, at this fine, calendar time sampling frequency, the variance process is approximately integrated. In particular, our estimate of ϕ is 0.96, a value which is almost on the boundary of the parameter space. As previously indicated, to test for the presence of a unit root in volatility we employ an ADF test for $\log(r^2)$, (the ADF specification embodying 20 lags of the difference of $\log(r_t^2)$.) The outcome of the test demonstrates that one can reject the hypothesised

[10]Before the estimation of all specifications, the scale factor in the measurement equation, $\log(\sigma^2)$, is removed.

unit root, although the difference between the test statistic and the critical value is quite small.[11]

Because of this very marginal test result, we go on to impose the restriction that $\phi = 1$, the results being shown in Panel 2 of Table 2. The variance of h_t can be seen to drop quite sharply, as does the maximised Quasi-Log Likelihood, and due to this latter fact, in all further specifications, we drop the unit root imposition, allowing ϕ to take any value between zero and one.

The behaviour of the derived standard deviation[12] in the unrestricted model is shown in Figure 6, alongside the behaviour of absolute residual returns. From the figure it is apparent that h_t tracks the underlying volatility of returns very well, but this observation masks a weakness of the specification. As outlined in previous sections, probably the most distinctive feature of the intra-daily volatility process is it's seasonality. In this basic specification there is no explicit treatment of that seasonal. Hence, when we examine the average behaviour of h_t over the intervals of one day, it becomes clear that all seasonal variation is picked up by the state variable. The comparison of the rescaled behaviour of h_t and that of $\log(r_t^2)$ is demonstrated in Figure 7. This has mixed effects: on the positive side it implies that the bias to parameters in the 'news' specification is likely to be reduced, but negatively, the state variable, h_t, now indicates little about the volatility clustering behaviour which the data may exhibit.

Despite this, and to provide a comparison later in the paper, we next estimate a non-seasonal SV specification which incorporates 'news' effects. The system consists of equation (2) and a version of equation (8), in which all seasonal parameters are set to zero.

The results of the SV/News specification are given in Table 3. First note that there is little change in the basic SV parameters, ϕ and σ_ν^2. Both are at almost precisely their level from the original model, ϕ is highly significant and still very close to unity. Of more interest are the 'news' coefficients. In the pre-announcement period the coefficients show that a significantly reduced measure of volatility in the period 15-30 minutes before announcement is followed by a positive significant impact in the 15 minutes immediately prior to release. The post-announcement period is characterised by an immediate large spike in volatility which dies away, non-monotonically, over at least the next hour. All of the estimated coefficients are highly significant. A graphical exposition of these announcement effects can be found in Figure 8.

Hence our preliminary results suggest that in the minutes immediately before an-

[11] The ADF(20) test statistic is -2.609, compared with a one-tailed critical value of -1.95 at 5%

[12] This is calculated as $e^{h_t/2}$ as in equation (3.1).

nouncement there may be either information leakage or closing-out trading, both of which could generate the higher than normal volatility. However, in the period from 15 to 30 minutes before announcement, markets are significantly less active, reflecting the possibility that traders slow their activity in anticipation of the upcoming news. On balance, the dominant pre-release impact seems to be greater volatility, both in terms of magnitudes and significance.

The response after release demonstrates the information contained in these data and the importance the FX market places upon it. The fact that volatility is persistently high for the hour post-announcement suggests that either the price formation process is slow, or that the information contained in the release data is only gradually extracted. Of course these results must be cautiously accepted, given the potential bias in estimation which the lack of a seasonal component may bring about.

4.2 Seasonal SV Models

As indicated at the end of the previous sub-section there is a danger in taking the results of the non-seasonal specifications at face value. We go on now to incorporate explicit seasonal elements into the specification as described in Section 3.2. The primary problem is the choice of which of the set of 144 Fourier terms to incorporate, hence, as outlined previously, we examine the seasonal periodogram which is shown in Figure 9.

As expected, the fundamental frequency is dominant, it's amplitude dwarfing that of any of the harmonics. The very high frequency elements add very little variation to the seasonal, only the first fifteen or so components being at all visible on the chart. We employ the six Fourier terms with the greatest associated amplitudes. These are the first, third, fourth, fifth, ninth and tenth elements. As shown later on in this section the inclusion of only these elements, along with the dummies for lunchtime in Japan, gives a perfectly satisfactory estimated seasonal representation.

We can now progress to the estimation of the Seasonal SV models. The first results, which are presented in Table 4, are for a model which incorporates the basic SV structure plus the seasonal only. Examining first the estimated parameters from the transition equation, there is little change in the autoregression coefficient; it rises only very slightly and remains highly significant. There is, however, a significant drop in the transition equation error variance. This is likely to be due to the removal of seasonal effects from the time-varying volatility component, h_t. All the coefficients of the seasonal representation are significant, (a joint LR test of their significance indicates that the hypothesis that all seasonal coefficients are identically zero can be strongly rejected,) although their numerical interpretation is not straightforward.

Hence we reconstruct the daily seasonal they represent, in both regimes, and both are shown in Figure 10. In comparison to Figure 5, which shows the average value of $\log(r^2)$ over the 288 daily intervals for summer and winter, there seems little [redacted] Of course the estimated seasonals are smooth relative to the average intra-daily patterns but they seem to pick up the general seasonal shape quite well. Figure 5 also shows some interesting features. First, as expected, the summer and winter seasonal coincide for the Far Eastern portion of activity, this being due to the lack of DST in Asia. Next our representations pick up a small spike in activity just after Japanese lunch. This may represent volatility engendered by trading on information which has been revealed over the lunch hour closure. Finally, European and North American trading activity can be seen to shift approximately 12 intervals to the right during winter months, reflecting their time changes relative to GMT.

The adequacy of our seasonal representation is emphasised in the autocorrelation function of the deseasonalised $\log(r^2)$ series.[13] Figure 11 plots this function and it is immediately apparent that the decaying, repeated U-shaped structure which can be seen in Figure 2 is almost completely removed. This compares favourably with the plot of deseasonalised returns from Andersen and Bollerslev (1994), which shows that their procedure does not completely remove the seasonal. One feature which does become more apparent though, is the seasonal structure at the weekly period. Also, there seems to be a very slow decline in the correlogram, although masked by the weekly seasonal, an indication of long memory in volatility. An examination of this property of the data is, however, beyond the scope of the current study.

It seems, therefore, that our trigonometric treatment of the seasonal is quite successful. This conclusion is re-affirmed by the average intra-daily behaviour of the state variable, h_t, derived from this model. A graphical examination of the average intra-daily behaviour of the state shows that the only distinctive feature of average 'underlying' volatility is a residual effect from Japanese lunch.[14]

4.3 The Combined Model

We can now move on to the final, combined model of seasonality and news. This consists of estimation of equations (2) and (8), allowing a maximum window for 'news' effects of 30 minutes pre- and 1 hour 15 minutes post-announcement. The

[13] Deseasonalised volatility is simply calculated as the values of $\log(r^2)$ after filtering the deterministic trigonometric and dummy variables.

[14] We exclude this graph in order to save space.

results from this model are presented in Table 5.[15]

As the seasonal coefficients directly tell us little about the seasonal pattern, and their magnitudes and significances are little changed from those in the previous subsection, we treat only the transition equation and announcement dummy parameters explicitly. A cursory examination of the former shows that little has changed here also. Both the autoregressive parameter and the transition equation error variance are very marginally reduced in magnitude from their levels in the previous estimation, although the significance of the autoregressive parameter has risen.

A far more noticeable alteration is apparent in the estimated 'news' coefficients. Earlier in the paper we referred to the potential bias to the announcement effects which may occur due to the omission of seasonal effects from the specification. Here, we see that this is precisely true. All news coefficients are now around 0.25 lower than in the previous estimation.[16] The downward change is exactly what we would expect, although the magnitude of the bias is quite small. Again, as mentioned in Section 4.1 this is likely to be due to the absorption of the seasonal by h_t in the models estimated without an explicit seasonal parameterisation.

Now, in the pre-announcement period our results of a distinctive quietening in the market are re-inforced. In the period 10 to 30 minutes before announcement the coefficients become more negative and significant, whereas there is a drop in both magnitude and significance for the positive impacts in the 10 minute period before release. Hence, the dominant impact is now one of reduced volatility pre-release.

In the post-announcement interval, there is again a general reduction in the magnitude of the coefficients of the order of about 0.25. What is still true, however, is that the positive volatility impact of announcements lasts for at least one hour, in line with the results derived in Ederington and Lee (1993). In fact the volatility effect is consistently positive until 1 hour 15 minutes after announcement when the first negative coefficient is encountered. A plot of the new announcement coefficients, alongside those derived from the non-seasonal news specification is shown in Figure 12.

Hence our results conform qualitatively with those of Ederington and Lee (1993). The quantitative comparison is, however, not as close . As mentioned in Section 2, their estimations demonstrate that the standard deviation of returns rises fivefold

[15] Again for brevity, we do not report the estimated seasonal parameters from the combined specification, both because they are little changed from the specification without 'news' effects and because they are not directly interpretable. They are available upon request from the author.

[16] This 0.25 decline in the parameters gives an approximate 15% reduction in the impact on derived standard deviation across the board.

in the interval immediately after an announcement, dropping to double the normal standard deviation in the following five minutes. Constructing the derived standard deviation from the corresponding parameters in our estimations gives a different picture. We predict an immediate post-announcement response of less than 3 times normal standard deviation which drops to just under twice the baseline level after ten minutes have elapsed. Hence, the impact of these announcements on the spot FX market is less pronounced than for the currency futures market.

So, the conclusions from the combined specification are as follows. The pre-release period seems to be characterised by overall volatility reduction, an effect which corresponds to dealers virtually shutting down activity in the face of the impending announcement. In the post-announcement period, the conclusion is that there is a prominent, immediate volatility impact which is eroded quite quickly over the following 10 minutes and from then on, dies out quite slowly. Again there is evidence of persistent and important informational effects from these macroeconomic and survey releases. The most prominent effects of announcements are intra-hourly. The study of DeGennaro and Shrieves (1995), employing an hourly observation window, necessarily misses all of this structure. Also, as most announcements are on the half-hour, their use of hourly observations implies that the observation containing a news item will contain both pre- and post-announcement periods. Disentangling the effects in these two periods seems, therefore, to be impossible. In order to examine announcement effects properly, an analysis at a very fine sampling frequency is essential.

4.4 Individual Announcements

Finally we present the volatility estimations in which the different announcements are treated individually. Which of our macroeconomic releases has most effect on the DM/Dollar spot rate? As previously noted, Ederington and Lee (1993) find that, of the present set of announcements, the Employment report, Trade figures, Retail Sales, Durable Goods and the PPI have the most prominent impact on the DM future's volatility in descending order. This also ties in with Harris (1995) who comments that the Employment report has become increasingly viewed as the key U.S. indicator by the markets.

Table 6 gives our results for the estimations where the news variable employed in each case is a simple announcement-specific dummy. It presents, for each piece of data, the volatility impacts 5 and 10 minutes post-release, the estimated persistence parameter for this increased volatility over the following hour and finally the implied percentage increase in return standard deviation for the five minutes immediately post-release (i.e. $e^{a_1/2}$.)

The Employment Report clearly has the greatest effect on volatility, the coefficient a_1 being almost one half as great again as that for the next most important and implying an instantaneous volatility jump of over 1000%. The report contains two key figures: payroll employment and the unemployment rate and perhaps this one large response incorporates two smaller impacts. Next come the Trade figures which engender, on average, a rise in return standard deviation of over 500%. Again this is unsurprising given the intuitive impact of exports and imports on the supply and demand for currency. The persistence of volatility is greater than average for both of the above announcements, possibly because both of these monthly documents contain multiple statistics and are lengthy and time-consuming to digest.

The next most important pair of announcements are the Retail Sales figures and the PPI report. Hence, the four most influential releases we derive from the spot FX data are also represented in Ederington and Lee (1993) in their top five for the DM future, demonstrating the similarity in importance across markets.

The Consumer Confidence figures, Durable Goods Orders and CPI figures then form a medium impact sub-group. These data show very similar immediate impacts, a standard deviation rise of around 300%, but the 10 minute response to the Durables figures is much greater than for the other pair and the persistence stronger. This announcement is the fifth of the group Ederington and Lee (1993) cite.

Finally there is a group of low impact announcements which comprises the Leading Indicators figures, the NAPM survey and the Industrial Production/Capacity Utilisation (IP/CU) results. It is clear that the IP/CU announcement has the smallest volatility impact across all dimensions, with the Leading Indicator figures being fairly important. The most surprising result of estimation is a ten minute impact for the NAPM which is small and negative, coupled with a negative persistence parameter, a result which implies damped oscillations in the NAPM volatility response!

Lastly, in Table 7, the results from the same individual specifications but using the absolute announcement forecast errors as our news data are presented. Rather than reporting the percentage standard deviation impact here, we include a different set of figures, containing the estimated immediate impacts, a_0, multiplied by the mean absolute forecast error for each particular release over our 12 month period.[17] Note that we also have two extra pieces of data which can be analysed here. This is due to the fact that we can split the Employment report into the unemployment rate and the payroll employment figures via their forecast errors, and can similarly separate

[17]This rescaling gives us a basis for the direct comparison of the 'news' impacts across announcements measured in differing units.

the Industrial Production and Capacity Utilisation figures.

The impact ranking which emerges broadly corroborates our results from the previously reported dummy variable specifications. The two main components of the Employment report are ranked first and second, although the difference between either of these immediate impacts and the next highest ranked is considerably diminished from the dummy results. This is to be expected as it is the combination of the unemployment rate and payroll figure volatility impacts which gives the total Employment report effect. Again, the next most important effect on volatility comes from the Mercantile Trade figures.

In comparison with the results of Ederington and Lee (1993) we again find that the four highest ranked from this study are represented in their top five, these being the unemployment rate, trade figures, durables and retail sales. The member of their five highest ranked announcements which does not conform with the results of this part of our study is the PPI release. In comparison to the dummy results, the scaled PPI impact has plummeted in rank. This may be due to the dummy results being dominated by a couple of very large price movements which are associated with large forecast errors. In this case, the linear specification in forecast error deals well with this variation in the data.

The NAPM, Leading Indicator and IP/CU figures are again towards the bottom end of the spectrum. There are, however, some anomalous estimation results associated with these releases. The leading indicator announcement now shows a negative persistence figure, the NAPM has almost zero persistence whilst the IP figures have a persistence parameter which is insignificantly different from unity.

So we can draw the following broad conclusions. The announcements which cause greatest post-release volatility are those associated with the Employment report and the Mercantile Trade report. Next in line come a group of releases including Retail Sales, Durable Goods orders and Consumer Confidence, all of which have large impacts on volatility also. Finally, the NAPM, Leading Indicators and IP/CU figures have consistently the smallest post-release impact.

5 Conclusions

In this work we have examined the importance of certain components of intra-daily FX volatility. Using a SV framework, based on that contained in Harvey, Ruiz, and Shephard (1994), we estimated seasonal patterns, announcement effects and an unobserved autoregressive component. Our results corroborate those of previous studies on seasonality, e.g. Andersen and Bollerslev (1994), which point to the prominence of this phenomenon in this market and the necessity of its inclusion in any intra-day volatility examination. The results from the announcement data show that these too are an important element in volatility determination, confirming that the results of Ederington and Lee (1993) carry over to the spot FX market in a qualitative sense, although the impact here is quantitatively smaller. Our final specification shows that markets seem to quieten down in anticipation of news releases, but that post-release there is a pronounced and persistent volatility impact. If the seasonal is omitted from the specification, then it is shown that the estimated 'news' parameters are overstated in magnitude, as one would expect.

Examination of individual announcements points to the Employment report and Trade figures being associated with extremely large volatility impacts. There are also consistent, large responses to Consumer Confidence, Retail Sales and Durable Goods order figures, whilst the NAPM, Leading Indicator and IP/CU releases have the smallest effect.

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Table 1

	Return	Residual	$\log(r^2)$
Mean	1.90E-06	0	-17.49
Variance	2.40E-07	2.40E-07	8.887
Skew	0.344	0.36	-1.27
Kurtosis	16.09	16.32	2.15
Q(20)	544.18	207.02	153715.8

Table 2

Panel 1

Baseline SV Model

	Coeff	s.e.	T-stat
ϕ	0.9546	0.0132	72.32
σ_v^2	0.457	0.1051	4.35
LogL			-179817

Panel 2

Restricted SV Model: ϕ=1

	Coeff	s.e.	T-stat
ϕ	1	-	-
σ_v^2	0.278	0.0066	42.22
LogL			-180486

Table 3

Estimates from SV/News Model

	Coeff	s.e.	T-stat
ϕ	0.954	0.0133	71.73
σ_v^2	0.456	0.1053	4.33
a_{-5}	-0.186	0.045	-4.16
a_{-4}	-0.273	0.047	-5.79
a_{-3}	-0.262	0.073	-3.55
a_{-2}	0.019	0.004	5.04
a_{-1}	0.415	0.078	5.29
a_0	0.493	0.078	6.32
a_1	2.376	0.142	16.72
a_2	1.533	0.173	8.86
a_3	1.390	0.219	6.36
a_4	1.184	0.052	22.59
a_5	1.004	0.157	6.38
a_6	0.869	0.225	3.86
a_7	0.730	0.133	5.49
a_8	0.979	0.146	6.72
a_9	0.317	0.025	12.49
a_{10}	0.664	0.177	3.76
a_{11}	0.345	0.012	28.05
a_{12}	0.355	0.068	5.22
a_{13}	0.804	0.099	8.13
a_{14}	0.371	0.046	8.01
a_{15}	-0.084	0.013	-6.45
Loglik			-179704

Table 4

Estimates from Seasonal SV Model
Panel 1: Trigonometric Parameters

	Coeff	s.e.	T-stat		Coeff	s.e.	T-stat
ϕ	0.962	0.0122	78.86	σ_v^2	0.309	0.0785	3.94
$\gamma_{1,1}$	-0.846	0.118	-7.18	$\gamma_{2,1}$	0.1	0.025	4.05
$\gamma_{1,3}$	0.520	0.026	20.33	$\gamma_{2,3}$	0.039	0.009	4.39
$\gamma_{1,4}$	0.133	0.007	19.34	$\gamma_{2,4}$	-0.082	0.023	-3.61
$\gamma_{1,5}$	-0.012	0.001	-9.18	$\gamma_{2,5}$	-0.003	0.001	-2.79
$\gamma_{1,9}$	0.137	0.009	15.19	$\gamma_{2,9}$	0.005	0.001	5.32
$\gamma_{1,10}$	0.139	0.003	49.66	$\gamma_{2,10}$	-0.006	0.001	-7.33
$\gamma^*_{1,1}$	-0.213	0.011	-19.05	$\gamma^*_{2,1}$	-0.156	0.015	-10.58
$\gamma^*_{1,3}$	-0.205	0.016	-13.06	$\gamma^*_{2,3}$	0.216	0.003	62.71
$\gamma^*_{1,4}$	0.360	0.013	26.7	$\gamma^*_{2,4}$	-0.179	0.011	-15.51
$\gamma^*_{1,5}$	0.196	0.032	6.1	$\gamma^*_{2,5}$	-0.05	0.007	-6.92
$\gamma^*_{1,9}$	-0.09	0.006	-14.62	$\gamma^*_{2,9}$	0.04	0.006	7.18
$\gamma^*_{1,10}$	0.032	0.003	10.89	$\gamma^*_{2,10}$	0.013	0.003	3.6

Table 4 (cont.)

Panel 2: Japanese Lunch Dummies

	Coeff	s.e.	T-stat
μ_1	-0.905	0.121	-7.49
μ_2	-1.012	0.327	-3.12
μ_3	-1.243	0.148	-8.41
μ_4	-1.430	0.145	-9.89
μ_5	-1.555	0.130	-11.97
μ_6	-1.580	0.090	-17.55
μ_7	-1.429	0.109	-13.13
μ_8	-1.206	0.139	-8.65
μ_9	-1.103	0.224	-4.92
μ_{10}	-1.270	0.385	-3.30
μ_{11}	-0.834	0.052	-16.05
μ_{12}	-0.319	0.022	-14.37
μ_{13}	0.949	0.110	8.61
μ_{14}	1.146	0.076	15.09
μ_{15}	0.975	0.095	10.30
LogLik			-179227.3

Table 5

Announcement Effects from Combined Model

	Coeff	s.e.	T-stat
ϕ	0.962	0.0122	78.85
σ_v^2	0.31	0.0786	3.94
a_{-5}	-0.29	0.050	-5.78
a_{-4}	-0.406	0.027	-14.96
a_{-3}	-0.426	0.035	-12.15
a_{-2}	-0.213	0.011	-19.59
a_{-1}	0.192	0.038	5.12
a_0	0.269	0.054	4.95
a_1	2.127	0.117	18.24
a_2	1.270	0.10	12.22
a_3	1.127	0.112	10.05
a_4	0.916	0.085	10.78
a_5	0.744	0.224	3.31
a_6	0.598	0.046	12.90
a_7	0.459	0.201	2.28
a_8	0.711	0.021	34.10
a_9	0.056	0.006	9.59
a_{10}	0.416	0.053	7.77
a_{11}	0.121	0.027	4.43
a_{12}	0.155	0.010	14.78
a_{13}	0.622	0.101	6.09
a_{14}	0.210	0.008	26.51
a_{15}	-0.205	0.015	-14.06
LogLik			-179174.6

Table 6

Individual Announcement Impacts using Dummy Specification

Announcement	a1	a2	Persistence	% s.d. Response
Employment	4.66	3.02	0.85	1000+
Trade	3.59	1.68	0.86	600+
Retail Sales	3.20	2.51	0.80	450+
PPI	3.04	1.95	0.76	450
Cons. Conf.	2.38	1.10	0.80	330
Durables	2.37	1.65	0.88	330
CPI	2.35	2.01*	0.74	325
Lead. Ind.	1.89	1.49	0.67	260
NAPM	1.86	-0.49*	-0.48	250
IP/CU	0.72	0.71	0.9	140

Note : as more-or-less all coefficients are significant, only those insignificant at 5% are indicated, with an asterisk.

Table 7

Individual Announcement Impacts using Absolute Forecast Errors

Announcement	a1	a2	Persistence	Scaled Impact
Unemp. Rate	19.72	13.20	0.87	2.96
Payroll Emp.	0.038	0.026	0.51	2.8
Trade	2.33	1.30	0.83	2.74
Retail Sales	4.47	2.93	0.88	1.75
PPI	5.83	4.42	0.79*	1.262
Cons. Conf.	0.45	0.17	0.74	1.84
Durables	0.88	0.37	0.90	2.09
CPI	12.34	8.41	0.70	1.65
Lead. Ind.	7.26	4.13	-0.92	1.06
NAPM	0.794	0.08	0.02*	1.56
Ind. Prod.	8.37	4.48	1.05	0.70
Cap. Util.	1.26	1.65	0.93	0.35

Note : as more-or-less all coefficients are significant, only those insignificant at 5% are indicated, with an asterisk.

Figure 1

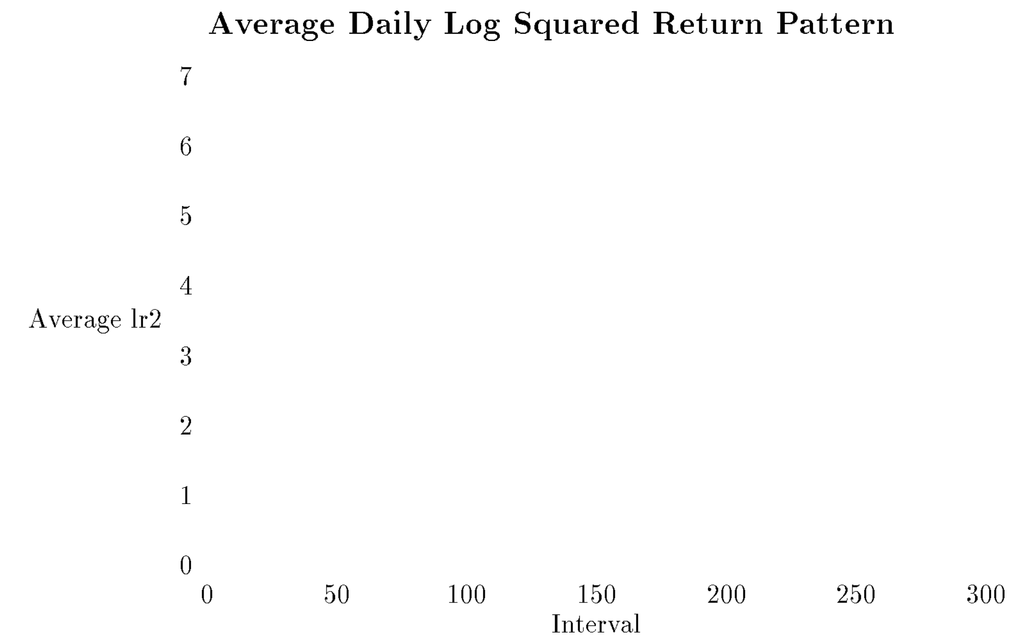

Figure 2

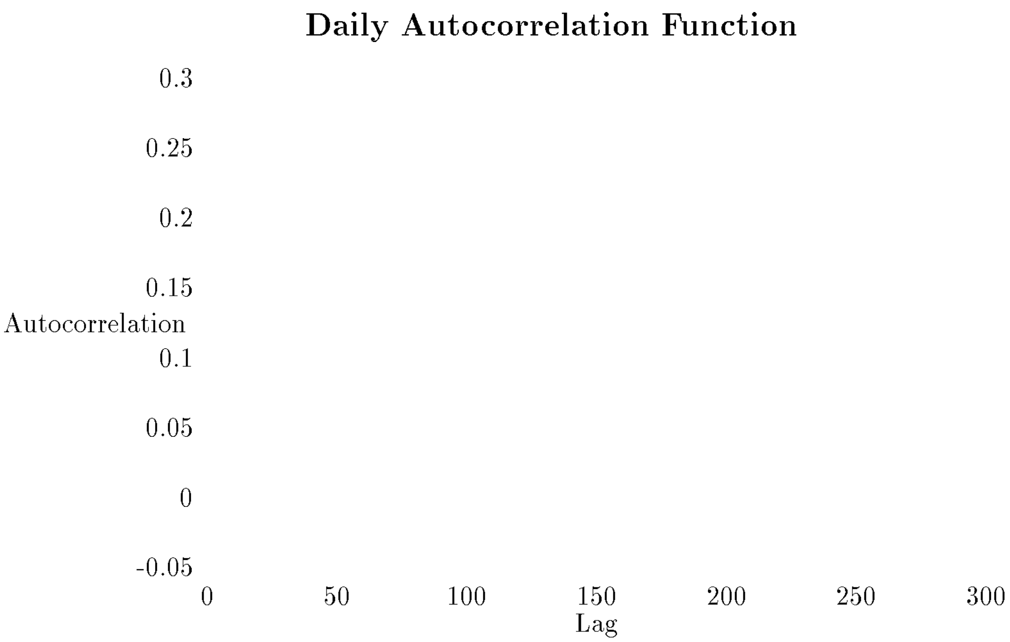

Figure 3

Average Weekly Log Squared Return Pattern

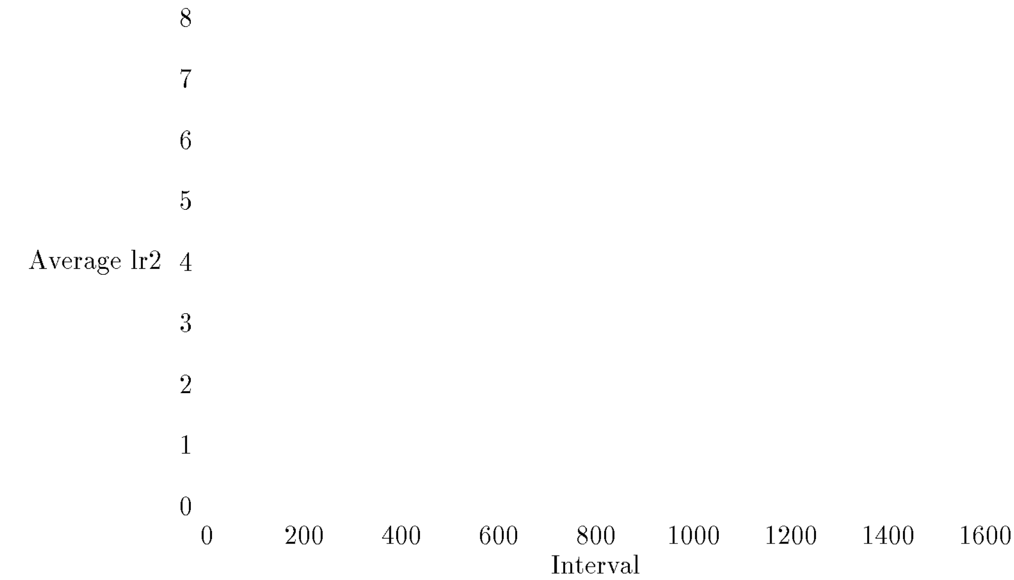

Figure 4

Weekly Autocorrelation Function

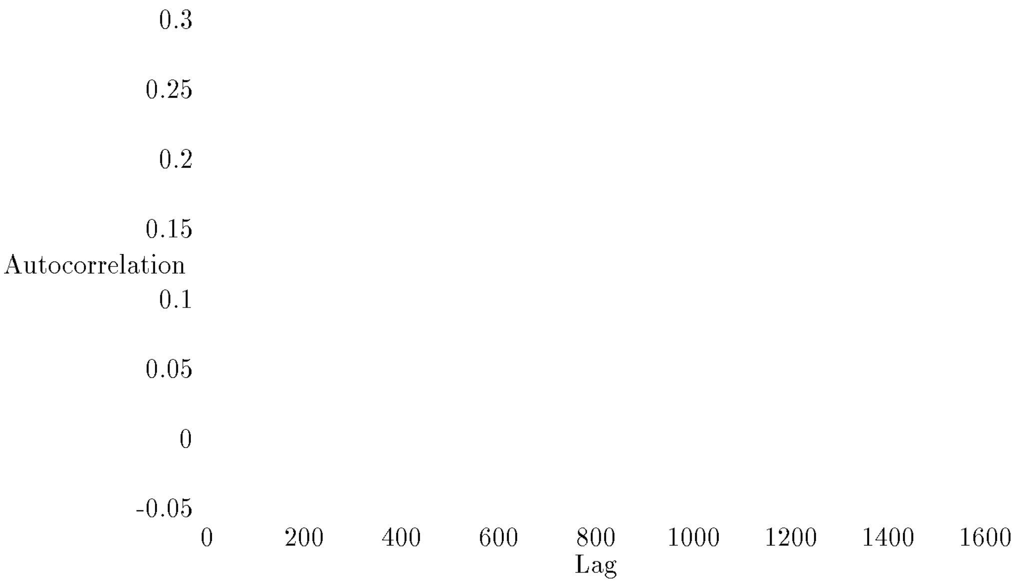

Figure 5

Average Daily Log Squared Return Pattern in Summer and Winter

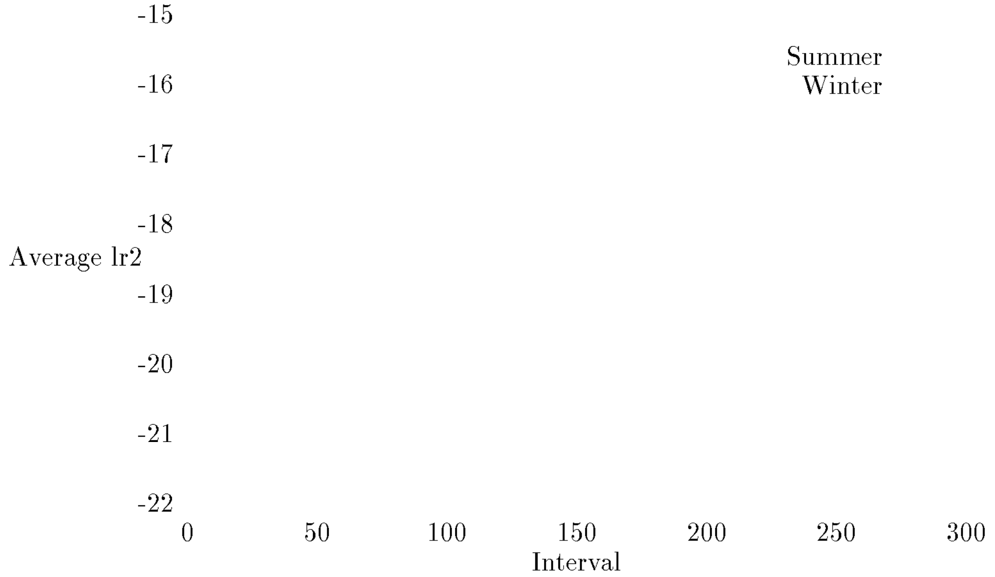

Figure 6

Comparison of Absolute Returns and Derived Volatility

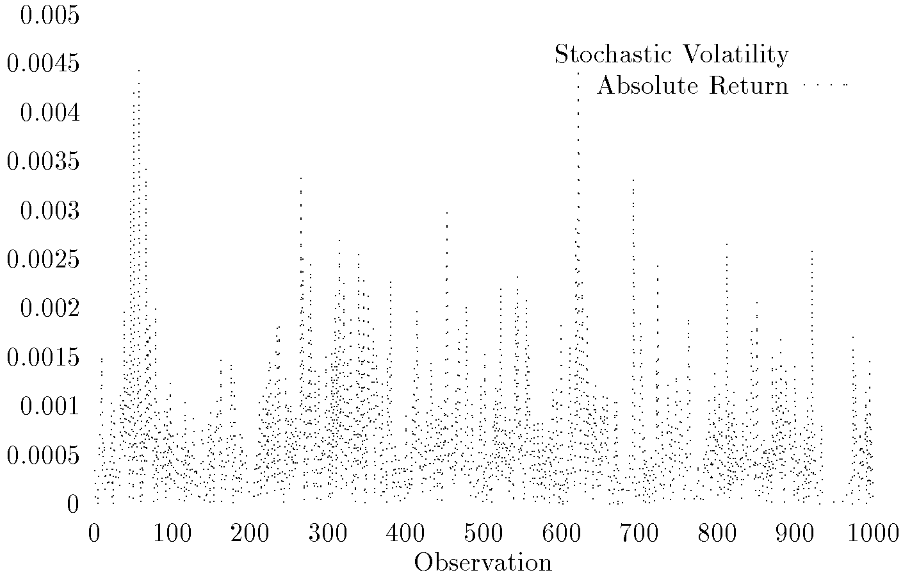

Figure 7

Average State Value from Non-seasonal Model and Log Squared Returns

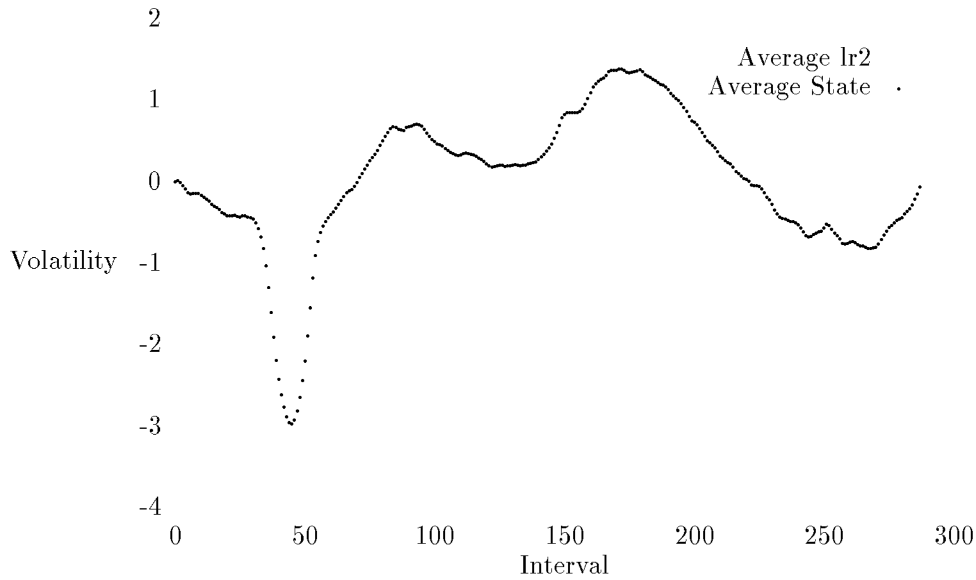

Figure 8

News Impacts from Non-Seasonal Model

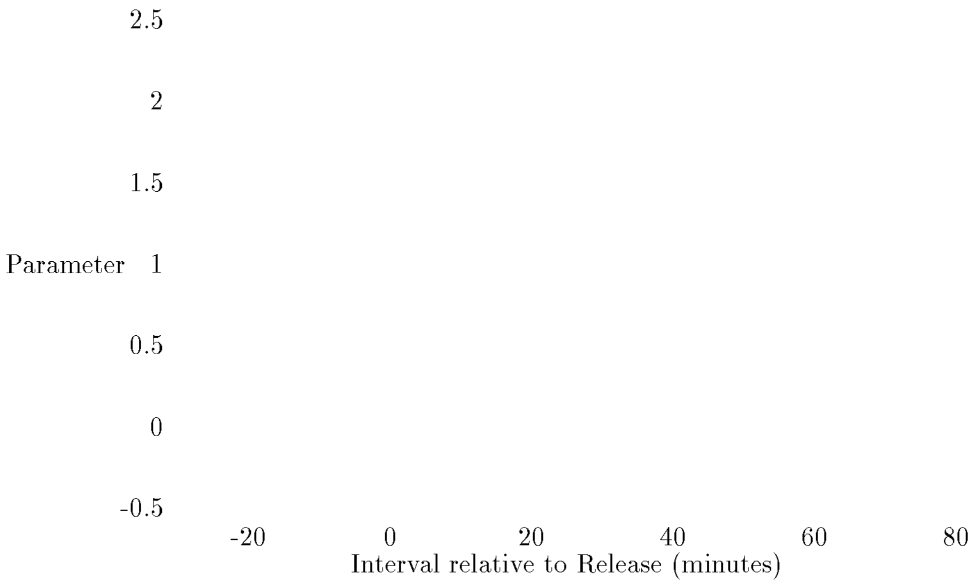

Figure 9

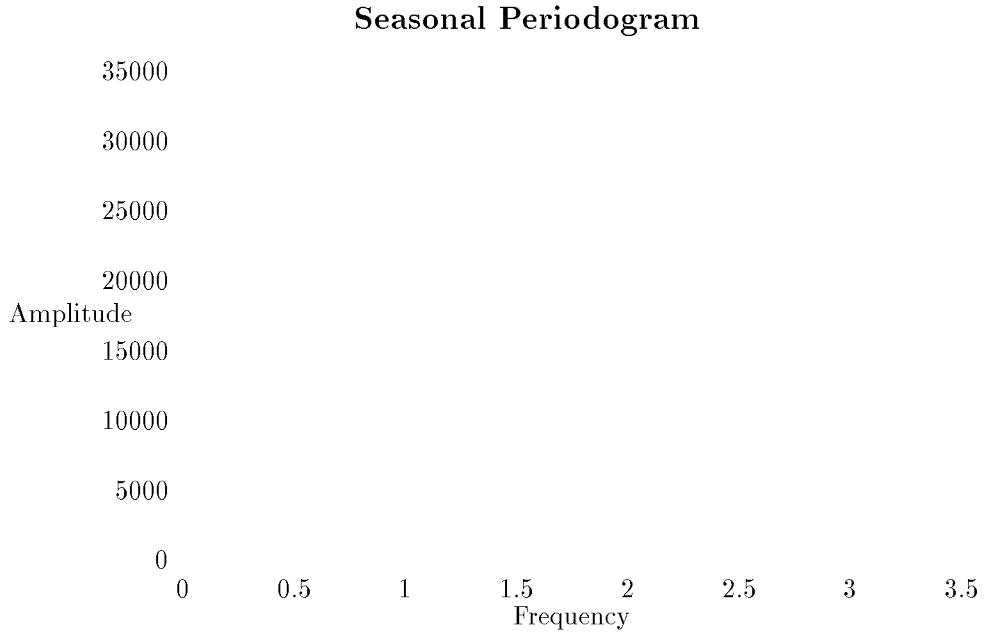

Figure 10

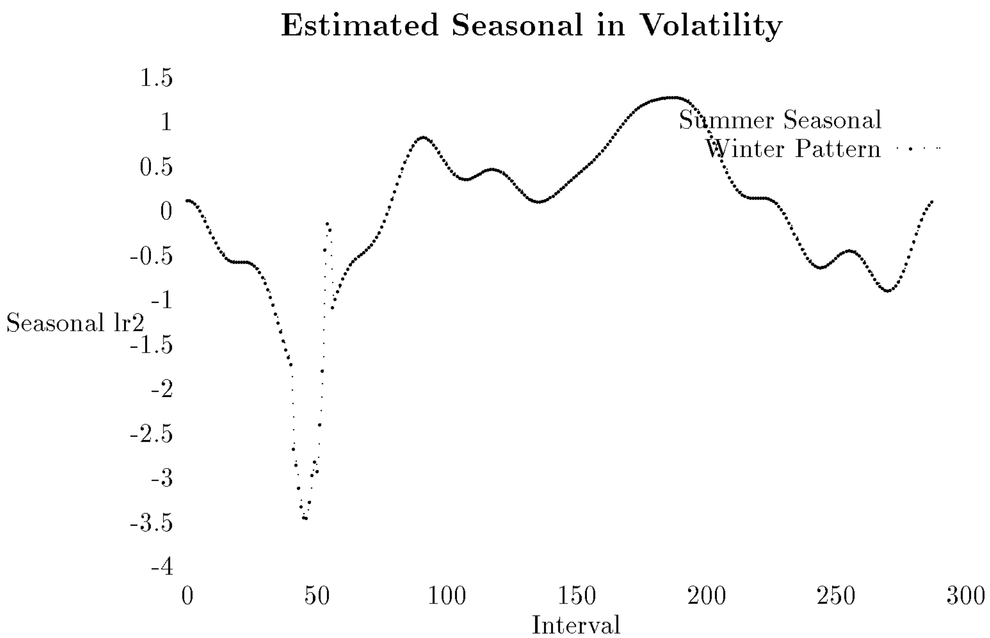

Figure 11

Weekly Autocorrelation Function for Deseasonalised Log Squared Returns

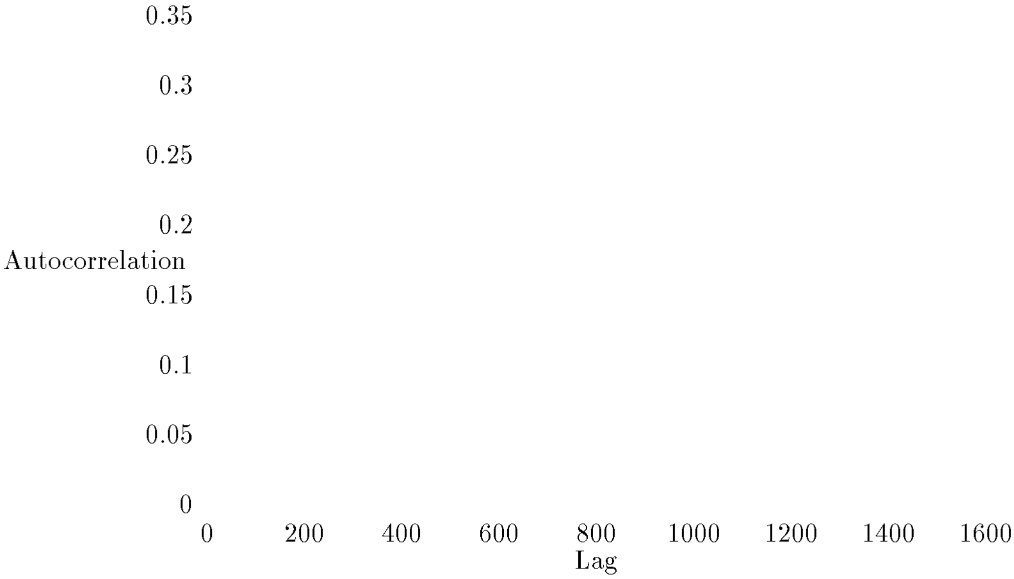

Figure 12

News Effects from Seasonal and Non-Seasonal SV Models