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DETERMINISTIC SEASONAL VOLATILITY IN A SMALL AND INTEGRATED STOCK MARKET: THE CASE OF SWEDEN*

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Using daily data for the Swedish stock market for the last two decades, it appears that no distinct and firm deterministic seasonal pattern for the conditional volatility for the Swedish stock market has been found. The daily turnover in the Swedish stock market has an impact on and to some extent eliminates seasonal patterns in conditional volatility. We can also conclude that a feedback from the US stock market to the conditional volatility in the Swedish market exists. The evidence from a simulation with 400 different trading rules also supports the hypothesis of a weak form of market efficiency. (JEL: G14)

1. Introduction

"October is one of the peculiarly dangerous months to speculate in stocks. The others are: July, January, September, April, November, May, March, June, December, August and February." This observation, which has been attributed to the well-known author Mark Twain, can be easily understood, as risk in the stock market is roughly the same for every month of the year. Thus, risk or volatility should not be significantly higher, for example, in March than it is in October. However, for the last decade or so, the popular business press has told us a different story. Almost every autumn the press voices fear of a stock market crash. October is the favourite month for this alleged event. Thus, according to the press, volatility on the stock market should be higher in the autumn and particularly high in October. No thorough explanation for this phenomenon has been given except that the stock market is very nervous in the autumn.

An interpretation of the business press hypothesis is that one can expect to find a deterministic seasonal pattern in the volatility of the stock market. The Mark Twain hypothesis says that this will not be the case. A quick glance at data for monthly standard deviation (unconditional volatility) for daily stock returns for the US and Sweden from 1986 to the end of October 1999, indicates that the difference between the highest and lowest monthly figures are roughly the same for the two stock markets.[1] However, if October '87 is excluded from the sample the gap between the highest and lowest value of the standard deviation is three times bigger in Sweden compared with the US.

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[1] *See Table 1 below and the table in the appendix for a more extensive presentation of the data.*

A rude conclusion drawn from these statistics, ignoring October ’87, is that the Mark Twain hypothesis might fit the US market but maybe not the Swedish stock market.

If a significantly different degree of volatility in the stock market can be observed for different months over a period of time, this of course is of interest for, among others, the participants in the financial markets. A deterministic seasonal volatility is also in conflict with the concept of an efficient capital market. Volatility or risk is for instance priced in the option market. An option contract on a stock or a stock index with a high expected risk in the future yields a higher premium than a contract with an expected lower risk.

Assume, just for the matter of argument, that a given stock has the same expected risk (business risk) for two months, *ceteris paribus*, where one of the months also displays a deterministic seasonal volatility. In this case the premium in the option market for the stock will vary for the two months despite the fact that the underlying expected business risk stays the same. This is of course not logical and very odd and there must be an explanation for this phenomenon. We will come back to this discussion and argue like Lamoureux and Lastrapes (1990) that the difference in conditional volatility for stocks is due to the amount of information that reaches the market.

The discussion of the efficiency of the stock market is often based on the random walk hypothesis. Seasonal deterministic volatility is inconsistent with the most restrictive form of the hypothesis that states that the dynamics of $\ln p_t$ (i.e., the logarithm of the stock price) are given by the following equation:

$$(1) \quad \ln p_t = \mu + \ln p_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim \mathrm{IID}(0, \sigma^2)$$

where μ is a constant drift parameter and ε_t is the independent and identically distributed (IID) increment with a mean 0 and variance σ^2.[2] A less restrictive version of the random walk hypothesis is obtained if the assumption of IID increments is relaxed and assuming independent but not identically distributed (INID) increments instead.[3] A random walk model with INID increments contains a more general price process; i.e., it allows for conditional or unconditional heteroskedasticity in the increments or time variation in the volatility of the model’s dependent variable.[4]

The assumption of INID increments seems to be a plausible assumption for financial asset prices over longer time spans. For stock markets around the world there have been countless changes in the economic, social, technological, institutional and regulatory environment in which stock prices are determined. The assertion that the probability law of daily stock returns has remained the same for the last ten, twenty or thirty years is implausible. A general empirical observation for asset prices is also that relative change in stock prices shows periods or clusters of higher or lower changes.

If dependent and non-identical increments in the error term of equation (1) are allowed**,** the conditional volatility for the stock market can be estimated**.** At the same time one can analyse whether seasonal deterministic volatility can be traced. Several studies have reported seasonal patterns in the conditional volatility of the stock market (see, e.g., Glosten *et al.*, 1993, and Hansson and Hördahl, 1997). Lamoureux and Lastrapes (1990) argue that the difference in conditional volatility for stocks is due to the amount of information that reaches the market. For example, the explanation for high volatility in October and January might be due to the amount of news that enters the market. We also know that in October and January the financial statements for the first three quarters of the year and for the full year, respectively, have been made public for many of the firms listed on the stock market.

The above-mentioned paper by Lamoureux and Lastrapes uses the so-called mixture distribution model based on Clark (1973). This

[2] Independence for the increments implies not only that they are uncorrelated ($[Cov(\varepsilon_t, \varepsilon_{t-k}] = 0$ for all $k \neq 0$) but also that any non-linear function of the increments is also uncorrelated. This can be interpreted as the orthogonality condition.

[3] The abbreviations for the two distributions of the increment discussed here are taken from Campbell et al. (1997).

[4] See Campbell et al. (1997) for a classification of different versions of random walk models.

model assumes that the number of trades per unit of time is a random variable and the price change per unit of calendar time is the sum of price changes occurring in the transactions that take place during the period. If the number of trades per unit of calendar time is serially correlated, then the conditional variance of returns, in calendar times, will display a GARCH-type (generalised autoregressive conditional heteroskedasticity) of behaviour.[5] Lamoureux and Lastrapes use the daily trading volume as a proxy for the mixing variable and show for the US market that including this variable in the conditional variance equation eliminates the GARCH effects. Andersen (1996) works with a modified mixture distribution model that distinguishes between two types of information arrival processes i.e. informed traders and noise traders.

The purpose of this paper is to test for the presence of a deterministic seasonal pattern in conditional and unconditional volatility for Swedish stock returns. A significant deterministic pattern is a form of inefficiency in the capital market because there is no logical reason why volatility as such should vary during the year. As already has been mentioned, data indicate a greater monthly spread in volatility in stock returns for Sweden than for Dow Jones. The mixture model will be a starting point for an analysis of seasonal deterministic volatility in the stock market. The starting hypothesis for this paper is that the observed seasonal deterministic volatility might be due to the flow of information to the market.

Accomplishing the test of the stated hypothesis will also implicitly be a test for information efficiency on stock returns in its weak sense. Working with GARCH models implies that both a variance and mean equation have to be specified. Testing for the weak form of market efficiency or the random walk hypothesis states, in plain language, that today's stock returns are independent of previous periods' stock returns (including all lagged value of all other economic variables) and the deviations of returns from its long term level (the constant drift parameter, i.e. μ in equation 1) are strictly "white noise".[6]

Our results indicate that the estimated conditional volatility for daily Swedish stock returns hardly shows any sign of deterministic monthly seasonal effects for a sample of daily data covering most of the 1990s. Thus the Mark Twain hypothesis cannot be rejected. We can also conclude that our test shows that the weak form of market efficiency for the Swedish stock market cannot be rejected if we employ a less restrictive random walk hypothesis.

2. *The mixture distribution model and GARCH modelling*

The starting point for the mixture distribution model, as already mentioned, is that the number of trades per unit of time is a random variable and the price change per unit of calendar time is the sum of price changes occurring in the transactions that take place during the period. Let δ_{it} denote the ith intraday equilibrium return increment in day t. This means, as already has been pointed out, that the number of trades per unit of time is a random variable and the price change per unit of calendar time is the sum of price changes occurring in the transactions that take place during the period. Accordingly the error term in equation (1) can be written as

$$(2) \qquad \varepsilon_t = \sum_{i=1}^{N_t} \delta_{it}$$

The random variable N_t is the mixing variable that measures the stochastic rate at which information flows into the market. ε_t is drawn from a mixture of distributions where the vari-

[5] *ARCH (Autoregressive conditional heteroskedasticity) models were introduced by Engle (1982) and generalised as GARCH models by Bollerslev (1986). These models are widely used in various branches of econometrics, especially in financial time series analysis. See Bollerslev, Chou and Kroner (1992) and Bollerslev, Engle and Nelson (1994) for surveys.*

[6] *Innumerable tests of the weak form of market efficiency have been performed and recorded in the literature. For an overview see Campbell et al. (1997), and Bollerslev and Hodrick (1995). For a test of Swedish data see for example Frennberg and Hansson (1993), and Berg and Lyhagen (1998). The last mentioned paper also carries out a test for long-run dependency in stock returns.*

ance of each distribution depends upon information arrival time. The assumption of equation (2) is that daily returns are generated by a subordinated stochastic process in which ε_t is subordinate to δ_{it}, and N_t is the directing process. If δ_i is IID with mean zero and variance σ^2 and N_t is sufficiently large, then the conditional distribution for ε_t is $\varepsilon_t | N_t \approx \text{IID}(0, \sigma^2 N_t)$. The conditional variance of ε_t can thus be written as

$$(3) \qquad \sigma^2_{\varepsilon_t | N_t} = E(\varepsilon_t^2 | N_t) = \sigma^2 N_t = h_t$$

Assume next that daily information flows are serially correlated and write N_t as a correlated process

$$(4) \qquad N_t = c_0 + c_1(L) N_{t-1} + u_t$$

where c_0 is a constant, $c_1(L)$ is a lag polynomial of order q, and u_t is white noise. The equation for the conditional variance for the residual can be obtained by substituting equation (4) into (3)

$$(5) \qquad \sigma^2_{\varepsilon_t | N_t} = \sigma^2 c_0 + \sigma^2 c_1(L) N_{t-1} + \sigma^2 u_t$$

Equation (5) generates the persistence in the conditional variance that is typical for asset prices and can be picked up by a GARCH model.

Several ways of dealing with the fact that the number of intraday equilibrium differs have been advocated in the literature (see Montalvo, 1999, for a brief survey). One possibility is to follow Lamoureux and Lastrapes and assume that daily trading volume can be used as a proxy for daily information flows into the market and that daily information flows are serially correlated. There is a discussion in the literature that trading volume plays an imprecise role for asset prices, but it is still likely that volume contains information about the dynamics of the asset markets.[7]

In our test we will use the trading volume on the Swedish stock market as a proxy for the mixing variable. We use a TGARCH model for this test, and we also test whether the risk (conditional variance) of stock returns is seasonally dependent. The TGARCH(1,1) model (T for threshold) for the conditional variance is specified in equation (6).[8] It is often observed in stock returns that bad news has a greater impact on volatility than good news. The TGARCH specification allows for testing whether downward movements in the market (bad news) are followed by higher volatility than upward movements (good news) of the same magnitude.[9] The equation can be written as:

$$(6) \qquad h_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \alpha_2 \varepsilon^2_{t-1} k_{t-1} + \beta h_{t-1} + \mathrm{B}\Pi$$

where $k_t = 1$ if $\varepsilon_t < 0$ and 0 otherwise.

If bad news has a greater impact on volatility than good news, a leverage effect exists, and we expect $\alpha_2 > 0$. The impact of good news will be α_1 while bad news has an impact of $\alpha_1 + \alpha_2$. The β parameter measures the degree of persistence in the conditional variance. The sum of the parameter values of alfa and beta measure the persistence in volatility shocks. If the sum of these parameters for the model is close to, but less than one, the shock dies out over time; a value close to one means that the shock will affect the conditional variance and the forecast of it for quite some time. If the sum of the parameters is equal to one the shock will affect volatility into the indefinite future.[10]

B and Π in equation (6), are vectors of parameters and other variables, respectively. The trading volume and dummy variables to discern eventual deterministic seasonal effects will be included in the Π vector. We will also include other variables in the vector that will be discussed later.

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[7] *See O'Hara (1995) for a survey of models for the market microstructure.*

[8] *The (1,1) in TGARCH(1,1) refers to the presence of a first order GARCH term (previous conditional variance) and a first order ARCH term (news about volatility from a previous period), respectively.*

[9] *To check the robustness of the empirical results presented in Table 2, the model has also been estimated with an EGARCH specification and similar conclusions could be drawn from this model specification. We are aware that alternative specifications have also been suggested for the estimation of periodic conditional heteroskedasticity, see, e.g., Engle and Russell (1998) and Bollerslev and Ghysels (1996).*

[10] *Models with the sum of these parameter values equal to one are called integrated GARCH models or IGARCH.*

To complete the GARCH model a mean equation has to be specified. If equation (1) is rearranged so that the lagged logarithmic stock price is moved to the left-hand side of the equal sign we get a function that says the relative stock returns will be a linear function of a constant and news (error term) – the mean equation. In the empirical test we will add a moving average term, MA(1), on the right-hand side of the mean equation to cope with serial correlation, which may be caused by non-synchronous trading in the stocks. Other right-hand variables will also be included, which will be discussed later.

3. *Data and descriptive statistics*

The data used in our test is the SIX Return Index for the Swedish stock market. The index is in nominal terms, and dividends are reinvested. The index is a value-weighted broad stock market index designed to measure the market performance of the Stockholm Stock exchange (SSE). The price used is the daily closing price. The daily turnover for the SSE A-list (SEK millions) together with the Dow Jones daily industrial average, Swedish Exchange rate (SEK/$) and the 6-month Stibor interest rate are also used as variables in the test. Closing rates have been used for these variables. Summary statistics for these variables are displayed in Table 1.

Twelve monthly dummies equal to one for the defined month (in all other cases equal to zero) and named after the respective month have been generated and used in the test. A dummy for holidays (i.e., Christmas, New Year, Easter, Whitsuntide etc.) which takes the value of one for the first trading day after the holiday

Table 1. Descriptive statistics for daily stock returns (in per cent) for the SIX Return Index and other variables. The full sample starts on 2 January 1986 and ends on 29 October 1999.

	Mean	Max	Min.	Std. Dev.	Skewness	Kurtosis	Obs.
Jan	0.17	7.19	–4.18	1.37	0.16	5.51	283
Feb	0.17	2.45	–5.43	1.03	–0.74	5.75	269
March	0.10	2.79	–2.51	0.88	–0.14	3.26	303
April	0.15	3.03	–4.16	0.98	–0.33	4.73	279
May	0.24	3.46	–3.15	0.82	–0.23	4.44	263
June	0.05	2.50	–3.15	0.75	–0.14	4.52	282
July	0.12	2.15	–3.28	0.79	–0.70	4.06	298
August	–0.09	4.63	–6.62	1.24	–0.58	6.93	305
September	–0.10	6.30	–3.89	1.29	0.22	6.54	292
October	–0.03	9.78	–9.14	1.94	–0.42	9.98	308
November	0.03	8.44	–5.71	1.56	0.50	8.44	264
December	0.09	4.32	–4.68	1.18	–0.03	4.67	252
October ‘87	–1.04	8.05	–9.14	4.03	–0.10	2.98	22
October ex.‘87	0.05	9.78	–7.76	1.66	0.05	11.01	286
After weekends	–0.01	9.78	–7.76	1.46	–0.44	10.27	610
All other days	0.09	8.44	–9.14	1.15	–0.13	10.62	2788
After holidays*	0.27	4.23	–4.78	1.43	–0.42	5.11	102
All other days	0.07	9.78	–9.14	1.20	–0.25	11.33	3296
Full sample	0.07	9.78	–9.14	1.21	–0.25	11.00	3398
2 January 1996 to 20 October 1992	0.03	8.05	–9.14	1.26	–0.65	11.95	1668
21 October 1992 to 20 October 1999	0.11	9.78	–7.34	1.16	0.27	9.41	1730
Daily turnover#	2142	28550	14	2689	2.01	8.98	3399
Dow Jones, daily stock returns	0.06	9.67	–25.65	1.10	–4.11	96.86	3398
Exchange rate (SEK/$)	6.92	8.65	5.09	0.83	0.09	1.86	3399
Interest rate	8.91	26.00	2.90	3.41	0.08	2.85	3157

* Holidays include Christmas, New Year, Easter, Whitsuntide etc.
\# Millions of SEK

and a dummy for weekends (non-holiday weekends) equal to one on Mondays after the weekend are also used.

The full sample for the SIX Return Index consists of 3398 observations that start on 1 January 1986 and end on 29 October 1999 – see Table 1. Stock returns on a monthly basis as well as returns per day after weekends and holidays are shown. Statistics for excluding October '87 from the sample and for October '87 separately together with statistics for the whole sample are also displayed in the table. According to the mean value of the stock returns, we can learn that for the sample period they seem to be higher in the first half of the year than in the second half. What is noteworthy is that there is almost no average return after weekends while return after a holiday is on average 0.27 per cent! For the full sample the average return is 0.07 percent, which will make up to an average return around 15 per cent on a yearly basis. Splitting the sample in two parts reveals a lower return and higher standard deviation for the period that ends on 20 October 1992 compared with the last part of the sample.

The standard deviation is highest for October and November. The lowest number can be found for June and July while the autumn shows higher figures. As already has been mentioned**,** the volatility for October '87 is high. Excluding this month from the sample**,** the remaining month of October has a standard deviation of 1.66 per cent, which is the highest for all the months in the sample. The highest and lowest value of the standard deviations for the Swedish stock market, excluding October '87, is three times bigger compared with the US market (see table in the appendix). According to observed standard deviations in Table 1 Sweden seems to have a greater variation in monthly returns than the US.

One remarkable feature is that average stock returns are highest in May at the same time as the standard deviation is quite low! Return per unit of risk for the month is 0.29. Even February and April show figures on a level with May's return per unit of risk. One explanation for the high returns for April and May is that dividend payments are concentrated to these two months.

Data for stock returns reveal that they do not match the normal distribution assumption that is common for many financial time series. Both skewness and kurtosis statistics indicate that the data distributions are not normally distributed. The kurtosis of the normal distribution is 3. If the kurtosis exceeds 3, the distribution is peaked (leptokurtic) relative to the normal. Our sample displays numbers from 3.26 to 9.98 for different months and 11.00 for the full sample.

We have also run Ljung-Box test statistics for serial correlation in levels and squares of the daily stock returns. This test reveals the possibility of dependence in both the first and higher moments of the return distribution. For both returns in levels and squares the test turns out to be significant up to the 200th order, not reported in the table. Accordingly both daily stock returns and squared daily stock returns are serially correlated.

4. *Specification and estimation results*

We have experimented with dummy variables for all months, Mondays after weekends and the first day after holidays in both the conditional mean and variance equation. In the mean equation a MA(1) term is included to capture the serial correlation, which may be caused by non-synchronous trading in the stocks. The lagged value of daily returns on the Dow Jones industrial average is included in the mean equation for the same reason. Quite a few Swedish stocks are traded on the US market and the non-synchronous trading has the effect that the stock market in Stockholm might adjust to yesterday's stock prices in New York and the information that has gathered in the prices while the exchange in Stockholm has been closed.[11]

A piece of empirical evidence that supports this hypothesis is that the null that daily returns in New York does not Granger cause Stockholm can be rejected for lags from one to one hundred.

[11] Stockholm lies 6 hours ahead of New York. Closing time in New York for the stock exchange is 11½ hours before opening in Stockholm.

The lagged value of daily returns on the Dow Jones industrial average has also been included in the variance equation. The argument is that this variable might capture the "nervous tension" of the world's stock market in an adaptive manner. We expect a negative impact of this variable; a fall (rise) in the stock prices in New York will increase (decrease) the tension in Stockholm and thus the conditional variance. In the variance equation the Swedish stock exchange (A-list) daily turnover (millions SEK) is included as a proxy variable for the mixing model as has been discussed.

Before we discuss the reported estimation result, it is worth mentioning that we also have tested for effects of exchange rates (SEK/$) and interest rates in the models. Neither of the variables turns out to be significant at the 5 per cent level in the conditional mean or variance equation. Previous research on US data has found that interest rates have an impact on the conditional variance, see Glosten *et al.* (1993).

We have chosen to show the estimation result of altogether four models specifying the variance model as a TGARCH(1,1). Model (1) in Table 2 gives the results when the turnover variable and the lagged value of Dow Jones daily returns are not included in the variance equation. In model (2) these two variables are included. Models (1) and (2) are estimated using the full sample. The remaining two models have the same specification as (2) but the sample is split into two equal parts. The reason for this split is to test the stability of the parameters in the models. The estimated equations are specified with all seasonal dummy variables but we have chosen to only display significant dummy variables – t-values greater than 1.96. At the bottom of the table statistics for different diagnostic tests for the residuals are shown.

The models have also been estimated without the monthly dummy variables and at the bottom of the table statistics for the adjusted R^2 from this experiment are displayed. Without exception the adjusted R^2 from these models is higher than for the models where the dummy variables are included. This is an indication that the monthly dummy variables do not improve the fit of the model. We have also run a F-test and testing whether the monthly dummy variables all jointly have zero coefficients. The result of this test, not reported in the table, was that we could not reject at the 5 per cent level the null of all the monthly dummy variables having zero coefficients.

The mean equation and market efficiency

Coming to the estimated parameters**,** the only dummy variable that had a significant impact in the conditional mean equation for most of the models was the variable for weekends. Neither the monthly dummy variables nor the holiday dummy variable had any significant impact in this model. The conditional mean model indicates that Mondays after ordinary weekends had a negative impact on expected return.[12]

However this is not entirely true. When the model is estimated for the last part of the sample, the weekend variable had no significant effect. Notice that for this period the MA(1) term is also insignificant. Thus, for the last sample period only two arguments appear in the mean equation, the constant and the lagged value of daily Dow Jones stock returns. The last variable is supposed to capture the effect of non-synchronous trading and does not, according to our point of view, jeopardise the efficient market hypothesis.

To support this last bold statement**,** simulation experiments with different trading rules on the daily Dow Jones stock returns have been carried out to investigate the possibility of earning money on the correlation between yesterday's stock price changes in the US and the price changes today in Stockholm. We have constructed trading rules for long and short positions in Swedish stocks conditional to yesterday's change in the Dow Jones index. The de-

[12] *Although the weekend variable ends up with a negative parameter this does not necessarily mean that it is possible to do arbitrage on this statistical regularity. A simple simulation with a trading rule that says sell on Friday and buy on Monday gives a slightly lower return than stay long for the whole period if buying and selling stocks is free of charge. Assuming a very low and unrealistic brokerage fee for each trade of 0.05 per cent gives approximately half the return compared to stay long. Higher and more realistic fees gradually eliminate all returns for this trading rule.*

Table 2. TGARCH estimates for daily stock returns for the SIX Return Index. Robust *t*-values inside parentheses.

	Jan. 2 1986 to Oct. 29 1999		Jan. 2 1986 to Oct. 20 1992	Oct. 21 1992 to Oct. 29 1999
	1	2	3	4
Constant	0.109	0.113	0.097	0.101
	(7.13)	(7.93)	(4.68)	(4.00)
Weekend	–0.140	–0.120	–0.238	
	(–3.52)	(–3.19)	(–4.83)	
Dow Jones (–1)	0.319	0.306	0.291	0.316
	(14.53)	(13.79)	(15.61)	(10.67)
MA(1)	0.109	0.115	0.210	0.027
	(5.64)	(5.82)	(7.56)	(0.98)
α_0	–0.017	0.012	0.098	0.060
	(–1.14)	(0.71)	(1.09)	(1.75)
α_1	0.060	0.056	0.054	0.052
	(2.62)	(2.44)	(1.89)	(1.26)
α_2	0.100	0.094	0.197	0.113
	(3.53)	(3.32)	(4.12)	(2.51)
β	0.841	0.834	0.714	0.808
	(46.55)	(47.06)	(23.48)	(21.00)
Weekend	0.203	0.148	0.159	
	(3.94)	(3.58)	(3.26)	
Holiday	0.323	0.273	0.239	0.279
	(3.94)	(4.12)	(2.91)	(2.27)
March			–0.198	
			(–2.37)	
May			–0.179	
			(–2.11)	
June		–0.031	–0.212	
		(–1.99)	(–2.50)	
August	0.086			
	(2.51)			
September			–0.204	
			(–2.40)	
Turnover*10^4		0.007	0.001	0.007
		(3.58)	(4.56)	(2.23)
Dow Jones (–1)		–0.064	–0.036	–0.070
		(–3.74)	(–2.52)	(–2.76)
Adjusted R^2	0.1114	0.1100	0.1280	0.0780
Log likelihood	–4633.3	–4594.4	–2148.1	–2414.5
Residual test				
Skewness	–0.26	–0.18	–0.53	0.14
Kurtosis	5.21	5.07	6.03	3.62
Jarque-Bara	730	628	716	33
Q(5)	0.07	0.04	0.02	0.68
Q(50)	0.31	0.21	0.00	0.72
Qsq(5)	0.19	0.09	0.84	0.03
Qsq(50)	0.99	0.88	0.97	0.65
Adjusted R^2 ex. monthly dummy variables	0.1150	0.1136	0.1365	0.0842

The *t*-values inside parenthesis computed from the quasi-maximum likelihood (QLM) heteroskedasticity consistent covariance described by Bollerslev and Woolridge (1992). The routine is available in EVIEWS 3.1. The test statistics for the Jarque-Bera test are $\chi^2(2)$ under the null of ND residuals. The rows for ‘Q(*n*)’ and ‘Qsq(*n*)’ give, respectively, the prob-value for the Ljung-Box statistic for standardised residuals and squared standardised residuals up to *n*th order of serial correlation.

sign for the simple rule was that if the Dow Jones index increases (decreases) by more (less) than 0, 0.5, 1.0, 1.5 or 2.0 per cent then the trading rule says stay long (short) from one to 40 days. We found that none of these 400 different trading rules could beat a long position in Swedish stocks for the whole sample period. An invested krona in Swedish stocks on 1 January 1986 should be worth 11.7 kronor at the end of October 1999. The highest value for a simulated trading rule was lower than staying in a long position; buying Swedish stocks after the Dow Jones index had increased by more than 0 per cent and stayed in that position for 31 days gave a return of 10.6 kronor. To receive this return from the trading strategy, no less than 97 trades had to take place. Our calculations are based on no brokerage fee for trading. Adding a normal brokerage fee for trade will substantially reduce this simulated return. Combining trading rules for long and short positions gave almost no return whatsoever on the Swedish krona invested.

At least one important conclusion can be drawn from the estimates of the mean equation. The Swedish stock market seems to become more and more information efficient, at least in its weak form, if the 1990's are compared with the 1980's. A fall of 0.05 units can be observed if one of the two reported adjusted R^2 is compared for model (3) with (4); the model for the last part of the sample explains less of the variance of daily returns. This is a measure of the increase in market efficiency and this fact should not come as a surprise since the stock market has become economically more and more important. An indicator of this is that the capitalisation ratio for the Swedish stock market rose from 20 to 40 per cent between 1986 and 1992. For the last seven years the ratio has tripled and amounted to some 120 per cent in 1999. At the same time the transparency of the market has probably gradually increased as a consequence of cheaper and cheaper computers and the cheap and free financial information on the Internet and other media. The introduction of E-trading for stocks with very low brokerage during last year and the fast growing demand for mutual funds has further enhanced this development.

The conditional variance equation and seasonal volatility

The estimated α and β parameters in the conditional variance equation indicate a high degree of persistence. The sum of α_1, α_2 and β is equal to one in model (1), indicating an integrated model, and is rather close to one for model (2). There is a distinct significant leverage effect in the first two models – bad news has a greater impact on conditional variance than good news. In the first three models both the dummy variables for weekends and holidays are significant and in the fourth only the dummy for holidays. In model (1) a significant dummy for August is detected which becomes insignificant when the variables for turnover and lagged daily Dow Jones returns are included – see model (2). However, in model (2) the dummy variable for June will have a negative impact. We have also experimented with excluding the lagged daily Dow Jones returns from the variance equation in model (2) – not reported in Table 2. The result was that the turnover variable was still significant at the 5 per cent level, but the dummy variable for June turned insignificant at the same time as the one for August became significant.

When the sample is divided into two parts, the dummy variables for March, May, June and September are significant when the first part of the sample is used, see model (3). These dummy variables have no significant impact for the last part of the sample and even the weekend dummy is not significant– see model (4).[13] Even if some of the monthly dummies turn out to be significant in a model, our earlier reported joint test does not support any impact of the monthly dummy variables.

The Jarque-Bara test indicates that the residuals are not conditionally normally distributed. When the assumption of conditional normality does not hold, the ARCH parameter estimates will still be consistent, but the estimates of the covariance matrix will not be consistent. We have used the method of heteroskedasticity con-

[13] *Estimating models (3)–(4) excluding lagged daily Dow Jones returns in the variance equation does not change the reported results.*

sistent covariance suggested by Bollerslev and Wooldridge (1992) to cope with that problem and to get consistent t-values for the parameters.

The reported prob-value of the Ljung-Box test statistics for standardised residuals and squared standardised residuals are test statistics for the presence of serial correlation for the 5^{th} and 50^{th} order. The test indicates a problem with autocorrelation for standardised residuals for both the 5^{th} and the 50^{th} order in model (3). Generally there is a tendency for autocorrelation at lower orders than 6 or 7 for standardised residuals in the three first models. At higher orders there is no significant autocorrelation and the same is true for model (4) concerning squared standardised residuals for very low orders.

As has been mentioned, Glosten *et al*. (1993) and Hansson and Hördahl (1997) have reported seasonal patterns in the conditional volatility of the US and Swedish stock market, respectively. Both studies use monthly data and for a sample from the beginning of the 1950s to the end of the 1980s the first study reports a significant deterministic seasonal volatility for October. The study of the Swedish market employs data from 1919 to 1992 and reports a positive impact for January and a negative impact for June and December. Comparing our result with Hansson and Hördahl met with difficulties since both the sample periods and data frequencies differ. Our results indicate that the Swedish stock market seems to become more and more information efficient during the last decade and hardly any presence of deterministic seasonal volatility can be detected.

5. *Conclusion – what has been found out, and is it of interest?*

We dare conclude that no distinct and firm deterministic seasonal pattern for the conditional volatility for the Swedish stock market has been detected – the Mark Twain hypothesis cannot be rejected. We found that the daily turnover on the Swedish stock market has an impact on conditional volatility and this variable to some extent eliminates seasonal patterns in the conditional volatility. The daily turnover is a proxy variable used to test the mixture distribution model. According to this model the conditional variance of returns will display a GARCH-pattern of behaviour if the daily number of trades on the stock market is serially correlated. We can also conclude that a feedback exists from the US stock market to the conditional volatility in the Swedish market.

One or two anomalies have also been found. For the models tested for the full sample period both the dummy variables for weekends and holidays have a positive impact on conditional volatility. For the first day after a normal weekend or holiday the model forecasts a higher volatility. One interpretation for this might be that there is a concentration to publish all kinds of bad news on the weekends. The effect on the market will be a lower return and higher volatility for these days.

If only the part of the sample that includes the 1990's is used, the weekend variable is not significant in the variance equation. The same is true for the mean equation, and in this equation even the MA(1) term is insignificant. The important conclusions that can be drawn from these results is that the Swedish stock market seems to become more and more information efficient, at least in its weak form, if the 1990's are compared with the 1980's. These conclusions hold despite the fact that the lagged values of the daily Dow Jones stock returns are included in the mean equation. This latter variable is supposed to capture the effect of non-synchronous trading and does not jeopardise the efficient market hypothesis. To prove the validity of this statement simulations of different trading strategies are conducted and compared with a long position in Swedish stocks. None of the 400 different trading strategies we have employed beat a long position in the stock.

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Appendix

Table. Descriptive statistics for daily stock returns for the Dow Jones industrial average. The full sample starts on 1 January 1986 and ends on 29 October 1999.

	Mean	Max	Min.	Std. Dev.	Skewness	Kurtosis	Obs.
Jan	0.13	4.47	–7.10	1.10	–0.97	9.84	283
Feb	0.13	2.51	–2.47	0.86	0.04	3.56	269
March	0.05	2.80	–3.08	0.87	–0.22	4.27	303
April	0.11	3.16	–4.93	0.97	–0.38	5.82	279
May	0.12	3.75	–2.79	0.90	0.16	4.34	263
June	0.04	2.33	–2.46	0.81	–0.08	3.55	282
July	0.08	2.20	–3.31	0.81	–0.63	4.10	298
August	–0.07	3.06	–6.58	1.01	–1.29	9.80	305
September	–0.02	4.86	–4.72	1.01	0.28	7.51	292
October	–0.02	9.67	–25.65	2.11	–5.90	74.37	308
November	0.06	3.16	–4.11	0.97	–0.78	5.86	264
December	0.12	3.46	–4.00	0.96	–0.05	5.43	252
October '87	–1.20	9.67	–25.65	6.76	–2.03	8.65	22
October ex.'87	0.07	4.60	–7.45	1.16	–1.42	14.69	286
After weekends	0.08	3.46	–25.65	1.50	–9.01	147.88	610
All other days	0.05	9.67	–7.16	0.99	–0.07	10.89	2788
After holidays*	0.25	4.60	–3.17	1.29	0.05	3.67	102
All other days	0.05	9.67	–25.65	1.09	–4.33	102.11	3296
Full sample	0.06	9.67	–25.65	1.10	–4.11	96.86	3398

* Holidays include Christmas, New Year, Easter, Whitsuntide etc.